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# Statistical Computing for Time-Series Forecasts via SAS Forecast Studio

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***Abstract* – In this article, for the purpose of teaching and training a larger audience of non-technical practitioners or forecasters (in various fields of study, such as, business, management, finance, economics, etc.), we present a step-by-step procedure to implement a (semi-automatic) way of Time-Series (TS) forecasting computation via SAS Forecast Studio 14.1 (SAS-FS) drop-down menu. This article will be very beneficial for beginner users in the above aforementioned fields of study, to quickly-and-easily implement their forecasts needs via SAS-FS computing software (for reasonably-assured timeliness and accuracy), in this increasingly fast-paced third-millennium business/working environment.**

***Keywords* – Time Series, SAS, SAS Forecast Studio, SAS-FS, forecasting, computing.**

## I. INTRODUCTION

In an increasingly fast-paced third-millennium business/working environment, a typical need in the business world is to project future counts of numerous types of items/products, in a timely manner. For instance, marketing research are interested in making projections of weekly or monthly items such as the weekly gallons sales in gasoline stations, monthly candy sales in a mini market, annual condo sales, etc.

For periodic business requirements in nowadays rapid machine-pace business world, most non-technical persons cannot model the academic-way of doing rigorous research, reading hundreds of pages of papers or software manuals just to learn and replicate existing methods/software, to make recurring future demands projections. Therefore, in this article, to close the gaps between what computationally is doable within timeliness datelines and what is reproducible by most non-technical persons, we briefly present computationally user-friendly and easy-to-learn way of forecasting, via SAS Forecast Studio (SAS-FS) version 14.1, here.

Past research, including Sypsas (1989) paper [1]; De Gooijer and Hyndman (2006) paper [2]; and Rahardja (2020) paper [3] reviewed all the available statistical Time-Series (TS) forecasting methods in the literatures. The former two earlier papers by Sypsas (1989) and De Gooijer and Hyndman (2006) paper [1–2] did not have the Unobserved Component Model (UCM) family as part of the literature review; while the latest Rahardja (2020) paper [3] has included UCM family.

As a brief recapitulation, the most recent review by Rahardja (2020) paper [3] discussed and categorized that there are 3-Family category of TS forecasting methods [4-13]. First, the Exponential Smoothing Model (ESM) family. Second, the Auto-Regressive Integrated Moving Average (ARIMA) model family. Third, the Unobserved Component Model (UCM) family.

The first family-model category, the ESM-family model has eight (8) models which can be translated into statistical computing procedures via the SAS-FS (point-and-clicks) drop-down menu [14]. Those eight (8) ESM-family models are Simple/Single ESM [4], Double ESM [5], Linear ESM [9], Damped Trend ESM [7], Additive

Seasonal ESM or Triple ESM [12], Multiplicative Seasonal ESM [11], Additive Winters ESM [10], and Multiplicative Winters ESM [13]. For the aforementioned first 4 ESM, Fomby [6] discussed them more thoroughly. For the last 4 ESM, Hyndman and Athanasopoulos [11] generalized the mathematical-statistics formulas.

The second family-model category, the ARIMA-family models, are a form of Box-Jenkins model [15]. ARIMA-family models decompose or filter the time series attributes in terms of parameters (*p*, *d*, *q*, and *P*, *D*, *Q*), using *Spectral Decomposition* algorithm. Those parameters are combination of its auto-regressive component (*p*), differencing (*d*), moving average component (*q*), and other predictor(s) time series. Thus, a generic ARIMA model consists of an autoregressive (AR) term, a moving-average term (MA), and for a time series that requires differencing, an integrated (I) element.

The third family-model category, the UCM-family category, is also called the Structural Models in the TS literature [8]. In typical statistical computing software, UCM decomposes or filters the response series into "components" using *Kalman-filtering* algorithm (instead of expressing the model equations as "parameters" as in the ARIMA scenario) in a convenient additive way, such as trend (intercept and slope), seasonality, cycles, autoregressive components, a regression term, and the irregular component, which is assumed to be Normally distributed White Noise with its corresponding variance.

