Dicle University
Journal of Engineering
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Research Article

Comparison of hybrid and non-hybrid models in short-term predictions on time series in the R development environment

Zeydin Pala [1,*], İbrahim Halil ÜNLÜK [2]

[1] Muş Alparslan University, Engineering Faculty, Department of Software Eng., Muş. Türkiye, https://orcid.org/0000-0002-2642-7788
[2] Muş Alparslan University, V. S. of Tech. Sci. Dept. of Electronics and Automation, Muş, Türkiye, https://orcid.org/ 0000-0002-6541-2714

ARTICLE INFO

Article history:

Received 25 February 2022
Received in revised form 26 May 2022
Accepted 2 June
Available online 28 June 2022

Keywords:

Time series analysis, short-term prediction, hybrid models, non-hybrid models

Doi: 10.24012/dumf.1079230

* Corresponding author

ABSTRACT

A single linear or nonlinear model may be insufficient to model and predict time series, as many time series often contain both linear and nonlinear components. Therefore, estimation results are tried to be improved by using collaborative models in time series short-term prediction processes. In this study, the performances of both stand-alone models and models whose different combinations can be used in a hybrid environment are compared. The mean absolute percentage error (MAPE) metric values obtained from two different categories were evaluated. In addition, the estimation performances of three different approaches such as equi-weighted (EW), variable-weighted (VW) and cross-validation-weighted (CVW) for hybrid operation were also compared.

The findings on the container throughput forecast of the Airpassengers dataset reveal that the hybrid model's forecasts outperform the non-combined model.

Introduction

Time series modeling and forecasting are extremely important in a wide range of practical applications. In the literature, several key models have been presented to improve the accuracy and efficiency of time series modeling and forecasting. Time series data and analytics are becoming increasingly important due to the massive generation of such data, for example, through the internet of things, the digitization of healthcare and the rise of smart cities.

In order to increase the quality of the prediction, it is a better approach to make predictions with combinations of some models instead of using the models alone. Such approaches can simultaneously handle features of a time series, such as trend and seasonality, but it is not always easy for estimators to choose the best model among those proposed. Time series can often be of different nature and the effects of external factors may differ from one model to another. Choosing the most appropriate model for forecasting purposes requires extensive experience in forecasting and time series nature as well as qualitative experience.

In many scientific studies, it is accepted that no single technique is better predictive than a combination of some techniques [1]. Collective learning is a special machine learning topic. It is an attempt to combine multiple models to provide overall higher accuracy and stable model performance. Historically, ensemble methodology is based on very strong theory and its use has been used successfully in complex data science scenarios [2]. Ensemble techniques emerge as model output collection techniques that have developed in the field of statistical and machine learning in the last decade.

None of the popular machine learning algorithms are built for time series prediction, and time series data needs to be preprocessed in order to be used for prediction [3]. The power of machine learning algorithms is based on cross validation. That is, the entire series is used in separate sections to train a single model. However, this situation is different from standard statistical time series algorithms, where a separate model is developed for each series. In practical research, professional statistical software is used to design experiments or analyze data already collected.

In this study, we used R software packages. R has emerged as a pretty good tool for scientific computational tasks over the last few decades and has found a consistent place in the application of statistical methodologies to analyze data. In order to use ensemble time series models in forecasting processes, first of all, it is necessary to include the Hybrid model library in the R programming and development environment. The hybrid package of the R development environment provides a convenient platform for assembling heterogeneous time series models. The main function that provides this task is the hybridModel function. This model takes a string of up to six characters as input, and each character represents a pattern. For example, the character a is used for auto.arima, e for ets, f for thetam, n for nnetar, s for stlm, and finally t for tbats.

The R development environment proves that hybrid models have better forecasting performance in short-term forecasting analyzes using time series. The four main contributions of this article can be summarized as follows:

(1) To use all combinations of statistics-based and deep learning-based models such as auto.arima, ets, thetam, nnetar, stlm and tbats in predictive analysis.

(2) To prove that the new hybrid model proposed in this study has higher accuracy and stronger stability, compared with the models used alone.

(3) To achieve lower MAPE values and higher accuracy in short-term forecasting with the proposed hybrid model.

(4) To compare predictions made with variable-weighted, equi-weighted, and cross-validation-weighted approaches when using hybrid models.

