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Single Versus Combined Forecasting: The Case Of Wind Run Data

Bushirat T. Bolarinwa
Ismaila A. Bolarinwa
Department of Statistics
The Federal Polytechnic, P.M.B. 55, Bida, Niger State, Nigeria

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Abstract

This article compared single to combined forecasts of wind run using artificial neural networks, decomposition, Holt-Winters' and SARIMA models. The artificial neural networks utilized the feedback framework while decomposition and Holt-Winters' approaches utilized their multiplicative versions. Holt-Winters' performed best of single models but ranked fourth, of all fifteen models (single and combined). The combination of decomposition and Holt-Winters' models ranked best of all two-model combinations and second of all models. Combination of decomposition, Holt-Winters' and SARIMA performed best of three-model combinations and ranked first, of all models. The only combination of four models ranked third of all models. The accuracy of single forecast should not be underestimated as a single model (Holt-Winters') outperformed eleven combined models. It is therefore, evident that inclusion of additional model forecast does not necessarily improve combined forecast accuracy. In any modeling situation, single and combined forecasts should be allowed to compete.

Keywords: Forecasting Model, Combined Forecast, Wind Run, Time Series

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Introduction

Courtesy of improved availability of computing facilities, it has become the practice to analyze time series data using a number of models. Because of inadequacies of single models in generating forecasts with desired level of accuracy sometimes, researchers have devised ways of improving the forecasts. Such efforts include combining forecasts from various models to arrive at single forecasts. The forecasts can be combined in various ways. Simple arithmetic mean and the median are some of the methods in the literature. Research involving combinations of forecasts include Bates and Granger (1969), Newbold and Granger (1974), Reid in Kendall and Ord (1990), Palm and Zelner (1992), and Aksu and Gunter (1992). More recent efforts include Zou and Yang (2004), Chen (2011), Clements and Harvey (2011), Constantini and Kunst (2011). Mancuso and Werner (2013) and Firmino, Neto and Ferreira (2014) provide good reviews of methods for combining forecasts.

Efforts at modeling wind run include Mohandes, Halawani, Rehman, and Hussain (2004), Jiang, Qin, Wu, and Sun (2015), Ambach (2016), Doucoure, Agbossou and Cardinas (2016), Iversen, Morales, Moller and Madsen (2016), Niu, Wang, Zhang and Du (2018). Others are Qureshi, Khan,. Zameer, and Usman (2017), Sun and Wang (2018), Sun, Jiang, Cheng, Liu, Wang, Fu and He (2018), Zhang, Yang, Guo and Zhao (2019), Jiang, Li and Li (2019), Nie, Bo, Zhang and Zhang (2020), Aslam (2020), Behnken, and Wächter and Peinke (2020). Although several methods for combining forecasts appear to be appealing, the fact remains that a simple average of forecasts might just be sufficient a combination for attaining desired level of accuracy.

The question of whether a single or a combined forecast is desirable depends on the data in question. Model performance does not also depend on sophistication. In modeling, parsimony is key. Emphasis should be on not just performance but also on simplicity. The simpler a model is, the more stable it tends to be. Complicated models can be very erratic. The logic behind combining forecasts is to improve accuracy by exploiting strength inherent in the individual models from which forecasts are generated. Elegance is clearly not the reason for combining forecasts. As fundamental as the decomposition method may appear to be, it could outperform sophisticated methods like SARIMA and its variants and even artificial neural networks models in a particular modeling situation. The performance of forecasts (based on a clearly defined criterion) on out-of-sample data is paramount. When single and combined forecasts are compared, the decision as to whether a single or combined forecast is appropriate can be objectively taken.

The focus of the article is to investigate the performance of four univariate time series models (Artificial neural networks (ANN),

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Decomposition, Holt-Winters' and SARIMA) and their combinations on wind run data.

The remainder of this article is arranged as follows: Section 2 presents the Theoretical Framework while Section 3 presents the Methodology. Results and Discussion is presented in Section 4 while the last section presents the Conclusion.

