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Forecasting Passenger Numbers in Saudi Arabian Airlines Flights

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Abstract:*Forecasting Is A Prediction Of Future After Studying The Past;It Is A Planning Tool That Helps Management For Budgeting, Planning, And Estimating Future Expectations. Exploring The Pattern Of The Data Is The Way To Select Appropriate Forecasting Techniques To The Data. Time Series Data For Passenger In Saudi Arabian Airlines Were Collected In Hijri And Gregorian Calendars, The Data Were Monthly For Ten Years In Gregorian, However, Hijri Data Were Only For About Three Years, The Data Was Transformed From Gregorian To Hijri To Complete The Missing Gab.The Data For Both Calendars Are Of Trend Pattern And Moderate Seasonality. Eightsuitabletime Series Forecasting Models Available In Minitab And Excel Software Are Checked To Apply For Both Hijri And Gregorian Data. These Time Series Forecasting Models Are: Naïve For Trend And Seasonality, Double Exponential Smoothing, Seasonal Exponential Smoothing, Decomposition, Trend Models,ARIMA, Regression For Seasonal Data And Combining Forecasts. Since The Trend Equation With Smaller Measures Of Errors Is Curvilinear, Many Alternatives Of The Regression For Seasonal Data Method Are Proposedwith Nonlinear Expressions Of The Time Independent Variable. The Nonlinear Expressions Are Different Power Terms And Also S-Curve Equation Of The Time Independent Variable.Each Forecasting Method Is Checked For Adequacy And For The Measures Of Forecasting Errors And The Best Method Is Used To Perform The Long-Term Forecasting For The Upcoming 5 Years.*

***Keywords** -Forecasting, Time Series, Gregorian And Hijri Calendars, Saudi Airlines Passengers.*

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I. Introduction

Air Passenger Forecasting Provides A Key Input Into Decisions Of Daily Operation Management And Infrastructure Planning Of Airports And Air Navigation Services, And For Aircraft Ordering And Design, Scarpel[1]. Planning To The Future Is One Of The Most Important Keys To Success, Forecasting Is The Way.

Air Transportation In Saudi ArabiaHas Undergone Considerable Expansions And Developments In The Past Years. There Are 25 International And Domestic Airports. The Number Of Passengers (Arriving & Departing) Handled By All Airports Increased At A Considerable Annual Rate.

The Saudi Arabian Airlines (Saudia) Took The Operational Responsibility To Run The Air Transportation Business In The Kingdom, And Has Made A Vital Contribution To The Development Of The Kingdom.SaudiaIs Constantly Endeavoring To Innovate, And To Plan Ahead For Improved Service To Customers. One Of The Improvements To The Current Business Is Forecasting And Analyzing The Air Travel Market.

This Study Try To Attempt The Forecasting Models In Order To Forecast Passenger Numbers In Saudi Arabian Airlines Flights. The Collected Data Were Monthly For Ten Years From January 2007G To July 2017G In Gregorian, However, Hijri Data Were Only From Muharram 1435H To Shawal 1438H, From Muharram 1428H To Dhu AL-Hijjah1434H, Monthly Numbers Of Passengers Were Calculated.

II. Literature Review

In Airline Industry, There Are Many Research Areas And Applications With Multiple Perspectives And Different Goals.Most Familiar Areas Are: Forecasting Total Passengers In A Specific Airport, Right-Size' An Airport, Passenger Trips Requested, Passenger Departures, Allocating Traffic Between Airports, Expected Passengers Between Two Cities, Air Passengers Between Two Countries, Passenger Demand At A State Level And The Number Of Domestic And International Airline Passengers.In Addition, Different Forecasting Methods Have Been Applied; The Forecasting Methods Can Be Divided Into Time Series Methods, Causal Methods And Judgmental Methods. All Methods Are Suitable For Different Purposes. Our Area Of Interest Is To Forecast The Number Of Passengers At A Month And Year Levels For A Specific Airline, Saudi Arabian Airlines (Saudia) In A Long-Term Basis.

For Example, In The Area Of Forecasting Total Passengers In A Specific Airport, A Paper [2] Aims To Obtain Accurate Forecasts With Prediction Intervals For The Monthly Time Series Of Total Passengers Onboard At The Amsterdam Schiphol Airport. Another Research Forecasts The Growth Of Air Traffic In Mehr Int'l Airport. For Forecasting, Three Main Methods Were Used: Trend Projection, Econometric Relationship, And Market And Industry Surveys [3].A Third Research Is Done For Forecasting Airport Passenger Traffic For Hong Kong, And Projecting Its Future Growth Trend From 2011to 2015 [4].A Fourth Research Is Done For Sofia Airport In Bulgaria [5] For Forecasting The Number Of Passengers Serviced Both In Annual And Monthly Terms. The Holt-Winters Exponential Smoothing Methods Have Applied In Its Both Variations Of Multiplicative And Additive Seasonality. In A Fifth Study [6], A Hybrid Approach Based On Seasonal Decomposition And Least Squares Support Vector Regression Model Is Proposed For Air Passenger Forecasting In Hong Kong International Airport (HKIA), Located In South China. The Sample Data Are Monthly Data Of Passengers At HKIA, Covering The Period From January 1999 To February 2013, With A Total Of 170 Observations.

