ForecastTB—An R Package as a Test-Bench for Time Series Forecasting—Application of Wind Speed and Solar Radiation Modeling

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Abstract: This paper introduces an R package ForecastTB that can be used to compare the accuracy of different forecasting methods as related to the characteristics of a time series dataset. The ForecastTB is a plug-and-play structured module, and several forecasting methods can be included with simple instructions. The proposed test-bench is not limited to the default forecasting and error metric functions, and users are able to append, remove, or choose the desired methods as per requirements. Besides, several plotting functions and statistical performance metrics are provided to visualize the comparative performance and accuracy of different forecasting methods. Furthermore, this paper presents real application examples with natural time series datasets (i.e., wind speed and solar radiation) to exhibit the features of the ForecastTB package to evaluate forecasting comparison analysis as affected by the characteristics of a dataset. Modeling results indicated the applicability and robustness of the proposed R package ForecastTB for time series forecasting.

Keywords: forecast; test-bench; data analysis; R; package; software; tool; time series; wind energy; solar energy

1. Introduction

Decision making is one of the most crucial tasks in many domains and often decisions are based on the most accurate forecast available in the respective domains. A large number of areas, such as energy [1,2], economics [3], infrastructure [4,5], health [6,7], agriculture [8,9], defense [10], education [11,12], technology [13,14], geo-science [15], climate [16] and structural engineering [17] among several others, are looking forward to benefits that can be achieved with time series forecasting. Time series are consecutive sequences of values ordered with respect to time. Statistically, it is represented by the theory of stochastic processes [18]. The notable feature of time series data is the time-based correlation between values such that the probability of occurrence of a value depends on future or past observations [19,20].

Standardizing the process of the forecasting methods comparison is associated with numerous challenges [21]. The apparent concern is the nature of the time series and selection of appropriate methods such as the complete variation from seasonality, trends, and random parameters, that should be handled with each method. For instance, one forecasting model may perform better for a seasonal time series but show poor accuracy as compared to other models for a trendy or a random one [22]. Besides, interpretations might be affected by the error metric selection, for example, Root mean square error (RMSE), as different metrics have different objectives [23].
The ForecastTB package can be helpful for professionals and researchers working in the field of data science and forecasting analysis. The salient features of the ForecastTB package are as follows:

- **Reduction in efforts and time consumption**: The ForecastTB package is designed to reduce the efforts and time consumption for the time series forecasting analysis. It avoids the repetitive steps in the analysis and leads to the promising comparative results report generation.

- **Truthful comparison assurance**: The ForecastTB package ensures a truthful and unbiased comparison of forecasting methods. Hence, this package may be considered a reliable tool for forecasting models based on industrial reports generation or scientific publications.

- **Reproducible research**: Along with unbiased comparisons, the ForecastTB package provides ease in reproducible research with minimum efforts. In other words, the forecasting comparison can be reproduced several times easily with the help of the ForecastTB package.

- **Stepping stone in machine learning automation**: Forecasting methods play a very important role in machine learning applications [24]. The ForecastTB package aims to evaluate the best performing forecasting method for a given time series dataset and this can be presented as a stepping stone in machine learning automation modeling. For example, on changing nature and patterns of the time series dataset, a machine learning application could automatically replace the existing forecasting methods based on the output of the ForecastTB package.

- **A handy tool**: The ForecastTB package is a handy tool, especially for researchers who are not comfortable with computer coding, since it is a plug-and-play module based package. A very simple syntax leads to very impressive and accurate forecasting comparison analysis.

This paper demonstrates the inspection of the ForecastTB package as a testbench for the comparative study of different forecasting methods [25]. The motivation behind this package is another R package, named imputeTestbench [26,27], which demonstrated great success in performing comparison analysis with time series imputation methods in several research studies [28–31]. The ForecastTB package aims at providing an evaluation toolset that overcomes the challenges of discovering the most suitable forecasting method along with a detailed comparative analysis. This package allows simulating random possibilities of different strategies including Monte-Carlo simulation. Values forecasted with several different methods are then compared with a user defined error metric. A couple of plotting functions are provided for overall forecast evaluation visualization. Besides, demonstration examples and case studies on natural time series datasets are discussed to showcase the usage of ForecastTB package.

## 2. Overview of ForecastTB

The ForecastTB package is a plug-and-play structured module as shown in Figure 1. It is used to compare the forecasting methods, which begins by forecasting time series with distinct strategies. Then the prediction accuracies are evaluated with the error metrics for all methods for several repetitions. The prediction_errors() function is employed for a forecasting method comparative evaluation with the consideration of various input parameters. It returns an object, which is the basic module in the package. Further this module can be updated with new methods and other parameters with append() and choose() functions. The Monte_Carlo() function is a further extension of the prediction_errors() module to compare distinct methods for randomly selected patches of the input time series. The remaining two functions, plotMethods() and plot_circle(), are used to visualize forecasted results and error summaries for the chosen methods. All functions, as a set of modules, are based on and connected with the object provided by the prediction_errors() function. Hence, the framework of the ForecastTB package is version-control-friendly. It means, in the future, new features in the next versions of the package, can be easily introduced.
2.1. The prediction_errors() function

The prediction_errors() is a primary function that compares the performance of different forecasting methods depending on various parameters supplied by user. The default methods included in prediction_errors() are ARIMA from the forecast package [38] and the Pattern sequence based forecast (PSF) method from the PSF package [39,40]. This statistical method, ARIMA, is most widely and frequently used in time series forecasting. It is comfortably modeled as compared to more complex approaches. Moreover, to avoid further complexity, the auto.arima() function in the forecast package [38] and psf() from the PSF package are used, which automatically estimates the model parameters required for the given dataset. With the following examples, we show the possibility of adding extra and user-defined methods as needed.

