



Forecasting Turkish electricity consumption: A critical analysis of single and hybrid models

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ABSTRACT

Forecasting of electricity consumption is a critical issue, due to its importance in the planning of the energy trading countries. Several new techniques such as hybrid models are used as well as classical single models to estimate electricity consumption. This study aims to get the best electricity consumption model of Türkiye. For this, the forecasting performances of single and hybrid electricity consumption models, SARIMA is the time series model, ANNs and MLPs are machine learning single models and SARIMA-ANNs and SARIMA-MLPs are hybrid models of machine learning, are compared. This study employs new hybrid models and examines whether the multiplicative model of Wang et al. or the combined model of Khashei and Bijari is superior to than Zhang's hybrid model commonly used as the ARIMA-hybrid model with well known flaws. The results show that hybrid models are more accurate than single time series/machine learning models when forecasting Turkish electricity consumption. Moreover, The Khashei and Bijari hybrid model outperformed the other models and it was determined as the best model for forecasting Türkiye's electricity consumption.

1. Introduction

Electricity consumption is increasing daily as it is utilized in industry, agriculture, and household. While the world's energy resources are rapidly decreasing, estimating the future consumption amount provides an important source of information in making prudential energy policies. For some countries, electricity is a product that is imported and exported. This trade significantly contributes to the sustainability of economies. Accurate forecasts of energy consumption are important parameters in deciding energy import-export agreements. Consumption of energy resources, a popular topic for researchers, is a global problem regarding of the increasing depletion of electrical energy resources.

Electricity consumption series generally have a difficult type of forecasting and predictive modeling problem due to the existence of linear and non-linear patterns. In literature, various methods based on conventional time series models, machine learning methods, and hybrid models have been used to estimate electricity consumption. The common purpose of these methods is to map the linear and/or nonlinear structure of the series and obtain the best estimation results by using this inference. In general, the conventional model approach such as ARIMA gives efficient estimators when the structure of the series is linear and

the model provides some basic assumptions such as autocorrelation and heteroskedasticity. Machine learning techniques, which are commonly used in different disciplines of data analysis are now widely employed for economic and financial data. Although, these techniques are successful in capturing both linear and non-linear structures, the series may not display pure linear or only non-linear structure. For the analysis of this type of series, the hybrid model approach in which the separated components of linear and nonlinear are modeled has been introduced to the literature by Zhang [1]. The Zhang [1] hybrid model, also known as the additive model, joints the linear and nonlinear structure of time series by using additive integration of ARIMA and ANNs models. Wang et al. [2] and Khashei&Bijari [3] developed their models by using multilayer perceptrons (MLPs), a class of artificial neural networks, for the prediction of nonlinear components of time series. Zhang [1] used the MLPs for the nonlinear prediction of his many hybrid model studies in the literature. MLPs are a type of most widely used artificial neural networks for time series prediction and forecasting. The model has trained the conventional back-propagation algorithm in Ref. [4]. It is seen that various specific ANN algorithms are used in the machine learning literature such as forward propagation, resilient back-propagation (Rprop) and globally convergent resilient back-propagation

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(GRprop).

Nomenclature

Symbol	Description	Abbreviation	Description
p	Autoregressive lag length of series	Hybrid-MLPs ^a	Zhang hybrid multilayer perceptrons
d	Order of differencing	Hybrid-MLPsb	Wang et al. hybrid multilayer perceptrons
q	Order of moving average	Hybrid-MLPsc	Khashei and Bijari hybrid multilayer perceptrons
P	Seasonal autoregressive lag length	Hybrid-ANNsa	Zhang hybrid artificial neural networks
D	Order of seasonal differencing	Hybrid-ANNsb	Wang et al. hybrid artificial neural networks
Q	Seasonal order of moving average	Hybrid-ANNsc	Khashei and Bijari hybrid artificial neural networks
s	Season length	GARCH	Generalized autoregressive conditional heteroscedasticity
Φ	Autoregressive parameter	WARCH	Winters with volatility EGARCH model
Θ	Seasonal autoregressive parameter	SEGARCH	Seasonal exponential form of the GARCH
θ	Moving average parameter	FTST	Forecasting, time-series technique
Θ	Seasonal moving average parameter	MNM	Modified Newton's method
Δ^d	Difference operator	RBF	Radial basis function
Δ_s^D	Seasonal difference operator,	GM	Grey model
L	Lag operator	MLR	Multiple linear regression
L^s	Seasonal lag operator	LS	Least squares
ε_t	Error term	SVM	Support vector machines
σ^2	Variance	BPNN	Back-propagation neural networks
Y_t	Univariate time series	SVR	Support vector regression
v	Vector of parameters	PSO	Partical swarm optimization
Ψ	Construction of the network and weights	FOA	Fundamentals of fruit fly optimization algorithm
w	Weights the network parameters as $w=(\alpha,\eta)$	SPSO	Seasonal partical swarm optimization
H	Number of hidden layer units	SFOA	Seasonal fundamentals of fruit fly optimization algorithm
A	Output layer in signal function	NP-GM	Newly priority grey prediction mode
I	Number of input layer units	OICGM	Optimized initial condition grey prediction model
η	Hidden layer in signal function	IRGM	Improved-response grey prediction model
α_0, η_{0i}	Bias terms	ETS	Exponential smoothing state space
f(.)	Activation function	FFNN	Feedforward neural networks
x_i	Input variable	ELM	Extreme learning machine
w_i	Weights corresponding to the input variable	DBN	Deep belief network
b	Bias term in logistic sigmoid function	GP	Gaussian process
e_t	Nonlinear component	DWT	Discrete wavelet transform
y_t	Actual values of the time series	EEMD	Ensemble empirical mode decomposition

(continued on next column)

(continued)

\hat{L}_t	Predicted values of the SARIMA model	MAED	Model for analysis of energy demand
\hat{N}_t	Predicted nonlinear component	LSSVM	Least square support vector machine
Ψ	Nonlinear ANNs function	IMGGM	Improved multivariable grey model
\mathcal{F}	Nonlinear ANNs function	SFOGM	Self-adaptive fractional weighted grey model
C	Constant parameter	GMC	Grey prediction model with convolution integral
T	Trend parameter	FOAGRNN	Generalized regression NN model with fly optimization algorithm
ma1	1st order moving average parameter	MGM	Multivariable grey model
sar1	1st order seasonal autoregressive parameter	SI	Seasonal index
sma1	1st order seasonal moving average parameter	MHW	Multiplicative Holt-Winters
p-value	Probability value	GA	Genetic algorithm
m	Embedding dimension	DGM	Discrete grey model
ϵ	Distance of embedding dimension	CFGM	Conformable fractional grey model
W_λ	Harvey ve Leybourne (2008) test statistic	CFGOM	Conformable fractional grey model in opposite-direction
W^*	Harvey ve Leybourne (2007) test statistic	CNNs	Convolutional neural networks
R2	Coefficient of determination	JS-CNNs	Jellyfish Search convolutional neural networks
Abbreviation	Description	DPSO	Discrete particle swarm optimization
		BPSO	Boolean particle swarm optimization
ARIMA	Autoregressive integrated moving average	MDPSO	Modified discrete particle swarm optimization
SARIMA	Seasonal autoregressive integrated moving average	ADAM	Adaptive momentum estimation
ANNs	Artificial neural networks	RMSProp	Root mean square error probability
MLPs	Multilayer perceptrons	SGDM	Stochastic gradient descent with momentum
Rprop	Resilient backpropagation	RS	Regression with seasonality
Grprop	Globally convergent resilient back-propagation algorithm	ES	Exponential smoothing
RMSE	Root mean square error	LSTM	Long short-term memory
MAE	Mean absolute error	FDGM	Fractional discrete grey model
sMAPE	Symmetric mean absolute percentage error	AFT	ARIMA combined with fourier transform
MASE	Mean absolute scaled error	AWT	ARIMA combined with wavelet transform
ADF	Augmented Dickey Fuller	XGBoost	Extreme gradient boosting
ZA	Zivot-Andrews	CatBoost	Categorical gradient boosting
LM	Lagrange Multiplier	SGM	Seasonal grey forecasting model
ARCH	Autoregressive conditional heteroskedasticity	DSGM	Grey forecasting model based on dynamic seasonal index
BDS	Brock Dechert and Scheinkman	RSGM	Grey forecasting model based on grey correlations seasonal index
DM	Diabold-Mariano		

Table 1

A comparison of current research against previous research on the hybrid model approach for electricity consumption.

