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Investigation of the Effects of Some Statistical Data Components on the Selection of Optimum Smoothing Constant

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Abstract

Simple exponential smoothing is one of the best forecast methods, especially for time series data. Its efficacy depends on a parameter called smoothing constant (α) which, if optimally determined, minimises the mean square error (MSE), the mean absolute error (MAE) and the mean absolute percentage error (MAPE). The widely used method for selecting the optimum smoothing constant is to conduct a grid search within a wide range of possible values of α using the trial-and-error method. Not only that this method involves the knowledge of advanced statistical processes, but it is also time-consuming, and its results are limited to the data being analysed. In order to eliminate these limitations, there is a need to develop a benchmark that will guide the users of simple exponential smoothing to select the optimum α without necessarily repeating the trial-and-error method once a value has been established for data of similar statistical components. This study investigated some statistical components (mean, standard deviation, range, number of observations and pattern) of data to determine which components could aid in the quick and easy determination of optimum smoothing constant. The study determined the optimum smoothing constants for 16 different data of varying statistical components, and found that mean, standard deviation, range and the number of data observations are not related to the optimum smoothing constants. However, the demand pattern is an excellent precursor to determining the optimum smoothing constant. The study recommends further study in developing a classification model for demand patterns in job shops.

Keywords: Simple exponential smoothing; optimum smoothing constant; trial and error; demand pattern; number of observations.

Introduction

The simple exponential smoothing method (SES) is one of the qualitative forecasting methods widely used in industries due to its accuracy and simplicity (Ostertagova and Ostertag 2012, Ravinder 2013a, Marpaung et al. 2019, Cetin and Yavuz 2020). The forecasting method gives more weight to the recent observations than the remote ones; this unequal weighting is achieved through a parameter called the smoothing constant, α (Mu'azu 2014). In addition, the accuracy of SES depends on the value of this constant; it also determines how responsive the forecast is to the historical data. The formula for exponential smoothing is:

$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1}) \qquad Eqn. 1$$

Where:

F_t = forecast for period (t),

F_{t-1} = forecast for period (t-1),

A_{t-1} = actual observation for period (t-1) and α = smoothing constant ($0 \leq \alpha \leq 1$).

The major issue in using the exponential smoothing method is the choice of the values of smoothing constants (α) that gives the least mean error (Paul 2011, Ravinder 2013b). Ravinder (2013a) suggested a selection of optimum α between 0.00 and 0.30 when the data observations are less than or equal to 12 and between 0 and 0.15 when the observations are more than 36. Although, using the trial-and-error method, Velumani et al. (2019) and Septiyana and Bahtiar (2020) got 0.30 and 0.20, respectively, for data with 12 observations, but Paul (2011), Olaniyi et al. (2018) and Gustriansyah (2017) got 0.83, 0.90 and 0.50 for data with 6, 8, and 9 observations, respectively. Not only that, Hassan and Dhali (2017), Adeniran and Stephens (2018), Karmaker (2017) and Gorgess and Zahra (2018) got 0.68, 0.90, 0.31 and 0.94 for data with 15, 17, 84 and 120 observations, respectively. The suggestion of Ravinder (2013a) lacked empirical justification. It could not be generalised based on the results from other researchers as presented above. Mu'azu (2014) proposed a mathematical model relating the optimum α to the number of observations (n). The model is shown in equation 2.

$$\propto = 1 - \left(\frac{n-1}{3n}\right) \ldots \ldots \ldots \ldots \ldots Eqn. 2$$

Using this model to determine the values of optimum smoothing constant for the numbers of observations discussed above shows no congruence between the optimum α from Mu'azu's model and those from other researchers using the trial-and-error method. This is clearly shown in Table 1.