Following are the arguments of the prediction_errors() function:

```
a <- prediction_errors(data = data, nval = 12,
ePara = c('RMSE', 'MAE'), ePara_name = c('RMSE', 'MAE'),
Method = c('ARIMA', 'PSF'), MethodName = c('ARIMA', 'PSF'),
```

Dependencies include additional packages for data manipulation (reshape2, [32]; stats, [33]), graphing (ggplot2, [34]; circlize, [35]; graphics, [33]; gridExtra, [36]; RColorBrewer, [37]), and forecast (forecast, [38]; PSF, [39–41]; decomposedPSF, [42]; methods, [33]).

Recently, a package in R was proposed for streamlining time series forecasting with limited facilities and features, named as predtoolsTS [43,44]. This tool assists in forecasting with the automated Auto-Regressive Integrated Moving Average (ARIMA) model [38] and only regression type algorithms from the caret [45] package in the closed environment. Beyond this, there is no facility to append new forecasting methods and updating the comparison environment as per the user’s need. On the contrary, the proposed ForecastTB package provides such multiple facilities along with the possibilities of introducing new features with a simple plug-and-play structure as discussed in the article.

Figure 1. The plug-and-play module of the ForecastTB package.
strats = 'Recursive', dval = length(data),
append_ = 0)

data:

A ts (stats) as input dataset (numeric object) to be evaluated. It is a time varied dataset for
comparison of performance and accuracy of forecasting methods.
nval:

An integer value to decide a number of values to be predicted while comparing the forecasting
methods. The default value is 12.
ePara:

The forecasted and observed values are compared with error metrics. The root-mean-squared
error (RMSE), mean absolute error (MAE), and mean absolute percent error (MAPE) [46] are the default
error metrics included in ForecastTB, but the individual metric can be opted using ePara = 'rmse',
'mae', or 'mape'. The error metrics are defined as:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} |X_i - \hat{X}_i|^2}$$  \hspace{1cm} (1)

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |X_i - \hat{X}_i|$$  \hspace{1cm} (2)

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \frac{|X_i - \hat{X}_i|}{X_i} \times 100\%,$$  \hspace{1cm} (3)

where $X_i$ and $\hat{X}_i$ are the observed and forecasted data at time $t$, respectively. $N$ is the number of data
for forecast evaluation.

Additionally, a new error metric of the user’s choice can be introduced in the following
manner: ePara = c("errorparametename"), where errorparametename is an external function
which returns desired error values for original and forecasted values. It is discussed in detail in
the following sections.
ePara_name:

A string of characters for the names of error metrics provided in ePara. In the prediction_errors() function, RMSE, MAE and MAPE are the default names for the error
parameters.
Method:

A string with method names that are used to forecast values with ARIMA, PSF and user-defined
methods. The ARIMA is a default method until the user changes it. For instance, Method = c("PSF")
will use only the PSF with the prediction_errors() function. New forecasting methods can be
included in prediction_errors() function with Method = c("test1(data, nval)") vector, where
\text{test1} is an external function which forecasts nval number of future values for input data and returns
the forecasted values. Such multiple functions can be added in the Method parameter. The external
function is expected to provide forecast methods using the recursive strategy.
MethodName:

A string of characters provided by user as one or more forecast methods passed to Method.
The default list of name of method in the prediction_errors() function is ARIMA.
strats:

A character string of names of forecasting strategies used for time series forecasting. The strategies used in the current version of the prediction_errors() function are Recursive and DirRec. In the recursive approach, the first value is predicted with a prediction model and then appended to the data-set. Fits to the same model are then used to predict the next value. In the DirRec approach, the first value is predicted with a model and appended it to the data-set. A new model is then fitted and used to predict the next value and so on. The default strategy in the prediction_errors() function is the Recursive one.

append_:

A flag that suggests if the function is used to append to another instance. The default flag is 1, which indicates newly added methods are compared with the default methods. When the flag is 0, all methods, excluding default methods, will be compared.

dval:

An integer that specifies the length of the data subset to be used for forecasting. The default value is the length of the data parameter.

With the default entities for all arguments, the prediction_errors() function generates an S4 object of class prediction_errors as the error profile for the forecasting methods. This prediction_errors() function returns two slots as output. The first slot is output, which provides Error_Parameters, indicating error values for the forecasting methods and error parameters defined in the framework, and Predicted_Values as values forecasted with the same forecasting methods. Further, the second slot is parameters, which returns the parameters used or provided to prediction_errors() function. This is illustrated in the following example:

```r
# 'AirPassengers' is a sample dataset in CRAN
prediction_errors(data = AirPassengers)

# An object of class "prediction_errors"
# Slot "output":
# $Error_Parameters
#   RMSE     MAE    MAPE  exec_time
# ARIMA 53.357458 45.662500 9.647511 1.248623
#
# $Predicted_Values
#   1   2   3   4   5   6   7
# Test values 417.0000 391.0000 419.0000 461.0000 472.0000 535.0000 622.0000
# ARIMA 425.5702 432.2525 489.0878 499.4493 539.9511 539.7919 536.0011
#
# $data
#   Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
# 1949 112 118 132 129 121 135 148 148 136 119 104 118
# 1950 115 126 141 135 125 149 170 170 158 133 114 140
# 1951 145 150 178 163 172 178 199 199 184 162 146 166
# 1952 171 180 193 181 183 218 230 242 209 191 172 194
```
2.2. The `append()` and `choose()` functions

The `append()` and `choose()` are functions to add new forecasting methods and choose the selected methods to and within the `prediction_errors` object. These functions make ForecastTB a handy plug-and-play tool for forecasting analysis. The `append()` function has the following arguments:

```r
append_(object = a, 
Method = c("test2(data,nval)"), MethodName = c('Test2'),
ePara = c('RMSE', 'MAE'), ePara_name = c('RMSE', 'MAE'))
```

object:

A `prediction_errors` object with two slots, output and parameters returned by the `prediction_errors()` function.

