Comparison of Linear Trend Analysis and Double Exponential Smoothing Methods for Predicting Chronic Disease Drug Needs

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Abstract: One of the factors influencing the standard of care given to patients and society is the process of identifying medical needs and accurately quantifying them. Therefore, finding new methods or mechanisms to evaluate the need for drugs has become essential. Due to faulty prediction methods, the Ministry of Health in Iraq was unable to achieve a precise match between actual consumption and estimated demand due to the employment of old methods. Therefore, the research aims to 1) select a suitable method from the two forecasting techniques, trend exponential analysis (TEA) and double exponential smoothing (DES), and 2) predict the needs for drugs for the next five years based on historical data. Accuracy measures (MAPE, MAD, and MSD) have been utilized as model selection criteria to best characterize the trend of estimating the demands of chronic drugs from 2017 to 2019. The results demonstrate a decrease in MAPE values in all medications compared with MAD and MSD. In addition, the MAPE of a DES technique for (Lovastatin = 3, Insulin = 12, Valproic acid = 4.36, Carbidopa = 1.74) is greater than the MAPE of a TEA (Lovastatin = 2, Insulin = 11, Valproic acid = 3.92, Carbidopa = 1.72). Depending on the value of MAPE, TEA was recognized as the optimal prediction model and can best fit for predicting the demand for chronic drugs in future needs. Annual forecasts using a trend exponential analysis for the quantities required for each drug from 2020 to 2024 show a significant increase in demand for all pharmaceuticals. Whereas insulin tablets are the smallest, with 559,367 packs in 2024, valproic acid is the largest, with 13,387,773 packs, indicating a shortage of competing drugs or an anticipated increase in patient numbers. The proposed method might be useful for inventory prediction at industrial sites as well.

1 INTRODUCTION

The research is significant because it has a direct bearing on safeguarding social and human health. Since medicines are related to human life and not like other commodities, an accurate assessment of medical organizations' needs for medications will help ensure that patients are treated properly. On the other hand, an inaccurate assessment could result in either a shortage of medications, which could endanger patient lives, or significant costs for healthcare organizations due to an excess of medications and expiration dates [1]. In addition, the institution bears additional costs because of contracting with local distributors from specialty retailers, as well as the additional time and effort required to complete this task. The actual volume of the drug exceeds the volume of the expected demand; the health institution will bear another type of cost represented by the cost of the surplus stock, the expiration of the medicines and their spoilage, and thus the waste of public money [2]. The lack of scientific methods for assessing drug needs in health departments in general and in medicines for chronic diseases particularly is an urgent problem, as is the inability to achieve an accurate match between the volumes of actual demand and expected [3], [4]. Approximately 80% of hospital costs are related to medical supplies. These numbers support the notion that efficient hospital management depends on medical supply inventory management in healthcare facilities [5]. The World Health Organization (WHO) has emphasized since 1980 the value of employing suitable inventory management strategies to evaluate the demands for medical supplies, particularly medications, and to steer clear of crude, surface-level approaches based on perception, experience, and conjecture. Because they rely on crude, rudimentary, and imprecise methodologies, these approaches are not scientific. For instance, the current year's drug needs are calculated using the estimate from the prior year + 10%, which produces unreliable findings. In addition, there are statistical methods for demand forecasting, such as time series and causal approaches [6].

The current research has focused on two statistical techniques (trend exponential analysis and double exponential smoothing) because of their simplicity and efficiency in tracking time series values over a specified number of periods of time. Additionally, they provide a comprehensive view of time-series data, improving the accuracy of forecasts.

2 RELATED WORK

Estimating medication demands remains a significant difficulty for hospitals and medical facilities, Modern techniques or mechanisms for evaluating the demand for medications in various health sectors are required since the process of accurately determining the need for medications is one of the most significant factors influencing the quality of services offered to patients. In order to improve demand estimation and reduce waste of public funds, this section will analyze the literature on the procedures for estimating the drug needs of hospitals and health centers.