Country	Time	Methodology	Conclusion
Taiwan	January 1993 to December 2007 (Monthly) [8]	WARCH, SEGARCH, SEGARCH-ANNs and WARCH-ANNs	WARCH-ANNs Hybrid Model
Malaysia	January 2009–December 2012 (Monthly) [9]	FTST, ANNs, MNM	MNM Hybrid Model
China	January 2011–December 2012 (Monthly) [10]	ARIMA, RBF, ANNs, Hybrid Growth Model(GM)	Hybrid GM
Türkiye	1970–2009 (Annual) [11]	MLR, ANNs, LS-SVM	LS-SVM Hybrid Model
China	January 2010–December 2015 (Monthly) [12]	SARIMA, BPNN, SVR, PSOSVR, FOASVR, SPSOSVR, SFOASVR	SFOASVR Hybrid Model
China	2003–2013 (Annual) [13]	GM, NP-GM, OICGM, IRGM	IRGM Hybrid Model
Türkiye	1970–2014 (Annual) [14]	ANNs, Zhang [1] Hybrid Model	Zhang [1] Hybrid Model
India	April 2004–December 2015 (Monthly) [15]	ETS, SARIMA, Wavelet Based Hybrid	Wavelet Based Hybrid Model
Province of Aceh (Indonesia)	January 2012–March 2017 (Monthly) [16]	Multiplicative SARIMA, Subset ARIMA, Feedforward Neural Networks (FFNN), ARIMA-FFNN, Multiplicative SARIMA-FFNN, Subset ARIMA-FFNN	ARIMA-FFNN and SARIMA-FFNN Hybrid Models
East Java (Indonesia)	January 2010–December 2016 (Monthly) [17]	ARIMA, ANNs, ARIMA-ANNs	ARIMA-ANNs Hybrid Model
California (USA)	January 2010–December 2010; April 2009–October 2011 (daily and weekly) [18]	Hybrid Deep Belief Network (DBN), Back Propagation NN, Generalized Radial Basis Function NN, ELM, SVR.	DBN Hybrid Model
Thailand	January 2005–December 2013 (Monthly) [19]	SARIMA -ANNs and SARIMA- GP (with Combine Kernel Functions)	SARIMA-GP Hybrid Model
Thailand	1993–2015 (Annual) [20]	ARIMA, ANNs, ARIMA-ANNs	ARIMA-ANNs Hybrid Model
Punjab	January 2013–December 2017 (Monthly) [21]	ARIMA-DWT(Discrete Wavelet Transform)	ARIMA-DWT Hybrid Model
Most Regions from the World	1949–2017 (Annual) [22]	ARIMA, Linear Regression, Hybrid ARIMA	Hybrid ARIMA
Taiwan	1965–2014 (Annual) [23]	ARIMA, ARIMA-SVR, ARIMA-GA-SVR, EEMD-ARIMA, EEMD-ARIMA-SVR, EEMD-ARIMA-GD-SVR	EEMD-ARIMA-GA-SVR Hybrid Model
China	1999–2018 (Annual) [24]	IMG, SFOGM, GMC, FOAGRNN, MGM	MGM
China	January 2010–December 2018 (Monthly) [25]	SI model, MHW-default, FOASVR, GASVR GA-MHW, FOA-MHW	FOA-MHW
China	1999–2016 (Annual) [26]	GM, DGM, CFGM, CFGOM	CFGOM
Türkiye	2007–2017 (Annual) [27]	MAED, ARIMA-LSSVM	ARIMA-LSSVM Hybrid Model
Taiwan	2013–2019 (Annual) [28]	CNNs Based Models	Hybrid JS-CNNs
U.S. and China	January 2005–September 2019 (Monthly) [29]	SVR, DPSO, BPPO, GA, MDPSO, BPNN, Holt-Winter, MDPSO-SVR, MDPSO-BPNN	MDPSO-SVR
Türkiye	January 2005–November 2018(Monthly) [30]	ADAM, RMSProp, SGDM	RMSProp
Brazil Regions	2002–2020 (Annual) [31]	RS, ES, ARIMA, RS + ES + ARIMA, ARIMA + RS, RS + ES	RS, RS + ES
Türkiye	1975–2021(Annual) [32]	SARIMA, LSTM-NN	LSTM-NN
China (Jiangsu)	2010–2020(Annual) [33]	GM, FDGM, Holt ES	GM
Ukraine	2013–2020 (Hourly) [34]	LM, LM-ARIMA, LM-LSTM, LM-ARIMA-LSTM	ARIMA-LSTM
Algeria	1980–2021(Annual) [35]	ARIMA, GM	GM
Brazil	January 1st of 1999–December 31st of 2019 (Daily) [36]	RS, ES, ARIMA, RS-ES, AFT, AWT, ANN	AWT
Türkiye	January 1990–December 2010 (Monthly) [37]	XGBoost-Based Hybrid Models, CatBoost-Based Hybrid Models	XGBoost-SSA
China	2010–2016(Quarterly) [38]	GM, SGM, DSGM, RSGM	FDSGM

In the study, we examine the forecasting performance of both single and hybrid methods in forecasting electricity consumption. The difference of this study from the earlier studies in the field of electricity consumption estimation is that it uses the Khashei&Bijari [3] and multiplicative Wang et al. [2] hybrid models developed recently in the study and it is the first study to examine whether these hybrid models are more successful than the additive Zhang [1] approach. When the structure of the series is uncertain and the linear and nonlinear patterns are not completely separated, model selection is difficult. To overcome these problems, we investigated whether a new hybrid model proposed by Khashei and Bijari [3] could capture linear and nonlinear autocorrelation structures in time series data sets more than traditional hybrid models.

After training data, the model results are compared by RMSE, MAE, sMAPE, MASE and R^2 error-based criteria and Diebold-Mariano [5] and Modified Diebold-Mariano test proposed by Ref. [6]. If hybrid models were more accurate, we revealed which hybrid model was more successful: The additive model of Zhang [1], the multiplicative model of Wang et al. [2], or the combined model of Khashei&Bijari [3]. We compared the MLPs models that utilized the conventional back-propagation algorithm versus ANNs models that utilized a modified GRprop algorithm proposed by Ref. [7].

Electricity is produced using limited natural resources. Therefore, it is considered necessary to forecast the amount of electricity consumption in the future to plan the use of current limited natural resources. The main purpose of this study is to use the weekly electricity consumption dataset and determine the most accurate prediction model for forecasting electricity consumption in Türkiye. It is the first study to examine whether new hybrid models, Khashei&Bijari [3] and Wang et al. [2], are more accurate than the Zhang [1] approach and also than single models for forecasting electricity consumption. The findings of the study show that using hybrid models in the forecasting of Türkiye's electricity consumption is better than single time series models or single machine learning models. In particular, Khashei&Bijari [3] hybrid model is found that it has the best forecasting performance in the study.

In the last two decades, a different type of hybrid model has been used in electricity consumption forecasting. The researchers combined different time series models with various machine learning methods to get accurate results in their hybrid model studies. These studies are summarized in Table 1.

It can be seen from Table 1 that many studies dealing with electricity consumption have found that using hybrid models for forecasting gives better estimates than single time series models or single machine learning models. In the studies conducted in the field of electricity

Table 2
Single models functions.

Model	Function
SARIMA	$\Phi(L^s)\theta(L)\Delta^d\Delta_s^D y_t = \theta_0 + \Theta(L^s)\theta(L)\epsilon_t$
ANNs	$Y_t = \psi(Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}, v) + v_t$
MLPs	$F(Y, w) = \alpha_0 + \sum_{h=1}^H \alpha_h f\left(\eta_{0h} + \sum_{i=1}^L \eta_{hi} y_i\right) + \epsilon_t$
Signal Function	$f(x) = w_1(x_1) + \dots + w_n(x_n) + b, i=1, \dots, n$
Logistic Sigmoid Function	$f(s) = F(w_1 x_1 + \dots + w_n x_n + b) = F\left(b + \sum_{i=1}^n w_i x_i\right) = (1 + e^{-s})^{-1}$

consumption estimation, it is seen that the hybrid model approach suggested by Zhang [1] is mostly used.

