Premier Journal of Engineering and Applied Sciences
Publication of Nigerian Society of Engineers, Ibadan Branch
P J E A S
Vol. 2, No. 4, 2021 ISSN:2734-3170

Development of an Expert System for Quick Determination of Optimum Exponential Smoothing Constant for Job Shop Sales Forecast

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ARTICLE INFO

Received: July, 2021
Accepted: October, 2021
Published: October, 2021

Keywords:
Exponential smoothing method
Smoothing constant
Expert system
Forecast
Optimality forecast-error.

ABSTRACT

Forecasting is a major decision for facilitating effective production planning and control of any manufacturing company. Though there are many methods of forecasting, the exponential smoothing method is one of the most widely used for a short-term sale on a routine basis, the method readily finds applications where uncertainties cloud the planning horizon. The accuracy of this method largely depends on the exponential smoothing constant (α) which ranges between 0 and 1, invariably, choosing an appropriate value of this constant is crucial to minimise the errors in forecasting. The errors could be measured using any of the error-metrics like; Mean Absolute Error (MAE), Mean Squared Error (MSE) or Mean Absolute Percentage Error (MAPE). The earlier researchers have relied on the trial-and-error method for selecting optimum values of exponential smoothing constant. Depending on the grid intervals, large volumes of iterations are mostly involved, which are time-consuming and could be less accurate when manually done. This study has developed an expert system that could consider all values between 0 and 1 depending on the grid interval to find an optimum smoothing constant that gives the least error within a short timeline with consistent accuracy. The Expert System was developed using Visual Basic Application programming language which makes it user-friendly and easily implementable. It was tested and validated using data from earlier researchers. When the results were compared; the Expert system's results are not only accurate but gives optimum exponential smoothing constants within a very short timeline. With this performance, the Expert System has enhanced the usability and accuracy of the exponential smoothing method and as well makes it possible for managers who are non-experts in forecasting to explore the versatility of the exponential smoothing method.

1. INTRODUCTION

Forecasting is a way of projecting into the future using historic data which can have a certain amount of random variation (Mu'azu, 2014; Paul, 2011). It is a crucial managerial decision that can make or mar the production planning of any organisation most especially when uncertainties cloud the planning horizon, a typical situation in a job shop environment (Karmaker, 2017). Forecasting makes planning and control more effective and the failure of many organisations has been attributed to lack of forecasting or using faulty forecasting methods (Hassan and Dhali, 2017; Mu'azu, 2014).

Accurate forecasting reduces unnecessary inventories, improves product availability and enhances the level of customer satisfaction which is the main driving force for profitability and sustainability of any organisation (Karmker, 2017). Forecasting methods can be broadly divided into three major categories; qualitative, time series and causal methods. The qualitative method includes; Delphi method, market research, panel consensus, visionary forecast and historical analogy, while time series includes; past average, moving average, exponential smoothing, box-Jenkins, x-11 and trend projection. The causal methods are; regression, econometric model, input-output model and life cycle analysis.

Most of the qualitative forecasting methods use past or historical data in the form of time series. A time series is a sequence of observations indexed by time, usually ordered in equally spaced intervals and correlated (Ostertagova and Ostertag, 2012). Paul (2011) considered exponential smoothing as the most widely used time-series technique and the most accurate of them, while Kabir and Moiisin (2011) recommend it for predicting level demand of a retail chain. It is simple to use and most commercial forecasting software makes use of it due to its flexibility and accuracy (Ravinder, 2013a; Hasan and Dhali, 2017; Mu'azu, 2014; Idris *et al*., 2020). Exponential smoothing is considered to be appropriate for forecasting data with no trend or seasonal pattern (Karmaker, 2017), hence, Idris *et al*. (2020) recommend it for job shops production planning and control due to the dynamic and stochastic nature of job shops.