Theoretical Framework

Artificial Neural Networks (ANN) Model

Traditional methods for analyzing time series include decomposition, exponential smoothing, SARIMA which are linear in nature. Meanwhile, not all series have linear underlying data generating process. To overcome the inability of linear models to capture nonlinearity that characterizes some time series data sets, ANN models among others came into being. It is a recent development and is gaining patronage by researchers owing to its capacity to model nonlinear phenomena. ANN models are a flexible, soft computing framework for modeling a broad range of non-linear problems (Zhang, 2003). They are termed *universal approximators* owing to their capacity to approximate a broad range of functions with high accuracy. Because of their capacity to model complex nonlinear systems, they have been identified as a viable alternative to traditional time series methods. According to Zhang, Patuwo and Hu (1998), a single hidden layer feedback network is the most widely used for modeling and forecasting time series. This network typically has an input layer, a hidden layer and an output layer. The relationship between the input $y_{t\text{-i}}$ (t=1, 2, …, p) and the output y_t for a one-output layer feedback model has the form

$$y_t = g\left[\alpha_0 + \sum_{j=1}^{h} \alpha_j f(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-i})\right] \quad (1)$$

where

$\alpha_i, \beta_{ij}\ (i = 0, 1, 2..., p;\ j = 1, 2..., h)$ are model parameters often called *connection weights*; f and g are respectively activation functions for hidden and output layers.

Decomposition Model

This is one of the oldest time series models. It is based on the theory that the time series variable is made up of four components (trend (T), seasonal (S), cyclical (C) and irregular (I)) which interact multiplicatively resulting in the multiplicative model

$$y_t = T.S.C.I \quad (2)$$

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or additively yielding

$$y_t = T + S + C + .I \tag{3}$$

Whenever it is desired to model seasonal data, emphasis is on seasonal rather than cyclical and hence, the cyclical component is merged into the irregular so that (2) becomes

$$y_t = T.S..I \tag{4}$$

and (3) translates to

$$y_t = T + S + .I \tag{5}$$

Cyclical component is emphasized for nonseasonal data modeling. Unlike several time series models whose parameters do not lend themselves readily to meaningful interpretation, the decomposition model parameters have clear and meaningful interpretations.

Holt-Winters' (H-W) Model

The exponential family of time series models started with the development of a single exponential smoothing model. The model was extended to incorporate trends by Holt (1957). This is called Double exponential smoothing model. Winters (1960) extended Holt (1957) model to include seasonal components resulting in H-W model. This model has two variants, namely the additive and the multiplicative version.

The additive version is of the form

$$l_t = \alpha(y_t - s_{t-p}) + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{6a}$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \tag{6b}$$

$$s_t = \delta(y_t - l_t) + (1-\delta)s_{t-p} \tag{6c}$$

$$\hat{y}_{t+k} = l_t + kb_t + s_{t-k-p} \tag{6d}$$

where $0 < \alpha < 1; 0 < \beta < 1 \, and \, 0 < \delta < 1$; $\alpha, \beta \, and \, \delta$ are smoothing constants accounting for the level, trend and the seasonal components respectively). l_t, b_t and s_t are smoothed estimates of the level, trend and the seasonal components at time t respectively. p is seasonality and equals 12 and 4 respectively for monthly and quarterly data. $\hat{y}_{t+k}$ is the k-step-ahead forecast.

The H-W method requires initial values to begin the estimation process. The values are

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$$l_p = \frac{1}{p}\sum_{i=1}^{p} y_i$$

$$b_p = \frac{1}{p^2}\sum_{i=1}^{p}(y_{p+i} - y_i)$$
and

$$s_i = y_i - l_p \qquad i = 1, 2, ..., p$$

The multiplicative version of the H-W model is of the form

$$l_t = \alpha \frac{y_t}{s_{t-p}} + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{7a}$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \tag{7b}$$

$$s_t = \delta \frac{y_t}{l_t} + (1-\delta)s_{t-p} \tag{7c}$$

$$\hat{y}_{t+k} = (l_t + kb_t)s_{t-k-p} \tag{7d}$$

The initial values for the multiplicative model differ from those of additive model in respect of the seasonal component, s_i. In this case,

$$s_i = \frac{y_i}{l_p} \qquad i = 1, 2, \ldots, p$$

SARIMA Model

SARIMA model is a linear model in which the time series variable y_t is assumed to be a function of its lagged values and some random shocks. The model was developed by Box and Jenkins (1976).