Subsequently, to implement/compute those aforementioned statistical TS forecasting methodologies in the above literatures, using available statistical computing software, is a different story. Therefore, the purpose of this article is to provide a brief easy-to-learn (step-by-step) beginner tutorial, for teaching and training purpose, to compute forecasts in a user-friendly (point-and-clicks) environment, via the SAS-FS version 2015 [14] which is also capable to run/produce a (Large-Scale) Batch Forecast (up to 1,000 forecasts, in one Batch Run). Note that familiarity with the 1976 Box-Jenkins [15] method and/or any of the above 3-Family category of TS forecasting methods [3–13] are not a pre-requisite to forecast via this (point-and-clicks from a drop-down menu) pathway/option, the SAS-FS software. Note that there are other software pathways/options than the SAS-FS, to compute statistical TS forecasts. However, those other pathways/options are beyond the scope of this paper.

In this article, the sections are organized as follow. In Section 2, we describe the data format requirement which are SAS-readable format. In Section 3, we present a step-by-step procedure to compute TS forecasts via SAS-FS 14.1 (point-and-click) drop-down menu. In Section 4, we summarize the discussion of our article. Finally, the conclusion is in Section 5.

## II. DATA

The TS data format requirement to input (import) into SAS computing system (which are SAS-readable format) is displayed in Table 1. The most common way is via an Excel file (with a file extension *.xls* or *.xlsx*), or a text file (with a file extension *.txt*).

Table 1. The Data Format Requirement to "input" (import) SAS.

| | A | B |
|---|---|---|
| 1 | DATE | VOLUME |
| 2 | 10/1/2000 | 6,962 |
| 3 | 11/1/2000 | 6,058 |
| 4 | 12/1/2000 | 4,477 |

| | | |
|---|---|---|
| 5 | 1/1/2001 | 13,794 |
| 6 | 2/1/2001 | 14,745 |
| 7 | 3/1/2001 | 15,549 |
| 8 | 4/1/2001 | 11,174 |
| 9 | 5/1/2001 | 9,707 |
| 10 | 6/1/2001 | 6,436 |
| 11 | 7/1/2001 | 6,760 |
| 12 | 8/1/2001 | 6,971 |
| 13 | 9/1/2001 | 6,340 |
| 14 | 10/1/2001 | 5,154 |
| 15 | 11/1/2001 | 3,652 |
| 16 | 12/1/2001 | 2,762 |
| 17 | 1/1/2002 | 8,228 |
| 18 | 2/1/2002 | 10,656 |
| 19 | 3/1/2002 | 12,604 |
| 20 | 4/1/2002 | 9,928 |
| 21 | 5/1/2002 | 9,216 |
| 22 | 6/1/2002 | 6,586 |
| 23 | 7/1/2002 | 6,475 |

In Table 1, the TS data are stored into two columns. The first column is for the 'DATE' (e.g., Oct-2000, Sep-2000, Nov-2000, etc). The second column is for the 'VOLUME' or counts of items. Note that the data series in Table 1 were merely arbitrary datasets entered into an Excel file, just for the purpose of illustration.

In the same way, without loss of generalities (WLOG), for multiple input volumes (counts) of items, one can stack the input data into the third, fourth, fifth, …, etc. columns of Table 1; and then Multi-Series Forecasts can be computed all-at-once, using SAS-FS.

### 2.1. *Import Data via SAS-EG to the SAS-FS 14.1 System*

There are many ways to import data into the SAS system. A typical way is via the SAS Enterprise Guide (SAS-EG) drop-down menu. The steps below are how to use SAS-EG System drop-down menu to import data (from our Desktop/Laptop Computer) to the SAS-FS 14.1 System.

(1) Open SAS-EG Program and type the 'libname' as follows.

libname data 'C:\SAS Data\Data';

(2) Next, go to Upper Left Panel and click File → Import Data → select the desired Excel file → (Dialog Box 1 of 4 pops out: Specify Data) click Browse → click Library then Data then Rename File Name then Save then click Next → (Dialog Box 2 of 4 pops out: Select Data Source) Click both boxes [if applicable] then click Next → (Dialog Box 3 of 4 pops out: Define Field Attribute) check those rows/columns attributes then click Next → (Dialog Box 4 of 4 pops out: Advance Option) click Finish.

