DEVELOPMENT OF DYNAMIC EXPONENTIAL SMOOTHING APPROACH FOR JOB SHOPS IN THE DEVELOPING NATIONS

MUSIBAUDEEN OLATUNDE IDRIS[1]*, GODWIN CHUKWUMA ENWEREM[2], BULIAMINU KAREEM[3]
[1*]Mechanical Engineering Department, Osun State University, Osogbo, Nigeria
[2]Mechanical Engineering Department, The Federal Polytechnic, Ede, Nigeria
[3]Mechanical Engineering Department, The Federal University of Technology, Akure, Nigeria

*__E-mail:__ musibaudeen.idris@uniosun.edu.ng **Phone No**:+234-806-089-2447

Abstract
In a production system, demand forecast is a key factor that guides the management's decisions and policies. Failure to have a reliable forecast has been identified to hinder the sustainability of small-scale industries most especially in the developing nations. Job shops in developing nations are mostly small-scale industries that are gradually fading out because of their inability to compete favourably with global competitions. To match this competition, the managements of job shops must adopt scientific methods in handling all the facets of production planning and control most importantly, determination of likely demands prior the production. This study developed a novel forecast method for a particular job shop in Nigeria who had previously relied on naïve method to forecast for its demands. The new method named, Dynamic Exponential Smoothing Approach (DESA) integrated Moving Average with Exponential Smoothing Approach to evolve a hybrid method suitable for the job shop based on its twelve months demand data. The efficacy of the approach was tested using common error metrics like Mean Absolute error (MAE), Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) and the results showed that DESA produced reliable forecasts of least MAPE for turning section (35.10%), electrical section (35.68%) and carpentry section (51.40%) when compared with the MAPE of forecasts from naïve, Moving average and exponential smoothing approach.

Keywords: Exponential smoothing approach; moving average; naïve; dynamic forecast; job shop; error metrics, sustainability

Introduction
There are two types of environments in manufacturing system. These environments are; flow shop and job shop. The flow shop uses continuous flow processes, it is commonly found in medium-to-high-volume production and all the jobs normally follow a similar pattern. In this method, the production capacity and resources are easily predictable and tractable because the demands are majorly make-to-stock (MTS) which make the production planning and control to be relatively independent of the customers' demands. On the other hand, demands in job shop are mostly make-to-order (MTO) system. Job shop is characterised with a low-to-medium volume production in which there is no definite work flow. The issues of market uncertainties, demand inequalities and resource limitations make the planning for job shop operation very dynamic and involving (Schaer et al, 2019). The complexity of the jobs in terms of the different operational requirements for its manufacture or processing and the infrastructural limitations in developing nations make the solution to job shop scheduling a dynamic one.

Appropriate job shop scheduling starts with the forecasting of the demand-supply chain (Kocaoglu et al, 2014). Demand forecasting enables product managers to plan future needs and to consequently make pertinent decisions (Prak & Teunter, 2019). A very good demand forecast will accelerate the flow of raw materials and services from the supplier through the transformation stages in the shops to the final delivery to the customers, thereby optimising the use of man-hours and machine-hours while meeting the due-date requirements (Idris, 2018). Forecasting determines which product to produce, the quantity the consumers will demand for and also predicts when these products will be demanded (Kocaoglu et al, 2014).

In literature, methods of forecasting are broadly grouped into; subjective methods and time-series analysis. Subjective methods such as methods on average of past data, regression models on historical data, causal or econometric models, among these methods, there is no single method that has successfully and consistently proved to be the best (Prak & Teunter, 2019) and also to improve their degree of accuracy, current researchers have focused on the combination of two or three methods, such efforts are well documented in (Prak & Teunter, 2019; De Menezes, 2000; Armstrong, 2001; Timmerman, 2006, Soll & Larrick, 2009; Wallis, 2011 and Thomson et al 2019).

The accuracy of any forecasting method is a factor of the methods used to determine its errors, reliability and the pattern of the data used (Schaer, 2019; Teunter & Duncan, 2009; Boylan et al, 2008). Among the common demand patterns include; Smooth, irregular, slow-moving, erratic, highly erratic, mildly intermittent and highly intermittent (Eavesi & Kingsman, 2004). In literature, there are scanty works that specifically study the job shop demands pattern; hence most early works arbitrarily used forecasting methods without considering the patterns of the data emanated from job shops (Eavesi & Kingsman, 2004).