Table 1: Comparison of optimum α between Mu'azu's model and trial-and-error method

Number of Observations (n)	Using Mu'azu's model	Optimum smoothing constant (MAE)	Authors
6	0.72	0.83	Paul (2011)
8	0.71	0.90	Olaniyi et al. (2018)
9	0.70	0.50	Gustriansyah (2017)
12	0.69	0.30	Velumani et al. (2019)
12	0.69	0.20	Septiyana and Bahtiar (2020)
15	0.69	0.68	Hassan and Dhali (2017)
17	0.69	0.90	Adeniran and Stephens (2018)
84	0.67	0.31	Karmaker (2017)
120	0.67	0.94	Gorgess and Zahra (2018)

Furthermore, a recent study by Prabowo et al. (2021) rejected a relationship between the number of observations of data and the optimum smoothing constant. Suppose the number of data observations could not be a pointer to selecting the optimum smoothing constant. In that case, there is a need to look for other statistical information that can aid the users of simple exponential smoothing in selecting an optimum smoothing constant.

For selecting appropriate forecasting methods, data classifications based on their patterns were tested and found to be effective. Williams (1984) analysed the demand data of a public utility and proposed a demand pattern categorisation based on variance partition to aid in selecting the best forecast method. The success of this work was limited to the particular data used in the paper, and when tested using other data, the classification could not yield an optimum result. Also, Varghese and Rossetti (2008) referred to this work to be problematic in its application to other similar data. Bartezzaghi et al. (1999) investigated the effects of different demand patterns on inventories under various experimental conditions. The result clearly shows that demand pattern impacts the determination of optimum inventories.

Similarly, Syntetos et al. (2005) proposed a demand categorisation method with recommendations for an appropriate cut-off value for the squared coefficient of variation (CV^2) and mean interval between non-zero demands. This method was closely adopted by Varghese and Rossetti (2008) to propose a demand categorisation for choosing an appropriate forecasting technique. The former and the latter's classifications were based on intermittent demand. Their objectives are to select an appropriate forecast method for the inventory system and not for the optimisation of exponential smoothing.

Freeble (n.d.) proposed a general classification of demand patterns using Average Demand Interval (ADI) and Square of the Coefficient of Variation (CV^2). The values of ADI and CV^2 were determined using equations 3 and 4, respectively.

$$ADI = \frac{Total\ number\ of\ periods}{Number\ of\ demand\ buckets} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots\ldots Eqn.3$$

$$CV^2 = \left(\frac{Standard\ deviation\ of\ an\ average\ population}{Value\ of\ a\ population}\right)^2 \ldots..\ldots Eqn.4$$

Based on these two dimensions, demand patterns were classified into; Smooth demand when ADI < 1.32 and CV^2 < 0.49, Intermittent demand when ADI ≥ 1.32 and CV^2 < 0.49, Erratic demand when ADI < 1.32 and CV^2 ≥ 0.49 and Lumpy demand when ADI ≥ 1.32 and CV^2 ≥ 0.49. The author emphasised the importance and relevance of knowledge of demand patterns in selecting appropriate forecast methods. These classifications are illustrated in Figure 1(a-d).

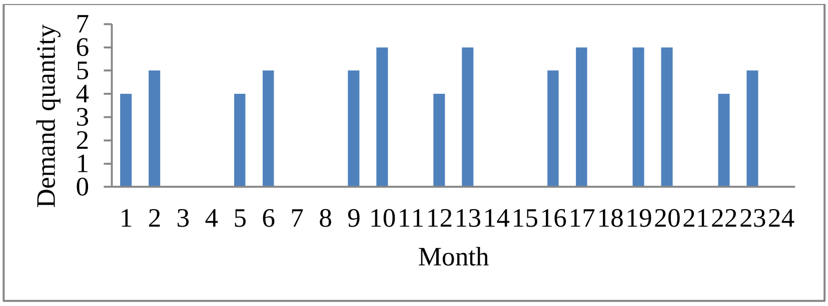

Figure 1a: Intermittent demand pattern.

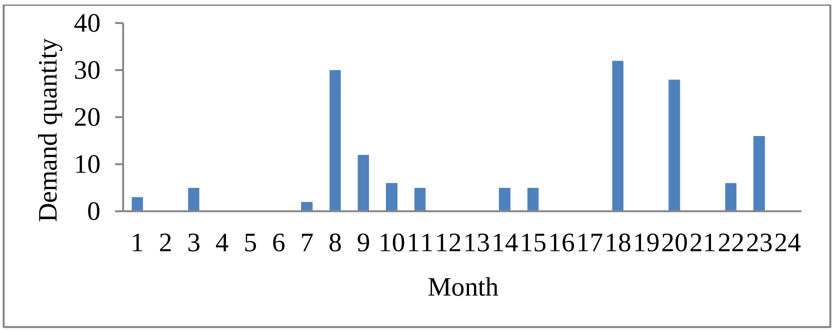

Figure 1b: Lumpy demand pattern.