Zhang [1] hybrid model assumption is that the relationship between the linear and non-linear components is additive. Nevertheless, this relationship may be multiplicative. Also, there is no guarantee that the residuals of the linear component may comprise pure non-linear patterns [39]. We apply the Zhang [1], Wang et al. [2], and Khashei&Bijari [3] hybrid models combining the linear SARIMA and the nonlinear ANNs and MLPs models. SARIMA-ANNs and SARIMA-MLPs hybrid models, are formed by combining the econometric method and machine learning methods. The difference of this study from the earlier studies in the field of electricity consumption estimation is that it uses the Wang et al. [2], and Khashei&Bijari [3] hybrid models developed recently in the study and it is the first study to examine whether these new hybrid models are more successful than the Zhang [1] approach and also than single models. In both Wang et al. [2] and Zhang [1] hybrid model approaches, the separate linear and nonlinear patterns of a time series are modeled separately. When the structure of the series is uncertain and the linear and nonlinear patterns are not completely separated, model selection is difficult. To overcome these problems, a novel hybrid model was proposed by Khashei and Bijari [3] can capture the linear and nonlinear autocorrelation structures in time series datasets more and better than conventional hybrid models. Since seasonal variations in electricity consumption series during the analyzed period, we use the SARIMA which is the time series model as a single model. Besides the SARIMA model, the ANNs and MLPs that are machine learning methods are also used as single models in the study. A detailed examination is made between the models and the important contributions of this study to the literature are summarized below.

1. To examine the structure of Türkiye's weekly electricity consumption series, we applied series [40,41] nonlinearity tests. Considering the non-linear structure of Türkiye's weekly electricity consumption series, using the single SARIMA model, one of the classical linear time series models, is not functional to improve the accuracy.
2. To determine which model is best suited for forecasting, a comprehensive comparison is made between the classical linear model (SARIMA), machine learning models (ANNs, MLPs) and three types of hybrid models. The traditional Zhang [1] and Wang et al. [3] hybrid models are used in different approaches, considering the linear and non-linear structure of the series separately. Unlike the studies in the literature [14,17,19,20,22], subcomponents in a time series may not be fully separated. Under this assumption, the Khashei&Bijari [3] hybrid model is used, and it is found to be an effective method in reducing the prediction error of the Turkish electricity consumption model.
3. To evaluate the forecast accuracy of electricity consumption models, in addition to the hybrid models are created with ANNs, hybrid models created with MLPs, which [4] specifically developed for time series. ANNs hybrid models have superior prediction performance to other models thanks to the GRprop algorithm [7] used, which utilizes the smallest absolute gradient (sag) and changes the learning rate.

4. The non-linear Turkish electricity consumption series may be completely nonlinear, decomposable nonlinear, or a nonlinear structure that cannot be fully decomposed. To model these three possible patterns; predictions are made with ANNs and MLPs used in completely nonlinear series, Zhang [1] and Wang et al. [3] hybrid models for decomposable (linearity-nonlinearity), and Khashei&Bijari [3] hybrid models for the structure that cannot be completely decomposed. ANNs Hybrid models running with the GRprop algorithm of [7], have been created and applied to obtain more accurate forecasting performance.

Following the introduction of the study, Section 2 gives information about ANNs and hybrid model methodology with performance comparison criteria and methodology of the tests. Section 3 describes the dataset. Section 4 displays the empirical findings of the single and hybrid models utilized. Section 5 presents a discussion. Finally, section 6 provides the conclusion of the study.

2. Methodology

In the study, we focus on the SARIMA model and two different machine learning methods, including the ANNs and MLPs. We also employed the three hybrid model approaches proposed by Zhang [1], Wang et al. [2] and Khashei&Bijari [3], respectively.

2.1. Single models

The multiplicative form of the SARIMA model is SARIMA(p,d,q)(P, D, Q)_s. Here p is the autoregressive lag length of the series, d is the order of differencing to make stationary series of degree d, q is the order of moving average, P is the seasonal autoregressive lag length of series, D is the order of seasonal differencing, Q is the seasonal order of moving average and s is the season length. The SARIMA model fitting process consists of four iterative steps: (i) identification of the SARIMA model structure, (ii) prediction of the coefficients, and (iii) performing diagnostic tests to residuals of the estimated model to select the best-fit model, (iv) out-of-sample forecasting [42].

Artificial neural networks are data-driven nonparametric models and have fewer prior assumptions than parametric models [43]. The ANNs have superior generalization capabilities. Indeed, ANNs can be robust and accurate in a nonstationary series whose characteristics may change over time. The fitting of the data with ANNs is made up of three basic steps: (i) determination of network construction, (ii) learning, and (iii) validation. The neural networks consist of an input layer, hidden layer (s), and output layer(s). The layers connect with synapsis which affects the output utilizing weights on them. Each layer has neurons that process the input signals received from the previous layer using activation functions and transfer them to the next layer. In our study, we tried the logistic sigmoid activation function for all ANNs and Hybrid ANNs models. The logistic sigmoid function is an S-shaped, nonlinear, monotonic function in the range (0,1) [44]. The signal function is defined as a linear combination of variables and weights.

The multilayer perceptron is a type of feedforward Artificial Neural Network with an input layer, one or more hidden layer(s) with their nonlinear activation functions, and an output layer utilizing a linear transfer function. In this study, we used the MLPs methodology of [4] that defines time series components, creates explanatory variables, and determines multilayer perceptrons for heterogeneous sets of time series by itself. Conventional multilayer feedforward algorithm with continuous, bounded and nonconstant activation functions can be approximate to actual values (y_i) well, if many hidden units are sufficient [45]. For this reason, the training data is optimized by conventional feedforward algorithm in Ref. [4] MLP approach. The functions list of SARIMA, ANNs and MLPs single models is represented in Table 2.

Table 3
Hybrid models functions.

Model	Nonlinear component	Nonlinear prediction function	Combined prediction function
Zhang [1]	$e_t = y_t - \hat{L}_t$	$\hat{e}_t = \hat{\Psi}(e_{t-1}, e_{t-2}, \dots, e_{t-N}) + \omega$	$\hat{y}_t = \hat{L}_t + \hat{N}_t$
Wang et al. [2]	$r_t = \frac{y_t}{\hat{L}_t}$	$\hat{r}_t = \hat{\Psi}(r_{t-1}, r_{t-2}, \dots, r_{t-N}) + \omega$	$\hat{y}_t = \hat{L}_t * \hat{N}_t$
Khashei&Bijari [3]	$e_t = y_t - \hat{L}_t$	$N_t^1 = \mathcal{F}^1(e_{t-1}, e_{t-2}, \dots, e_{t-p})$ $N_t^2 = \mathcal{F}^2(y_{t-1}, y_{t-2}, \dots, y_{t-j})$ $N_t = \mathcal{F}^3(N_t^1, N_t^2)$	$\hat{y}_t = \mathcal{F}(e_{t-1}, e_{t-2}, \dots, e_{t-p}; \hat{L}_t, y_{t-1}, y_{t-2}, \dots, y_{t-j})$

Table 4
Unit root tests.

Test	Test -statistics	critical value(%1)	critical value(%5)	Critical value(%10)	
ADF(C)	y_t	-1.77051	-3.45	-2.87	-2.57
ADF(C)	Δy_t	-8.58217***			
ADF (C, T)	y_t	-7.27804***	-3.99	-3.42	-3.13
ADF (C, T)	Δy_t	-8.57308***			
ZA (Break in C)	y_t	-1.3195	-5.34	-4.8	-4.58
ZA (Break in C)	Δy_t	-8.12330***			
ZA (Break in T)	y_t	-2.1277	-4.93	-4.42	-4.11
ZA (Break in T)	Δy_t	-7.53650***			

(i)The unit root null hypothesis is the non-stationary against the alternative.
(ii) (***) means that the probability values are lower that 5 %.

2.2. Hybrid models

(S)ARIMA model construction can capture the only linear pattern of the time series. If the linear and nonlinear patterns are separable, the residuals of the (S)ARIMA model involves the nonlinear part of the time series. It is very important to check the linear and nonlinear structure of the residuals. If linear structure is still observed in residuals after (S)ARIMA modeling, (S)ARIMA model will not be sufficient. To capture the nonlinear and potential linear patterns in the residuals and the original data, nonlinear modeling is employed. In this case, the hybrid model approach is often used to analyze the different types of separable data construction. In the study, we focus on three hybrid models which are called Zhang [1] hybrid model, Khashei&Bijari [3] hybrid model and Wang et al. [2] hybrid model which are summarized in Table 3. In the Zhang [1] hybrid model, the linear subcomponent is estimated using linear estimation methods such as ARIMA or SARIMA, the nonlinear subcomponent is estimated using machine learning methods such as ANNs and then the two estimated values are added up.