Literature review

In the literature, forecasting models are generally classified into three categories [4]. The first group consists of time series [5]–[10] or statistics-based methods [11], while the second group is artificial intelligence-based methods (machine learning [12], deep learning [13] , genetic algorithm [14]. The last group is hybrid methods based on statistics and deep learning or a combination of genetic algorithms and other models [11].

Artificial intelligence-based models started to become popular between 1992-2006, and the intensive use of vector support machines contributed to the development of machine learning in the field of artificial intelligence. Furthermore, as compared to statistical models, machine learning models offer clear benefits in processing complicated nonlinear data, particularly in terms of short-term consumption forecasting accuracy [15]. In recent years, more and more scientists have started using intelligent algorithms such as fuzzy theory models, support vector machine models, and neural network. Although smart algorithms offer more advantages than standard algorithms, they also have certain inherent drawbacks, such as high calculation times, sluggish convergence speed, and easiness of early convergence. As a result, the optimization prediction model is still a hotly debated research area [16].

Recently, hybrid models have been used extensively by researchers for time series estimation. Smyl et al. suggested a hybrid estimating technique for the M4 competition that combines the exponential smoothing model with sophisticated long-short-term memory (LSTM) neural networks in a single framework. Exponential smoothing equations are used for the method to effectively capture the main components of individual series, such as seasonality and level, while LSTM networks are used to allow for nonlinear trends and cross-learning [3]. Zhang et al. proposed a hybrid methodology combining ARIMA and ANN models for linear and nonlinear modeling. Experimental results with real datasets conclude that the combined model further improves the prediction accuracy achieved by either of the models used separately [17]. Ma et al. combined a basic statistical time series model with a machine learning algorithm in their work. More specifically, they sequentially combined an ARIMA model called NN-ARIMA with a basic neural network model. According to the experimental results, the proposed approach significantly reduces the mean square error and thus improves the accuracy of the estimation [18]. Castillo et al. proposed a hybrid fuzzy fractal approach to estimate confirmed covid-19 cases and deaths for ten countries based on time series [19]. Based on variable mode decomposition, particle swarm optimization, and deep belief networks, Li et al. suggested a hybrid forecasting model of monthly Henry Hub natural gas prices [20]. Gao et al. proposed a new hybrid forecasting model based on a support vector machine and an improved artificial fish swarm algorithm to predict annual natural gas consumption [21]. Atici and Pala used the hybrid model in their study for the Ionospheric foF2 parameter estimation [22]. Qiao et al. proposed a hybrid model for hourly gas consumption in their study [16]. Tseng et al. proposed a hybrid gray model to predict seasonal time series [23]. Chang et al. proposed a new hybrid model for electricity price estimation. In their study, the authors proposed a hybrid model based on Adam optimized LSTM neural network and wavelet transform [24]. Du et al. proposed a new hybrid model for short-term wind energy prediction in their study. The focus of their work was on improving forecast accuracy and stability, single-step and multi-step wind energy forecasting, and comprehensive performance validation of forecast models [25]. Meira et al. combined bootstrap aggregation, univariate time series estimation methods and modified regularization routines in their study. They introduced a new type of bagging that uses maximum entropy bootstrap and a modified regularization routine that keeps the data generation process in the community [26].

Unlike the aforementioned literature, in this study, the HybridModel library of the R development environment is proposed to achieve higher accuracy and stability on the same time series. The proposed system consists of four different approaches: One of them is used as an approach in which independent models play a role alone in the prediction process, while the second, third, and fourth approaches are hybrid-based as variable-weighted, equal-weighted and cross-validation-weighted, respectively.

Methodologies

As a specific topic of machine learning, collective learning is generally concerned with combining multiple models to provide higher accuracy and stable model performance. Community methodology has played a role in successful scenarios in complex data science applications. The ForecastHybrid library is a library designed for the R programming language. This library, which is used in the RStudio environment, has been used in many researches before [3], [22], [27], it offers a common forecast by combining the forecasting capabilities of many functions individually in the forecast library used in the same environment. Here, time series future predictions are made with single-model [12] and multi-model approaches using the hybrid model library in the R programming language environment.