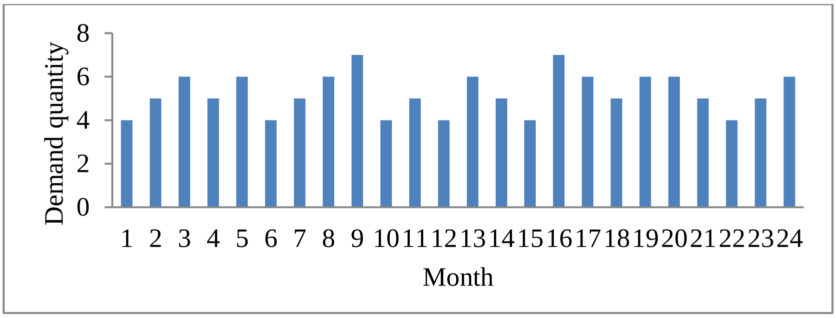

Figure 1c: Smooth demand pattern.

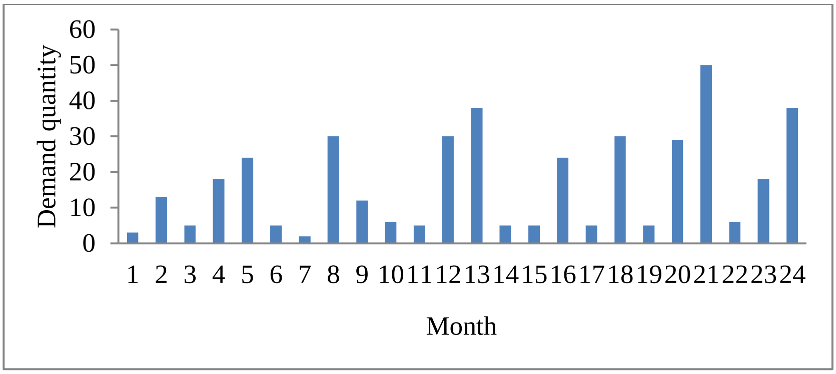

Fig. 1d: Erratic demand pattern.

Pearson Education (2007) also classified demand patterns into horizontal, trend, seasonal and cyclical patterns to select an appropriate forecast method. These classifications are shown in Figure 2 (a-d).

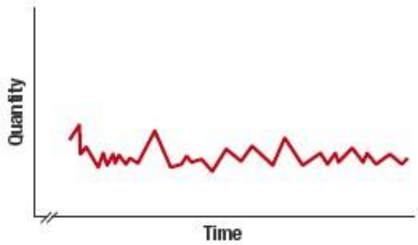

Figure 2a: Horizontal demand pattern.

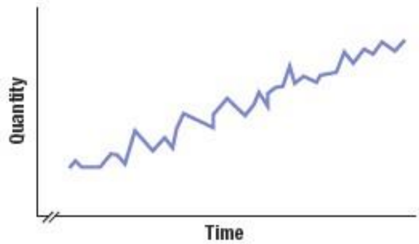

Figure 2b: Trend demand pattern.

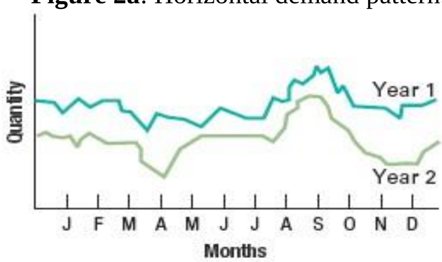

Figure 2c: Seasonal demand pattern.

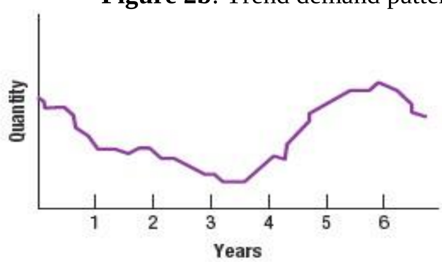

Figure 2d: Cyclical demand pattern.