There are two types of exponential smoothing; simple exponential smoothing and double exponential smoothing. In this work, simple exponential smoothing method was considered. Simple exponential smoothing is appropriate for a series that moves randomly above and below a constant mean that has no trend and no seasonal pattern nor consistent pattern of growth (Yorucu, 2003; Mu'azu, 2014). Gardner (1985; 2006) and Idris *et al*. (2020) provide a detailed review of the exponential smoothing method. The formula to calculate simple exponential smoothing method is as given in Equation 1.

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

Where: F_t is forecast at period t; F_{t-1} is forecast for the immediate past period; A_{t-1} is the actual value of the immediate past period; α is the exponential smoothing constant ($0 \leq \alpha \leq 1$). Exponential smoothing is an intuitive forecasting method that uses constant that assigns weights to current demands and previous forecasts to arrive at the new forecasts. This constant, commonly referred to as exponential smoothing constant (α) represents a percentage of the forecast error, its value determines the accuracy of simple exponential smoothing method (Ravinder, 2013b; Mu'azu, 2014; Hasan and Dhali, 2017; Karmaker, 2017). Determination of an appropriate value of exponential smoothing constant that will minimize some functions of forecast error; such as Mean Absolute Error (MAE), Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) has been widely researched (Enns, 1995; Dielman, 2006; William and Friedhelm, 1974; Paul, 2011; Ravinder, 2013a; and Mu'azu, 2014). However, Ravinder (2013b) opines that there is no consistent guideline in the forecasting literature on how it could be selected.

Dated back to the work of Brown (1963) to the current works, selection of the best α has attracted different approaches and has been a major challenge confronting the users of exponential smoothing method. Mu'azu (2014) reported some values that were suggested by earlier researchers; such as, values between 0.05 and 0.50, between 0.2 and 0.4, between 0.7 and 0.9. All these suggestions lacked empirical support and there is no theoretical reason that was made available to support their positions. However, Xie *et al.* (1997) proposed trial-and-error method to find the value that minimises forecast errors. Based on trial-and-error method, Cho (2003) proposed grid search method while Paul (2011) also suggested a pattern grid search approach.

Grid search method is a process of scanning a set of parameters to select certain values by employing a method of trial and error, in this context, the grid values start with zero (0) and end with one (1), using pattern of increasing search by a constant value (k), the grid generates values ranging from 0, k, $2k$, $3k$…1. Mu'azu (2014) suggested that the optimal smoothing constant can be obtained by an exhaustive grid search between 0.1 and 1.0 with 0.1 as an incremental value. With this incremental value of 0.1, ten (10) possible values of α will be tested. These possible values, ten (10), were considered as "textbook-type problems" by Ravinder (2013b) hence a wide range of values between 0 and 1 was recommended by selecting smaller incremental values. Having a small incremental value, say 0.01 or 0.001 will result in 100 and 1000 values of α to be tested respectively, thereby increasing the possibility of having the best forecast result. Testing hundred or thousand possible values becomes a herculean task; hence an expert system that will not only work with high speed but with utmost accuracy is needed.

In recent time, taking into consideration the characteristics of job shops, researchers have begun to tap the potential capabilities of Artificial Intelligence (AI) techniques not only for job shop forecasting but for scheduling and other production and control systems of job shops (Kathawala and Allen, 1993; Khalil and Shanker, 1997; Metaxiotis *et al*., 2002; Sayed *et al.*, 2010; Castrillon *et al*., 2011; Adekunle *et al*., 2014). An Expert System is a branch of AI which serves as a computer program that answers or solves difficult problems. It possesses set of facts, heuristics or knowledge about specific domain of human expertise and by manipulating these facts intelligently it is able to make useful inferences for the user of the system (Sweeney, 1989; Oguoma *et al.*, 2020). It is cheaper compared to human experts in the long-term scenario; however, it may be costly to develop but easy and cheap to operate. In addition, expert system allows automation of many tasks that could not be effectively handled by human experts (Collopy *et al*., 2001). Sweeney (1989) opines that using an expert system for forecasting gives accurate results within a short time. It also provides easy access to relevant databases and the effect of variations in data could easily be explored.