In most of the job shops in the developing nations, there are scanty records from the previous jobs and the nature of each job hardly similar to others, these warrant the use of forecast methods that will rely on few past data and the one that will permit judgmental or experts' opinion (Idris, 2010). Exponential Smoothing Approach (ESA) was considered as appropriate forecast method for job shops considering these features (Aderoba, 2000 and Kareem & Aderoba, 2003) however Willemain et al (1994) considered ESA to be inappropriate for estimating demands in job shops because job shops exhibit intermittent pattern of demand. In the works of Hsu et al (2006) and Shakeel et al (2016) data from job shops were used to test the accuracy of various forecasting methods and their results showed that ESA was better than Moving Average and Simple Weighted Average (SWA).

However, the former limited the data used to the indirect consumables needed in the job shops while the latter considered the aggregate demand in the job shop. Forecasting demand in a job shop based on these two criteria could not be relied upon because one of the peculiarities of job shops is the discrete nature of its production system, that is, each section of the job shop is independent and demand of a section may not necessarily affect the demand of other sections as it occurs in the case of flow shops.

Other researchers have shown that, ESA when combined with other forecasting methods produces more accurate results (Schaer, 2019 and Thomson et al, 2019). Based on this recent approach, this study combined moving average and exponential smoothing approach to evolve a new approach called Dynamic Exponential Smoothing Approach (DESA). This method is dynamic in nature because of the effects of the moving average on the traditional Exponential Smoothing Approach. The study also treated individual activity centres of the job shop which to the best knowledge of the authors, there is no work that has specifically develop forecast method for each of the major activity centres in job shops.

Material and Methodology

The study forecast for five major activity centres of a particular job shop located in Osogbo, Osun State, Nigeria. These centres are; turning, milling, welding, electrical and carpentry sections. The company is a typical job shop that specialises in the repairs and fabrication of metal, wood and electrical parts and machines. The company uses naïve method to forecast for the demands of each centres, as a result of this, there were wide variations between the forecasts and the actual demands which led to wastage of resources, failure in meeting the due dates and in general, poor planning and control of its activities. The new method (DESA) along with other forecast methods (naïve, moving average and Exponential Smoothing Approach) is used to forecast for jobs for five centres of the job shop. The actual demands of the centres for a period of twelve (12) months were used as basis to find the degree of accuracy of these methods using Mean Absolute Error/Deviation (MAE or MAD), Mean Square Error/ Deviation (MSE or MSD) and Mean Absolute Percentage Error (MAPE). The results showed that DESA is more reliable when compared with the results of naïve, moving average and Exponential Smoothing Approach.

Development and evaluation of Dynamic Exponential Smoothing Approach
Exponential smoothing approach (ESA) and moving average (MA) were integrated to develop Dynamic Exponential Smoothing Approach (DESA). The new approach takes into consideration the peculiarities of job shops, dynamism and scanty availability of past data before selecting the two methods used for this purpose.

Exponential Smoothing Approach (ESA)
In using exponential smoothing approach to predict for the current period (f_t), only three pieces of data are needed (Eq. 1). These are; the most recent forecast (f_{t-1}), the actual demand that occurred for that forecast period (a_{t-1}) and a smoothing constant (α). The value of smoothing constant ranges between 0 and 1 (Karmaker, 2017), it determines the level of smoothing and the speed of reaction to differences between forecasts and actual occurrences. The value for this constant is arbitrary and is determined both by the nature of the product and the feelings of the managers as to what constitute a good response rate.

Stevenson and Hojati (2005) and Karmaker (2017) opine that defining the value of smoothing constant is a matter of judgment or trial and error. The Exponential Smoothing equation is shown in Eq.1.

$$f_t = f_{t-1} + \alpha(a_{t-1} - f_{t-1}) \quad (1)$$

ESA places most weight on the more recent data, giving estimates that are highest just after a demand and lowest just before a demand (Eavesi & Kingsman, 2004). This method is suitable for forecasting data with no clear trend or seasonal pattern, it is consider to be the most widely used of all forecasting techniques that requires little computation and mostly used when data pattern is approximately horizontal (i.e., there is neither cyclic variation nor pronounced trend in the historical data) (Ostertagova & Ostertag, 2012). The idea of exponential smoothing is to smooth the original series the way the moving average does and to use the smoothed series in forecasting future values of the variable of interest.