(Source: https://slideplayer.com/slide/5177687/)

To the best of knowledge of the authors of this paper, no work has investigated the effects of demand patterns on selecting the optimum smoothing constant (α). Most of the available studies focus on determining appropriate forecast methods, and they are mostly narrowed to the inventory system (Williams 1984, Bartezzaghi et al. 1999, Varhgese and Rossetti 2008, Boylan et al. 2008). This paper aimed to investigate if there is a relationship between the mean, standard deviation, range and demand patterns of data and its optimum smoothing constant.

Materials and Methods

The data used for this study were adapted from Muscatello and Coccari (2000) and referred to as data 1. The elements in data 1 were re-arranged in three different ways to produce data 2, data 3 and data 4. These four data had the same mean, standard deviation and range, but different patterns. The study also generated another set of data by multiplying each element in data 1, 2, 3 and 4 by 1.5, 2.0, and 2.5 to produce data 1b, 1c, 1d, 2b, 2c, 2d, 3b, 3c, 3d, 4b, 4c, and 4d. With these processes, 16 data were produced, which were categorised as shown in Table 2, and the actual data are shown in Tables 3a and 3b, while Figures 3a–3e show the demand patterns for each of the data.

Table 2: Categories of data used

	Same MSR but different P	Same MSR but different P	Same MSR but different P	Same MSR but different P
Same P but different MSR	Data 1	Data 1b	Data 1c	Data 1d
Same P but different MSR	Data 2	Data 2b	Data 2c	Data 2d
Same P but different MSR	Data 3	Data 3b	Data 3c	Data 3d
Same P but different MSR	Data 4	Data 4b	Data 4c	Data 4d

M = mean, S= standard deviation, R = range, P = Pattern.

Table 3a: Data used for the study

Month	Data 1	Data 2	Data 3	Data 4	Data 1b	Data 1c	Data 1d	Data 2b	Data 2c	Data 2d
1	430	512	398	436	645	860	1075	768	1024	1280
2	420	436	512	420	630	840	1050	654	872	1090
3	436	420	420	501	654	872	1090	630	840	1050
4	452	398	477	452	678	904	1130	597	796	995
5	477	477	452	532	715.5	954	1192.5	715.5	954	1192.5
6	420	430	430	512	630	840	1050	645	860	1075
7	398	532	532	477	597	796	995	798	1064	1330
8	501	514	420	514	751.5	1002	1252.5	771	1028	1285
9	514	501	514	410	771	1028	1285	751.5	1002	1252.5
10	532	420	410	430	798	1064	1330	630	840	1050
11	512	452	436	398	768	1024	1280	678	904	1130
12	410	410	501	420	615	820	1025	615	820	1025

Source: Adapted from Muscatello and Coccari (2000).

Table 3b: Data used for the study (continuation)

Month	Data 3b	Data 3c	Data 3d	Data 4b	Data 4c	Data 4d
1	597	796	995	654	872	1090
2	768	1024	1280	630	840	1050
3	630	840	1050	751.5	1002	1252.5
4	715.5	954	1192.5	678	904	1130
5	678	904	1130	798	1064	1330
6	645	860	1075	768	1024	1280
7	798	1064	1330	715.5	954	1192.5
8	630	840	1050	771	1028	1285
9	771	1028	1285	615	820	1025
10	615	820	1025	645	860	1075
11	654	872	1090	597	796	995
12	751.5	1002	1252.5	630	840	1050

Source: Adapted from Muscatello and Coccari (2000).

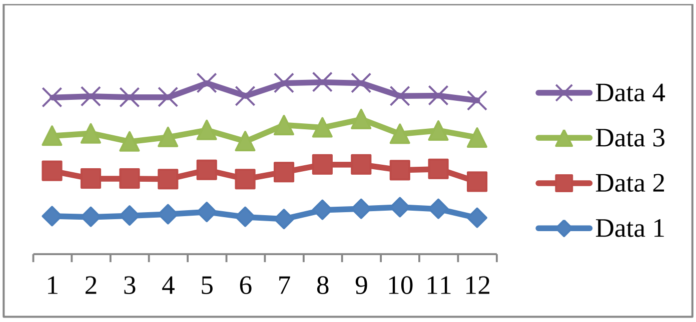

Figure 3a: Set A (Same mean, standard deviation and range with different demand patterns).