Method, MethodName, ePara and ePara_name:

These parameters are with similar meaning as that supplied to the `prediction_errors()` function. The `ePara` and `ePara_name` parameters of the `append()` function automatically get synced with the `prediction_errors()` function. The `append()` function returns the error profile for the forecasting methods along with newly added ones in the form of an updated `prediction_errors` object.
Further, the choose() function helps the user to manipulate the prediction_errors object, by allowing selection of the desired methods existing in the object. The choose() function has the following argument:

choose_(object)

object:

A prediction_errors object returned by the prediction_errors() or append_() function. The syntax of the choose() function is discussed in the following example. The variable c is an object with three forecasting methods comparisons. After provide the c object to the choose() function, it returns the following output showing names of forecasting methods attached in the c object and asks the index number of method to be removed from the same object. Finally, it stores the newly updated object in the variable d.

```r
## > d <- choose_(object = c)
## Following are the methods attached with the object:
## [,1] [,2] [,3]
## Indices "1" "2" "3"
## Methods "ARIMA" "DPSF" "xyz"
## Enter the indices of methods to remove:2
```

After removing one of the methods with the choose() function, a new object d is returned as follows:

```r
## > d@output
## $Error_Parameters
##   RMSE   MAE   MAPE   exec_time
## ARIMA 2.3400915 1.9329816 4.2156087 0.1328349
## xyz 4.0909453 3.3250000 7.1517742 0.4336619
##
## $Predicted_Values
##   1   2   3   4   5   6   7   8
## Test values 39.40000 40.90000 42.40000 47.80000 52.40000 58.00000 60.70000 61.80000
## ARIMA 37.41933 37.69716 41.18252 46.29926 52.24804 57.10696 59.71774 59.41173
## xyz 4.0909453 3.3250000 7.1517742 0.4336619
##
## $Predicted_Values
##   9  10  11  12
## Test values 58.20000 46.70000 46.60000 37.80000
## ARIMA 56.38197 51.4756 46.04203 41.52592
## xyz 57.00000 54.20000 39.70000 42.80000
```

In this way, the append() and choose() functions provide features to manage the desired forecasting methods in the prediction_errors object with simple and single lined syntax. Besides, these functions avoid repetitive computation and execution of the methods which are already attached in the prediction_errors object.

2.3. The plot.prediction_errors() and plot_circle() functions

The plot.prediction_errors() and plot_circle() functions allow users to plot the S4 object of the prediction_errors class. The plot.prediction_errors() is an S3 method, in which, along with the prediction_errors object, it optionally accepts other variables in used to describe plots in R, such as, legends, axes, labels, and so forth. This function plots a bar-chart of error values and execution time and line plots of forecasted values with significant color changes for different forecasted methods. The plot generated plot.prediction_errors() consists of a dynamic margin size
with which forecasted values can be included if required. The `plot.prediction_errors()` function syntax and usage are discussed below:

```
plot.prediction_errors(object = a, ...)
```

Furthermore, the `plot_circle()` function provides a polar plot for showing forecasted values, especially if these are seasonal values. This plot shows how forecasted observations are behaving on an increasing number of seasonal time horizons. The syntax of the `plot_circle()` function is similar to that of `plot.prediction_errors()` one, as shown below:

```
plot_circle(object = a, ...)
```

### 2.4. The `monte_carlo()` function

Monte-Carlo sampling is a very popular strategy to compare the performance of forecasting methods. In this strategy, multiple patches of a dataset are selected randomly and then tests of the performance of the forecasting methods are executed. It returns the average of error values obtained for each data patches. The most notable feature of the Monte-Carlo strategy is that it ensures an accurate comparison of forecasting methods and avoids the biased results which might be obtained by chance.

The `monte_carlo()` function has the following arguments:

```
monte_carlo(object, size, iteration, fval, figs)
```

**object:**

An S4 object of the `prediction_errors` class with two slots, output and parameters returned by the `prediction_errors()`, `append()` or `choose()` functions. The `monte_carlo()` function tunes itself based on parameters returned by the object.

**size:**

An integer value representing the length of the patches from the time series dataset used in the Monte Carlo strategy. The input dataset is referred from the `prediction_errors` object.

**iteration:**

A numeric value representing the iterations to be used by the Monte-Carlo strategy.

**fval:**

A flag, when it is on (`fval = 1`), the `monte_carlo()` function return the output along with the forecasted values for each iteration. The default value of `fval` is 0, that returns only the error values in RMSE in each iteration.

**figs:**

A flag to plot with the `plot.prediction_errors()` function for each iteration in Monte-Carlo strategy when `figs = 1`. The default value of `figs` is 0 and it does not return any plots.

This way, the `monte_carlo()` function returns the error values along with the mean values for the provided forecasted methods in each iteration of the Monte-Carlo strategy. This function can be used as a quick tool to create an intuition of best-suited forecasting method for a given time series dataset.
3. A Case Study: Performance of Forecasting Methods on Standard Natural Time Series

This section presents a case study to introduce the use of the ForecastTB package as a test-bench to compare the performance of time series forecasting methods. The methods used in the case study are the \texttt{auto.arima()}, \texttt{ets()}, \texttt{psf()}, and \texttt{lpsf()} that are frequently used R functions for time series forecasting. The two standard datasets used in this example are \texttt{nottem} and \texttt{sunspots}. The \texttt{nottem} is the average air temperatures recorded at Nottingham Castle in degrees Fahrenheit from 1920 to 1930 (\texttt{datasets} package, [33]). Similarly, the \texttt{sunspots} is mean relative sunspot numbers from 1749 to 1983 (\texttt{datasets} package, [33]). Both datasets are measured on monthly basis.