SARIMA (*p*, *d*, *q*) X (*P*, *D*, *Q*) is of the form

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D y_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \tag{8}$$

where *p*, *d*, *q* are integers and represent the number of autoregressive parameters, the order of nonseasonal differencing and number of moving average parameters in the model respectively. *P*, *D* and *Q* are seasonal counterparts of *p*, *d* and *q*. When *P*, *D* and *Q* are all zero, SARIMA becomes ARIMA. This is appropriate when data is not seasonal. If in addition, $d = 0$, ARIMA becomes ARMA implying that no differencing is required on the data to attain stationarity.

Fitting SARIMA models is iterative in nature and entails the following:

i) Postulate general class of models
ii) Identify a tentative model
iii) Estimate parameters of identified model

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iv) Perform diagnostic checking
v) Use model for forecasting and control.

Methodology

Data

Average monthly wind run data covering January 2000 to December 2015 were collected from NCRI, Baddegi, Bida, Niger State, Nigeria. Data for January 2000 to December 2014 were used for modeling while the remaining data were used for out-of-sample model performance.

Model and Estimation

Four models (ANN, Decomposition, H-W and SARIMA) were involved in the study.

ANN Model

The ANN model fitted is of the form stated in (1). Six different model architectures:

$$\text{ANN}\ (12, h, 1)\ h = 1, \ldots, 6$$

were fitted.

The models were estimated (trained) by a method known as *backpropagation learning algorithm*. The activation function for the hidden and the output layer is bipolar sigmoid function defined:

$$f(x) = \frac{1 - \exp(-x)}{1 + \exp(-x)} \qquad (9)$$

Decomposition Model

The multiplicative model of form (4) was fitted. The trend was represented by a simple linear model whose parameters were estimated by ordinary least squares while the seasonal component was estimated by ratio-to-moving average method.

Holt-Winters's Model

The multiplicative version of the Holt-Winters' model specified in (7a) to (7d) was fitted.

The smoothing parameters were each allowed to take on 0.1, 0.2,…, 0.9. A total of 729 parameter combinations were involved and the best combination was selected on the basis of 1-step-ahead mean square error. The resulting model was then used for forecasting.

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SARIMA Model

SARIMA model of the form specified in (8) was fitted. Model parameters were estimated by nonlinear least squares. Diagnostic procedure adopted Ljung-Box statistics due to Ljung and Box (1978). Just like the other diagnostic tests, it is based on the principle that for model adequacy, the residuals should behave like a *white noise process*.

Principle for Combining Forecasts

Forecasts were combined by taking arithmetic mean of single forecasts. This remains the most employed method for combining forecasts.

The naming nomenclature for the models follows:

ANN: A
Decomposition: D
H-W: H
SARIMA: S

A combination of models was indicated by '+', sign. For example, A+D implies a combination of ANN and decomposition models.

Results and Discussion

Results of analysis are hereby, condensed and discussed.

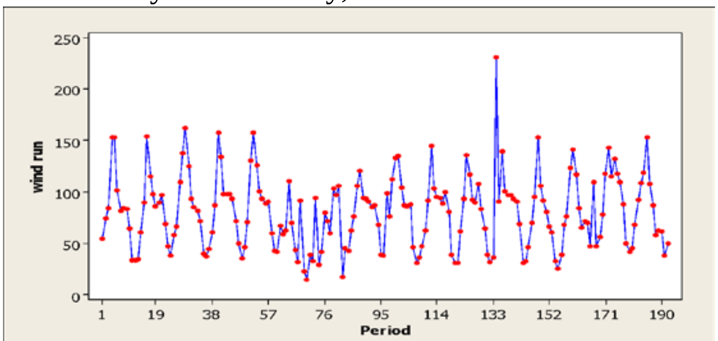

Fig. 1. Time series plot of wind run (January 2000-December 2015).