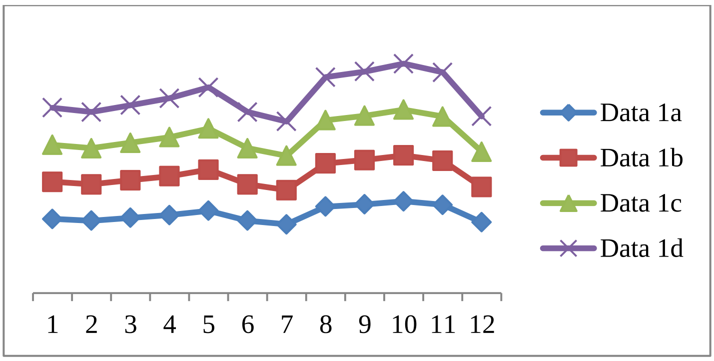

Figure 3b: Set B (Different mean, standard deviation and range with same demand pattern 1).

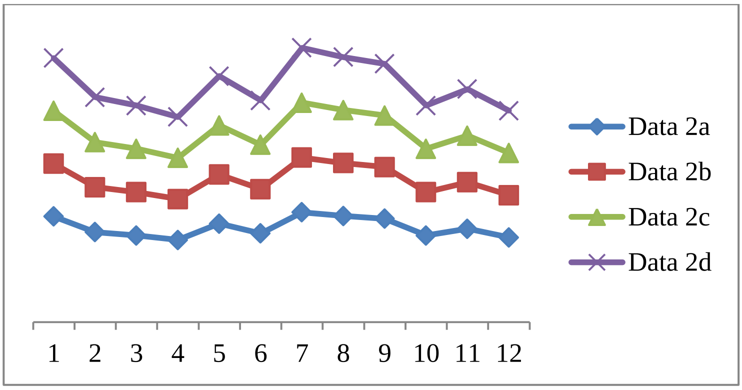

Figure 3c: Set C (Different mean, standard deviation and range with same demand patterns 2).

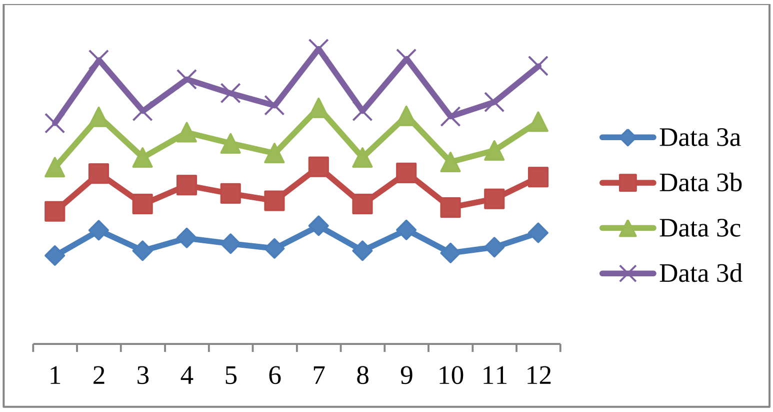

Figure 3d: Set C (Different mean, standard deviation and range with same demand patterns 3).

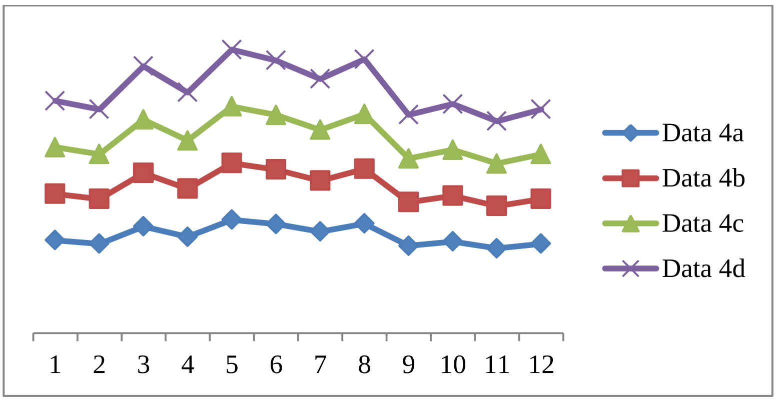

Figure 3e: Set D (Different mean, standard deviation and range with same demand patterns 4).