In 2021, A Pamungkas et al. [7] compared exponential smoothing methods for Forecasting Marine Fish Production in Pekalongan Waters; the study used data from Pekalongan Fishing Port, Central Java, from January 2011 to December 2020 to predict marine fish production. The data has analyzed using data exponential smoothing methods, with the mean absolute percentage error (MAPE) value as a criterion. The Holt Winter Exponential Smoothing method has found to be reasonable with a MAPE value of 37.878, indicating its potential for enhancing regional income and community livelihoods in the marine fisheries sector. Whereas the Holt's-Winter exponential smoothing method's root mean square error (RMSE) for the model data is 675,073. When compared to the double exponential smoothing (Holt's linear trend) and Holt's-Winter exponential smoothing approaches, the MAPE and RMSE values are the minimum. Good fisheries management aims to offer data with reliable records since forecasting success has inextricably linked to the data that is available. The fishing community's and fishermen's support and knowledge of the importance of accurately reporting production data can boost forecasting accuracy, which in turn can help fisheries industrialization succeed.

In 2021, Ameera W. Omer et al. [8] compared Brown's and Holt's Double Exponential Smoothing (DES) models for forecasting generation electrical in the Kurdistan region. The data used from 2010 to 2020 showed trending modeling, indicating that both DES approaches can be used with Stratigraphic and Minitab software. The optimal value of α in DES Brown is 0.22, and the optimal MAPE is 9.23616%, while in DES Holt, it is 0.95 and the optimal β is 0.05. Both approaches are capable of predicting generation electrical. Depending on the optimization that has been done for α and β. The method used by DES Holt has a lower MAPE than that of DES Brown. Future studies will optimize either by altering the initialization procedure or by optimizing the parameters using different non-linear programming techniques.

In 2023, Ajiono T.H. [9] compared three forecasting methods: linear regression, exponential smoothing, and weighted moving average. The linear regression method had the smallest error value (MAD 27.83), MSE 1152.1, and MAPE 8.1%. The method predicted 502 students with a tracking signal value within the standard deviation distribution and moving range limits. The linear regression method is acceptable for future decision-making due to its accuracy and ability to produce trending data movement patterns over a long period. According to the findings of a comparison between linear regression and exponential smoothing methods with alpha 0.1 and 0.5. The tracking signal's movement between 1 and -1 falls inside the control range, demonstrates how time and actual variables are related in time series data. However, because the method's truth is debatable, the research has not employed the moving range. Comparing it to the exponential smoothing and time series moving average Holt-Winter forecasting techniques has advised for future study.

In 2024, Ansari Saleh Ahmara et al. [10] compare Single Exponential Smoothing (SES) and Double Exponential Smoothing (DES), the two primary forms of exponential smoothing techniques used in business forecasting. These two approaches had used in this study to analyze monthly passenger car registration data from 2019 to 2022 in Canada. Root Mean Square Error (RMSE) was the main metric used to assess each method's performance. In contrast to DES, which produced larger RMSE values (14.0769), Single Exponential Smoothing

(SES) demonstrated the best performance, with the lowest RMSE of 13.07859 for an alpha of 0.6. Since the Single Exponential Smoothing method has a lower Root Mean Square Error (RMSE) than the Double Exponential Smoothing method, it is the most effective method for forecasting the passenger-car registration data in Canada, according to the results of forecasting using both techniques.

3 MATERIALS AND METHODS

Data was gathered from one of Baghdad's authorized pharmacies, since it is one of the medical establishments that provides drugs for chronic illnesses for hospitals and health centres. Furthermore, these establishments lack quantitative tools for estimating demand and rely only on qualitative approaches, resulting in a mismatch between actual and expected demand. The study's sample of chronic disease pharmaceuticals was chosen because of the continuous requirement for significant amounts of these drugs, which necessitates precise annual demand forecasting. Furthermore, these medications are also considered life-saving, so their availability is a priority for the Ministry of Health. Data had been analysed in Jupyter Notebook and Minitab software. The models that were used to describe the behavior of variables that change over time are transformed into growth models. This study used the methods of trend analysis and double exponential smoothing.