Fig.1 presents the time plot of the wind run data. The data exhibit marked seasonality. Except for an obvious spike, the pattern is consistent.

Table 1. Mean square errors of ANN models

Model	MSE
ANN(12, 1, 1)	1841.443
ANN(12, 2, 1)	1290.777
ANN(12, 3, 1)	1286.062
ANN(12, 4, 1)	1256.616
ANN(12, 5, 1)	1254.338*
ANN(12, 6, 1)	1404.694

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Table 1 presents the mean square errors for the six fitted ANN models. ANN (12, 5, 12) has produced the least MSE and was hence used to forecast values for January to December 2015. The forecasts are presented in Table 2.

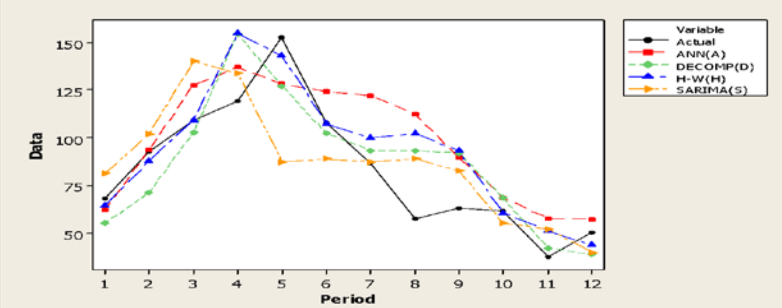

Fig. 2. Actual values and forecasts for single models.

Actual values and forecasts (for January to December 2015) of single models are presented in Fig. 2. The forecasts expectedly portray a mixture of underestimation and overestimation by the individual models. Some of the forecasts are widely different between models.

Table 2. Forecasts, MSE and overall ranking of single models

		Model			
Period	**Actual value**	**ANN**	**DECOMP**	**H-W**	**SARIMA**
Jan	68.18	62.3907	55.3048	64.3429	81.538
Feb	92.7	93.7621	71.3321	87.8622	101.951
Mar	109.12	127.7325	102.8621	109.4224	140.150
Apr	119.09	136.9394	154.3041	154.7129	133.915
May	152.70	128.4807	127.1996	143.0960	87.404
Jun	108.07	124.1186	102.4828	107.4531	88.968
Jul	86.92	122.1879	93.5010	99.9193	87.404
Aug	57.77	112.5253	93.3998	102.2596	88.968
Sept	63.0	89.5391	91.8983	93.1742	82.716
Oct	61.64	68.6437	68.4629	60.6469	55.328
Nov	37.8	57.8023	42.3627	51.4530	52.407
Dec	50.34	57.4463	38.9580	44.0435	39.987
MSE	-	582.4781	410.6553	390.4711	649.8144
Rank		14	8	4	15

Table 2 presents the actual values and forecasts for January to December 2015, the period set aside for comparison purposes. Out of four single models, Holt-Winters' produced the least mean square error of 390.4711 based on forecasts for 12 months. Holt-Winter's is next, followed by ANN and SARIMA is the last. The Holt-Winter's model is ranked fourth however, of the fifteen cases (single and combined) considered. The simpler models (Decomposition and Holt-Winter's) have outperformed the

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sophisticated models in this instance. This implies that model performance in a particular situation does not depend on sophistication but rather on suitability for the data. Simpler models can outperform more sophisticated models in several instances.

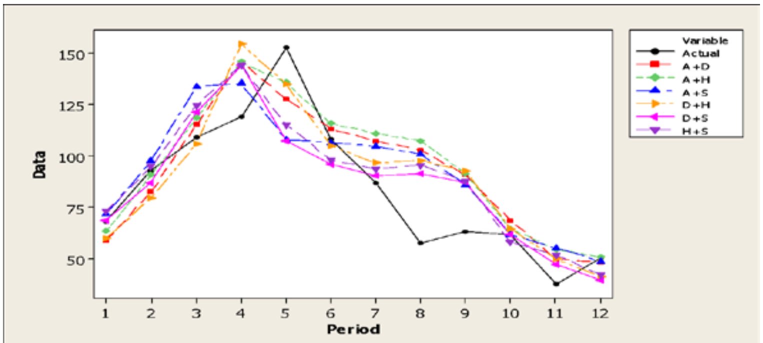

Fig. 3. Actual values and forecasts for 2-model combinations.