Expert systems are widely used for planning, forecasting, scheduling, monitoring and process control (Collopy *et al.*, 2001). Employing expert systems for forecasting process has been widely researched, the recent of which is Barrow *et al*. (2020) that investigated the ways to increase the reliability of exponential smoothing forecasts using an automated robust estimation from statistics and machine learning perspectives. Brown *et al.* (2020) concluded by advocating for more research on blended statistics and machine learning approaches which by an extension, this paper have accomplished by developing an expert system that increases the usability and reliability of exponential smoothing method by automating the selection of exponential smoothing constant which will reduce the errors resulting from trial-and-error method of selecting exponential smoothing constants.

2. METHODOLOGY

Expert system consists of major components as shown in Figure 1. The procedures for developing an expert system, specifically involve; acquisition of relevant knowledge, structuring and applying the knowledge and finally testing the system (Jabbar and Khan, 2015).

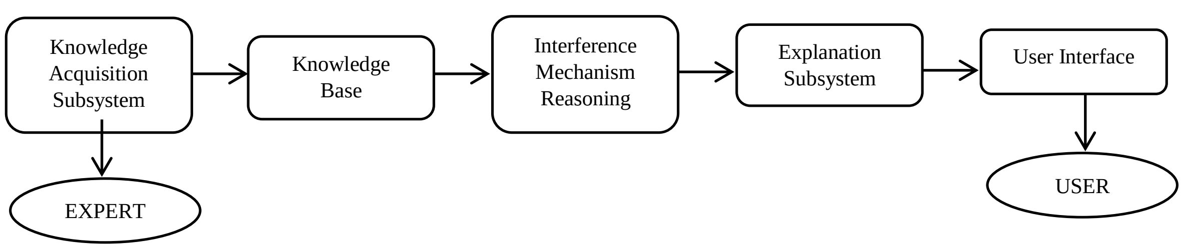

Figure 1: Expert System Components (Oguoma *et al*., 2020)

2.1 Acquisition of Knowledge

The knowledge required for the development of this Expert System is the procedure to determine the best exponential smoothing constant (α) that will minimise the forecast errors. Forecast error (e) is the difference between the forecast values with their corresponding ex-post actual values as given in Equation 2. Among the error metrics that could be used to determine the errors are; Mean Absolute Error (MAE), Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). Discussion on the most appropriate among these three metrics, especially for job shop forecasts, is available in Kim and Kim (2016), Kolassa (2020) and Idris *et al*. (2020). However, the three metrics were used for the Expert System developed in this study. The three metrics can be determined using the formula provided in Equations 3, 4 and 5 for MAE, MSE and MAPE respectively.

$$e_t = (A_t - f_t) \qquad (2)$$

$$MAE = \frac{\left(\sum_{t=1}^{n} |e_t|\right)}{n} \qquad (3)$$

$$MSE = \frac{\left(\sum_{t=1}^{n} e_t^2\right)}{n} \qquad (4)$$

$$MAPE = \frac{\left(\sum_{t=1}^{n} \frac{|e_t|}{A_t}\right)}{n} \qquad (5)$$

Where: e_t is error at period t; A_t is the actual for period t and f_t is the forecast value for period t. To have minimum values for MAE, MSE and MAPE, the error at period t (e_t) must tend to zero. That is $f_t \approx A_t$ (forecast value at period t must "almost equal to" actual value at period t). To determine the best α that will produce f_t that will nearly equal A_t ,the first step is to generate all the possible α's. Values of α range between 0 and 1, this shows that if the interval between consecutive α is k the possible number of α can be obtained using Equation 6 (where N is an integer number). The values of possible α is as given in Equation 7. Moreover, forecast values depend on the value of α; hence Equation 8 gives the likely forecast values depending on the values of α. Furthermore, errors from forecast values using different values of α is given in Equation 9. Optimum value of α is the one that gives the least error among the errors in Equation (9) and is as presented in Equation 10.