Linear (trend) analysis. A linear trend equation is constructed from the data using standard least squares methods, in which the dependent variable is the time series [11], [12] and the independent variable is the row (sequence) number. The forecasting equation has the following form (1) [13]:

$$Ft = a + bt. \tag{1}$$

Where F_t = forecast for time period t, a = y-intercept, b = slope of the trend [14].

The slope shows how much is added (or subtracted if b is negative) from each period to the next. It places the largest weights in the estimates at the two ends of the row, while rows closer to the middle have little effect on the estimates [15].

Double exponential smoothing [16]. This method allows you to get short-term forecasts. Dynamic estimates were calculated for two components by level and trend. Prediction based on double exponential smoothing models a time series using a simple linear regression equation, where Y is the dependent variable, b_0 is the intersection point, and b_1 is the slope that slowly changes over time. The algebraic form of the linear exponential smoothing model, like the simple exponential smoothing model, can be expressed in various ways [17, 18]. The "standard" form of this model is usually expressed as follows: S' denotes a separately smoothed series obtained by applying simple exponential smoothing to series Y; that is, the value of S' in period, t is described by the (2) [13]:

$$S'(t) = \alpha Y(t) + (1 - \alpha) S'(t - 1). \tag{2}$$

With simple exponential smoothing, let S(t+1) = S'(t) at this point. Then let S" denote a doubly smoothed series obtained by applying simple exponential smoothing (using the same a) to the series S' [16]:

$$S''(t) = \alpha S'(t) + (1 - \alpha) S''(t - 1). \tag{3}$$

Finally, the forecast of Y'(t + 1) is given by the (4) [16]:

$$Y'(t + 1) = a(t) + b(t). \tag{4}$$

Where a(t) = 2S'(t) - S"(t) is the calculated level for the period t, b(t) = (a/(1-a)) (S'(t) - S"(t)) is the expected trend for the period t.

4 ANALYSIS OF THE ASSESSMENT OF MEDICATION NEEDS FOR THE TREATMENT OF CHRONIC DISEASES

Table 1 shows the indicators of the error in forecasting the demand for medicines in the sample under study. The table shows data on the actual demand and annual estimated (projected) volumes of medicines in accordance with the methods used in the Department of Medical Clinics of Iraq for 2017-2019. The table shows a large discrepancy between the projected volume of purchased medicines and the actual demand for them in 2017-2019. To determine the prediction errors for each drug and for each year, it is necessary to subtract the actual values from the predicted values. Negative values indicate an increase in the volume of expected demand compared to the volume of actual demand. However, if the value of the forecasting error turns out to be positive, it means that the actual demand is higher than the expected demand. This situation has not shown in the table, which indicates that there has been no shortage of medicines in these years. Table 1 illustrates the high percentage of absolute error, which confirms the inaccuracy of forecasts and the inappropriateness of the method used to assess drug needs in healthcare departments, including departments of popular medical clinics. Expiration dates, as well as rental, transportation, and shipping costs, should be taken into account in the drug needs assessment process. With the help of a statistical program, the data was evaluated using different statistical models, and the best statistical model was selected, which describes these data using the average absolute error indicator. This indicator was chosen because for large time series [3], it better evaluates the ratio of predicted and actual values studied than the other two indicators, the average squared error and the average absolute deviation.

Table 1: Comparison of projected and actual drug volumes for the period from 2017 to 2019.