In the Wang et al. [2] hybrid model, similar to the Zhang [1] hybrid model, the linear subcomponent is estimated using linear estimation methods such as ARIMA or SARIMA. After the prediction of the linear component \hat{L}_t , by contrast to the Zhang [1] hybrid model, a ratio of the y_t and \hat{L}_t is represented to the nonlinear part of the time series:

In the traditional hybrid approach, the relationship between the linear and nonlinear components may not be additive and this misunderstanding may cause a poor relationship between the components and degrade performance if there is a different type of relationship except for additive or multiplicative between the linear and nonlinear elements. Also, the residuals of the linear component may contain nonlinear patterns and this inverse pattern assumption may lead to misleading results [3]. The Khashei&Bijari [3] hybrid model approach is quite different than the traditional hybrid model approaches. According to this approach, a time series is considered a function of both linear and nonlinear components. In the first step, the SARIMA method is performed to the series, and predicted values of SARIMA and model residuals are decomposed. Finally, the linear and nonlinear structures that are assumed to be decomposed are reused in the ANNs model. Therefore, the Khashei&Bijari [3] hybrid model can be a solution to capture the linear and nonlinear autocorrelation structures of series better than the hybrid model approaches of both Zhang [1] and Wang et al. [2], if the linear and nonlinear subcomponents are not separable.

3. Data

The electricity consumption (ktoe) series has been obtained from the weekly statistical bulletins of the Republic of Türkiye Ministry of Energy and Naturel Resources website [46] for the period from the June 3, 2013 to the March 1, 2020. The R program was used in our analysis. The data pre-processing was applied to the daily dataset on the site and the daily dataset was converted to a weekly dataset (W represents weekly data). The 2014:W38, 2016:W3, and 2017:W21 missing data points were estimated by interpolation techniques. We applied a logarithmic transformation to the series for scaling. To investigate the non-stationarity problem, which is frequently observed in time series, ADF [47] unit root test and ZA [48] unit root test with one structural break were applied to the series and the results are shown in Table 4.

Results of the ADF [47] and ZA [48] tests given in Table 4 show that for the ADF [47] test with intercept and ZA tests with break in intercept and slope, the series has a unit root at a level as they are not more negative than table values at 1 %, 5 %, and 10 % significance levels. Electricity series is not found stationary at level. After the application of unit root tests to the series and determining that it is not stationary at

Table 5
Training and test data.

Dataset	SARIMA	ANNs models
Training Data	2013:W22-2018:W42	2013:W28-2018:W42
Test Data	2018:W43-2020:W08	2018:W43-2020:W08
All Data	2013:W28-2020:W08	2013:W28-2020:W08

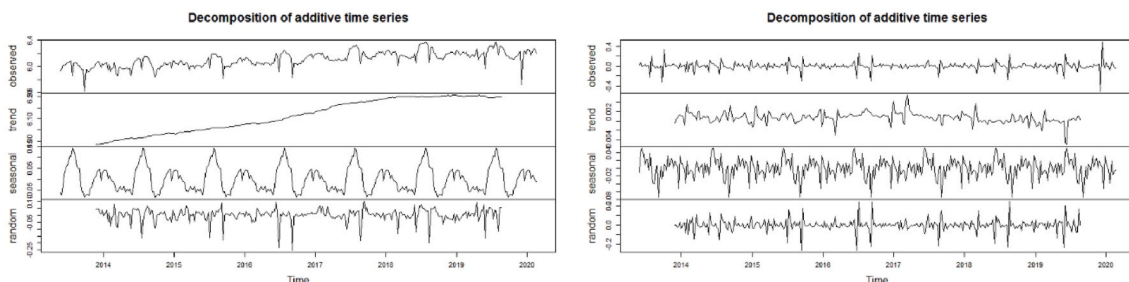


Fig. 1. Decomposition of the electricity series.

Table 6
SARIMA coefficients and nonlinearity tests.

	Constant	ma1	sar1	sma1
Estimate	-0.9446***	-0.6526***	0.8570***	-0.6916***
Standart Error	0.00163	0.0963	0.142	0.2101
Breusch-Godfrey Serial Correlation Test				12.41 (p-value = 0.26)
Engle's LM-ARCH Test				0.50652 (p-value = 0.48)
Jarque-Bera Normality Tests				1072.5 (p-value = 0.00)
BDS and Harvey-Leybourne Nonlinearity Tests of The SARIMA Model Residuals				
m	$\epsilon = 0.0274$	$\epsilon = 0.0549$	$\epsilon = 0.0823$	$\epsilon = 0.1098$
2	9.9451(0.00)	7.5237(0.00)	3.8732(0.00)	1.1505(0.25)
3	10.8277(0.00)	8.0752(0.00)	4.1868(0.00)	1.1670(0.24)
4	11.2027(0.00)	7.7882(0.00)	3.8933(0.00)	0.8881(0.37)
5	12.3200(0.00)	7.4024(0.00)	3.4514(0.00)	0.5409(0.59)
	W_i	$W_{\%10}$	$W_{\%5}$	$W_{\%1}$
	24.86***	16.51***	16.78***	17.26***

- (i) (***) refers the statistic is significant at the 1 % level.
- (ii) The null hypothesis of no serial correlation is not rejected (BG-LM statistic value = 12.41, p-value = 0.26).
- (iii) The LM-ARCH heteroskedasticity test satisfying the null hypothesis that the ARCH effect does not exist is performed on the residuals (LM-statistics = 0.506652, p-value = 0.48).
- (iv) The null hypothesis of the normal distribution of the JB Test is rejected (JB = 1072.5, p-value = 0.00).
- (v) Critical values of Harvey et al. [41] test for 1 %, 5 % and 10 % are 9.21, 5.99 and 4.60, respectively.
- (vi) Critical values of Harvey and Leybourne [40] test for 1 %, 5 % and 10 % are 13.27, 9.48 and 7.77, respectively.

level, the series is first differenced to eliminate the non-stationary problem. This is confirmed by the ADF [47] test [τ -value = -7.27804, p-value = 0.00] and ZA [48] tests [$t_{\text{intercept}} = 8.1233$, p-value = 0.00; $t_{\text{trend}} = -7.5465$, p-value = 0.00]. The decomposition graphs of the non-stationary and the stationary series are given in Fig. 1.

It is seen in Fig. 1, that the deterministic seasonal and trend effects of the non-stationary series are disappeared, after first differencing. Following the stationarity process, we split the dataset into the test and training parts at a ratio of 80:20. The training dataset with 281 data points is used to fit the SARIMA. Because we are using the 6-lagged dataset, the training set with 275 data points are used to fit the ANNs and Hybrid ANNs, models. The test dataset consist of 70 data points that are used the comparison of the out-of-sample forecasting accuracies of the predicted models. The periods of the training and test datasets are shown in Table 5.

Table 7
RMSE comparison criteria by different number of repetition of single and hybrid methods.

Number of Repetation	MLPs	ANNs	Hybrid MLPs ^a	Hybrid MLPs ^b	Hybrid MLPs ^c	Hybrid ANNs ^a	Hybrid ANNs ^b	Hybrid ANNs ^c
5	0.1037683	0.00674	0.08253	0.091683	0.10395	0.00762	0.00888	0.00821
10	0.1037662	0.00696	0.08247	0.091685	0.01046	0.00642	0.00888	0.00655
15	0.1037666	0.00673	0.08247	0.091685	0.10477	0.00629	0.00890	0.00641
20	0.1037663	0.00638	0.08246	0.091682	0.10509	0.00575	0.00887	0.00726
25	0.1037667	0.00665	0.08247	0.091681	0.10462	0.00605	0.00889	0.00627

- (i) a, b, c represent the Zhang [1], Wang et al. [2] and Khashei&Bijari [3] Hybrid models, respectively.

(ii) $RMSE = \sqrt{\frac{\sum_{t=1}^n (y_t - \hat{y}_t)^2}{n}}$.