$$N = \frac{k+1}{k} \qquad (6)$$

$$\alpha = \{0, \quad k, 2k, \dots, and\ (N-1)k\} \qquad (7)$$

$$\left\{\begin{array}{c} f_t^0 = F_{t-1} \text{ when } \alpha = 0 \\ f_t^k = F_{t-1} + k(A_{t-1} - F_{t-1}) \text{ when } \alpha = k \\ f_t^{2k} = F_{t-1} + 2k(A_{t-1} - F_{t-1}) \text{ when } \alpha = 2k \\ . \\ . \\ . \\ f_t^{(N-1)k} = F_{t-1} + k(N-1)(A_{t-1} - F_{t-1}) \text{ when } \alpha = k(N-1) \end{array}\right\} \qquad (8)$$

$$\left\{\begin{array}{c} \boldsymbol{\varepsilon^0} = \mathrm{A}_{\boldsymbol{t}} - f_t^0 \text{ when } \alpha = 0 \\ \boldsymbol{\varepsilon^k} = \mathrm{A}_{\boldsymbol{t}} - f_t^k \text{ when } \alpha = k \\ \boldsymbol{\varepsilon^{2k}} = \mathrm{A}_{\boldsymbol{t}} - f_t^{2k} \text{when } \alpha = 2k \\ . \\ . \\ . \\ \boldsymbol{\varepsilon^{k(N-1)}} = \mathrm{A}_{\boldsymbol{t}} - f_t^{k(N-1)} \text{when } \alpha = k(N-1) \end{array}\right\} \qquad (9)$$

$$\boldsymbol{\varepsilon}^{\delta} = \mathrm{Min}\left\{\boldsymbol{\varepsilon}^{\mathbf{0}}, \boldsymbol{\varepsilon}^{\boldsymbol{k}}, \boldsymbol{\varepsilon}^{\mathbf{2}\boldsymbol{k}} \ldots \boldsymbol{\varepsilon}^{\boldsymbol{k}(\boldsymbol{N}-\mathbf{1})}\right\} \qquad (10)$$

2.2 Structuring the Expert System

Most of the expert systems were rule-based approach (Trivedi and Nagori, 2014; Rossini, 2000). This is an approach where a set of rules are established and the user effectively moves from a starting point to some answer or output by answering a set of questions. The Expert System developed in this paper is a modified rule-based approach where the sets of rules are; determination of exponential constants, determination of forecasts values using different exponential constants in turn, determination of errors using MAE, MSE and MAPE and finally determination of the best exponential constant that gives the least MAE, MSE and MAPE. The Expert System is structured based on the algorithm shown in Figure 2; using the algorithm the code of the Expert System was written.