Moving Average (MA)
Moving Average is a time series constructed by taking averages of several sequential values of another times series. Moving average is used to describe this procedure because each average is computed by dropping the oldest observation and including the next observation. Variations on moving averages allow the number of points in each average to change. While moving averages are very simple methods, they are often building blocks for more complicated methods of time series smoothing, decomposition and forecasting (Hyndman, 2009). A moving average is obtained by calculating the mean for a specified set of values (a_t) and then using it to forecast the next period. That is, for n period moving average, the moving average forecast at time t (MA_t) is

$$MA_t = \frac{1}{n}\left(a_{t-1} + a_{t-2} + ...a_{t-n}\right) \qquad (2)$$

Eq. 2 can as well be written as

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$$MA_t = \frac{1}{n}\left(\sum_{i=t-n}^{t-1} a_i\right) \qquad (3)$$

Where

$$t \succ 2 \text{ and } n \geq 2 \qquad (4)$$

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Moving average can become naïve method if "n", period of forecasting is set to be 1. In this situation, the next forecast will always be equal to the previous actual demand. That is;

$$MA_t = a_{t-1} \qquad (5)$$

The user of any naïve forecasting method is not concerned with causal factors, those factors that result in a change in actual demand. For this reason, the naïve forecasting method is mostly used to create a forecast to check the results of more sophisticated forecasting methods (Nordmeyer, 2018).

The New Forecast Method: Dynamic Exponential Smoothing Approach (DESA)

Since the activities and demand pattern in job shop is dynamic, the authors considered the dynamic nature of moving average as important for forecasting for demands in job shops. They also considered the exponential smoothing approach which was preferred for data with no clear trend or seasonal pattern in producing Dynamic Exponential Smoothing Approach (DESA).

DESA was produced by first using Moving Average to find the current forecast and the result is later integrated into Exponential Smoothing Approach as shown in Eq. 6.

$$f_t = MA_t + \alpha(MA_t - f_{t-1}) \qquad (6)$$

Substituting Eq. 3 in Eq. 6 gives

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$$f_t = (1+\alpha)\left[\frac{1}{n}\left(\sum_{i=t-n}^{t-1} a_i\right)\right] - \alpha f_{t-1} \qquad (7)$$

To forecast for the current period (t), a smoothing constant, an immediate past forecast f_{t-1} using DESA, and n-past actual values "a_i" are needed.

Where $t \succ 2$ *and* $n \geq 2$ (8)

To start the algorithm, naïve method could be used for the immediate past forecast f_{t-1}

Forecast Errors

Accuracy is the major criterion to validate the best forecast method, and the method that gives the least error is considered to be the best method (Hyndman, 2006). Forecast error involves comparing a set of predictions with their corresponding ex-post actual values. There are a variety of error metrics that could be used for assessing forecast performances, notable among them are; the mean squared error (MSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) (Thomson et al, 2019).

Despite that there are various error metrics to determine the most appropriate forecast methods; there is no agreement among the researchers as to which one gives the best result (Thomson et al, 2019 and Ostertagova, 2012). Forecast error (e) is mathematically expressed as the difference between the forecast values (f) with their corresponding ex-post actual values (a). (Eq. 9). The three common error metrics , MSE, MAE and MAPE are mathematically expressed in Eq. 10, Eq. 11 and Eq. 12 respectively.

$$e_t = (a_t - f_t) \quad (9)$$

$$MAE = \frac{1}{n}\left(\sum_{t=1}^{n}|e_t|\right) \quad (10)$$

$$MSE = \frac{1}{n}\left(\sum_{t=1}^{n}e_t^2\right) \quad (11)$$

$$MAE = \frac{1}{n}\left(\sum_{t=1}^{n}\frac{|e_t|}{a_t}\right)X100\% \quad (12)$$

Considering all these common metrics for determining forecast accuracy, Ostertagova and Ostertag (2012) noted that MAPE is the most useful measure to compare the accuracy of forecasts since it measures relative performance. Also, it has advantages of scale-independency and interpretability. However, MAPE has the significant disadvantage that it produces infinite or undefined values for zero or close-to-zero actual values (Kim & Kim, 2016). Thus, using MAPE, when two or more forecasting methods are compared, the one with the minimum MAPE can be selected as the most accurate.