(3) Next, check in the library\Data directory whether our SAS data set with the extension "*.sas7bdat*" file is truly existed in the directory. Alternatively, you can check on the Left Lower Panel, by scrolling down to the corresponding directory and see whether the file with extension "*.sas7bdat*" file is existed there.

(4) If the SAS file in Step 3 is existed/ready, then we can start SAS-FS to forecast using the data imported to the SAS system.

## III. TS-FORECAST COMPUTING VIA SAS-FS VERSION 14.1

In this section, after we input (import) the TS-data (from our Desktop/Laptop computer with Windows Operating System) to the SAS-computing system (with a SAS-readable format), we present a pathway of SAS Computing to

produce forecasts (series of future projections): via the SAS Forecast Studio (SAS-FS) version 14.1 of the year 2015 [12].

The SAS-FS is a user-friendly forecasting software for users to point-and-click from a drop-down menu. Most importantly, the SAS-FS is designed to do Batch Forecasts (up to 1,000 variables of forecasts can be produced, in one Batch Run). Beyond 1,000 forecasts, one can run second batch, third batch, etc. Hence, also suitable for users who need to produce large number of forecasts annually, for example, in the order of 10,000 per year. Clearly, such high-volume forecasts cannot be affordably reached, in a timeliness manner in nowadays business operations, via SAS Manual Coding pathway (one series at-a-time); although such manual-coding pathway can produce highly accurate forecasts since many of the detailed options can be manually controlled/modified. On the contrary, many of the detailed options cannot be manually controlled/modified, using the SAS-FS pathway, since the drop-down menus have very limited options.

After experiencing hundreds of series forecasts via SAS-FS, we can say that the overall level of expected accuracy is up to around 80%. This is as realistic/good as it can be, in nowadays real-world computing capability.

The SAS-FS has up to 28 baseline/candidate models (or 56 baseline/candidate models, with their log transformations) included in their Model Repository (as shown on Figure 1).

Model Repository

The project contains the following models. These can be added to the model lists of individual series:

| Name | Details | Type | Description |
|---|---|---|---|
| ADDWINTERS | ESM: Additive (Winters) Seasonal Smoothing. | Default | |
| AIRLINE | Y = D=(1 s) Q=( 1 )( 1 )s NOINT | Default | |
| ARIMA000011NOINT | Y = D=(s) Q=( 1 )s NOINT | Default | |
| ARIMA011100NOINT | Y = P=( 1 )s D=(1) Q=( 1 ) NOINT | Default | |
| ARIMA012011NOINT | Y = D=(1 s) Q=( 1 2 )( 1 )s NOINT | Default | |
| ARIMA022011NOINT | Y = D=(1 1 s) Q=( 1 2 )( 1 )s NOINT | Default | |
| ARIMA200100 | Y = P=( 1 2 )( 1 )s | Default | |
| ARIMA210011NOINT | Y = P=( 1 2 ) D=(1 s) Q=( 1 )s NOINT | Default | |
| ARIMA212011NOINT | Y = P=( 1 2 ) D=(1 s) Q=( 1 2 )( 1 )s NOINT | Default | |
| DAMPTREND | ESM: Damped-Trend Linear Exponential Smoothing. | Default | |
| DOUBLE | ESM: Double (Brown) Exponential Smoothing. | Default | |
| I_191_C3_201803_MLE | VOLUME = D=(1) Q=( 1 ) NOINT | Custom | |
| LINEAR | ESM: Linear (Holt) Exponential Smoothing. | Default | |
| LINEARSEASONALDUMMIES | AIR = NOINT + LINEAR + SEASONAL | Default | |
| LINEARTREND | Y = CONST + LINEAR | Default | |
| LINEARTRENDAR | Y = P=( 1 2 3 )( 1 )s + LINEAR | Default | |
| LOGADDWINTERS | ESM: Additive (Winters) Seasonal Smoothing. Transfo... | Default | |
| LOGAIRLINE | LOG(Y) = D=(1 s) Q=( 1 )( 1 )s NOINT | Default | |
| LOGARIMA000011NOINT | LOG(Y) = D=(s) Q=( 1 )s NOINT | Default | |
| LOGARIMA011100NOINT | LOG(Y) = P=( 1 )s D=(1) Q=( 1 ) NOINT | Default | |
| LOGARIMA012011NOINT | LOG(Y) = D=(1 s) Q=( 1 2 )( 1 )s NOINT | Default | |
| LOGARIMA022011NOINT | LOG(Y) = D=(1 1 s) Q=( 1 2 )( 1 )s NOINT | Default | |
| LOGARIMA200100 | LOG(Y) = P=( 1 2 )( 1 )s | Default | |
| LOGARIMA210011NOINT | LOG(Y) = P=( 1 2 ) D=(1 s) Q=( 1 )s NOINT | Default | |
| LOGARIMA212011NOINT | LOG(Y) = P=( 1 2 ) D=(1 s) Q=( 1 2 )( 1 )s NOINT | Default | |
| LOGDAMPTREND | ESM: Damped-Trend Linear Exponential Smoothing. T... | Default | |
| LOGDOUBLE | ESM: Double (Brown) Exponential Smoothing. Transfo... | Default | |
| LOGLINEAR | ESM: Linear (Holt) Exponential Smoothing. Transform ... | Default | |
| LOGLINEARSEASONALDUMMIES | LOG(AIR) = NOINT + LINEAR + SEASONAL | Default | |
| LOGLINEARTREND | LOG(Y) = CONST + LINEAR | Default | |
| LOGLINEARTRENDAR | LOG(Y) = P=( 1 2 3 )( 1 )s + LINEAR | Default | |
| LOGMEAN | LOG(Y) = CONST | Default | |
| LOGRWWD | LOG(Y) = D=(1) | Default | |
| LOGSEASONAL | ESM: Additive Seasonal Exponential Smoothing. Tran... | Default | |
| LOGSEASONALDUMMIES | LOG(AIR) = NOINT + SEASONAL | Default | |
| LOGSIMPLE | ESM: Simple Exponential Smoothing. Transform = LOG. | Default | |
| LOGWINTERS | ESM: Multiplicative (Winters) Seasonal Smoothing. Tr... | Default | |
| LSMADWN | ESM: Additive (Winters) Seasonal Smoothing. Transfo... | Default | |
| LSMDAMP | ESM: Damped-Trend Linear Exponential Smoothing. T... | Default | |
| LSMDOUB | ESM: Double (Brown) Exponential Smoothing. Transfo... | Default | |
| LSMLIN | ESM: Linear (Holt) Exponential Smoothing. Transform ... | Default | |
| LSMSEAS | ESM: Additive Seasonal Exponential Smoothing. Tran... | Default | |
| LSMSIMP | ESM: Simple Exponential Smoothing. Transform = LOG. | Default | |
| LSMWINT | ESM: Multiplicative (Winters) Seasonal Smoothing. Tr... | Default | |
| MEAN | Y = CONST | Default | |
| RWWD | Y = D=(1) | Default | |
| SEASONAL | ESM: Additive Seasonal Exponential Smoothing. | Default | |
| SEASONALDUMMIES | AIR = NOINT + SEASONAL | Default | |
| SIMPLE | ESM: Simple Exponential Smoothing. | Default | |
| SMADWN | ESM: Additive (Winters) Seasonal Smoothing. | Default | |
| SMDAMP | ESM: Damped-Trend Linear Exponential Smoothing. | Default | |
| SMDOUB | ESM: Double (Brown) Exponential Smoothing. | Default | |
| SMLIN | ESM: Linear (Holt) Exponential Smoothing. | Default | |
| SMSEAS | ESM: Additive Seasonal Exponential Smoothing. | Default | |
| SMSIMP | ESM: Simple Exponential Smoothing. | Default | |
| SMWINT | ESM: Multiplicative (Winters) Seasonal Smoothing. | Default | |
| WINTERS | ESM: Multiplicative (Winters) Seasonal Smoothing. | Default | |

Fig. 1. The 56 Time-Series models in the repository of the SAS-FS version 14.1.

When we open SAS Forecast Studio, the "Projects" window appears. This window lists all projects that the user owns or has permission to see based on the credentials used to log on to the software. New projects can be created from this window. New projects open in the "Forecasting View" by default. Existing projects open to the view that was open when they were last closed. SAS Forecast Studio has four main compartments or views. These are the Forecasting view, Modeling view, Series view, and Scenario Analysis view.