Drugs	Forecasting Needs (1)		
	2017	2018	2019
Lovastatin	2,500,000	16,000,000	2,133,650
Insulin	485,000	564,000	722,660
Valproic_acid	22,000,000	24,120,000	21,400,000
Carbidopa	7,000,000	9,500,000	8,500,000
Drugs	Actual Consumption (2)		
	2017	2018	2019
Lovastatin	657,300	657,300	657,300
Insulin	47,500	47,500	47,500
Valproic_acid	5,133,960	5,133,960	5,133,960
Carbidopa	1230,880	1230,880	1230,880
Drugs	Prediction Error (1-2)		
	2017	2018	2019
Lovastatin	-1,842,700	-686,136	-863,318
Insulin	-43,7500	-463,790	-526,860
Valproic_acid	- 16,866,040	- 17,266,200	- 13,961,880
Carbidopa	-5,769,120	-5,518,940	-4,174,980
Drugs	Absolute Error (3)		
	2017	2018	2019
Lovastatin	1,842,700	686,136	863,318
Insulin	43,7500	463,790	526,860
Valproic_acid	16,866,040	17,266,200	13,961,880
Carbidopa	5,769,120	5,518,940	4,174,980
Drugs	Absolute Error Percentage (3/1)*100		
	2017	2018	2019
Lovastatin	73%	42%	40%
Insulin	90%	82%	72%
Valproic_acid	76%	71%	65%
Carbidopa	82%	58%	49%

Table 2: Selection of the best method for forecasting the need for chronic diseases medicines according to criterion of minimum accuracy.

Accuracy Measures of TEA	Trend Exponential Analysis (TEA)			
	Lovast atin	Insulin	Valpro ic acid	Carbidopa
MAPE	2	11	3.92	1.72
MAD	22201	9577	2.52	7.80
MSD	55448 9401	1031814 01	7.16	6.86
Accuracy Measures of DES	Double Exponential Smoothing (DES)			
	Lovast atin	Insulin	Valpro icacid	Carbidopa
MAPE	3	12	4.36	1.74
MAD	24963	10768	2.84	8.78
MSD	70227 5406	1306819 57	9.07	8.68

Table 3: Brief description of the trend exponential analysis model.

Drugs	Descript ion	Years		
		2017	2018	2019
Lovastat in	Actual	657300	913864	1270332
	Trend	640649	947165	1253681
	Detrend (error)	16650.7	33301.3	16650.7
Absolute Error Percentage		2.5%	3.5%	1.3%
Insulin	Actual	47,500	100,102	195,800
	Trend	40,317	114,467	188,617
	Detrend (error)	7182.7	14365.3	7182.7
Absolute Error Percentage		17.8%	12.5%	3.8%
Valp- roic acid	Actual	5133960	6853800	7438120
	Trend	5323213	6475293	7627373
	Detrend (error)	189253	378507	189253
Absolute Error Percentage		3.5 %	5.8%	2.4%
Carbi- dopa	Actual	1230880	3981060	4325020
	Trend	1631917	3178987	4726057
	Detrend (error)	401037	802073	401037
Absolute Error Percentage		24.5%	25.2%	8.4%

5 ACCURACY INDICATORS

The purpose of using two forecasting methods was actually to compare the estimates obtained and decide which forecasting method provides the best forecast results based on three accuracy indicators. These accuracy measures are the mean absolute percentage error (MAPE), mean absolute deviation (MAD), and standard deviation (MSD). The most suitable model will be the model with minimal accuracy indicators (MAPE, MAD, and MSD) [18, 19], which will be selected and used to assess the needs for medicines for chronic diseases for the next five years (2020-2024).

The average absolute percentage error (MAPE) expresses the prediction accuracy of the model as a percentage [20, 21]. Since MAPE's results are simple to understand, it is frequently employed. For example, a MAPE value of 14% means that the average difference between the predicted and actual value is 14%. MAPE can be calculated using the following (5) [16, 18]:

$$MAPE = [\sum | (yt - yt\hat{}) | /n] * 100, (yt \neq 0). \quad (5)$$

Where y_t - is the actual value, $y_t^{\wedge}$- is the predicted value, and n - is the number of observations.