In the following examples, the whole comparison analysis and visualization are done for the \texttt{nottem} dataset, but only the error values are shown for the \texttt{sunspots} dataset. The following are the two functions that represent forecasting methods. These methods include LPSF and PSF methods from the \texttt{decomposedPSF} [42] and \texttt{PSF} [39] packages. These functions consume time series dataset and \texttt{nval} as input parameters and return the forecasted values as a string.

```r
library(decomposedPSF)
test1 <- function(data, nval){
  return(lpsf(data = data, n.ahead = nval))
}
library(PSF)
test2 <- function(data, nval){
  a <- psf(data = data, cycle = 12)
  b <- predict(object = a, n.ahead = nval)
  return(b)
}
```

The following code chunk is the main function in the ForecastTB package, in which performance of ARIMA along with the above mentioned (PSF and LPSF) methods are compared for the \texttt{nottem} time series for next 12 months forecast. The output of the function is saved in the variable \texttt{a1} as an S4 object of \texttt{prediction_errors} class.

```r
a1 <- prediction_errors(data = nottem, nval = 12,
  Method = c("test1(data, nval)", "test2(data, nval)"),
  MethodName = c("LPSF","PSF"),
  append_ = 1)
a1
```

```
## An object of class "prediction_errors"
## Slot "output":
## $Error_Parameters
##   RMSE    MAE   MAPE    exec_time
## ARIMA 2.3400915 1.9329816 4.2156087 0.2290468
## LPSF  5.3525306 4.5916667 9.6590830 0.2280521
## PSF  2.2454324 1.9450000 4.1462600 0.1007819

## $Predicted_Values
##        1     2     3     4     5     6     7
## Test values 39.40000 40.90000 42.40000 47.80000 52.40000 58.00000 60.70000
## ARIMA 37.41933 37.69716 41.18252 46.29926 52.24804 57.10696 59.71674
## LPSF  38.55000 37.10000 34.90000 43.15000 45.50000 52.40000 55.95000
## PSF  38.38000 37.56000 41.80000 45.46000 52.96000 57.14000 61.68000
```
## Test values 61.80000 58.20000 46.70000 46.60000 37.80000
## ARIMA 59.41173 56.38197 51.4756 46.04203 41.52592
## LPSF 61.45000 60.40000 57.2500 49.75000 42.60000
## PSF 59.20000 56.68000 49.6000 42.56000 40.38000

### Slot "parameters":

```r
## $data
## Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
## 1920 40.6 40.8 44.4 46.7 54.1 58.5 57.7 56.4 54.3 50.5 42.9 39.8
## 1921 44.2 39.8 45.1 47.0 54.1 58.7 66.3 59.9 57.0 54.2 39.7 42.8
## 1922 37.5 38.7 39.5 42.1 55.7 57.8 56.8 54.3 54.3 47.1 41.8 41.7
## 1923 41.8 40.1 42.9 45.8 49.2 52.7 64.2 59.6 54.4 49.2 36.3 37.6
## 1924 39.3 37.5 38.3 45.5 53.2 57.7 60.8 58.2 56.4 49.8 44.4 43.6
## 1925 40.0 40.5 40.8 45.1 53.8 59.4 63.5 61.0 53.0 50.0 38.1 36.3
## 1926 39.2 43.4 43.4 48.9 50.6 56.8 62.5 62.0 57.5 46.7 41.6 39.8
## 1927 39.4 38.5 45.3 47.1 51.7 55.0 60.4 60.5 54.7 50.3 42.3 35.2
## 1928 40.8 41.1 42.8 47.3 50.9 56.4 62.2 60.5 55.4 50.2 43.0 37.3
## 1929 34.8 31.3 41.0 43.9 53.1 56.9 62.5 60.3 59.8 49.2 42.9 41.9
## 1930 41.6 37.1 41.2 46.9 51.2 60.4 60.1 61.6 57.0 50.9 43.0 38.8
## 1931 37.1 38.4 38.4 46.5 53.5 58.4 60.6 58.2 53.8 46.6 45.5 40.6
## 1932 42.4 38.4 40.3 44.6 50.9 57.0 62.1 63.5 56.3 47.3 43.6 41.8
## 1933 36.2 39.3 44.5 48.7 54.2 60.8 65.5 64.9 60.1 50.2 42.1 35.8
## 1934 39.4 38.2 40.4 46.9 53.4 59.6 66.5 60.4 59.2 51.2 42.8 45.8
## 1935 40.0 42.6 43.5 47.1 50.0 60.5 64.6 64.0 56.8 48.6 44.2 36.4
## 1936 37.3 35.0 44.0 43.9 52.7 58.6 60.0 61.1 58.1 49.6 41.6 41.3
## 1937 40.8 41.0 38.4 47.4 54.1 58.6 61.4 61.8 56.3 50.9 41.4 37.1
## 1938 42.1 41.2 47.3 46.6 52.4 59.0 59.6 60.4 57.0 50.7 47.8 39.2
## 1939 39.4 40.9 42.4 47.8 52.4 58.0 60.7 61.8 58.2 46.7 46.6 37.8

## $nval
## [1] 12

## $ePara
## [1] "RMSE" "MAE" "MAPE"

## $ePara_name
## [1] "RMSE" "MAE" "MAPE"

## $Method
## [1] "ARIMA" "test1(data, nval)" "test2(data, nval)"

## $MethodName
## [1] "ARIMA" "LPSF" "PSF"

## $Strategy
## [1] "Recursive"

## $dval
The object \( a_1 \) shows the comparison of ARIMA, PSF, and LPSF methods in addition to the parameters provided by users and the defaults ones, whenever not provided. Imagining a case that the user wishes to attach a new method in the object \( a_1 \). Though this could be done with the `prediction_errors()` function, as discussed above, this will lead to the execution of all methods which were already available in the object. To avoid such redundant calculations and executions, the `append()` function could be used. The Error, Trend, Seasonal (ETS) method from the `forecast` package is framed in a function as follows:

```r
library(forecast)
test3 <- function(data, nval){
  b <- as.numeric(forecast(ets(data), h = nval)$mean)
  return(b)
}
```

The object \( a_1 \) is updated with ETS method into object \( c_1 \) with the `append()` function and returns the error parameters as shown below:

```r
c1 <- append_(object = a1, Method = c("test3(data,nval)"), MethodName = c("ETS"))
c1@output$Error_Parameters
## RMSE    MAE    MAPE  exec_time
## ARIMA  2.3400915  1.9329816 4.2156087    0.2290468
## LPSF   5.3525306  4.5916667 9.6590830    0.2280521
## PSF    2.2454324  1.9450000 4.1462600    0.1007819
## ETS    31.41914256 28.87699844 56.31295348  0.04888916
```

Further, the object \( c_1 \) is plotted with the S3 method `plot.prediction_errors()` as follows and are shown in Figure 2. This figure shows the forecasting errors (bar plot) and forecasted values (line plot) for all methods attached in object \( c_1 \).

```r
d1 <- plot(c1)
```

From Figure 2, it can be observed that the performance of the ETS method is not satisfactory for the `nottem` time series dataset. In this case, the user can omit the unwanted method from object \( d1 \) with the `choose()` function as shown below. After providing the object as input to the `choose()` function, it returns the names of forecasting methods available in the `prediction_errors` object with respective indices, and asks the user to enter the indices of the methods to be removed from the object. In the following code chunk, index 4 for the ETS method is provided by the user and this results in a new object \( e_1 \), which is nothing but the object \( d1 \) without the ETS method. The `choose()` function permits the user to remove multiple numbers of methods from the object, where the user needs to enter multiple numbers in a vector format.
Figure 2. Forecasting errors (in bar plot) and forecasted values (in line plot) for methods attached in the object c1.

```r
# > e1 <- choose_(object = c1)
# Following are the methods attached with the object:
# [,1] [,2] [,3] [,4]
# Indices "1" "2" "3" "4"
# Methods "ARIMA" "LPSF" "PSF" "ETS"
# Enter the indices of methods to remove:4
# > e1@output$Error_Parameters
#        RMSE         MAE        exec_time
# ARIMA 2.5233156 2.1280641   0.1963789
# LPSF  2.3915796 1.9361111   0.2990961
# PSF  2.2748736 1.8301389   0.1226711

3.1. Adding New Error Metrics

As described in the earlier section, RMSE, MAPE, and MAE are the default error metrics assigned to ForecastTB. All these error metrics compare the forecasting methods in different perspectives [26]. Based on the information provided by each metric, users should use an appropriate one. All of these metrics are used internally within the `prediction_errors()` function.

Additionally, new error metrics can be added using an approach similar to that used for adding forecasting methods described in earlier sections. The following code demonstrates how the percentage change in variance (PCV, [47]) is added to the existing object as an additional error metric:

\[
PCV = \left| \frac{\text{var(Predicted)} - \text{var(Observed)}}{\text{var(Observed)}} \right|
\]

where \(\text{var(Predicted)}\) and \(\text{var(Observed)}\) are variance of predicted and observed values.

The user-defined error function should be provided in an R script with two mandatory input arguments, that is, the same length vectors of observed and forecasted values. The defined function
should return a summary of the errors or differences. The function and its name must be supplied to the ePara and ePara_name argument of the prediction_errors() function, respectively.

```r
# error metric to include with 'prediction_errors()' function
pcv <- function(obs, pred){
  d <- (var(obs) - var(pred)) * 100/ var(obs)
  d <- abs(as.numeric(d))
  return(d)
}
```

The following code chunk shows how the new error function is attached to the prediction_errors object and corresponding update are observed with the plot() function, as shown in Figure 3.

```r
a1 <- prediction_errors(data = nottem, nval = 24,
Method = c("test1(data, nval)", "test2(data, nval)")
MethodName = c("LPSF","PSF")
ePara = "pcv(obs, pred)"ePara_name = 'PCV',
append_ = 1)
a1@output$Error_Parameters
```

```r
## RMSE MAE MAPE PCV exec_time
## ARIMA 2.8191449 2.3527391 4.9283784 17.3881625 0.1586161
## LPSF 2.2180209 1.7208333 3.6520057 28.7072293 0.3137138
## PSF 2.404563 1.781872 3.726139 23.872712 0.109726
```

```r
b1 <- plot(a1)
```

![Figure 3. A plot showing the new error function in prediction_errors object.](image-url)
3.2. A Polar Plot

The ForecastTB package provides a polar plot of showing forecasted values, especially if the time series dataset shows seasonality as shown in Figure 4. This plot shows the nature of forecasted values and how these values are behaving on an increasing number of time horizons. The numbers on the circle shows the forecasted time steps. Several forecasting methods are suitable for short-range forecasts but fail to maintain the accuracy for longer horizons. This proposed plot is capable of reflecting this feature in a more intuitive way. In Figure 4, the yellow-colored line for the ARIMA method is moving away from the test values as the time horizon proceeds.