The following steps are the procedure to Generate Forecast Automatically using SAS-FS 14.1 Default Functionality.

(1) If accessing the Desktop version of SAS Forecast Studio, permissions are needed to create and modify projects and data sources. If accessing the Client/Server version of SAS Forecast Studio, an account is needed. The SAS administrator in your organization can tell you how to access SAS Forecast Studio in your organization.

(2) In the Desktop version, click Start → SAS → SAS Forecast Studio.

(3) Click NEW to create a new project. If this is our new session, there will be no existing projects unless projects were set up for us.

(4) [Step 1 of 8] Name the project → click Next.

(5) [Step 2 of 8] Click the Library on the Left Panel where the desired Data Set is located. Then select the data set desired to be forecasted → click Next.

(6) [Step 3 of 8] Assign 'BY' variables that form the basis of a data hierarchy. If a single series is to be forecast, then there is no associated hierarchy to the data → click Next.

(7) [Step 4 of 8] Click the down arrow next to the 'TIME ID VARIABLE' and select 'DATE' as the time ID → click Next.

(8) [Step 5 of 8] Assign Roles to Variables in the Data. We must specify at least one dependent variable. For the Dependent Variables, select 'sum of values' for the Accumulation → click Next.

(9) [Step 6 of 8] This step specifies data preparation options. Typically, no data preparation is necessary → click Next. Our project is now set up and we are ready to generate forecasts. The lead forecast horizon is set at say, 12 weeks or approximately 3 months into the future → click Next.

(10) [Step 7 of 8] Finish Creating Project. If needed, we can click 'Change other forecasting settings'. Else, click Next.

(11) [Step 8 of 8] Lists optional actions. Click Finish to generate the forecast.

(12) Summary results are displayed first. The default 'model selection criteria' in the SAS-FS is Mean Absolute Percent Error (MAPE). Click Close. The created project opens in the 'Forecasting View' (see Figure 2) by default. For just an illustration purpose, the Figure 2 displayed an arbitrary screenshot example of what a 'Forecasting View' of the SAS-FS version 14.1 should look like. A completely made-up data series were exported from an Excel file format (see Table 1) into the SAS-FS system (as appeared on Figure 2), just for the purpose of a point-and-show display.