In The Area Of Research For 'Right-Size' An Airport To Provide A Good Baseline For Estimating Future Traffic Over The Short And Long Run. A Report [7] Focus Was On A More Balanced Approach Which Took Into Account Airport Capacity Constraints As Well As The Demand Part Of The Equation. Forecasts Were Based On A Survey Of Some 300-Airport Members And A "Blend" Of Methodologies Including Data Of Econometric Variables, And Estimates Based On Airline Capacity Considerations.

Another Area Of Research Is About Passenger Trips Requested And Ridership. Passenger Trip Requests Include All Trips Completed, No-Shows, Cancellations And Trips Denied. Ridership Refers To Passenger Trips Completed. It Involves Detailed And Scientific Examination, Both At The System And Regional Levels, Of Trends And Movements In Trip Demand And Its Constitutive Elements Such As Cancellations, No-Shows, Missed Trips, And Trips Completed [8].

Another Area Of Research Is For Domestic And International Passenger Departures. As An Example, A Technical Note [9] Is Performed For New Zealand. Annual Data From 1988 To 2010 Are Used To Develop The International Departure Module, With Those From 1998 To 2010 For The Domestic Module. The 2011 And 2013 Air Passenger Departure Numbers Are Used To Evaluate Forecasting Performance. The Naïve 2 Model Is Used For Comparison (Benchmarking) Purpose Only.

One Area Of Research Isto Allocating Traffic Between Airports.One Report [10] Is Applied To The UK's Airports. It Examined The Scale And Timing Of Any Requirement For Additional Capacity To Maintain The Position Of An Aviation Hub And To Identify And Evaluate How Any Need For Additional Capacity.The Report Assess Issues Raised About The National Air Passenger Allocation Model (NAPAM) That The Airports Commission Used To Forecast The Allocation Of Traffic Between Different UK Airports.

Another Areaof Researchis To Predict The Number Of Expected Passengers Between Two Cities For A Given Time Interval. Based On Such Forecasts, Airlines Can Make Decisions Regarding New Routes Or Additional Flights On Existing Routes. Hsu And Wen [11] Apply Grey Theory And Multi-Objective Programming To Develop Series Of Models To Forecast Airline City-Pair Passenger Traffic. GroscheEt Al. [12] Presented Two Gravity Models To Estimate The Air Passenger Volume Between City-Pairs. APaper [13] Presents Two Gravity Models For The Estimation Of Air Passenger Volume Between City-Pairs. The Models Include Variables Describing The General Economic Activity And Geographical Characteristics Of City-Pairs Instead Of Variables Describing Air Service Characteristics.

Another Area Of Research Is To Forecast Air Passenger Demand. BonsEt Al. [14] Collected 37 Studies And 204 Observations, And Indicated That Air Passenger Demand Is Largely Determined By Spending Capacity Of Customers.KuoEt Al. [15] Employed Artificial Neural Network (ANN) To Establish A Mathematical Model With Multiple Inputs And Multiple Outputs, And The Results Indicated That This Model Mayaccurately Forecast The Air Transport Demand For Routes.A Paper [16] Analyzed The Characteristics Of The US Air Passenger Demand In Order To Properly Forecast It. The Paper Implemented The Most Commonly Used Or Developed Models For Estimating And Forecasting The Air Transportation Demand.

Another Area Of Research Is About The Annual Flow Of Air Passengers Between Two Countries On A Bi-Directional Basis. Hsu And Wen [17] Develop Time Series GM(1,1) Models By Using Grey Theory To Forecast Total Number Of Passengers In 10 Country-Pair Traffic. KuoAnd Chen [18] Employed Artificial Neural Networks To Forecast The Airline Passenger And The Air Cargo Demand From Japan To Taiwan.Back-Propagation Neural Network Was Employed To Forecast The Air Passenger Demand From Egypt To Saudi Arabia. The Factors Which Influence Air Passenger Were Identified, Evaluated And Analyzed By Applying The Back-Propagation Neural Network On The Annual Data From 2000 To 2010 By Using Visual Gene Developer Package[19].A Report [20] Contains Annual Forecasts Of Air Passenger Flows For Almost 4,000 Country Pairs Over The Next 20 Years (2014-2034) On An Origin-Destination Basis. ThemainFocus Is On The Largest Country-Pair Relationships,In Addition To Almost 800 Country Pair Relationships That Are Likely To Exceed It