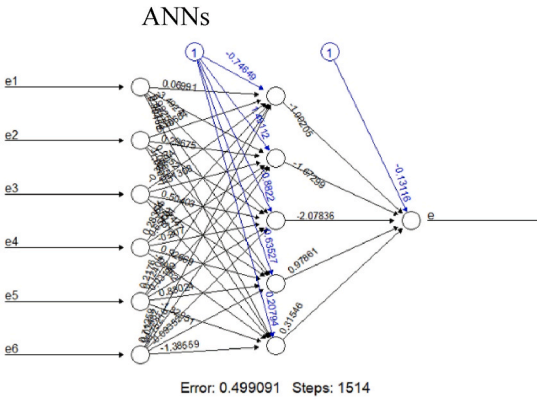
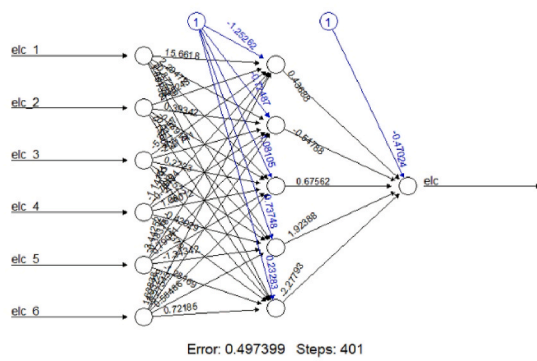
4. Results

The SARIMA(p,d,q) (P,D,Q) method is used in the short term forecasting of stationary electricity time series. To predict the proper (p,d,q) and (P,D,Q) parameters of the model, the Box-Jenkins [49,50] transformation was applied to series. A set of candidate models are predicted using various SARIMA parameters and the best SARIMA model conformed to the regression assumptions is chosen using AIC criteria. The model with the lowest AIC values [-2.54584] is selected as SARIMA (0, 0,1) (1,0,1) (52). The SARIMA (0,0,1) (1,0,1) (52) satisfies the autocorrelation and heteroscedasticity assumptions and having significant coefficients is selected as the best model. We perform the Breusch-Godfrey Serial Correlation Test [51,52] to investigate autocorrelation, Engle's LM-ARCH Test [53] to examine the ARCH effect in the residuals, and the Jarque-Bera (JB) [54] Test to search whether the distribution of the residuals conforms to normal distribution. After estimating the SARIMA model, we also apply Brock, Dechert, and Scheinkman and LeBaron (BDS) [55,56] Test and Harvey-Leybourne [40], Harvey et al. [41] nonlinearity tests to detect the existence of non-linearities of the residuals. This is important because a failure to recognize the non-linearity of a time series can often lead to poor parameter estimates [57]. The results of the best model and the nonlinearity tests are shown in Table 6.

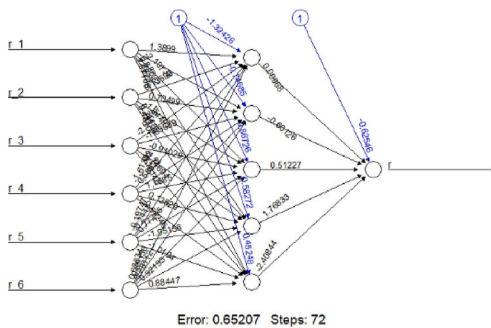
In Table 6, the statistics of the BDS test for different embedding dimensions (m) and within a distance (ϵ) of each other. It is obtained from the BDS test results, we can reject the null hypothesis that the data is independently and identically distributed (i.i.d) in three distance values (0.0274, 0.0549, 0.0823). It means that nonlinearity as well as chaotic dependence exist in the residuals.

In Table 6 displays the test statistics of [40,41]. Based on the test results, the null hypothesis that the data is linear is rejected. So, the test result proves the hypothesis that the distribution of the residuals of the SARIMA model is nonlinear. Nevertheless, according to the BDS test results, the for ($\epsilon = 0.1098$) and 4 dimensions (m = 2,3,4,5) null hypothesis can not be rejected. It could mean that the linear and nonlinear components may have not been separated and there may be still linearity in the residuals. Therefore, In addition to the ANNs, different types of SARIMA-ANNs hybrid methods were applied to the data.

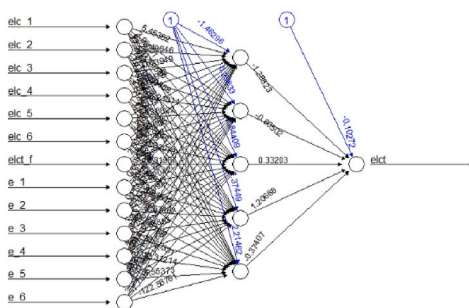
The commonly used ANNs algorithm is back-propagation, one of the various ANNs algorithms in the literature, but it has difficulties selecting the controlling hyperparameters, layer size, learning rate, and momentum [58]. Because of this reason, in our study, we have used the GRprop algorithm [7] that utilizes the smallest absolute gradient (sag) and changes the learning rate. The logistic sigmoid function was used as the activation function for ANNs, Zhang [1] hybrid ANNs, Wang et al. [2] hybrid ANNs, and Khashei&Bijari [3] hybrid ANNs models. Because the nonlinear logistic sigmoid function restricts the model to the input values between 0 and 1, the ANNs have trouble modeling the trended time series [39]. suggest that the utilization of the stationary time series is a solution to this problem. In this study, we employed six lagged stationary electricity series as input variables of the ANNs model. In addition, We used six lagged residuals of the SARIMA for Zhang [1]



SARIMA-ANN^a



SARIMA-ANN^b



SARIMA-ANN^c

Fig. 2. Diagrams of single and hybrid ANNs algorithms.

hybrid model, six lagged ratio of the SARIMA model residuals and the electricity series for the Wang et al. [2] hybrid model and predicted SARIMA model values, all of the six lagged electricity series and six lagged SARIMA residuals for Khashei&Bijari [3] model as input variables. To obtain the optimum number of repetitions hyperparameters (Rep), the out-of-sample error-based forecasting criteria of different numbers of repetitions are compared for the ANNs and the three hybrids ANNs and hybrid ANNs models. The error-based RMSE results are represented in Table 7.

There are various methods for the detection of the number of neurons in hidden layer (HN). In practice, HN can be calculated using three different rules. First, the HN must be between the size of the input and the size of the output layers. Second, the HN must be less than double the size of the input layer. Third, HN must be equal to $2/3 \times ((\text{size of input layer}) + (\text{size of output layer}))$ [59]. Based on these three rules, the number of neurons is calculated as 5. The threshold is the stopping criterion of the ANNs algorithm and the value of the lowest bound for the partial derivatives of the error function. Fig. 2 shows the GRprop algorithm diagrams of the single and three hybrid ANNs models,

In the single ANNs, the algorithm reached the minimum threshold value of (0.01018) at an error of (0.497399) and the number of steps was 10. The algorithm of the Zhang [1] Hybrid ANNs reached the minimum threshold value of (0.02088) at an error of (0.586695) and the number of steps was 10. In the Wang et al. [2] Hybrid ANNs, the algorithm reached the minimum threshold value of (0.011191) at an error of (0.64344) and the number of steps was 2462. The algorithm of the Khashei&Bijari [3] Hybrid ANNs reached the minimum threshold value of (0.010049) at an error of (0.28541) and the number of steps was 13281.

After training data, the model results are compared by RMSE, MAE, sMAPE, MASE and R^2 error-based criteria. We also applied DM [5] and modified DM test proposed by Ref. [6] to compare the models. If the hybrid model is more accurate, we have revealed which hybrid model was more successful: The additive model of Zhang [1], the multiplicative model of Wang et al. [2], or the combined model of Khashei&Bijari [3]. We compared the MLPs models that utilized the conventional backpropagation algorithm versus ANNs models that utilized a modified GRprop algorithm proposed by Ref. [7].

According to Table 8, the findings indicate that the Mean absolute scaled error (MASE) of the Hybrid-ANNs^a model is 50.429 %, which is slightly less than the Hybrid-ANNs^c's 50.940 % in the test sample. Although the results are close to each other, in general, they revealed that the Hybrid-ANNs^c model outperformed the other models with the lowest RMSE (0.0792), MAE (0.04463), sMAPE (1.24124), and the highest R^2 (0.42) values in test data. The predictive ability of training sample RMSE = 0.0539, MAE = 0.03285, sMAPE = 1.17621, MASE = 0.47010 and $R^2 = 0.46$ showed that the Khashei&Bijari [3] Hybrid model (Hybrid-ANNs^c) model is also superior to other models for forecasting the electricity consumption in Türkiye.

We can suggest that not only for the within-sample period but also for the out-of-sample, the Khashei&Bijari [3] model outperforms to capture the linear and nonlinear patterns of the electricity series. The out of sample forecasting of the models is also given in Fig. 3. In Fig. 3, the line and dotted dash represent the real values and fitted values of the electricity consumption, respectively.

The use of the ANNs, Zhang [1] Hybrid ANNs and Khashei&Bijari [3] Hybrid ANNs methods to forecast electricity consumption of Türkiye significantly increases the predictions and forecasting accuracy compared to the SARIMA Single Method. It has been concluded that the Khashei&Bijari [3] Hybrid ANNs method has superior performance to the SARIMA and the other Hybrid methods in out-of-sample forecasting.