Performance evaluation

Many different metrics can be used in the literature to evaluate the performance of models used in time series forecasting [28], [29]. In this study, mean absolute percentage error (MAPE) [30] metric, which is easier to interpret and have better accuracy than others, were preferred. The lower the MAPE value, the better the method.

$$\boldsymbol{MAPE} = \frac{\mathbf{1}}{\boldsymbol{n}}\sum_{t=1}^{n} \frac{|y_t - \hat{y}_t|}{|y_t|} x100\ (\%) \qquad (1)$$

Where y_t, is the time series value at time t, $\hat{\boldsymbol{y}}_t$ is the estimated prediction, n is the number of data points available in the sample.

Results and Discussion

Four different approaches were used in the time series forecasting analysis performed in this study. One of these approaches is independent and the remaining three are carried out using hybrid models. Airpassengers monthly time series was used in all four different approaches. Airpassengers time series is in the "datasets" library in the R development environment and consists of 144 months of observation data. In the forecast analysis, 132 months of data were used for training, while the remaining 12 months of data were used for testing. The data used for training and testing processes constitute 91% and 9% of the total data, respectively. Six models were used independently in the first approach. One of these models used is deep learning and the others are statistical-based architectures. Models TBATS, ETS, THETAF, ARIMA, STLF and NNTAR can be used standalone, whereas tbats (t), ets (e), thetam (f), auto.arima (a), stlm (s), and nnetar (n) models were used in the hybrid environment, respectively.

The MAPE metric values obtained in the estimation process using independent models are given in Table 1. MAPE values express the error made as a percentage, and smaller values indicate higher accuracy. For example, while the prediction error of the NNTAR model, which makes the best prediction in this approach, is 3.29%, the prediction accuracy is 96.71%. In this approach, the mean MAPE value for six different models was calculated as 4.36%.

Table 1. MAPE metric values of 6 different models obtained as a result of 12-month estimation of Airpassengers time series

Model	**MAPE (%)**
NNTAR	3.29
TBATS	3.35
ARIMA	4.18
ETS	4.65
THETAF	5.32
STLF	5.39
Average	**4.36**

Figure 1 shows 12-month forecast graphs in the 80% and 95% range based on the MAPE metrics of the TBATS, ETS, THETAF, ARIMA, STLF, and NNTAR models.

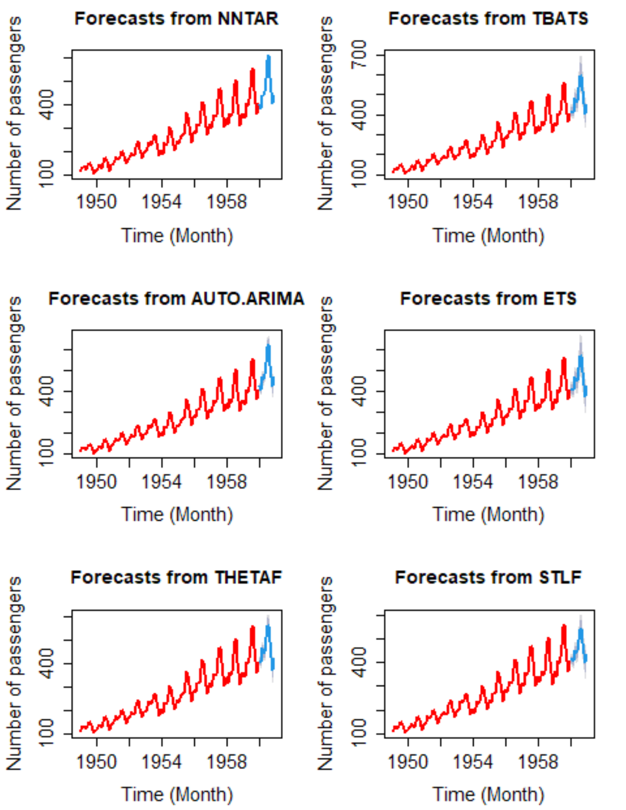

Figure 1. Representation of 12-month forecasts with prediction ranges of 80% and 95% utilizing six distinct deep learning and statistics models

As seen in Figure 1, the dark shaded region contains 80% of the projected intervals. In other words, with an 80% likelihood, each prospective value is expected to be in the dark shaded range. The light shaded area displays 95% prediction intervals. These forecasting intervals are a helpful way to demonstrate variability in the prediction. In this case, the forecast is assumed to be reliable, and thus the forecast intervals are very narrow. The blue line is the average of potential future values, which we call the point forecasts.