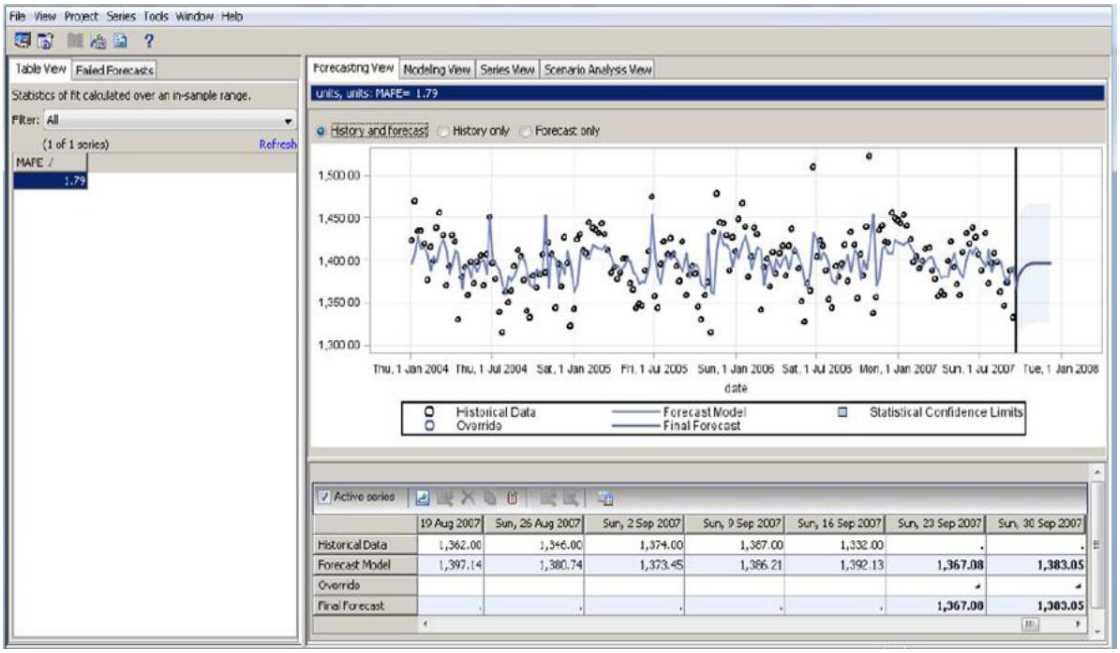


Fig. 2. An Arbitrary Screenshot Example of A 'Forecasting View' of the SAS-FS version 14.1.

(13) Click the 'Model View'. The Model View contains information about all candidate models considered for the active series; this includes information about what model was selected, that is, the forecast model, associated parameter estimates and model diagnostic information. The forecast model for the series is the candidate model with the best fit. Here (in SAS-FS context), this is generated model with the smallest associated value of MAPE. Note that MAPE is one of the most common accuracy measures in Business Forecasting (SAS-FS, version 2015) [14]. As a selection criterion, we choose the model with the smallest value of MAPE.

(14) To select the Model Selection Criteria, at the Upper Left Panel, click Project → Forecasting Settings. Alternative criteria, for example, Akaike Information Criteria (AIC). Holdout Samples can be activated and changed under the Model Selection settings.

(15) To examine how each candidate model performs across all supported fit statistics, select Series → Compare Models → Statistics of Fit. We then see model that seems reasonably robust to a change in the selection statistic.

(16) To directly compare the forecast plots from two or more models, select Series → Compare → Plot (or click the 'Plot' tab from the Upper Panel, next to the 'Statistics of Fit' tab). Note that there is distinction between Custom and Generated models in the forecasting system.

(17) [To copy the series and paste it back to our Excel spreadsheet] Finally, we can highlight the (final) forecast series. Next, right-click and copy them. Then, paste it at a Notepad (or Wordpad) as a 'text' [to get rid of the Rich Text Formatting (RTF); else, with the RTF we cannot directly paste it as values at our Excel file]. Highlight and copy those pasted values again at the Notepad; and now paste it at Excel file. Lastly, we can aggregate them (say, from monthly forecasted values to yearly forecasts). Done.

We note that in this short article, the SAS-FS step-by-step procedure is intended just for a quick-and-easy overview of the basic (semi-automatic) forecast via SAS-FS drop-down menu, so that the beginner users can get a basic comfort level to proceed to many more other options that they can dive-in and/or explore further. To dive-in

for deeper guidance/reference, see the full-version of the 332-page (2015) SAS Forecast Studio [14] online documentation, available via google search, and as listed in the reference section of this article; and/or take the formal SAS training courses.

## IV. Summary Discussion

In this article, we have presented a (basic) step-by-step procedure to compute (baseline) Time-Series forecasts via the SAS Forecast Studio (SAS-FS) version 14.1 software. This (basic) step-by-step TS forecast procedure via the SAS-FS (semi-automatic) drop-down menu is user friendly and easy-to-implement by many beginner users. User friendly because the software can produce forecast in just several point-and-clicks. Easy-to-implement because it does not require much technical backgrounds (such as advanced math, stat, and computer programing skills). Hence, this article will be beneficial for many beginners or non-technical practitioners or forecasters in various fields of study such as, business, management, finance, economics, etc. to quickly learn and produce the basic/baseline forecasts (in reasonably-assured timeliness and accuracy), in nowadays fast-pace business working environment with up to around 80% accuracy level. For a higher accuracy forecast possibility, one needs to consult some highly-technical and very-experienced statisticians.

## V. Conclusion

The presented step-by-step (point-and-clicks) procedure for a basic (baseline) statistical Time-Series forecast via SAS-FS will be useful for teaching-and-training purpose and helpful especially for many non-technical practitioners and/or Large-Scale forecasters (for multi-volume or batch forecasts, up to 1,000 forecasts, in one Batch Run) in the various fields of study. To improve forecast accuracy from a baseline forecast (outputted by SAS-FS), resorting to subject-matter expert statisticians via a SAS Manual-Coding [16–20] option is necessary; and is beyond the scope of this article.