The study used the expert system developed by Idris et al. (2021) to find the optimum smoothing constant for each of the 16 data. The expert system employed the trial-and-error method to determine the optimum smoothing constants by testing 100 possible α and selecting the optimum values from the tested ones. The results are shown in Table 4, and a sample of the results produced by the expert system for data 1 is shown in Figure 4.

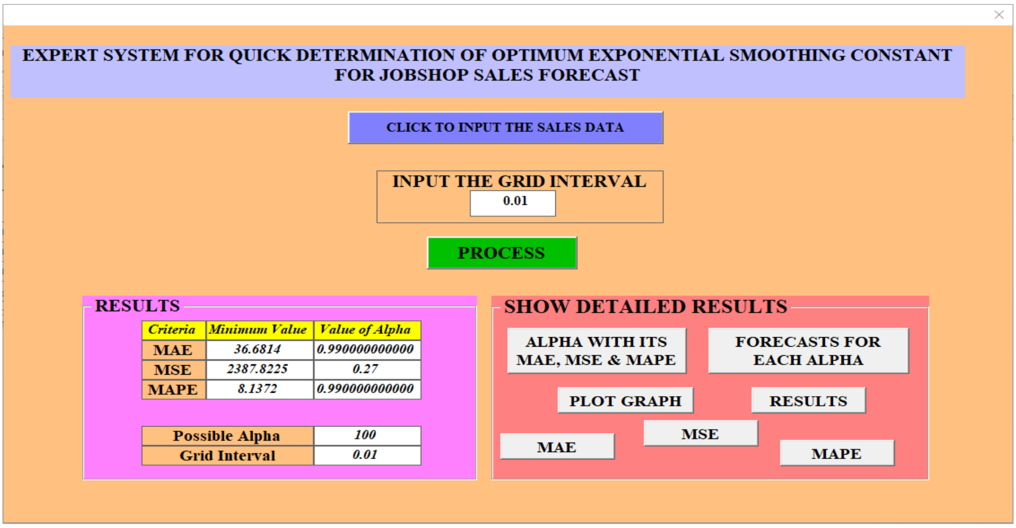

Figure 4: Results produced by the expert system for data 1.

Results and Discussion

Four research questions (RQ) were formulated to investigate if some statistical data components (mean, standard deviation, range and pattern) affect the selection of optimum smoothing constant. The RQ are:

RQ1: Is there any relationship between the optimum smoothing constant and the mean of data?

RQ2: Is there any relationship between the optimum smoothing constant and the standard deviation of data?

RQ3: Is there any relationship between the optimum smoothing constant and the range of data?

RQ4: Is there any relationship between the optimum smoothing constant and the pattern of data?

Table 4 shows the values of optimum smoothing constants for each of the 16 data.

Table 4: The optimum smoothing constants for each of the data

Set	Data	Mean	Standard deviation	Range	Pattern	Optimum α based on: MAE	MSE	MAPE
A	Data 1	458.50	46.55	134	Pattern 1	0.99	0.27	0.99
	Data 2	458.50	46.55	134	Pattern 2	0.78	0.69	0.81
	Data 3	458.50	46.55	134	Pattern 3	0.19	0.26	0.16
	Data 4	458.50	46.55	134	Pattern 4	0.65	0.56	0.66
B	Data 1b	687.75	69.82	201	Pattern 1	0.99	0.27	0.99
	Data 2b	687.75	69.82	201	Pattern 2	0.78	0.69	0.81
	Data 3b	687.75	69.82	201	Pattern 3	0.19	0.26	0.16
	Data 4b	687.75	69.82	201	Pattern 4	0.65	0.56	0.66
C	Data 1c	917.00	93.09	268	Pattern 1	0.99	0.27	0.99
	Data 2c	917.00	93.09	268	Pattern 2	0.78	0.69	0.81
	Data 3c	917.00	93.09	268	Pattern 3	0.19	0.26	0.16
	Data 4c	917.00	93.09	268	Pattern 4	0.65	0.56	0.66
D	Data 1d	1146.25	116.36	335	Pattern 1	0.99	0.27	0.99
	Data 2d	1146.25	116.36	335	Pattern 2	0.78	0.69	0.81
	Data 3d	1146.25	116.36	335	Pattern 3	0.19	0.26	0.16
	Data 4d	1146.25	116.36	335	Pattern 4	0.65	0.56	0.66