![Polar Plot](image)

**Figure 4.** A polar plot to represent forecasted values.

3.3. Monte-Carlo Strategy

The code chunk below shows Monte-Carlo simulation on nottem time series with `monte_carlo()` function. This function is supplied with above mentioned `prediction_errors` object `a1`. It is also supplied with size of each data patch in each iteration as 144 and the number of iterations as 10. The flag parameters `fval` and `figs` are set to 0, in order to avoid display of forecasted values and comparison plots for all iterations in the Monte-Carlo simulations. The effect of these flags is further discussed in the vignette published in ForecastTB package.

```
monte_carlo(object = a1, size = 144, iteration = 10, fval = 0, figs = 0)
```

|   | ARIMA   | LPSF        | PSF       |
|---|---------|-------------|-----------|
| 19| 3.597220| 5.415615    | 5.228346  |
| 18| 4.547199| 5.411696    | 5.257050  |
| 67| 2.080661| 5.062059    | 4.747707  |
### 2.894787 5.392858 5.197034
### 2.641607 5.885326 5.140588
### 2.103611 4.739618 4.648975
### 2.522385 5.253795 5.140588
### 2.152816 4.889250 5.129120
### 3.193709 4.854308 4.949747
### 3.960024 5.834563 5.746631
### Mean 2.969402 5.273909 5.104855

This output shows the performance of ARIMA, LPSF, and PSF methods on nottem time series for 10 different time patches. The first column in the output shows the numeric number as an index in time series from which the data patch is selected for the analysis. Besides, the last row shows the averaged error values for all methods and it ensures more accurate and unbiased performance of the forecasting methods.

Furthermore, the following code chunk shows an object to compare the performance of forecasting methods on the sunspots time series and further a more rigorous comparison is done with Monte-Carlo simulations.

```r
x1 <- prediction_errors(data = sunspots, nval = 24,
Method = c("test1(data, nval)", "test2(data, nval)"),
MethodName = c("LPSF","PSF"),
append_ = 1)
x1@output$Error_Parameters
```

```
## RMSE MAE MAPE exec_time
## ARIMA 67.141209 59.680909 95.074983 0.755336
## LPSF 45.251790 38.436458 37.283434 1.459494
## PSF 34.834718 28.803750 28.943332 0.496691
```

The flag parameters fval and figs in following monte_carlo() function are not provided, hence these flags takes the value 0 as default.

```
monte_carlo(object = x1, size = 600, iteration = 10)
```

```
## ARIMA LPSF PSF
## 2012 34.416174 24.383396 46.38433
## 252 20.804560 15.604257 15.56385
## 1524 14.008383 42.509944 22.56851
## 1081 5.928826 57.622837 23.16030
## 977 27.636099 35.118654 28.71433
## 734 16.529586 19.400491 21.04473
## 826 47.850499 26.893230 32.96957
## 1467 20.846583 17.438523 12.10345
## 484 29.408694 41.441812 31.73321
## 668 6.505468 7.243862 15.30992
## Mean 22.393487 28.765701 24.95522
```

It is interesting to know that, for the full-length sunspots time series, the PSF method was observed to be the best among the selected methods with the prediction.error() function, where last 24 values of the dataset were forecasted. Whereas, for the Monte-Carlo simulation, with rigorous iterations, ARIMA outperformed with a significant error difference as compared to PSF and LPSF methods. In this way, the monte_carlo() function can be used in comparing forecasting methods by avoiding the biased results that can be obtained by chance.
4. Case Study Related to the Energy Application

In the current research, it is important to validate the proposed R package `ForecastTBI` based on real-world applications. In this manner, a reliable and feasible application can demonstrate the capacity of the developed R package forecasting code. Wind speed and solar radiation data of two meteorological stations (Robinson and Watford City) located in the North Dakota, USA, were used to test the predictability performance of the LPSF: modified pattern sequence-based forecast and PSF—pattern sequence-based forecast models. Three time scales were examined for the forecasting of 12 steps ahead of each scale including daily, weekly, and monthly. The modeling result was tested using several statistical performance metrics (RMSE, MAE, and MAPE), time convergence, and graphical presentation. The data span covers 20 years of historical data over the period (1 January 2000 to 31 December 2019). Three models were developed for modeling verification including support vector machine (SVM), decomposed pattern sequence-based forecast (DPSF), and hybridized ensemble empirical mode decomposition with Autoregressive integrated moving average (EEMD-ARIMA).

4.1. Statistical Performance Metrics Results

Following several established studies from the literature on wind speed and solar radiation prediction, RMSE, MAE, and MAPE are the commonly used statistical metrics for forecasting evaluation [48]. Those metrics can give an informative evaluation of the prediction capacity. For the Robinson station, the forecasting results attained the minimal values of the absolute error measures for the applied models—LPSF (RMSE = 7.57 and 71.6, MAE = 5.34 and 61.52 and MAPE = 35.84 and 28.22) and PSF (RMSE = 8.47 and 74.74, MAE = 7.0 and 63.65 and MAPE = 57.69 and 26.93) for the daily scale wind speed and solar radiation; LPSF (RMSE = 3.75 and 66.17, MAE = 3.2 and 47.36 and MAPE = 32.82 and 23.72) and PSF (RMSE = 3.3 and 59.33, MAE = 3.57 and 49.72 and MAPE = 24.5 and 21.88) for the weekly scale wind speed and solar radiation; LPSF (RMSE = 2.09 and 99.8, MAE = 1.58 and 82.74 and MAPE = 19.15 and 33.79) and PSF (RMSE = 1.6 and 39.32, MAE = 1.19 and 32.51 and MAPE = 13.77 and 10.84) for the monthly scale wind speed and solar radiation, respectively (Table 1). In comparison with the SVM, DPSF and EEMD-ARIMA, the LPSF and PSF models revealed an acceptable prediction enhancement. For instance, wind speed prediction was improved using the LPSF model by (86.04%, 42.77%, and 19.22%) based on the RMSE metric against the SVM, DPSF, and EEMD-ARIMA models, respectively. Whereas, solar radiation prediction accuracy was enhanced by (74.41%, 43.83% and 16.08%) using the LPSF model and RMSE metric over the SVM, DPSF and EEMD-ARIMA models, respectively.