Mean absolute deviation (MAD) – shows by what number of units, (for example, the number of packages of medicines, units), the forecast deviated on average up or down. MAD can be calculated using the following (6) [18]:

$$MAD = \sum | (yt - yt\hat{})| /n. \quad (6)$$

Where y_t - is the actual value, - $y_t^{\wedge}$- is the predicted value, and n is the number of observations.

Moving Standard deviation (MSD) – allows you to amplify the most significant errors. Characterizes the variability of deviations during the period under review. MSD can be calculated using the following (7) [18]:

$$MSD = \sum | (yt - yt\hat{})|2 /n, \quad (7)$$

where y_t - is the actual value; $y_t^{\wedge}$ - is the predicted value, n - is the number of observations.

6 RESULTS AND DISCUSSIONS

In this study, the methods of trend analysis and double exponential smoothing had compared according to the criterion of minimum accuracy (Table 2).

The data shown in Table 2 showed that when comparing the accuracy indicators of these two models, both MAD and MSD are quite large for both models. At the same time, the trend exponential model has the lowest MAPE values compared to other models; therefore, this method provides a better match to the data and is suitable for predicting Iraq's future needs for chronic. Trend analysis' superiority over double exponential smoothing due to its simplicity and accuracy, its ability to produce trending data movement patterns over a long period, and its efficiency in handling sudden changes and unclear seasonal patterns. It builds a structural model based on historical patterns, making it more stable for long-term forecasts. In this regard, at the end of the article, a five-year forecast of drug needs for chronic diseases has calculated using an exponential trend model.

Table 4: Comparison of percentage values of the total absolute error.

Drugs	The percentage of absolute error (2017)		The percentage of absolute error (2018)		The percentage of absolute error (2019)	
	Traditional method	Quantitative method	Traditional method	Quantitative method	Traditional method	Quantitative method
Lovastatin	73%	2.5%	42%	3.5 %	40%	1.3 %
Insulin	90%	17.8 %	82%	12.5 %	72%	3.8 %
Valproic acid	76%	3.5%	71%	5.8 %	65%	2.4 %
Carbidopa	82%	24.5 %	58%	25.2 %	49%	8.4 %

Table 5: Forecasts of chronic disease medication volumes for the period from 2020 to 2024.

Drugs	Forecast Years				
	2020	2021	2022	2023	2024
Lovastatin	1560197	1866713	2173229	2479745	2786261
Insulin	262767	336917	411067	485217	559367
Valproic_acid	8779453	9931533	11083613	12235693	13387773
Carbidopa	6273127	7820197	9367267	10914337	12461407

Table 3 shows a decrease in the error of forecasting the demand for medicines compared to the results of Table 1. The actual demand data and annual estimated volumes were obtained using an exponential trend model for forecasting. We also noted that Carbidopa's prediction errors are significantly higher than other drugs due to some stochastic factors such as Parkinson's patient mortality rates and treatment doses, affecting need estimation because disease stages are not taken into account when estimating the required quantities, leading to higher error rates since patients in advanced stages need higher treatment doses compared to early stages.

From Table 1 it can be seen that the largest prediction error occurred for insulin in 2017 and amounted to 90% due to the presence of accumulated insulin residues in popular clinics and department stores over the previous year. The lowest error rate was 40% for Lovastatin in 2019, which means an increase in the withdrawal of this drug and the expiration of the remainder over the previous year. In Table 3, there is a slight deviation in the actual and projected values for drug consumption over the analyzed time period.