Evaluation of Dynamic Exponential Smoothing Approach

The accuracy of Dynamic Exponential Smoothing Approach (DESA) was evaluated using data collected from a job shop. The job shop has five production centres. These sections are turning, milling, welding, electrical and carpentry section. Jobs executed by each of these centres for a period of twelve months were extracted from the company records. The data is presented in table 1.

Table 1 - Number Jobs Executed for 12 months in the Job shop

Months	Turning Centre	Welding Section	Milling Section	Electrical Services	Carpentry Section
1st	33	27	25	21	14
2nd	37	6	10	2	8
3rd	13	33	5	12	37
4th	15	32	5	26	23
5th	28	17	11	28	6
6th	20	35	3	31	24
7th	34	34	8	23	14
8th	29	25	9	12	13
9th	11	19	37	28	29
10th	27	6	28	17	27
11th	16	21	34	29	12
12th	11	18	20	37	15

Source: A year Demand Record of Abiola Electrical & Metal Fabrication Company, Osogbo(2018)

Determination of forecasts using Naive Approach

Naïve approach is simply a forecast method that considers the immediate past actual demand to be the current forecast. That is

$$f_t = a_{t-1} \qquad (13)$$

Where $t > 1$

This approach is mostly used for comparison with the forecasts generated by the other sophisticated methods (Dhakal, 2017). In computing this method, the first period cannot be determined since there is no prior value or data for the immediate past value. That is, the forecasts only exist from the second month.

For instance, forecast for the fifth month (f_5) for turning centre is 15 which is the actual value for the fourth month (a_4) while forecast for tenth month (f_{10}) in welding section is 19, which is the actual value for the ninth month (a_9).

The absolute forecast error in this situation for turning centre is

$$e_5 = (|a_5 - f_5|) = |28 - 15| = 13 \qquad (14)$$

While absolute forecast error for welding is

$$e_5 = (|a_5 - f_5|) = |6 - 19| = 13 \qquad (15)$$

Determination of forecasting using Moving Average approach (MA)

In using moving average approach, the forecast for the next period is the average of a specified number (n) of the most recent past observations, with each observation receiving the same weight. Hence, the forecast for the period less than the specified period cannot exist. That is $t \geq n + 1$. In this work, three (3) months moving average was used, for this reason, forecasts only exist from the fourth months.

Using the same illustrations as used above, forecast for the fifth month (f_5) for turning centre using MA is

$$MA_5 = \frac{1}{n}(a_4 + a_3 + a_2) = \frac{1}{3}(15 + 13 + 37) = 22 \qquad (16)$$

In this situation, the absolute forecast error is;

$$e_5 = (|a_5 - f_5|) = |28 - 22| = 6 \qquad (17)$$

while forecast for tenth month (f_{10}) in welding section is

$$MA_{10} = \frac{1}{n}(a_9 + a_8 + a_7) = \frac{1}{3}(19 + 25 + 34) = 26 \qquad (18)$$

And the absolute forecast error in welding section in the tenth month using MA is;

$$e_{10} = (|a_{10} - f_{10}|) = |6 - 26| = 20 \qquad (19)$$

Determination of forecasts using Exponential Smoothing Approach (ESA)

In this work, 0.6 was used as the smoothing constant (α), a value favoured by many researchers (Karmaker, 2017). In using ESA, the current forecast can only be determined if there is available immediate past forecast and its corresponding actual demand. Hence, forecasts could not be established for the first and second months. Naïve method was used to forecast for the second month in this situation.