| Methods       | Wind Speed | Solar Radiation | Execution Time | Execution Time |
|---------------|------------|-----------------|----------------|----------------|
|               | RMSE       | MAE             | MAPE           | RMSE           | MAE             | MAPE           | Execution Time |
| LPSF          | 7.57       | 5.34            | 35.84          | 0.55           | 71.60           | 61.52          | 28.22          | 0.49           |
| PSF           | 8.47       | 7.00            | 57.69          | 0.42           | 74.74           | 63.65          | 26.93          | 1.06           |
| SVM           | 54.28      | 49.02           | 472.57         | 0.43           | 279.86          | 237.87         | 93.45          | 0.30           |
| DPSF          | 13.24      | 11.07           | 73.07          | 1.12           | 127.47          | 115.48         | 42.43          | 1.63           |
| EEMD-ARIMA    | 9.38       | 7.99            | 74.56          | 0.25           | 85.32           | 64.96          | 33.35          | 0.23           |

Table 1. The statistical performance of the forecasting wind speed and solar radiation at Robinson station for the daily, weekly and monthly time scale for the applied (LSPF and PSF) and the comparable predictive models (i.e., SVM, DPSF and EEMD-ARIMA).
Table 1. Cont.

| Methods   | Wind Speed | Solar Radiation |
|-----------|------------|-----------------|
|           | RMSE       | MAE             | MAPE            | Execution Time |
|           | RMSE       | MAE             | MAPE            | Execution Time |
| LPSF      | 3.75       | 3.20            | 32.82           | 0.19           |
| PSF       | 3.30       | 2.57            | 24.50           | 0.50           |
| SVM       | 13.51      | 10.73           | 117.89          | 0.30           |
| DPSF      | 3.40       | 2.74            | 24.28           | 1.64           |
| EEMD-ARIMA| 2.73       | 2.33            | 24.60           | 0.44           |

| Methods   | Wind Speed | Solar Radiation |
|-----------|------------|-----------------|
|           | RMSE       | MAE             | MAPE            | Execution Time |
|           | RMSE       | MAE             | MAPE            | Execution Time |
| LPSF      | 2.09       | 1.58            | 19.15           | 0.47           |
| PSF       | 1.60       | 1.19            | 13.77           | 0.35           |
| SVM       | 8.66       | 7.11            | 77.86           | 0.18           |
| DPSF      | 1.73       | 1.49            | 16.65           | 0.95           |
| EEMD-ARIMA| 1.93       | 1.63            | 19.55           | 0.19           |

For Watford City station, the best forecasting results achieved for the proposed LPSF and PSF models with minimum values of (RMSE, MAE, and MAPE). Statistically, the performance metrics accomplished were; LPSF (RMSE = 6.67 and 162.74, MAE = 5.48 and 158.21 and MAPE = 39.85 and 156.09) and PSF (RMSE = 6.98 and 131.67, MAE = 5.73 and 123.64 and MAPE = 41.45 and 125.34) for the daily scale wind speed and solar radiation; LPSF (RMSE = 2.95 and 70.21, MAE = 2.04 and 55.65 and MAPE = 23.68 and 26.74) and PSF (RMSE = 2.18 and 80.83, MAE = 1.79 and 68.79 and MAPE = 21.33 and 32.76) for the weekly scale wind speed and solar radiation; LPSF (RMSE = 1.98 and 115.18, MAE = 1.7 and 90.65 and MAPE = 20.16 and 42.48) and PSF (RMSE = 1.43 and 32.09, MAE = 1.17 and 25.23 and MAPE = 13.84 and 8.77) for the monthly scale wind speed and solar radiation, respectively (Table 2). The statistical results of the Watford City station demonstrated more or less similar predictability performance of wind speed and solar radiation in comparison with the benchmark models (i.e., SVM, DPSF and EEMD-ARIMA).

Table 2. The statistical performance of the forecasting wind speed and solar radiation at Watford City station for the daily, weekly and monthly time scale for the applied (LSPF and PSF) and the comparable predictive models (i.e., SVM, DPSF and EEMD-ARIMA).

| Methods   | Wind Speed | Solar Radiation |
|-----------|------------|-----------------|
|           | RMSE       | MAE             | MAPE            | Execution Time |
|           | RMSE       | MAE             | MAPE            | Execution Time |
| LPSF      | 6.67       | 5.48            | 39.85           | 0.48           |
| PSF       | 6.98       | 5.73            | 41.45           | 0.67           |
| SVM       | 39.51      | 36.36           | 377.76          | 0.26           |
| DPSF      | 10.48      | 9.02            | 64.90           | 1.77           |
| EEMD-ARIMA| 9.20       | 8.20            | 64.60           | 0.27           |
Table 2. Cont.