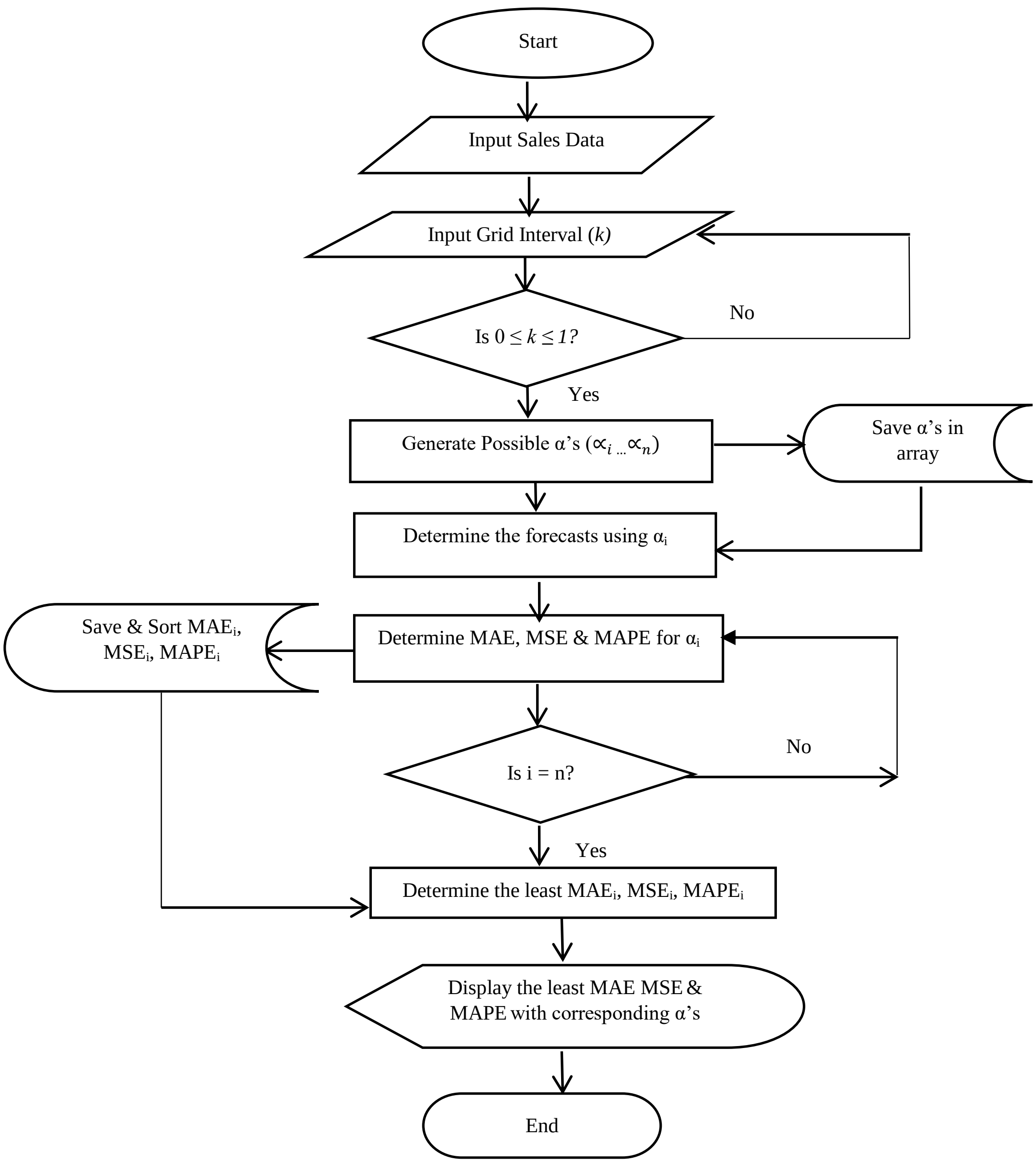

Figure 2: The Expert System Algorithm

Language for Coding the Expert System: Visual Basic Application (VBA) macro is the programming language used for writing the Expert System source code. The main advantage of this language is that it is a rapid application development tool that, by default, has visual controls or components with their attributes and actions which only need a few additional lines of code for more functionality (Kovar, 2005). It is user-friendly and can easily interface with database on Microsoft's Office applications such as Excel or Access (Hassan *et al*., 2006). The language is readily available on all Microsoft Office products hence its availability is guaranteed without requiring any special hardware or software.

2.3 Testing the System

Classical data from Paul (2011) and Karmaker (2017) were used to test and validate the expert system.

3. RESULTS AND DISCUSSION

This section presents the results produced by the Expert System in finding the optimum exponential smoothing constants (α) that give minimum MAE, MSE and MAPE. The data used were gotten from the works of Paul (2011) and Karmaker (2017). The duo used trial and error method to find the minimum MAE and MSE. This method, trial and error, is not only susceptible to human error but also time-consuming. It is also practically impossible to be used where a large volume of sales data is involved. The results of their works and the results from the Expert System are reported.

Case I

Paul (2011) used a company's historical sales data to determine the best exponential smoothing constant that will minimise MAE and MSE. The author tested 20 different exponential smoothing constants through trial and error method. With the same data, the Expert System tested 100 and 1000 different exponential smoothing constants and the results of the three iterations are shown in Table 1.