Determination of the fifth forecast for turning section and tenth forecast for welding section using ESA are illustrated in equations (20 to 23).

$$f_5 = f_4 + \alpha(a_4 - f_4) = 22 + 0.6(15 - 22) = 18 \qquad (20)$$

In this situation, the absolute forecast error is;

$$e_5 = (|a_5 - f_5|) = |28 - 18| = 10 \qquad (21)$$

Also tenth forecast for welding section will be

$$f_{10} = f_9 + \alpha(a_9 - f_9) = 28 + 0.6(19 - 28) = 23 \quad (22)$$

And the absolute forecast error in welding section in the tenth month is;

$$e_{10} = (|a_{10} - f_{10}|) = |6 - 23| = 16 \quad (23)$$

Determination of forecasts Dynamic Exponential Smoothing Approach (DESA)

This approach was developed by integrating moving average and exponential smoothing approach, hence, it shared the features of moving average approach which invariably makes it impossible to generate forecasts for the first three months.

In using DESA for the two instances used above, for the fifth forecast for turning section

$$f_5 = MA_5 + \alpha(MA_5 - f_4) = 22 + 0.6(22 - 13) = 27 \quad (24)$$

the forecast error is;

$$e_5 = (|a_5 - f_5|) = |28 - 27| = 1 \quad (25)$$

Also for the tenth forecast for welding section will be,

$$f_{10} = MA_{10} + \alpha(MA_{10} - f_9) = 26 + 0.6(26 - 32) = 23 \quad (26)$$

And the absolute forecast error in welding section in the tenth month is;

$$e_{10} = (|a_{10} - f_{10}|) = |6 - 23| = 17 \quad (27)$$

Results and Discussion

Based on the data collected from turning, welding, milling, electrical and carpentry section of Abiola Electrical & Metal Fabrication Company, Osogbo in 2018 as shown in table 1, forecasts were generated using naïve, moving average, exponential smoothing and the dynamic exponential smoothing approach. These forecasts were presented in Tables 2, 3, 4, 5 and 6 for the centres respectively.

Table 2 - Forecasts for Turning Centre

Months	Actual Sales	NAÏVE	ESA	Moving Average	DESA
1st	33				
2nd	37	33	33		
3rd	13	37	35		
4th	15	13	22	28	13
5th	28	15	18	22	27
6th	20	28	24	19	14
7th	34	20	22	21	25
8th	29	34	29	27	29
9th	11	29	29	28	27
10th	27	11	18	25	23
11th	16	27	23	22	22
12th	11	16	19	18	16

Table 3- Forecasts for Welding Centre

Months	Actual Sales	NAÏVE	ESA	Moving Average	DESA
1st	27				
2nd	6	27	27		
3rd	33	6	14		
4th	32	33	26	22	33
5th	17	32	29	24	18
6th	35	17	22	27	33
7th	34	35	30	28	25
8th	25	34	32	29	31
9th	19	25	28	31	32
10th	6	19	23	26	23
11th	21	6	13	17	13
12th	18	21	18	15	17

Table 4 - Forecasts for Milling Section

Months	Actual Sales	NAÏVE	ESA	Moving Average	DESA
1st	25				
2nd	10	25	25		
3rd	5	10	16		
4th	5	5	9	13	5
5th	11	5	7	7	8
6th	3	11	9	7	7
7th	8	3	6	6	6
8th	9	8	7	7	8
9th	37	9	8	7	6
10th	28	37	25	18	25
11th	34	28	27	25	24
12th	20	34	31	33	38

Table 5: Forecasts for Electrical Services Centre

Months	Actual Sales	NAÏVE	ESA	Moving Average	DESA
1st	21				
2nd	2	21	21		
3rd	12	2	10		
4th	26	12	11	12	12
5th	28	26	20	13	14
6th	31	8	13	15	16
7th	23	31	24	22	25
8th	12	23	23	21	18
9th	28	12	17	22	24
10th	17	28	23	21	19

11th	29	17	20	19	19
12th	37	29	25	25	28

Table 6- Forecasts for Carpentry Section

Months	Actual Sales	NAÏVE	ESA	Moving Average	DESA
1st	14				
2nd	8	14	14		
3rd	37	8	10		
4th	23	37	26	20	37
5th	6	23	24	23	14
6th	24	6	13	22	27
7th	14	24	20	18	12
8th	13	14	16	15	16
9th	29	13	14	17	18
10th	27	29	23	19	19
11th	12	27	25	23	25
12th	15	12	17	23	21

Figures 1, 2 and 3 show the forecast errors using Mean Absolute Error (MAE), Mean Square Error (MSE) and Mean Absolute Percentage Error respectively for each of the section using different forecast methods.