Source: Authors.

Table 4 was used to answer the research questions 1, 2, 3, and 4. Considering the four (4) data in set A having the same value of mean (458.50), the same value of standard deviation (46.55) and the same value of range (134), the values of optimum smoothing constants were not the same. The values of optimum smoothing constants for MAE are; 0.99, 0.78, 0.19, 0.65, for MSE are; 0.27, 0.69, 0.26, and 0.56 and also for MAPE the values are; 0.99, 0.81, 0.16 and 0.66. This shows that the optimum smoothing constant does not depend on the mean, standard deviation and range of data.

Considering set B with 687.75, 69.82, and 201 as mean, standard deviation and range, respectively, the optimum smoothing constants for all the data in set B are not the same. This was also obtained for sets C and D, where the data with the same mean value have different values of optimum smoothing constants. These results further buttress the fact that the value of the optimum smoothing constant does not depend on the values of mean, standard deviation and range of data. Hence, research questions 1, 2 and 3 are rejected.

For the fourth research question: Is there any relationship between the optimum smoothing constant and the pattern of data? To answer this question, from Table 4, considering the data that have the same pattern, such as data 1, 1b, 1c, and 1d with a different range, mean and standard deviation, the data have the same optimum smoothing constant; 0.99 (MAE), 0.27 (MSE) and 0.99 (MAPE). Also, the four data with the same pattern 2 (2, 2b, 2c and 2d) have the same values of optimum smoothing constant; 0.78 (MAE), 0.69 (MSE) and 0.81 (MAPE). This is also applicable for other data with the same patterns 3 and 4. This result shows that the value of optimum smoothing constants of data could only be the same if the data have the same pattern irrespective of their range, mean and standard deviation values. This result is similar to the result of Varghese and Rossetti (2008), which was used for selecting the appropriate forecast method.

Conclusion

Simple exponential smoothing is a versatile forecasting technique widely used for time series data; it finds applications in most forecast software due to its precision, flexibility and simplicity. Its accuracy depends on a parameter called the smoothing constant (α). The selection of this parameter is mostly by the trial-and-error method. The most effort made to find the optimum smoothing constant by the earlier researchers was only made for the data in which it is analysed. No report was found that recommends any statistical component that could aid the selection of optimum smoothing constant. This study determined the optimum smoothing constant for sixteen data grouped into; data with different means, range, and standard deviation but the same pattern, and data with different patterns but the same means, range, and standard deviation. It was found that data with the same pattern but different mean, range, and standard deviation have the same optimum smoothing constant. Data with different patterns but the same mean, range, and standard deviation have different optimum smoothing constants. The study also refutes the claim that an optimum smoothing constant is related to the number of observations in data. The study hereby recommends further study on the classification of demand patterns to facilitate quick selection of optimum smoothing constant.

Conflict of Interest: No conflict of interest, financial or other, exists.

References

Adeniran AO and Stephens MS 2018 The dynamics for evaluating forecasting methods for international air passenger demand in Nigeria. *J. Tour. Hosp.* 7(4): 1-11.

Bartezzaghi E, Verganti R and Zotteri G 1999 Measuring the impact of asymmetric demand distributions on inventories. *Int. J. Prod. Econ.* 60: 395-404.

Boylan JE, Syntetos AA and Karakostas GC 2008 Classification for forecasting and stock control: A case study. *J. Oper. Res. Soc.* 59: 473-481.