## VI. Dedication

The author would like to thank, praise, and dedicate this manuscript to her God and Savior, Lord Jesus Christ, who always inspires, guides step-by-step, loves, and blesses her abundantly. *Soli Deo Gloria*.

## VII. Disclaimer

This research represents the author's own work and opinion. It does not reflect any policy nor represent the official position of the U.S. Department of Defense nor any other U.S. Federal agency nor any commercial company.

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## References

[1] Sypsas, P.T. (1989). Identifying patterns in multiple time series data. Journal of Information and Optimization Sciences, Vol.10, No. 3, pp. 471–494.
[2] De Gooijer, J.G., Hyndman, R.J. (2006). 25 years of time series forecasting. International Journal of Forecasting, Vol. 22, No. 3, pp. 443–473.
[3] Rahardja, D. (2020). Statistical methodological review for time-series data. Journal of Statistics and Management Systems, Vol. 23, No. 8, pp. 1445–1461.

[4] Brown, R.G. (1959). Statistical forecasting for Inventory control, McGraw-Hill: New York, NY.
[5] Brown, R.G. (1962). Smoothing, Forecasting and prediction of discrete time series, Prentice Hall: New Jersey, NJ.
[6] Fomby, T.B. (2008). Exponential smoothing models. Class Notes Version 6. Department of Economics. Southern Methodist University, Dallas, TX, June 2008.
[7] Gardner, E. S., & McKenzie, E. (1985). Forecasting trends in time series. Management Science, 31(10), 1237–1246. https://doi.org/10.1287/mnsc.31.10.1237
[8] Harvey, A.C. (1989). Forecasting, Structural time series models, and the Kalman Filter. Cambridge University Press.
[9] Holt, C. E. (1957). Forecasting seasonals and trends by exponentially weighted averages (O.N.R. Memorandum No. 52). Carnegie Institute of Technology, Pittsburgh, USA. https://doi.org/10.1016/j.ijforecast.2003.09.015
[10] Winters, P.R. (1960). Forecasting sales by exponentially weighted moving averages. Management Science, 6, 324–342. https://doi.org/10.1287/mnsc.6.3.324
[11] Hyndman, R.J., and Athanasopoulos, G. (2018). Forecasting principles and practices. Monash University, Australia. https://otexts.org/fpp2/
[12] Fried R., George A.C. (2011). Exponential and holt-winters smoothing. In: Lovric M. (eds) International Encyclopedia of Statistical Science. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-04898-2_24
[13] Chatfield, C. (1978). The Holt-Winters Forecasting Procedure. Journal of the Royal Statistical Society. Series C (Applied Statistics), 27(3), 264-279. doi:10.2307/2347162.
[14] SAS Institute Inc. (2015). SAS® Forecast Studio 14.1: User's Guide. Cary, NC: SAS Institute Inc. https://support.sas.com/documentation/onlinedoc/forecast/14.1/fsug.pdf [accessed on 29 May 2021].
[15] Box, G.E.P., and Jenkins, G.M. (1976). Time series analysis: Forecasting and control, John Wiley & Sons, Inc., Hoboken, New Jersey.
[16] SAS Institute Inc. (1995). SAS manual SAS/ETS Software: Time series forecasting system, Version 6, First Edition, pp. 225–235. Cary, NC: SAS Institute Inc.
[17] SAS Institute Inc. (2013). Base SAS® 9.4 Procedures Guide: Statistical procedures, Second edition. Cary, NC: SAS Institute Inc.
[18] SAS Institute Inc. (2014). SAS/ETS® 13.2 User's guide: The ESM procedure, Chapter 14, pp. 810–839. Cary, NC: SAS Institute Inc.
[19] SAS Institute Inc. (2018). SAS/ETS® 15.1 User's guide: The ARIMA procedure, Chapter 7, pp. 186–305. Cary, NC: SAS Institute Inc.
[20] SAS Institute Inc. (2014). SAS/ETS® 13.2 User's guide: The UCM procedure, Chapter 34, pp. 2304–2412. Cary, NC: SAS Institute Inc.

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