We also applied the DM [5] and Modified DM test proposed by Ref. [6] to out-of-sample forecasting errors to determine whether the prediction accuracies are significantly different. DM [5] test concentrates on prediction accuracy and compares and measures the prediction performance of the hybrid models with other types of models [60]. The

Table 8
Forecasting comparisons.

Method	Training Sample					Test Sample				
	RMSE	MAE	sMAPE	MASE	R ²	RMSE	MAE	sMAPE	MASE	R ²
ARIMA(0,0,1)(1,0,1) [54]	0.0648	0.04212	1.36595	0.60974	0.21	0.08231	0.05232	1.36677	0.59717	0.37
MLPs	0.0734	0.04256	1.90570	0.60913	0.0005	0.10377	0.0538	1.92751	0.61403	0.0012
ANNs	0.0632	0.04048	1.47811	0.52924	0.26	0.07988	0.04651	1.32770	0.53076	0.407
Hybrid-MLPs ^a	0.0643	0.04169	1.34064	0.59662	0.23	0.08246	0.05162	1.33803	0.58917	0.37
Hybrid-MLPs ^b	0.0672	0.04081	1.52737	0.58403	0.16	0.09168	0.05126	1.84860	0.58506	0.22
Hybrid-MLPs ^c	0.0727	0.04245	1.54394	0.60749	0.0209	0.10396	0.05264	1.36978	0.60083	0.0047
Hybrid-ANNs ^a	0.0652	0.04178	1.35302	0.55172	0.21	0.08215	0.05147	1.30164	0.50429	0.37
Hybrid-ANNs ^b	0.0685	0.04094	1.57447	0.58585	0.13	0.09411	0.05175	1.61783	0.59060	0.18
Hybrid-ANNs ^c	0.0539	0.03285	1.17621	0.47010	0.46	0.0792	0.04463	1.24124	0.50940	0.42
#of Obs						282				
Total Obs						351				
% of Total Obs						80 %				

(i) a, b, c represent the Zhang [1], Wang et al. [2] and Khashei&Bijari [3] Hybrid models, respectively.

$$(ii) RMSE = \sqrt{\frac{\sum_{t=1}^n (y_t - \hat{y}_t)^2}{n}}, MAE = \frac{\sum_{t=1}^n |y_t - \hat{y}_t|}{n}, sMAPE = \frac{1}{2} \sum_{t=1}^n \frac{|y_t - \hat{y}_t|}{(|y_t| + |\hat{y}_t|)/2}, MASE = mean \left(\left(\frac{e_t}{\left(\frac{1}{T-1} \right) \sum_{t=2}^T |y_t - y_{t-1}|} \right) \right), R^2 = \frac{\sum_{t=1}^n (\hat{y}_t - \bar{y}_t)^2}{\sum_{t=1}^n (y_t - \bar{y}_t)^2}.$$

results of the Diebold-Mariano [5] two-sided and Modified Diebold-Mariano tests are represented in Table 9 and Table 10, respectively.

In Table 9, the null hypothesis means of the two-sided Diebold-Mariano [5] test that the observed differences between the performances of two predicted models using the test data are not significant while the alternative hypothesis means that the observed differences between the performances of two predicted models are significant. The Diebold-Mariano [5] test statistics are compared with $t_{\alpha/2, 0.05}$ at $df = 70$ and the 5 % significance level. According to the results in Table 9, there are significant differences between the out-of-sample prediction accuracy of the SARIMA-ANNs [1.6466, $p = 0.10$], SARIMA-Zhang [1] Hybrid ANNs [1.7325, $p = 0.09$] and SARIMA-Khashei&Bijari [3] Hybrid ANNs models [1.7982, $p = 0.08$].

In Table 10, we compared the models that reject the null hypothesis of the Diebold-Mariano [5] test. This test performs the modified DM test of [6]. The null hypothesis is that these methods have the same forecast accuracy against the alternative hypothesis is that Model 2 more accurate than Model 1. According to the test results displayed in Table 10, the ANNs, Hybrid-ANNs [1], Hybrid-ANNs [3] models are more accurate than SARIMA method [1.6466, $p = 0.05$; 1.7325, $p = 0.04$; 1.7982, $p = 0.04$].

5. Discussion

In the current research, Turkish weekly electricity consumption forecasting was carried out using 9 different methods, namely SARIMA and MLPs, ANNs, Hybrid MLPs Zhang [1], Hybrid MLPs Wang et al. [2], Hybrid MLPs Khashei&Bijari [3], Hybrid ANNs Zhang [1], Hybrid ANNs Wang et al. [2] and Hybrid ANNs Khashei&Bijari [3] models, respectively. Time series forecasting is a univariate modeling exercise that uses historical information for the modeled variable. The methods used in this modeling take into account the situations in which the series has a nonlinear distribution. It can be said that these models are data-oriented: While ARIMA is a favorable method for linear time series, ANN and MLP and their hybrid models can be applicable in modeling nonlinear time series.

Generally, additive and multiplicative hybrid models are preferred in time series modeling in Literature. However, these models are only applicable provided that linear and nonlinear structures can be separated in the series. In cases that cannot be completely separated, using the Khashei&Bijari [3] hybrid model will increase accuracy by reducing prediction errors.

Back-propagation, a commonly used ANNs algorithm is one of the

various ANNs algorithms in the literature, but has difficulties selecting the controlling hyperparameters, layer size, learning rate, and momentum [58]. Because of this inability, the GRprop algorithm [7] that utilizes the smallest absolute gradient (sag) and changes the learning rate may be a solution. Using GRprop in ANN Hybrid models can be effective in increasing model performance (Fig. 2).

Türkiye's weekly electricity consumption series is non-linear (Table 6). It cannot be determined whether the linear and nonlinear structure can be separated. When comparing models that examine both structures with different approaches, the Khashei&Bijari [3] Hybrid ANN model utilizing the GRprop algorithm has superior performance in predicting the Turkish electricity consumption.

6. Conclusions

Since electricity consumption is effective information for the application of rational energy policies, it is very important to obtain accurate estimates. Thus, in this study, The ARIMA, ANNs, and MLPs single methods and the three types of ARIMA-ANNs, and three types of ARIMA-MLPs hybrid models were implemented to the electricity consumption series of Türkiye and then the prediction and forecasting performances of these models were compared by using RMSE, MAE, sMAPE, MASE and R² criteria and two types of Diebold-Mariano [5] test. The experimental results show:

The combined hybrid model of Khashei&Bijari [3] SARIMA-ANNs was found the most successful model in both prediction and forecasting accuracy. In this case, where the linear and non-linear structures are inseparable, it has shown a more successful performance than traditional hybrid models thanks to its capability to capture both patterns. Also, it is concluded that the relationship between linear and nonlinear subcomponents is not multiplicative or additive.

Each model calculated with ANNs was compared with the computed with its corresponding MLPs. The comparison criteria were found very close to each other for in-sample performance. According to the out-of-sample comparison criteria, the GRprop algorithm [7] used in ANNs is more successful than the conventional backpropagation algorithm used in MLPs for the single, additive Zhang [1] hybrid and combined Khashei&Bijari's [3] hybrid models. However, for Wang et al. [2] multiplicative hybrid model, SARIMA-MLPs with conventional backpropagation performed more accurately than SARIMA-ANNs with the GRprop algorithm of [7].