Table 1: Comparison between the Results from Paul (2011) and the Expert System

						Value of α	
	No of trial	MAE	MSE	MAPE	MAE	MSE	MAPE
Paul's method	20	1.858	8.031	-	0.83	0.83	-
The Expert System	100	1.7946	6.1811	15.2554	0.82	0.38	0.82
	1000	1.794	6.1811	15.2504	0.823	0.379	0.823

From Table 1, the least Minimum Absolute Error (1.794), and the least Minimum Squared Error (6.1811) were given by the Expert System when 1000 different exponential smoothing constants were tested. The values of exponential smoothing constant that give the least MAE and MSE are 0.823 and 0.379 respectively. In the case of trial-and-error method used by Paul (2011), 0.83 gives 1.858 MAE while 0.88 gives 8.031 MSE. It is obvious from this that the MAE of the Expert System (1.794) is lower compared with 1.858 of manual trial and error method. This is so because the Expert System considered a wide range of alternative.

It can also be observed from the table that there is a significant difference in the least MSE given by the Expert System, 6.1811 when compared with 8.031 of Paul's. This is likely to be a result of human error which is a common occurrence in a manual method, which expert system eliminates. This is inconsonant with the submission of Rossini (2000) that using expert systems for forecasting eradicates human errors. Figure 3 and Figure 4 show the outputs of the Expert System when Paul (2011) data was used for 100 and 1000 trials respectively.