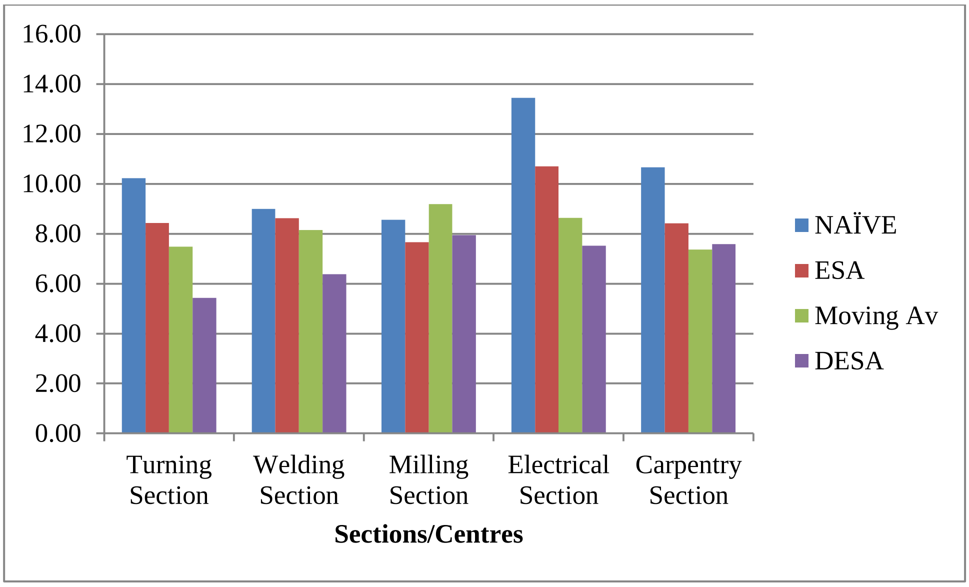

Fig. 1: *MAE* for different forecast methods

Fig. 1 shows the pictorial values of Mean Absolute Error (MAE) for the four methods used. The result shows that DESA had the least error in turning (5.43), welding (6.38), and electrical sections (7.52) while ESA and MA had the least error in milling (7.66) and carpentry (7.37) sections respectively. In these two sections, DESA was the second best with 7.95 and 7.58 in milling and carpentry sections respectively, while naïve method, which was the method employed by the company, had the highest Mean Absolute Error in all the sections except milling section. The MAE results revealed that after DESA, moving average approach could have been the best method for the company.