SARIMA-ANNs models of Zhang [1] and Khashei&Bijari [3] were found more successful than SARIMA and MLPs single models except for ANNs. However, Wang et al. (2013) [2] SARIMA-ANNs model is not

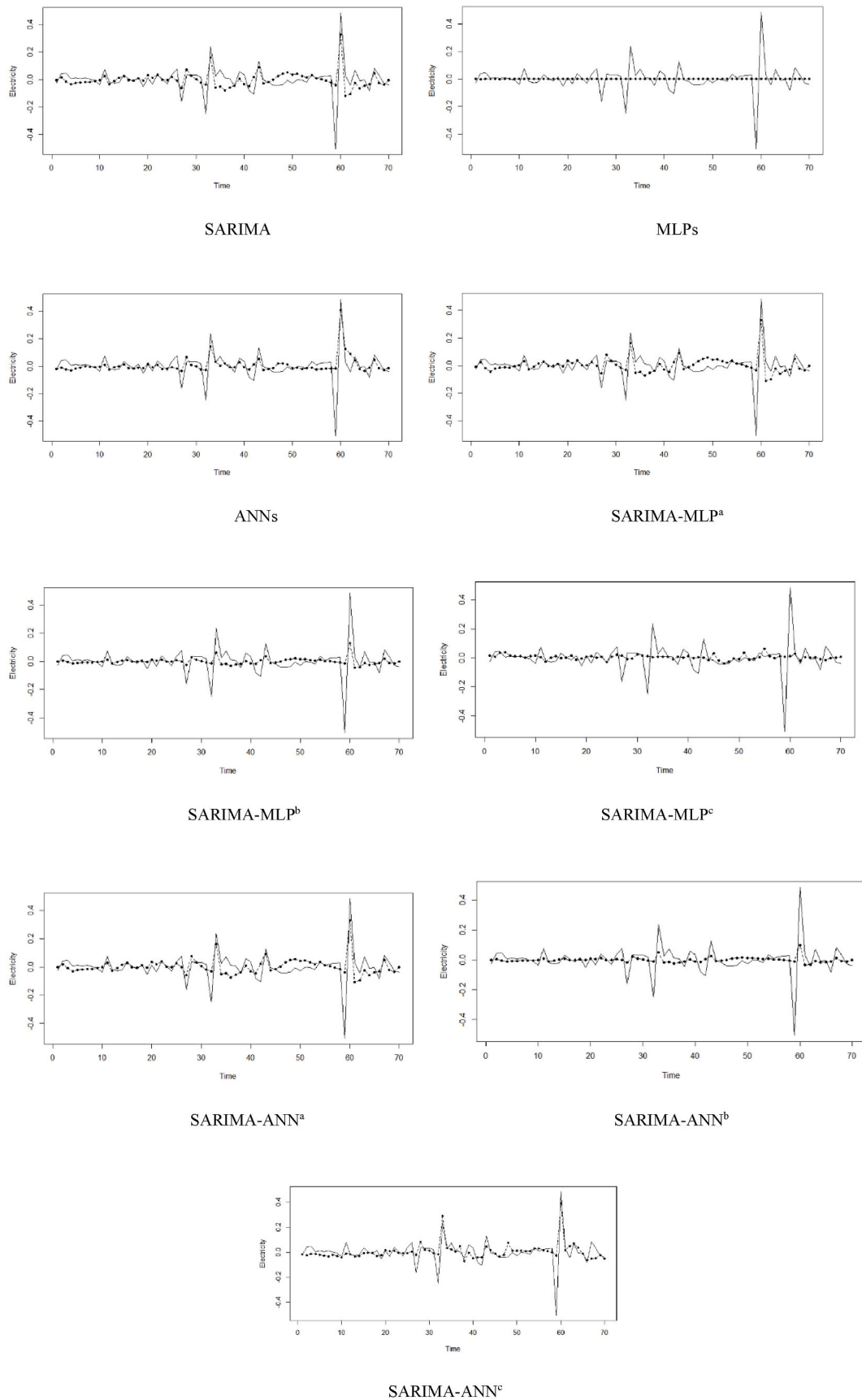


Fig. 3. Out-of-sample forecasting comparison graphs.

Table 9

Diebold-Mariano test (two-sided).

Method	SARIMA	MLPs	ANNs	Hybrid-MLPs ^a	Hybrid-MLPs ^b	Hybrid-MLPs ^c	Hybrid-ANNs ^a	Hybrid-ANNs ^b
MLPs	0.2236 (0.82)							
ANNs	1.6466 (0.10)*	1.0879 (0.28)						
Hybrid-MLPs ^a	1.1228 (0.26)	0.3279 (0.74)	1.4422 (0.15)					
Hybrid-MLPs ^b	0.2545 (0.80)	0.9496 (0.34)	0.9634 (0.34)	0.0855 (0.93)				
Hybrid-MLPs ^c	0.0459 (0.96)	0.6469 (0.52)	0.8810 (0.38)	0.1464 (0.88)	0.4188 (0.68)			
Hybrid-ANNs ^a	1.7325 (0.09)*	0.3536 (0.72)	1.3925 (0.17)	0.4621 (0.65)	0.0508 (0.96)	0.1691 (0.87)		
Hybrid-ANNs ^b	0.122 (0.90)	0.9961 (0.32)	0.9932 (0.32)	0.0264 (0.98)	0.7842 (0.44)	0.3196 (0.75)	0.0587 (0.95)	
Hybrid-ANNs ^c	1.7982 (0.08)*	1.3200 (0.19)	0.5695 (0.57)	1.6071 (0.11)	1.2493 (0.22)	1.1390 (0.26)	1.5946 (0.11)	1.2357 (0.22)

(i) a, b, c represent the Zhang [1], Wang et al. [2] and Khashei&Bijari [3] Hybrid models, respectively.

(ii) (*) means that the probability values are lower than 10 %.

(iii) The Diebold-Mariano [5] test statistics is $DM = \frac{\bar{d}}{\sqrt{\frac{2\pi f_d(0)}{T}}} \sim N(0, 1)$.**Table 10**

Modified Diebold-Mariano test.

Method	ANNs	Hybrid-ANNs ^a	Hybrid-ANNs ^c
SARIMA	1.6466 (0.05)**	1.7325 (0.04)**	1.7982 (0.04)**

(i) a, c represent the Zhang [1] and Khashei&Bijari [3] Hybrid models, respectively.

(ii) (**) means that the probability values are lower than 5 %.

(iii) The Modified Diebold-Mariano test statistic is $MDM = \left[\frac{n+1-2h+n^{-1}h(h-1)}{n} \right]^{\frac{1}{2}} (DM) \sim t_{(n-1)}$.

more successful compared to single models. As a result, it was concluded that the hybrid models created by ANNs are more accurate than single models except for the multiplicative Wang et al. [2] hybrid model.

In conclusion, the hybrid models ensure better forecasting performance than the single models in the forecasting of Türkiye's electricity consumption. ANNs GRprop algorithm [7] is a more efficient algorithm than the classical back-propagation in forecasting Türkiye's electricity consumption series. In addition, whether the linear and nonlinear components are separable, machine learning techniques and hybrid models can be a solution to the modeling of chaotic series.

CRedit authorship contribution statement

Ebru Çağlayan-Akay: Conceptualization. **Kadriye Hilal Topal:** Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

- [1] Zhang GP. Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing* 2003;159–75.
- [2] Wang L, Zou H, Su J, Li L, Chaudhry S. An ARIMA-ANN hybrid model for time series forecasting. *Syst Res Behav Sci* 2013;30(3):244–59.
- [3] Khashei M, Bijari M. A novel hybridization of artificial neural networks and ARIMA models for time series forecasting. *Appl Soft Comput* 2011;11(2):64–2675. <https://doi.org/10.1016/j.asoc.2010.10.015>.
- [4] Crone SF, Kourentzes N. Feature selection for time series prediction – a combined filter and wrapper approach for neural networks. *Neurocomputing* 2010;73:1923–36. <https://doi.org/10.1016/j.neucom.2010.01.017>.
- [5] Diebold FX, Mariano RS. Comparing predictive accuracy. *J Bus Econ Stat* 1995;13(3):253–63.
- [6] Harvey D, Leybourne S, Newbold P. Testing the equality of prediction mean squared errors. *Int J Forecast* 1997;13(2):281–91.
- [7] Anastasiadis AD, Magoulas GD, Vrahatis MN. New globally convergent training scheme based on the resilient propagation algorithm. *Neurocomputing* 2005;64:253–570.
- [8] Pao HT. Forecasting energy consumption in taiwan using hybrid nonlinear models. *Energy* 2009;34:1438–46.
- [9] Ozoh P, Abd-Rahman S, Labadin J, Apperley M. A comparative analysis of techniques for forecasting electricity consumption. *International Journal of Computer Applications* 2014;88(15):8–12.
- [10] Meng M, Shang Wei, Niu D. Monthly electric energy consumption forecasting using multiwindow moving average and hybrid growth models. *Hindawi Publishing Corporation Journal of Applied Mathematics* 2014:1–7.
- [11] Kaytez F, Taplamacioglu MC, Camb E, Hardalac F. Forecasting electricity consumption: a comparison of regression analysis, neural networks and least squares support vector machines. *Electrical Power and Energy Systems* 2015;67:431–8.
- [12] Cao G, Wu L. Support vector regression with fruit fly optimization algorithm for seasonal electricity consumption forecasting. *Energy* 2016;115:734–45.
- [13] Xu N, Dang Y, Gong Y. Novel grey prediction model with nonlinear optimized time response method for forecasting of electricity consumption in China. *Energy* 2017;118:473–80.
- [14] Aydođdu G, Yıldız O. Forecasting the annual electricity consumption of Turkey using a hybrid model. In: *IEEE 2017 25th signal processing and communications applications conference (SIU)*; 2017. p. 1–4.
- [15] Deb M, Chakrabarty TK. A wavelet based hybrid SARIMA-ETS model to forecast electricity consumption. *Electronic Journal of Applied Statistical Analysis* 2017;10:408–30.
- [16] Fahmi F, Sofyan H. Forecasting household electricity consumption in the province of Aceh using combination time series model. 2017 international conference on electrical engineering and informatics october 18-20 2017, banda aceh, Indonesia (ICELTICs 2017): 98-102.
- [17] Wibowo W, Dwijantari S, Hartati A. Time series machine learning: implementing ARIMA and hybrid ARIMA-ANN for electricity forecasting modeling. In: Mohamed A, et al., editors. *Communications in computer and information science: soft Computing in Data Science*, vol.788; 2017. p. 126–39.
- [18] Li C, Ding Z, Yi J, Lv Y, Zhang G. Deep belief network based hybrid model for building energy consumption prediction. *Energies* 2018;11(242):1–26.
- [19] Suksawang P, Suphachan S, Kaewnuch K. Electricity consumption forecasting in Thailand using hybrid model SARIMA and Gaussian process with combine kernel function technique. *Int J Energy Econ Pol* 2018;8(4):98–109.