Fig. 3 is a plot of actual values and forecasts for six 3-model combinations involved. The scenario portrayed is a little different from that of single models. Differences between forecasts have closed up.

Table 3. Forecasts, MSE and overall ranking of combinations of two models

		Model					
Period	**Actual value**	**A+D**	**A+H**	**A+S**	**D+H**	**D+S**	**H+S**
Jan	68.18	58.8478	63.3668	71.9644	59.8239	68.4214	72.9405
Feb	92.7	82.5471	90.8122	97.8566	79.5972	86.6416	94.9066
Mar	109.12	115.2973	118.5775	133.9413	106.1423	121.5061	124.7862
Apr	119.09	145.6218	145.8262	135.4272	154.5085	144.1096	144.314
May	152.70	127.8402	135.7884	107.9424	135.1478	107.3018	115.25
Jun	108.07	113.3007	115.7859	106.5433	104.968	95.7254	98.2106
Jul	86.92	107.3007	111.0536	104.796	96.7102	90.4525	93.6617
Aug	57.77	102.9626	107.3925	100.7467	97.8297	91.1839	95.6138
Sept	63.0	90.7187	91.3567	86.1276	92.5363	87.3072	87.9451
Oct	61.64	68.5533	64.6453	61.9859	64.5549	61.8955	57.9875
Nov	37.8	50.0825	54.6277	55.1047	49.9079	47.3849	51.93
Dec	50.34	48.2022	50.7449	48.7167	41.5008	39.4725	42.0153
MSE	-	419.1956	443.1515	494.4266	380.429	413.2819	399.2567
Rank		11	12	13	2	9	6

Combined forecasts for two-model combinations are presented in Table 2. Model (D+H), signifying combination of Decomposition and Holt-Winters' forecasts outperformed other models in this category. The combination is ranked second of all cases under consideration. It has outperformed all single model forecasts. This implies that combined forecasts do not necessarily outperform single forecasts. For instance, decomposition

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and H-W models have individually performed better than all 2-model forecasts except combined decomposition and H-W models. This is understandable since the two models have performed better than other single models in their individual capacities.

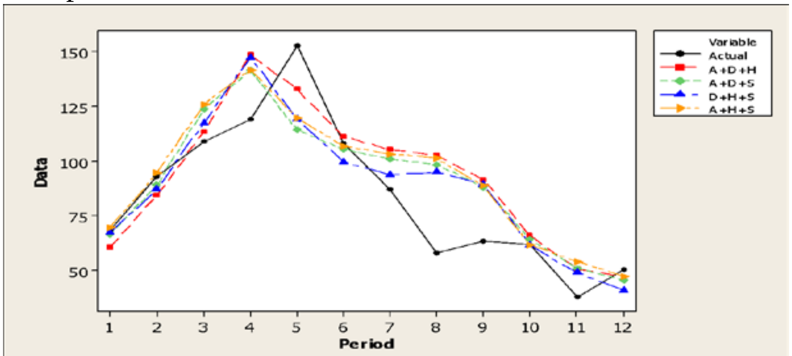

Fig. 4. Actual values and forecasts for 3-model combinations.

Only four 3-model cases are involved. The forecasts are depicted in Fig. 4. The figure portrays a scenario where forecasts are not radically different, similar to that of 2-model combinations.