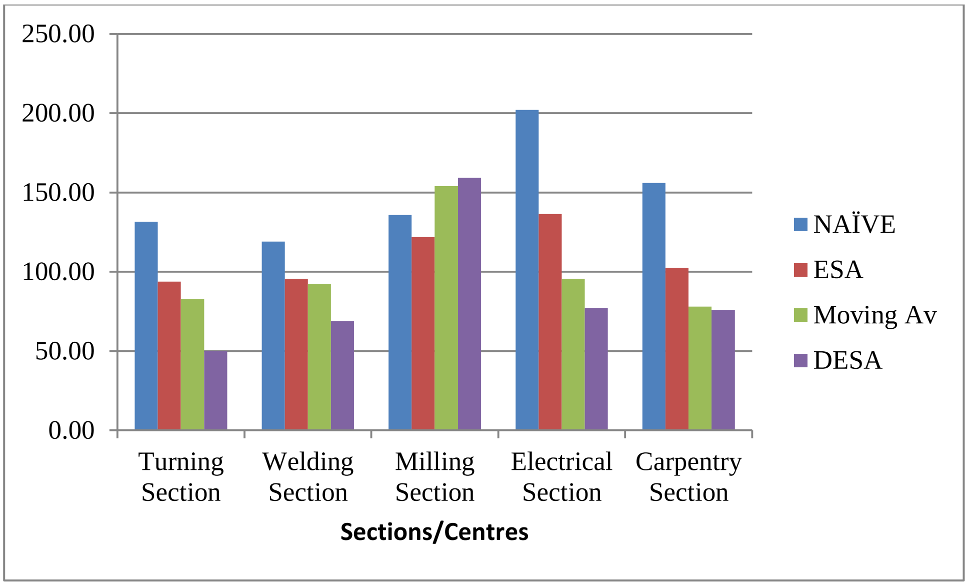

Figure 2: *MSE* for different forecast methods

Figure 2 reveals the performances of all the four methods for each of the sections using the Mean Square Error (MSE) metric. The result showed that DESA had the least mean square error in turning (50.12), welding (68.94), Electrical (77.16) and carpentry (75.98) while ESA had the least mean square error in milling. In overall, MA was next to the best in all the five sections.

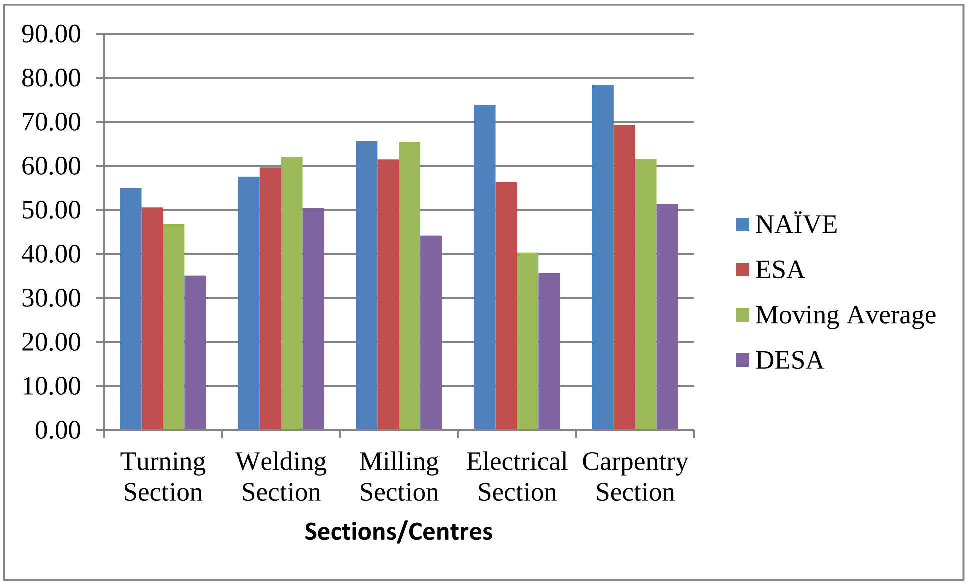

Fig. 3: *MAPE* for different forecast methods

In fig. 3, the Mean Absolute Percentage Error (MAPE) results show that DESA is more accurate when compared with other methods with MAPE values of 35.10%, 50.39%, 44.16%, 35.68% and 51.40% for turning, welding, milling, electrical and carpentry sections respectively. While moving average method followed with 46.79%, 40.35% and 61.63% in turning, electrical and carpentry sections respectively. In the other two sections, naïve and ESA are second to the best in welding and milling, respectively with 57.56% and 61.47%.

The result of this study shows that DESA is the best forecast method when compared with naïve, ESA and MA for this particular job shop. The results collaborates the fact that MAPE is the best forecast accuracy metric that could be employed where there is random demand pattern (Hyndman, 2006) and the argument that planning and control in job shop cannot be treated on aggregate basis but on independent level is also confirmed by the result of this work.

Conclusion

This study developed a forecast method by integrating moving average and ESA to evolve a dynamic forecast method called Dynamic Exponential Smoothing Approach (DESA). This approach, even though it is a derivative of ESA and moving average, when tested using different forecast accuracy metrics, such as MAE, MSE and MAPE gives better results than ESA, and moving average when used independently. The model was validated using data collected from a job shop located in Osun State, Nigeria. The model, not only reduced the errors from the methods previously employed by the company, but also gives easy approach for predicting job demands for the shops activities which eventually reduced the problems of production planning and control in job shops. This model could be adopted by job shops having similar demand pattern.

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