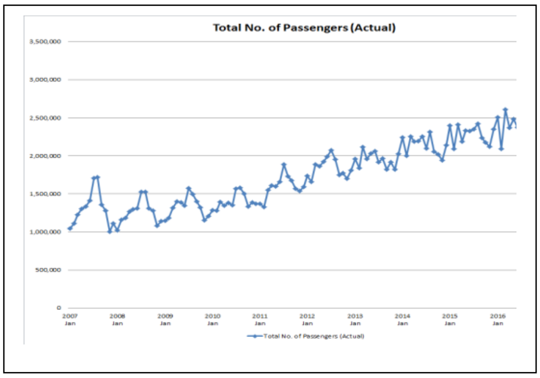
Over The Coming 20 Years.Another Study Is To Forecasting Air Transport Passenger Demand At A State Level, For Example A Paper [21] Proposed An Econometric Dynamic Model (EDM) To Estimate The Air Transport Passenger Demand Based On Economic Indicators. The Case Study Is About The Mexican Air Transport IndustryIdentified For Each Predicted Year.

AnotherStudy [22] Employed The Back-Propagation Neural Network And Genetic Algorithm To Forecast The Air Passenger Demand In Egypt (International And Domestic). Anotherresearch Is About Forecasting The Number Of Domestic And International Airlinepassengers In Saudi Arabia[23]. The Method Used Is The Neural Network Technique To Forecast The Number Of Passengers. Results Indicated That The Oil Gross Domestic Product,Population Size And Per Capita Income Were Found To Be The Most Contributingvariables That Affect The Number Of Passengers In The Saudi Arabian Airline Sectors.AnotherStudy [24] Tests The Ability Of Several Time-Series Models For Predicting The Monthly Number Of Enplaned/Deplaned Air Passengers In Canada For Three Market Segments: Domestic, Transborder And International Flights.

III. Data Collection

Monthly Data For Passenger Numbers In Saudi Airlines Are Collected For The Last Ten Years; The Data In The System Are Only Available In Gregorian Dates Due To The Nature Of Original Inputs And The System Setup. As An Exception Case, Passenger Numbers Are Provided In Hijri Dates Only From Muharram 1435H To Shawal 1438H, Whereas For Gregorian Dates, The Data Are Available From January 2007G To July 2017G Based On The Request [25].

The Gregorian Data Are Converted To Hijri To Complete The Missing Gab Using A Special Average Daily Number Of Passengers. Figure1 Shows The Plots For The Number Of Passengers In Gregorian And Hijri Calendars. Both Figures Indicate An Upward Trend And A Possible Seasonality.From Fig. 1, It Is Clear That Both Time Series Have An Upward Trend. To Explore The Seasonality Patterns For The Time Series Data In Gregorian And Hijri Calendars The Following Methods Are Used [26]: Scatter Diagrams, Autocorrelation Functions, x^2Goodness-Of-Fit Test, Seasonality Indexes Using Ratio To Moving Average, Plot Of Changes In The Seasonal Pattern And AutoregressionTo Assess Strength Of Seasonality. New Methods Are Proposed To Assess The Seasonality Of The Data And Moreover To Identify Which Months Of The Year Have Better Seasonality, These Methods Are: Month's Orders, Measures Of Dispersion For Seasonality Indexes (Range, Quartile Deviation, Average Deviation And Standard Deviation). The Results Obtained From All The Applied Methods Clarify That Both Data Have A Weak Seasonality And The Gregorian Data Is Slightly Better In Seasonality Than Hijri Data.



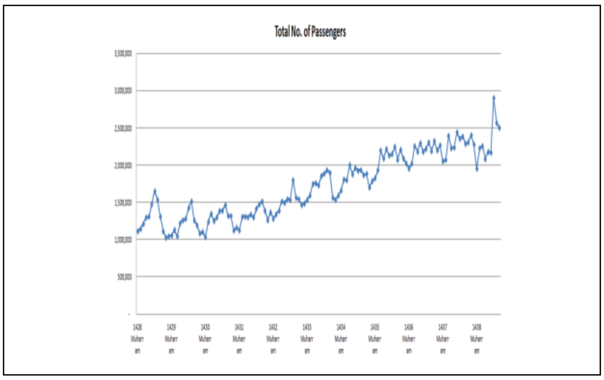


Figure 1: Plots For The Number Of Passengers In Gregorian And Hijri Calendars.