In the second, third and fourth stages of the analysis, estimations were made using equi-weighted (EW), variable-weighted (VW) and cross-validation-weighted (CVW) approaches, respectively. Among the hybrid model approaches, auto.arima (a), ets (e), thetam (f), nnetar (n), stlm (s) and tbats (t) models were used. Combinations of six different models, at least dual, were calculated as in equation (2).

$$C(n,r) = \frac{n!}{r!(n-r)!} \qquad (2)$$

Here, the n parameter represents the number of models that can be used together in the hybrid model, while the r parameter represents the multiple situations used together.

In this case, for 15, 20, 15, 6 and 1 forecast analysis, C(6.2), C(6.3), C(6.4), C(6.5) and C(6.6) model combinations were used. The MAPE metric values of the analyzes of the EW, VW and CVW approaches using the hybrid model using dual-model, triple-model, quartet-model, quintuple-model and six-model are given in Table 2, Table 3, Table 4, Table 5 and Table 6, respectively [31].

In Figure 2, the graphs of the best dual models of the EW, VW and CVW hybrid approaches are given as nt, fn and nt, respectively. In Figure 3, the graphs of the best triple models of EW, VW and CVW hybrid approaches are given as aen, aen and aen.

Table 2. MAPE metric values of 15 forecasting processes obtained with the help of EW, VW and CVW approaches using dual hybrid model

Dual-model	**EW MAPE Test (%)**	**VW MAPE Test (%)**	**CVW MAPE Test (%)**
fn	3.20	2.87	3.31
nt	2.89	2.92	2.91
ae	2.99	3.00	3.02
an	3.01	3.10	2.94
af	3.01	3.23	3.06
en	2.89	3.26	2.96
ft	3.54	3.30	3.64
et	3.37	3.44	3.42
at	3.41	3.46	3.39
as	3.60	3.62	3.87
ns	3.55	3.95	3.75
st	3.93	4.04	4.12
es	4.61	4.61	4.62
ef	4.99	4.78	4.99
fs	4.95	4.96	4.91
Average	**3.60**	**3.64**	**3.66**

Table 3. MAPE metric values of 20 forecasting processes obtained with the help of EW, VW and CVW approaches using triple hybrid model

Triple-model	**EW MAPE Test (%)**	**VW MAPE Test (%)**	**CVW MAPE Test (%)**
aen	2.76	2.81	2.80
afn	2.79	2.83	2.85
fnt	3.03	2.93	3.07
ant	2.90	2.96	2.91
aef	3.23	3.03	3.34
ent	3.02	3.07	3.03
aet	3.09	3.08	3.10
aft	3.10	3.10	3.11
ans	3.08	3.19	3.25
ast	3.45	3.47	3.56
nst	3.34	3.55	3.43
efn	3.67	3.58	3.76
aes	3.60	3.61	3.78
eft	3.82	3.61	3.94
afs	3.67	3.64	3.87
ens	3.69	3.89	3.79
fns	3.83	3.92	3.93
est	3.89	3.95	4.02
fst	3.98	4.04	4.10
efs	4.85	4.69	4.83
Average	**3.44**	**3.45**	**3.52**

Table 4. MAPE metric values of 15 forecasting processes obtained with the help of EW, VW and CVW approaches using quad hybrid model

Quad-model	**EW MAPE Test (%)**	**VW MAPE Test (%)**	**CVW MAPE Test (%)**
afnt	2.88	2.85	2.90
aefn	2.96	2.90	2.97
aent	2.85	2.93	2.90
aeft	3.16	3.10	3.19
efnt	3.19	3.14	3.27
anst	3.12	3.20	3.21
afns	3.23	3.23	3.43
aens	3.23	3.33	3.36
aest	3.40	3.43	3.56
afst	3.45	3.45	3.62
fnst	3.50	3.58	3.64
enst	3.44	3.60	3.54
aefs	3.70	3.64	3.85
efns	3.91	3.93	3.98
efst	4.02	3.96	4.12
Average	**3.34**	**3.35**	**3.44**

Table 5. MAPE metric values of 6 forecasting processes obtained with the help of EW, VW and CVW approaches using quintuple hybrid model

quintuple-model	**EW MAPE Test (%)**	**VW MAPE Test (%)**	**CVW MAPE Test (%)**
aefnt	3.00	2.99	3.02
afnst	3.19	3.22	3.31
aenst	3.19	3.25	3.25
aefns	3.38	3.38	3.49
aefst	3.51	3.46	3.66
efnst	3.58	3.62	3.62
Average	**3.31**	**3.32**	**3.39**