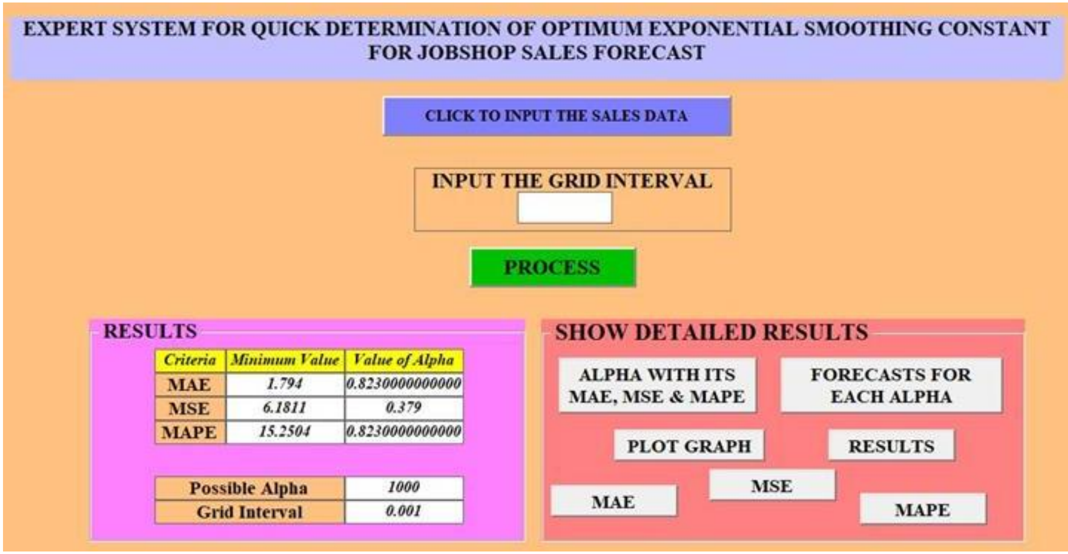

Figure 3: Output of the Expert System Using Paul (2011) Data with 100 Trials

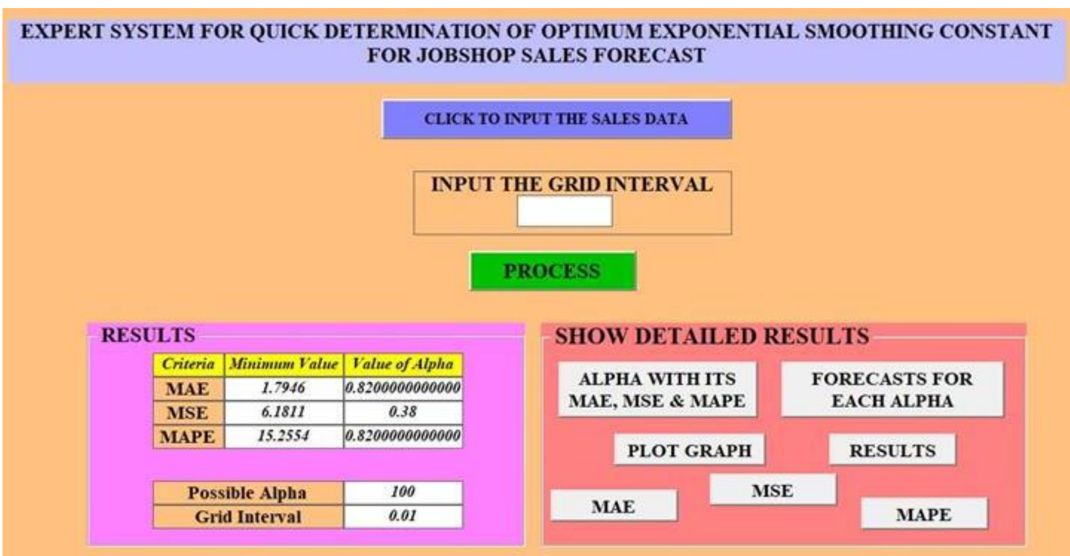

Figure 4: Output of the Expert System Using Paul (2011) Data with 1000 Trials

Case II

Karmaker (2017) also used actual sales data of a company from 2010- 2016 (84 sales data) and for different 20 values of exponential smoothing constant, MSE and MAE were calculated using trial and error method. The method produced 0.14 and 0.31 exponential smoothing constants for the least MSE (53.4288) and MAE (6.0205) respectively. The Expert System was also used to find the least MSE, MAE and MAPE by testing 100 and 1000 different exponential smoothing constants. Table 2 shows the results of the three iterations.

Table 2: Comparison between the Results from Karmaker (2017) and The Expert System

					Value of α		
	No of trial	MAE	MSE	MAPE	MAE	MSE	MAPE
Karmaker's method	20	6.0205	53.4288	-	0.31	0.14	-
The Expert System	100	6.020	53.429	9.856	0.31	0.14	0.29
	1000	6.020	53.429	9.856	0.31	0.14	0.29

From Table 2 the results produced by the Expert System are the same as the results of Karmaker (2017) this shows that the Expert System developed is reliable and valid. Though the results of Karmaker (2017) are the same as that of Expert System, the time taken to complete the task using manual method is quite longer than the few seconds taken by the Expert System to accomplish the same task and most importantly, the procedures for finding the optimum exponential smoothing constants by the Expert System are replicable. Figures 5 and 6 show the outputs of the Expert System when Karmaker (2017) data was used for 100 and 1000 trials respectively.