IV. Basic Forecasting Techniques

ForecastingTechniques Are Classified Into Three Main Divisions: Time Series, Causal And Judgmental. The Time Series Forecasting Models Attempt To Predict The Future By Using The Historical Data, Causal (Regression) Forecasting Models Incorporate The Variables Or Factors That Might Influence The Quality Being Forecasting Into The Forecasting Model. Judgmental Forecasts Or Judgmental Adjustments To Forecasts Are Typically Based On Domain Knowledge. Domain Knowledge Is Any Information Relevant To The Forecasting Task Other Than Time Series Data And In Principle, More Information Should Lead To Better Forecasts.Fig.2 Shows The Forecasting Techniques In Minitab And Excel Software [27, 28] Which Will Be Used To Solve The Present Problem. Table1shows The Main Characteristics Of The Suitableforecasting Techniques For Trend And Seasonal Time Series Data [29].

4.1. Naïve Forecasting Method For Trend And Seasonality

The Naïve Forecast Assumes That The Best Predictors Of Future Values Are The Most Recent Data Available. It Is Easy To Apply And Good Way To Start Thinking About Forecasting. This Method Is Used For A Very Short-Term Forecast Of An Event For Which There Is No Much Historical Data. It Can Be Used To Predict Only One Period Ahead For Non-Seasonal Data And One Year Ahead For Seasonal Data. The Method Has A Simplest Formula For Stationary Data And Other Formulas For Trend And Seasonal Data [30].The Simplest And The Trend Formulasare Used To Predict Only One Period Ahead. Therefore, We Will Use The Trend And Seasonality Formula In Order To Be Able To Forecast One Year Ahead (12 Forecasting Periods). The Naïve Technique Is Adjusted To Combine Seasonal And Trend Estimates Using The Following Naïve Formulafor Monthly Data:

$$\hat{Y}_{t+1} = Y_{t-11} + \frac{(Y_t - Y_{t-1}) + \ldots. + (Y_{t-11} - Y_{t-12})}{12} = Y_{t-11} + \frac{Y_t - Y_{t-12}}{12}$$

The Formula Is Applied For Both The Gregorian And Hijri Data, Checking The Autocorrelation Functions Concludes That Residuals Are Not Random For Both The Gregorian And Hijri Data.

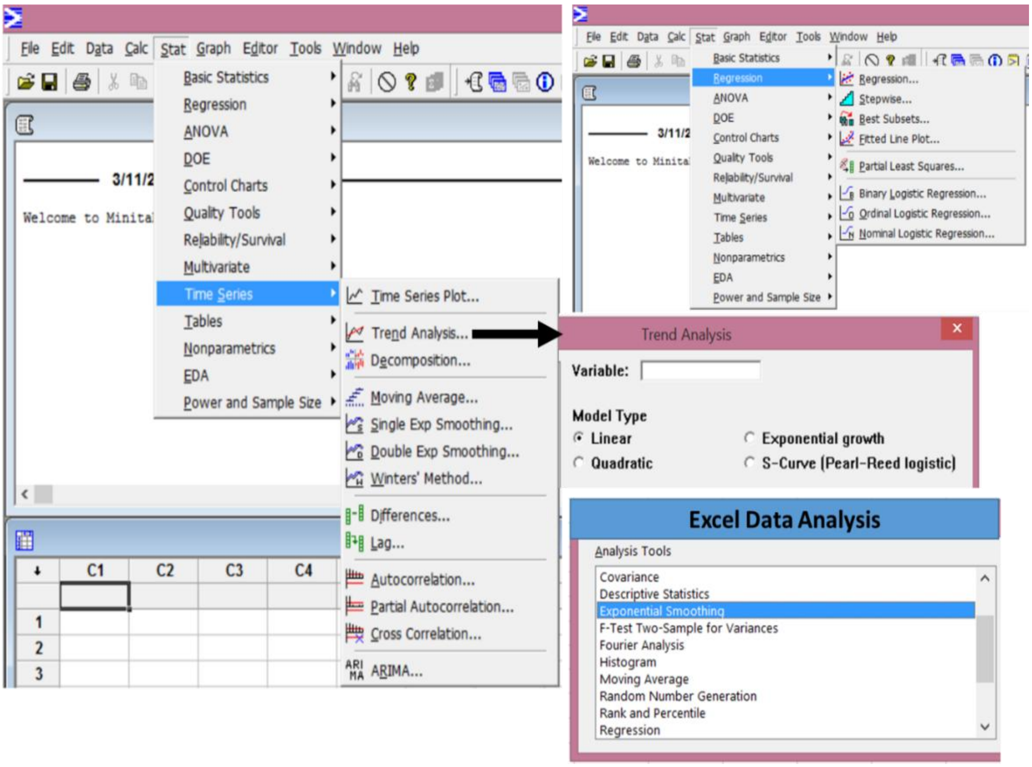


Figure 2: Forecasting Techniques InMinitab And Excel Software.