- [20] Jaisumroum N, Teeravarapug J. A hybrid modeling of long term electricity consumption forecasting based on ARIMA and ANN: the case of Thailand with projection. *Int J Eng Technol* 2018;7(2.28):20–3.
- [21] Kaur H, Ahuja S. A Hybrid ARIMA and discrete wavelet transform model for predicting the electricity consumption of Punjab. *Int J Innovative Technol Explor Eng* 2019;8(11):1915–9.
- [22] Mukhairez HHA. Medium-term forecasting for electricity end use. *international journal of intelligent computing research (IJICR)* 2019;10(1):967–70.
- [23] Kao Y-S, Nawata K, Hiang C-Y. Predicting primary energy consumption using hybrid ARIMA and GA-SVR based on EEMD decomposition. *Mathematics* 2020;8: 2–26.
- [24] Han X, Chang J. A hybrid prediction model based on improved multivariable grey model for long-term electricity consumption. *Electrical Engineering* 2020;103: 1031–43.
- [25] Jiang W, Wu X, Gong Y, Yu W, Zhong X. HolteWinters smoothing enhanced by fruit fly optimization algorithm to forecast monthly electricity consumption. *Energy* 2020;193:116779.
- [26] Xie W, Wu W-Z, Liu C, Zhao J. Forecasting annual electricity consumption in China by employe a conformable fractional grey model in opposite direction. *Energy* 2020;202(2020):117682.
- [27] Kaytez F. A hybrid approach based on autoregressive integrated moving average and least-square support vector machine for long-term forecasting of net electricity consumption. *Energy* 2020;197:1–12.
- [28] Chou J-S, Truong D-N, Kuo CC. Imaging time-series with features to enable visual recognition of regional energy consumption by bio-inspired optimization of deep learning. *Energy* 2021;224:120100.
- [29] Bao Y, Shen L, Zhang X, Huang Y, Deng C. A novel MDPPO-SVR hybrid model for feature selection in electricity consumption forecasting. 2022, 06658. arXiv:2206.
- [30] Kavas HG. Forecasting Turkey Electricity consumption with deep learning BI-LSTM model. *J Sci Technol* 2022;1(1):24–33.
- [31] Velasquez CE, Zocatelli M, Estanislau FBGL, Castro VF. Analysis of time series models for Brazilian electricity demand forecasting. *Energy* 2022;247:123483.
- [32] Bilgili M, Pinar E. Gross electricity consumption forecasting using LSTM and SARIMA approaches: a case study of Türkiye. *Energy* 2023;284:128575.
- [33] Du X, Wu D, Yan Y. Prediction of electricity consumption based on GM(1,Nr) model in Jiangsu province, China. *Energy* 2023;262:125439.
- [34] Grandon TG, Schwenzler J, Steens T, Breuing J. Electricity demand forecasting with hybrid statistical and machine learning algorithms: case study of Ukraine. 2023, 05174. arXiv:2304.
- [35] Kadri R, Kahoui H, Sahed A. Electricity consumption forecasting in Algeria: a comparison of ARIMA and gm (1, 1) models. *Globalization and Business* 2023;8 (16):15–24.
- [36] Luzia R, Rubio L, Velasquez CE. Sensitivity analysis for forecasting Brazilian electricity demand using artificial neural networks and hybrid models based on Autoregressive Integrated Moving Average. *Energy* 2023;274:127365.
- [37] Li X, Wang Z, Yang C, Bozkurt A. An advanced framework for net electricity consumption prediction: incorporating novel machine learning models and optimization algorithms. *Energy* 2024;296:131259.
- [38] Li C, Qi Q. A novel hybrid grey system forecasting model based on seasonal fluctuation characteristics for electricity consumption in primary industry. *Energy* 2024;287:129585.
- [39] Taskaya-Temizel T, Casey M. A Comparative study of autoregressive neural network hybrids. *Neural Network* 2005;18:781–9.
- [40] Harvey DI, Leybourne SJ. Testing for time series linearity. *Econometrics Journal* 2007;10:149–65.
- [41] Harvey DI, Leybourne SJ, Xiao B. A powerful test for linearity when the order of integration is unknown. *Studies in Nonlinear Dynamics & Econometrics* 2008;12 (3). Article 2.
- [42] Chen K-Y, Wang C-H. A hybrid SARIMA and support vector machines in forecasting the production values of the machinery industry in Taiwan. *Expert Syst Appl* 2007; 32(1):254–64.
- [43] Zhang GP. A combined arima and neural network approach for time series forecasting. In: Zhang GP, editor. *Neural networks in business forecasting*. USA: Idea Group Inc.; 1988.
- [44] Zadeh MR, Amin S, Khalili D, Singh VP. Daily outflow prediction by multi layer perceptron with logistic sigmoid and tangent sigmoid activation functions. *Water Resource Management* 2010;24(11):2673–88.
- [45] Hornik K. Approximation capabilities of multilayer feedforward networks. *Neural Network* 1991;4:251–7.
- [46] ETKB. EİGM Raporları, Periyodik raporlar, <https://enerji.gov.tr/eigm-raporlari>.
- [47] Dickey DA, Fuller Fuller WA. Distribution of the estimators for autoregressive time series with a unit root. *J Am Stat Assoc* 1979;74(366a):427–31.
- [48] Zivot E, Andrews DWK. Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business & Economic Statistics* 1992;10 (3):251–70.
- [49] Box GEP, Jenkins GM, Bacon DW. Models for forecasting seasonal and nonseasonal time series. In: Harris B, editor. *Spectral analysis of time series*. New York: Wiley; 1967. p. 271–311.
- [50] Box GEP, Jenkins GM. *Time series analysis: forecasting and control*. San Francisco: Holden-Day; 1968.
- [51] Breusch TS. Testing for autocorrelation in dynamic model. *Australian Economic Papers* 1978;17:334–55.
- [52] Godfrey LG. Testing for higher order serial correlation in regression equations when the regressors include lagged dependent variables. *Econometrica* 1978;46: 1303–10.
- [53] Engle RF. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society* 1982;50(4):987–1007.
- [54] Jarque CM, Bera AK. A test for normality of observations and regression residuals. *International Statistical Review* 1987;55:163–72.
- [55] Brock WA, Dechert WD, Scheinkman J. A test for independence based on the correlation dimension. University of Houston, and University of Chicago; 1987. Working paper, University of Winconsin at Madison.
- [56] Brock WA, Dechert WD, Scheinkman JA, Lebaron B. A test for independence based on the correlation dimension. *Econometric Reviews* 1996;15:197–235.
- [57] Bisaglia L, Gerolimetto M. Testing for (non)linearity in economic time series: a Monte Carlo comparison, vol. 3. University of Padua, Department of Statistical Sciences; 2014. Working paper series.
- [58] Kim KJ. Financial time series forecasting using support vector machines. *Neurocomputing* 2003;55:307–19.
- [59] Heaton JT. *Introduction to neural networks for java*. second ed. St. Louis: Heaton Research Inc.; 2008.
- [60] Jiang F, Wu W, Peng ZA. Semi-parametric quantile regression random forest approach for evaluating multi-period value at risk, in: *Control conference (CCC), 2017 36th Chinese, IEEE*, 5642–5646.