Table 4 compares the percentages of forecasting errors for a sample of studies in accordance with the methods used in popular medical clinics and quantitative methods suitable for forecasting over the specified years. There is a decrease in the percentage of absolute error when using quantitative models. Thus, it can be said that quantitative forecasting models are the most suitable for forecasting demand and reducing errors in the forecasting process. The use of these models for assessing drug needs leads to improved forecasting accuracy and appropriate and acceptable results. Then, using linear exponential analysis, the required volumes of each drug were predicted for the period from 2020 to 2024 (Table 5). The table shows that insulin tablets account for the smallest number in it. In the year 2024, its number reached 559,367 packages, and it is one of the traditional medicines for the treatment of high blood sugar levels. The highest estimated number in the table is indicated for valproic acid, which amounted to 13387773 packages in 2024. Demand for this drug will increase compared to 2020. For 4,608,320 packages, which may be due to the lack of competing drugs in this area and, possibly, to the expected increase in the number of patients, since this drug is used to treat epilepsy. Annual forecasts show a marked increase in demand for all medicinal substances. For example, a marked increase in demand for insulin may indicate an increase in the number of diabetics, especially those suffering from this disease, at the local or global level, since, according to estimates by the World Health Organization, there are about 200 million people with diabetes worldwide. It is also seen that the demand for Lovastatin has increased over the past five years, indicating an increase in the proportion of patients with elevated cholesterol levels. Annual forecasts also show a marked increase in demand for Carbidopa and Valproic Acid, which indicates the absence of competing drugs in this group of drugs. From the above, we find that the future assessment of drug needs may influenced by random factors, such as the appearance of a new competing drug or a recommendation, or the detection of side effects on medicines, rising drug prices, the spread of diseases and epidemics, and other external factors such as natural disasters. All this affects consumer demand and then the assessment of the quantitative and qualitative needs of the population. Therefore, a combination of quantitative and qualitative forecasting methods should be used to ensure results that are more accurate.

7 CONCLUSIONS

Accurate forecasting of medicines in hospitals and health centres, leads to improved patient care and inventory management, thereby conserving public funds. The current study has accomplished the following:

1) In this paper, two types of time series methods, namely linear regression (trend) analysis and double exponential smoothing, are compared to select the suitable method to predict chronic medication needs in a hospitals. The two methods were compared using three accuracy criteria (MAPE, MAD, and MSD) to evaluate the accuracy of the predictions we achieved;
2) Predicting the needs for drugs for the next five years based on the current dataset.

The results have showed the following:

- Linear regression analysis is more suitable for predicting drug needs, because it has the lowest error rate compared to the double exponential smoothing method. Therefore, it was used to assess the future needs for chronic medications;
- The decrease in the values of error measures in the linear regression model indicates the suitability of its characteristics with the characteristics of demand behavior, so it can be said that a linear regression analysis is suitable quantitative model for all drugs;

- The decrease in the percentage of error in time series models compared to the percentage of error caused by the use of traditional methods in the health services is an indicator of the suitability of time series models for the purposes of forecasting demand and estimating needs for medicines more accurately.

Therefore, the study recommends the need to use a combination of quantitative and qualitative forecasting methods, and to present the results of forecasting using time series to a committee of experts or officials in pharmacies and stores, taking into account random factors that may arise in the environment of healthcare institutions and that may affect the assessment of drug needs.

The proposed approach to forecasting is characterized by relative simplicity and intuitive clarity of researchers. This approach can be successfully applied not only in the field of pharmacology but also in industry, for example, when forecasting the acquisition of spare parts volumes, as well as to solve any other tasks in which forecasting methods are used. The study faced some limitations related to the short duration of historical data due to the unavailability of accurate data for some drugs, as well as missing data for some previous years. Due to the COVID-19 pandemic, drug data has not been considered for years after 2019, as the old data does not match the new reality, which makes it difficult to model and predict these phenomena.

8 FUTURE WORK

This research and the results obtained may help open the way for other researchers to continue in this field, complete existing work, or expand upon it. Prospects for this research include the following:

- Modifying the proposed method to predict the value of two or more future points in the times series, rather than predicting the value of a single future point in the time series.
- Applying the proposed system to other time series fields, such as weather, company sales, and other application.
- Developing a time series forecasting system using machine learning.
- Testing the robustness of predictions over longer periods or additional chronic diseases.

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