Table1: Forecasting Techniques Characteristics.

Method	Pattern Of Data	Time Horizon	Type Of Model	Minimal Data Requirements	
				Nonseasonal	Seasonal
NaïveFor Trend And Seasonality	T ,S	S	TS	1	1 X S
DoubleExponential Smoothing (Holt's)	T	S	TS	4	
Seasonal Exponential Smoothing (Winter's)	T,S	S	TS		2 X S
Classical Decomposition	T, S	S	TS		5 X S
Exponential Trend Models	T	I , L	TS	10	
S-Curve Fitting	T	I , L	TS	10	
GompertzModels	T	I , L	TS	10	
Growth Curves	T	I , L	TS	10	
ARIMA (Box-Jenkins)	ST,T,C,S	S	TS	24	3 X S
Regression With Time Series Data	T ,S	I , L	TS		6 X S

Pattern Of Data: **ST**, Stationary; **T**, Trended; **S**, Seasonal; **C**, Cyclical.

Time Horizon: **S**, Short Term (Less Than Three Months); **I**, Intermediate; **L**, Long Term
Type Of Model: **TS**, Time Series; **C**, Causal.
Seasonal: **S**, Length Of Seasonality.
Variable: **V**, Number Variables.

4.2 Exponential Smoothing Methods

Exponential Smoothing Methods Are Based On Averaging (Smoothing) Past Values Of A Series In A Decreasing Exponential Manner, With More Weight Being Given To The More Recent Observations.Double Exponential Smoothing (Also Called Holt's Method) Smooths The Data When A Trend Is Present,It Uses Two Constants ($0<\alpha$ and$\beta< 1$) For The Level And The Slope (Trend)And Is Better At Handling Trends.The Constants α, $\beta$and γCan Be Selected Subjectively, A Grid Of Values Could Be Developed, Then Selecting The Ones Producing The Lowest Forecasting Errors [32]. A Common Approach In Minitab Software Is A Nonlinear Optimization Algorithm To Find Optimal Constants.

When The Data Show Trend And Seasonality, A Third Equation Is Introduced In Order To Take Care Of Seasonality. The Model Will Have Three Constants ($0<\alpha$, $\beta$and $\gamma< 1$) To Deal With The Level, Trend And Seasonality. The Constants α, βAndγ Can Be Selected Subjectively Or By Minimizing An Error Such As MSE.

There Are Two Variations To This Method That Differ In The Nature Of The Seasonal Component. The Additive Method Is Preferred When The Seasonal Variations Are Roughly Constant Through The Series, While The Multiplicative Method Is Preferred When The Seasonal Variations Are Changing Proportional To The Level Of The Series [33]. The Additive And Multiplicative Methods Are Applied For Both Gregorian And Hijri Data Using Minitab Software. The Additive Model Gives Smaller Measures Of Errors For All Values Of Parameters Α, Β And Γ. The Smallest Measures Of Errors Are Obtained For The Model With Parameters α, $\beta$and γ= 0.2, 0.1and 0.1 Respectively For The Gregorian Data And For Parameters Of 0.4, 0.1 And 0.1 For The Hijri Data. The Autocorrelation Functions Of Residuals Show That Residuals Are Not Random For All Tested Values Of Parameters α, $\beta$and γ.

4.3 Classical Decomposition

Time Series Decomposition Involves Separating A Time Series Into Several Distinct Components. There Are Three Components That Are Typically Of Interest:T_t, A Deterministic, Nonseasonal Trend Component. This Component Is Sometimes Restricted To Being A Linear Trend, Though Higher-Degree Polynomials Are Also Used. S_t, A Deterministic Seasonal Component With Known Periodicity. This Component Captures Level Shifts That Repeat Systematically Within The Same Period (E.G., Month Or Quarter) Between Successive Years. I_t, A Stochastic Irregular Component,. There Are Two Forms Of Classical Decomposition: An Additive Decomposition And A Multiplicative Decomposition. The Additive Model Treats The Time Series Values As A Sum Of The Components; It Works Best When The Seasonal Variation Is Relatively Constant Over Time.The Multiplicative Model Treats The Time Series Values As The Product Of The Components; It Works Best When The Seasonal Variation Increases Over Time [34].

Both The Multiplicative And Additive Models Are Applied For Both Gregorian And Hijri Data Using Minitab Software, The Additive Model Shows Smaller Measures Of Errors Than The Multiplicative Model. The Autocorrelation Functions For The Additive And Multiplicative Models For Both Gregorian And Hijri Data Show That Residuals Are Not Random.