Table 6. MAPE metric values of 1 forecasting processes obtained with the help of EW, VW and CVW approaches using six hybrid model

Six-model	**EW MAPE Test (%)**	**VW MAPE Test (%)**	**CVW MAPE Test (%)**
aefnst	3.26	3.28	3.40

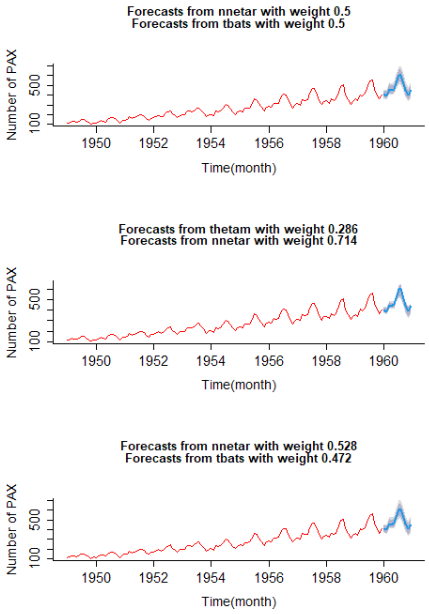

Figure 2. Prediction plots of best dual models of hybrid EW, VW and CVW approaches

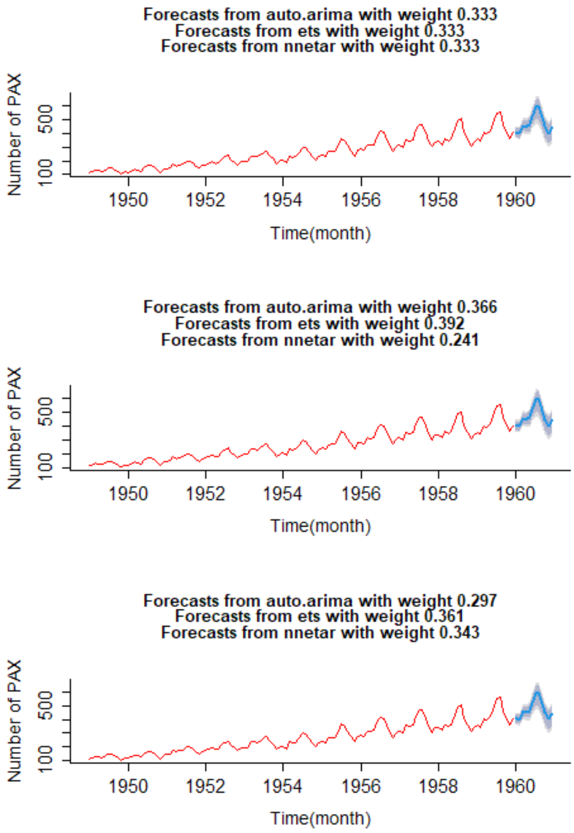

Figure 3. Prediction plots of best triple models of hybrid EW, VW and CVW approaches.

1. As a result of the estimations made using single models, the MAPE average obtained was found to be 4.36%. The MAPE average values obtained as a result of hybrid dual-model analyzes performed with EW, VW and CVW approaches were obtained as 3.60%, 3.64% and 3.66%, respectively.
2. The MAPE mean values obtained as a result of hybrid triple-pattern analyzes performed with EW, VW and CVW approaches were obtained as 3.44%, 3.45% and 3.52%, respectively.
3. The MAPE average values obtained as a result of hybrid quad-pattern analyzes performed with EW, VW and CVW approaches were obtained as 3.34%, 3.35% and 3.44%, respectively.
4. The MAPE mean values obtained as a result of hybrid quintuple-pattern analyzes performed with EW, VW and CVW approaches were obtained as 3.31%, 3.32% and 3.39%, respectively.
5. The MAPE mean values obtained as a result of the hybrid six-model analyzes performed with the EW, VW and CVW approaches were obtained as 3.26%, 3.28% and 3.40%, respectively.
6. The accuracy of the predictions made with hybrid models gave better results than those made with single models.

Conclusion

In this study, the results of six models used alone in the estimation process were compared with the results of the models used in the hybrid environment. Our results show that collaborative model results are better than non-collaborative model results.
The main conclusion is that the hybrid set of forecasts can yield lower MAPE than either of the non-combined model forecasts.

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