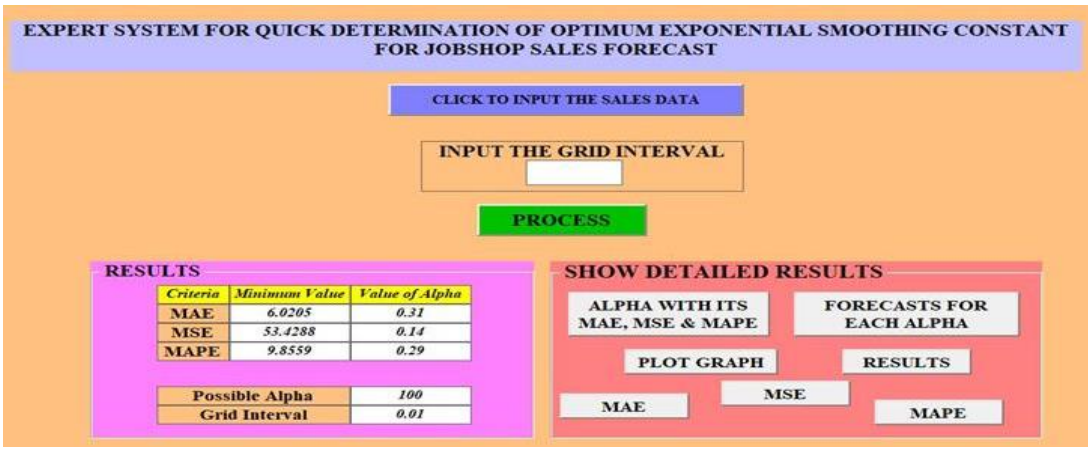

Figure 5: Output of the Expert System Using Karmaker (2017) Data with 100 Trials

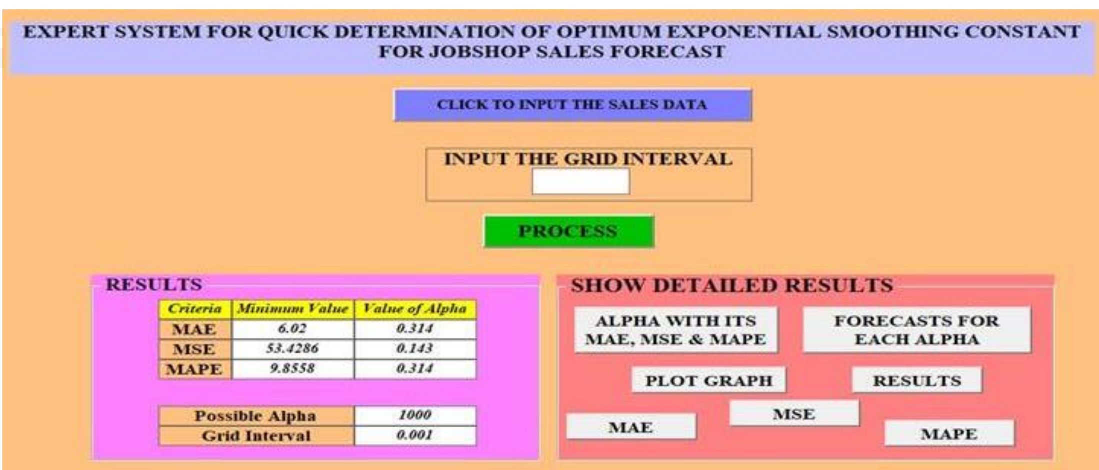

Figure 6: Output of the Expert System Using Karmaker (2017) Data with 1000 Trials

4. CONCLUSIONS

Accurate forecasting of product demand is an essential tool for effective management of manufacturing systems and most especially in job shops where the production planning is clouded with uncertainty. The simple exponential smoothing approach is one of the best qualitative forecasting methods suitable for job shop environment due to its accuracy and simplicity. However, the accuracy of simple exponential smoothing method largely depends on the value of exponential smoothing constant (α) which its selection between 0 and 1 is based on arbitrary or trial-and- error method of selection. These methods of selection, due to the longer time it takes, most especially when a large number of choices has to be tested or due to likely human error that may occur, makes the application less appealing to the users. In this study, an Expert

System was developed that could test up to 10,000 choices of exponential smoothing constant (α) to select the best one that minimises MAE, MSE and MAPE within a reasonable timeline.

The Expert System was tested using data from Paul (2011) and Karmaker (2017). Each of the duos tested 20 different values of smoothing constants using trial-and-error method in selecting the optimum smoothing constants. The Expert system developed in this study used the same data and tested 100 and 1000 different values of smoothing constants in selecting the optimum values for each of the data. The optimum values were compared and it was found that the results from the expert system give least errors and more reliable because it devoid of likely human errors and the results were given within a reasonable timeline despite considering a large number of choices. Hence, this Expert system can be used to quickly determine the optimum smoothing constant from large number of values irrespective of the size of the data.

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