4.4 Trend Forecasting Models

Atime Series May Show Gradual Shifts Or Movements To Relatively Higher Or Lower Values Over A Longer Period. If A Time Series Plot Exhibits This Type Of Behavior, Then A Trend Pattern Exists. Trend Analysis Can Be Explored Using The Autocorrelation Function As Follows [35]:

- A Significant Relationship Exists Between Successive Time Series Values.
- The Autocorrelation Coefficients Are Large For The First Several Time Lags, And Then Gradually Drop Toward Zero As The Number Of Periods Increases.
- The Autocorrelation For Time Lag 1: Is Close To 1, For Time Lag 2: Is Large But Smaller Than For Time Lag 1.

Data That Increase By A Constant Amount At Each Successive Time Period Shows A Linear Trend. Data That Increase By Increasing Amounts At Each Successive Time Period Show A Curvilinear Trend. Exponential Trend Can Be Fitted When A Time Series Starts Slowly And Then Appears To Be Increasing At An Increasing Rate Such That The Percentage Difference From Observation To Observation Is Constant. It Is Achieved By Allowing The Level And The Slope To Be Multiplied Rather Than Added [36]. The S-Curve Model Fits The Pearl-Reed Logistic Trend Model, This Accounts For The Case Where The Series Follows An S-Shaped Curve. S-Shaped Curves Are Numerous And Different Not Only By Essence, But Mostly By Names

[37].The Gompertz Model Is One Of The Most Frequently Used Sigmoid Models Fitted To Growth Data And Other Data. It Is Well Known And Widely Used In Many Aspects Of Biology. It Has Been Frequently Used To Describe The Growth Of Animals And Plants, As Well As The Number Or Volume Of Bacteria And Cancer Cells [38].

Both Figures Of The Autocorrelation Functions For The Gregorian And Hijri Data Are Closely Similar And Show That There Exists A Significant Relationship Between Successive Time Series Values; There Is A Trend Pattern For Both The Data In Gregorian And Hijri Calendars.

Minitab Software Has These Types Of Trend Models:Linear, Quadratic, Exponential Ands-Shaped Curves.The Comparison Between The Basic Measures Of Forecasting Errors For The Trend Methods For Hijri And Gregorian Data Is Shown In Table 2.

Table 2: Measures Of Errors For The Trend Methods.

Forecasting Trend Methods	Measurements Of Forecasting Errors					
	Hijri			Gregorian		
	MAPE	MAD	MSE	MAPE	MAD	MSE
Linear	8.15899	130585	2.70690E10	8.09168	134362	2.91006E10
Quadratic	7.68115	125341	2.49286E10	7.81780	130828	2.76991E10
Exponential	7.71733	126520	2.54160E10	7.79366	131573	2.82148E10
S-Curve	7.66434	128221	2.69169E10	7.67063	130744	2.84155E10

From The Measures Of Forecasting Errors, The Quadratic Trend Model Has Two Smallest Measures Out Of Three For The Hijri Data, While The S-Curve Has Two Smallest Measures Out Of Three For The Gregorian Data.

4.5 Autoregressive Integrated Moving Average (ARIMA)

The Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) Method Is One Of The More Complicated Methods Used To Forecast Data. It Is Popular Because It Can Forecast For All Data Patterns, And Because It Is Often One Of The Most Accurate Forecasting Tools Available. ItDoes Not Assume Any Particular Pattern In The Historical Data. The Model Fits Well If The Residuals Are Small And Randomly Distributed. If The Specified Model Is Not Satisfactory, The Process Is Repeated Using A New Model, And The Final Model Is Used For Forecasting.

ARIMA Command Appears As ARIMA(p,d,q) Where p Is The Order Of The Autoregressive Part (AR), d Is Amount Of Differencing (Integration, I) And q Is The Order Of The Moving Average (MA). The Choice Of The Parameters Will Depend On The Patterns In The Autocorrelation Functions (ACF) And The Partial Autocorrelation Functions (PACF).

An ARIMA Model Including Seasonal Parameters Is Written As ARIMA(p,d,q)(P,D,Q). It Is Sometimes Called SARIMA, The S Stands For The Word Seasonal. The Second Set Of Parameters Refer To The Seasonal Autoregression (P), Seasonal Differencing (D), And Seasonal Moving Average (Q) [39].

Since The Data Of The No. Of Passengers For Both Gregorian AndHijri Calendars Are Non-Stationary (Trend); Thus, Differencing Process Is Required And Thedata Seems To Be Stationary After One Lag Differencing. Figs.3and 4 Show Graphs For The Autocorrelation Function (ACF) And Partial Autocorrelation Function (PACF) For Gregorian And Hijri Data After One Lag Differencing.