Cetin B and Yavuz I 2020 Comparison of forecast accuracy of Ata and exponential smoothing. *J. Appl. Stat.* 48: 2580-2590.

Freeble N.D. Demand classification: why forecastability matter, retrieved from http://frepple.com/blog/demand-classification/

Gorgess HM and Zahra LSA 2018 Using exponential smoothing models in forecasting about the consumption of gasoline in Iraq. *J. Coll. Basic Ed.* 24(100): 121-132.

Gustriansyah R 2017 Analisis metode single exponential smoothing dengan Brown exponential smoothing pada kasus memprediksi kuantiti penjualan produk farmasi di apotek. *Prosiding Seminar Nasional Teknologi Informasi dan Multimedia* 2017: 3.5-7 – 3.5-12.

Hassan MB and Dhali MN 2017 Determination of optimal smoothing constants for exponential smoothing method & Holt's method. *Dhaka Univ. J. Sci.* 65(1): 55-59.

Idris MO, Kareem B Adeboye BS Enwerem GC and Adekanye SA 2021 Development of an Expert System for Quick Determination of Optimum Exponential Smoothing Constant For Job Shop Sales Forecast. *Prem. J. Eng. Appl. Sci.* 2*(*4).

Karmaker CL 2017 Determination of optimum smoothing constant of single exponential smoothing method: a case study. *Int. J. Res. Industrial Eng.* 6(3): 184-192.

Marpaung NL, Salim KR, Amri R and Ervianto E 2019 Application of Single Exponential Smoothing in Forecasting Number of New Students Acceptance. *Int. J. Technol. Eng. Stud.* 5(6): 169-182.

Mu'azu HG 2014 New approach for determining the smoothing constant (α) of a single exponential smoothing method. *Int. J. Sci. Technol.* 3(11): 717-727.

Muscatello JR and Coccari RL 2000 Savings with a formal forecasting system: A case study. *J. Business Forecasting* 19: 19-21.

Olaniyi AA, Adedotun KO and Samuel OA 2018 Forecasting methods for domestic air passenger demand in Nigeria. *J. Appl. Res. Ind. Eng.* 5(2): 146-155.

Ostertagova E and Ostertag O 2012 Forecasting using simple exponential smoothing method. *Acta Electrotechnica et Informatica* 12(3): 62-66.

Paul SK 2011 Determination of exponential smoothing constant to minimise mean square error and mean absolute deviation. *Glob. J. Res. Eng.* 11(3).

Pearson Education 2007 Demand Patterns– Time Series The repeated observations of demand a service. *Forecasting Chapter 13 © 2007 Pearson Education slideplayer 3/39* retrieved from https://slideplayer.com/slide/5177687/.

Prabowo A, Tripena A, Pratama DA, Mamat M, Sukono and Bon AT 2021 Determination the smoothing constant that minimises mean absolute error and mean square deviation. *Proceedings of the 11th Annual International Conference on Industrial Engineering and Operations Management, Singapore March* 7(11): 3825- 3835.

Ravinder HV 2013a Forecasting with exponential smoothing-What's the right smoothing constant? *Rev. Business Inf. Syst.* 17(3): 117-126.

Ravinder HV 2013b Determining the optimal values of exponential smoothing constants– Does solver really work*? Am. J. Bus. Ed.* 6(3): 347-360.

Septiyana D and Bahtiar A 2020 Usulan perbaikan peramalan produksi ban PT. XYZ melalui pendekatan metode exponential smoothing. *J. Ind. Manuf.* 5(1): 13-17.

Syntetos AA, Boylan JE and Croston JD 2005 On the Categorisation of Demand Pattern. *J. Oper. Res. Soc.* 56: 495-503.

Varghese V and Rossetti M 2008 A classification approach for selecting forecasting techniques for intermittent demand. In: Fowler J and Mason S (Eds) *Proceedings of the 2008 Industrial Engineering Research Conference.*

Velumani P, Nampoothiri N, and Aparnadevi R 2019 Prediction of construction projection duration and cost using earned value management. *Int. J. Eng. Adv. Technol.* 9(1S4): 437-441.

Williams TM 1984 Stock control with sporadic and slow-moving demand. *J. Oper. Res. Soc.* 35: 939-948.