Table 4. Forecasts, MSE and overall ranking of combinations of three models

		Model			
Period	**Actual value**	**A+D+H**	**A+D+S**	**D+H+S**	**A+H+S**
Jan	68.18	60.6795	66.4112	67.0619	69.4239
Feb	92.7	84.3188	89.0151	87.0484	94.5251
Mar	109.12	113.339	123.5815	117.4782	125.7683
Apr	119.09	148.6521	141.795	147.644	141.8558
May	152.70	132.9254	114.3614	119.2332	119.6602
Jun	108.07	111.3515	105.1898	99.6346	106.8466
Jul	86.92	105.2027	101.031	93.6081	103.1704
Aug	57.77	102.7282	98.2977	94.8758	101.251
Sept	63.0	91.5372	88.0511	89.2628	88.5395
Oct	61.64	65.9178	64.1449	61.4928	61.5395
Nov	37.8	50.5393	50.8573	48.7409	53.8874
Dec	50.34	46.8159	45.4638	40.9962	47.1589
MSE	-	398.5755	407.1498	368.922	413.8417
Rank		5	7	1	10

Table 3 presents all possible combinations of three models. Model (D+H+S) is not only the best in this category, it is the overall best of all combinations as it is ranked first. Once again, the individual performances of decomposition and H-W have come into play. The two combined with SARIMA model have produced the overall best model. This is an interesting output of combination of simplicity with sophistication.

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Table 5. Forecasts, MSE and overall ranking of a combination of four models

Period	Actual value	A+D+H+S
Jan	68.18	65.8941
Feb	92.7	88.7269
Mar	109.12	120.0418
Apr	119.09	144.9679
May	152.70	121.5451
Jun	108.07	105.7556
Jul	86.92	100.7531
Aug	57.77	99.2882
Sept	63.0	89.3319
Oct	61.64	63.2704
Nov	37.8	51.0063
Dec	50.34	45.1087
MSE	-	383.238
Rank		3

The forecasts for the only four combined models are presented in Table 5. The combination is ranked overall third. It has indeed justified efforts at combining the forecasts as it has performed better than all single model cases. Results have shown that combined forecasts are better as far as wind run forecasting is concerned. The best of single model has performed worse than the best of combined forecasts from two-model, three-model and four-model forecasts. It is therefore worthwhile to combine forecasts as doing so tends to improve accuracy.

Table 6. Average ranks for different model structure (Case of 12-month forecasts)

Model structure	Average rank
Single	10.25
Double	8.83
Triple	5.75
Quadruple	3.00

Average ranks presented in Table 6 suggest that the 4-model forecasts are typically better than others, followed by 3-model forecasts, then 2-model forecasts and lastly, single model forecasts. Combined forecasts have shown supremacy.

Table 7. Absolute errors and ranks based on 1-step-ahead forecasts

Model	Absolute error	Rank
ANN (A)	5.7893	10
DECOM (D)	12.8752	14
H-W (H)	3.3178	6
SARIMA (S)	13.358	15
A+D	9.3322	13
A+H	4.8132	9
A+S	3.7844	7

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D+H	8.3561	12
D+S	0.2414	1
H+S	4.7605	8
A+D+H	7.4825	11
A+D+S	1.7688	4
D+H+S	1.1181	2
A+H+S	1.2439	3
A+D+H+S	2.2859	5

Table 7 presents absolute errors for all cases based on 1-step-ahead forecast. Just like the earlier comparisons that were done on the basis of forecasts for 12 months, combined forecasts have shown once again its supremacy over single forecasts. Model (D+S) has performed best on basis of absolute error, followed by D+H+S and then A+H+S. The best performer of single models is Holt-Winters' occupying the sixth position.

Table 8. Average ranks for different model structure (1-step-ahead forecasts)

Model structure	**Average rank**
Single	10.25
Double	12.50
Triple	5.00
Quadruple	1.25

Average ranks obtained from 1-step-ahead forecasts are presented in Table 8. The behavior is not radically different from that of 12-month forecasts displayed in Table 6 except that single models typically perform better than 2-model forecasts in the case of 1-step-ahead forecasting.

Conclusions

This article has modeled wind run series using four different forecasting models and compared single to combined forecasts. Combined forecasts were found to be better than single forecasts on a short term and long term basis. The combination of decomposition, Holt-Winters' and SARIMA models performed best. Holt-Winters' model performed better than eleven combined models, suggesting that combined models are not always better. It is therefore evident that inclusion of additional model forecast does not necessarily improve combined forecast accuracy but tends to do so. In modeling situations, single and combined forecasts should be allowed to compete as doing so will assist in determining which of single and combined forecasts is appropriate.

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