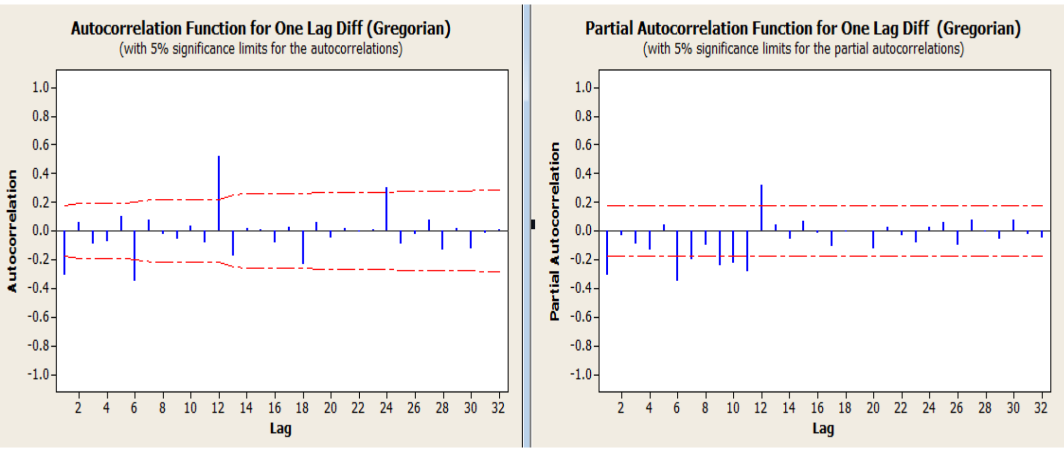


Figure 3:ACFAndPACFFor Gregorian Data After One Lag Differencing.

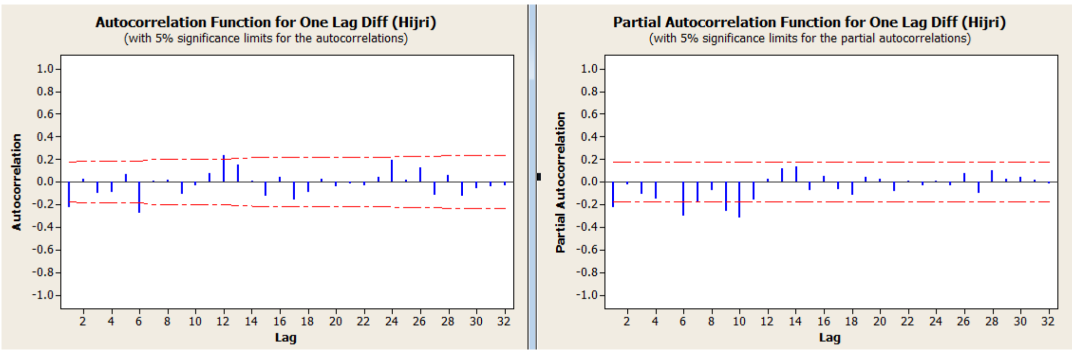


Figure 4: ACF AndPACF For Hijri Data After One Lag Differencing.

Both The Autocorrelation And Partial Autocorrelation Function For The Two Types Of Data Don't Give Clear ARIMA Models. For Gregorian Data, TheAutocerrlation Function Has Spikes At Lags: 1, 6, 12 And 24, And The Partial Autocorrelation Function Has Spikes At Lags: 1, 6, 7, 9, 10, 11 And 12. So A Possible Suitable ARIMA Model Is (1,1,1)(1,0,2). For Hijri Data, TheAutocerrlation Function Has Spikes At Lags: 1, 6 And 12, And The Partial Autocorrelation Function Has Spikes At Lags: 1, 6, 7 And 10. So A Possible Suitable ARIMA Model Is (1,1,1)(0,0,1). Other ARIMA Models Are Tested Also, And Results Are Compared With Respect To MS Values And Autocorrelation Function Of Residuals. Minitab Software Is Used To Carry Out The Calculations, But Because The Number Of Passengers Are Large, The Results Cannot Be Converged. As A Solution, The Number Of Passengers Is Divided By1000 And Then Corresponding Results Concerning Errors And Forecasting Will Be Multiplied By 1000.

From The Results, It Is Concluded That The Best ARIMA Model With The Smallest MS Value And With Random Residuals Is (1,1,3)(1,0,3) For Gregorian Data And (1,1,1)(1,0,3) For Hijri Data. Figure 5 Presents The Autocorrelation Functions For Residuals Of The Best Gregorian And Hijri Models.