| Methods  | Wind Speed | Solar Radiation |
|----------|------------|-----------------|
|          | RMSE       | MAE  | MAPE  | Execution Time | RMSE       | MAE  | MAPE  | Execution Time |
| Weekly Scale |           |      |       |               |             |      |       |               |
| LPSF     | 2.95       | 2.04 | 23.68 | 0.79          | 70.21       | 55.65 | 26.74 | 0.22               |
| PSF      | 2.18       | 1.79 | 21.33 | 0.44          | 80.83       | 68.79 | 32.76 | 0.96               |
| SVM      | 11.05      | 8.60 | 94.95 | 0.26          | 117.46      | 89.32 | 53.93 | 0.53               |
| DPSF     | 2.28       | 1.61 | 17.26 | 2.16          | 134.15      | 124.54 | 61.43 | 1.21               |
| EEMD-ARIMA | 1.87       | 1.55 | 17.56 | 0.38          | 147.10      | 126.24 | 71.94 | 0.23               |
|          |            |      |       |               |             |      |       |               |
| Monthly Scale |           |      |       |               |             |      |       |               |
| LPSF     | 1.98       | 1.70 | 20.16 | 1.30          | 115.18      | 90.65 | 42.48 | 1.05               |
| PSF      | 1.43       | 1.17 | 13.84 | 0.71          | 32.09       | 25.23 | 8.77  | 0.49               |
| SVM      | 3.34       | 2.74 | 31.63 | 0.37          | 3739.78     | 3231.79 | 1719.36 | 0.52           |
| DPSF     | 1.90       | 1.67 | 19.46 | 1.79          | 102.93      | 92.20  | 35.60 | 1.76               |
| EEMD-ARIMA | 1.30       | 1.02 | 11.29 | 0.73          | 65.96       | 58.27  | 26.29 | 0.39               |

The convergence execution time is one of the essential modeling components in the field of soft computing and modeling aspects [49]. With respect to the convergence execution time of the developed models, the LPSF and PSF revealed a very faster time learning process with an acceptable execution process.

4.2. The Graphical Presentation of the Developed Forecasting Models

Figure 5a–c reported the performance metrics and time execution results of the wind speed forecasting daily, weekly, and monthly in the form of a bar chart. For all investigated time scales, the LPSF and PSF models revealed a slightly similar performance to the DPSF and EEMD-ARIMA. However, the SVM model showed very poor predictability performance and this can be explained due to the essential tuning procedure required for the SVM model for the internal parameters, that were not adopted or focused on in this research [50,51]. Figure 6a–c indicated the performance metrics and time execution results of solar radiation forecasting for the daily, weekly, and monthly scales at the Robinson station. It is clearly seen that the monthly scale solar radiation for LPSF, PSF, DPSF, and EEMD-ARIMA models were similar. However, the SVM model still reported the lowest capacity. Figure 7a–c displayed the forecasting capacity of the proposed and comparable forecasting models for wind speed modeling at Watford City station. For the daily and weekly wind speed scales, the LPSF and PSF models exhibited a distinguished performance against the results of SVM models. Yet, the monthly scale results of the LPSF, and PSF models were slightly poorer and similar to the ones attained by DPSF and EEMD-ARIMA. Figure 8a–c reported the performance of the solar radiation forecasting Watford City station and for all molded time series scales. For the daily scale, Figure 8a shows that the performance of the DPSF and EEMD-ARIMA models is superior to that of the LPSF models and PSF models. This might be due to the high stochasticity of the solar radiation process on a daily scale and thus the proposed models could not capture the actual trend. On the weekly base scale, the DPSF and EEMD-ARIMA models indicated the worst forecasting potential, even worse than the SVM model. Whereas, similar performance attained using LPSF, PSF, DPSF, and EEMD-ARIMA models for the monthly scale of solar radiation other hand, for the monthly.
Figure 5. The bar chart of the performance metrics and time execution results of wind speed forecasting for the daily (a), weekly (b) and monthly (c) at Robinson station.

Figure 6. Cont.
Figure 6. The bar chart of the performance metrics and time execution results of solar radiation forecasting for the daily (a), weekly (b) and monthly (c) at Robinson station.

Figure 7. The bar chart of the performance metrics and time execution results of wind speed forecasting for the daily (a), weekly (b) and monthly (c) at Watford City station.
5. Discussion

This article proposed and demonstrated the ForecastTB package as a test-bench for comparing the time series forecasting methods as a crucial step towards more formal time series analysis. This demonstration is further described with some case studies to show how characteristics of the temporal correlation structure can influence the forecast accuracy. The ForecastTB package greatly assists in comparing different forecasting methods and considering the characteristic of the time series dataset.

Also, this paper explains how new forecasting methods and error metrics can be introduced in the comparative test-bench. As such, the package allows users to include additional forecasting methods for comparison, which can be extremely useful given the capability of R to interface with other programming languages (e.g., mat1ab for MatLab [52], Rcpp for compiled languages [53] and many other). Finally, a simple plug-and-play module based architecture of the ForecastTB to append or remove several forecasting methods and error metrics makes it a robust and handy tool to evaluate forecasting analysis.

It is worth mentioning that forecasting different time scale wind speed and solar radiation is highly essential for multiple energy sources harvesting [54–56]. Providing an accurate and reliable forecasting intelligent computer aid models for wind speed and solar radiation can contribute to the base knowledge of friendly energy sources and sustainable green cities. To the best knowledge of the current research, the feasibility of the LPSF and PSF models is evidenced to be capable to module related energy datasets.
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Abbreviations
The following abbreviations are used in this manuscript:

- **ARIMA** Auto Regressive Integrated Moving Average
- **CRAN** The Comprehensive R Archive Network
- **ETS** Error, Trend, Seasonal
- **LPSF** Modified Pattern Sequence based Forecast
- **MATLAB** Matrix Laboratory
- **MAE** Mean Absolute Error
- **MAPE** Mean Absolute Percentage Error
- **PCV** Percent Change in Variance
- **PSF** Pattern Sequence based Forecast
- **RMSE** Root Mean Square Error

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