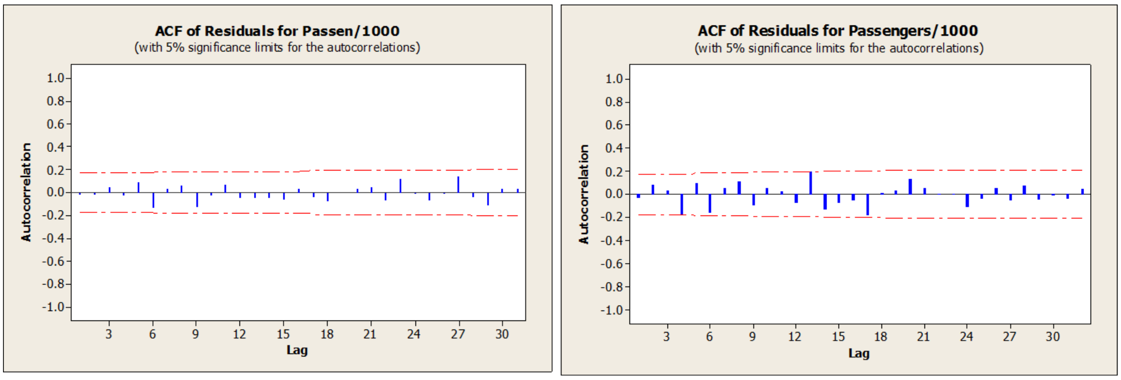


Figure 5: Autocorrelation Functions For Residuals Of The Best Gregorian And Hijri Models.

4.6Using Regression ToForecast Seasonal Data

A Regression Model Can Be Used In Order To Forecast The Seasonal Data,The Model Is Closely Aligned With An Additive Decomposition Is Considered. In This Model, The Seasonality Is Handled By Using Dummy Variables In The Regression Function. A Seasonal Model For Monthly Data With A Time Trend Is:

$Y_t = B_0 + B_1 t + B_2 S_2 + B_3 S_3 + \ldots\ldots + B_{12} S_{12} + \varepsilon_t$

Where:

Y_t= The Variable To Be Forecast,

T = TheTime Index,

S_2= A Dummy Variable That Is 1 For The Second Month Of The Year; 0 Otherwise,

S_3= A Dummy Variable That Is 1 For The Third Month Of The Year; 0 Otherwise,

………………,

S_{12}= A Dummy Variable That Is 1 For The Twelfth Month Of The Year; 0 Otherwise,

ε_t=The Errors, Assumed To Be Independent And Normally Distributed With Mean Zero And A Constant Variance.,

$B_0, B_1, B_2, B_3, \ldots\ldots, B_{12}$ = The Coefficients To Be Estimated.

The Twelve Months Are Described With Only Eleven Dummy Variables; The First Month Is Handled By The Intercept Term B_0 In Equation (A1). To See This, For First Month Data, S2 = S3 = … = S12 = 0, And The Expected Level Is:

$E(Y_t) = B_0 + B_1 t$

For Second-Month Data, S2 = 1 And S3 = S4 = …. = S12 = 0, Where The Expected Level Is:

$E(Y_t) = B_0 + B_1 t + B_2 = (B_0 + B_2) + B_1 t$

Similar Patterns Emerge For The Third, Forth, ….., And Twelfth Months.

The Forecast For The First Month Of An Upcoming Year Can Be Computed By Putting S_2, S_3, …… ,S_{12}= 0 As Follows:

$Y_t = B_0 + B_1 t$

Where *t*= The Serial Number Of The Period *t* To Be Forecasted,

An Examination Of Residuals Is A Crucial Component, It Is Important To Compute The Residual Autocorrelations To Check The Independence Assumption. Lack Of Independence Can Drastically Distort The Conclusions Drawn From *T* Tests. Moreover, The Independence Assumption Is Particularly Risky For Time Series Data [29].

The Minitab Software Is Used For The Gregorian Data, The Results Show Thatthe F Statistic And Its P-Value (0.000) Clearly Indicate That The Regression Is Significant, But The *T* Statistic For X2, X4, X6, X9, X10 And X12are Small With Relatively Large P –Value (> 0.05).Therefore, The Regression Is Significant, But Each Of These Predictor Variables Are Not Significant.Then, The Regression Model Cannot Be Used In This Manner;There Are Three Methods To Deal With This Situation: Regression Method, AllPossible Regressions (Best Subsets Regression) And Stepwise Regression [29]. The Same Procedure Is Repeated For The Hijri Data. Table8 Shows The Dummy Variables For Hijri Data For The Three Methods.

Regression Diagnostics AndResidual Analysis

An Examination Of The Residuals Is A Crucial Component For The Determination Of Model Adequacy. The Two Assumptions For The Regression Model Are:

- The Errors Are Normally Distributed.
- The Errors Should Be Independent.

All The Regression Equations For Both Gregorian AndHijri Data Arechecked To Perform Diagnostics Of The Regression And Analyze The Residuals. The Histogram Of The Residuals Provides A Shape Check On The Normality Assumptions;Fig. 6 Showsan Example Of The Normality Test Of Residuals For The Regression Method For The Gregorian And Hijri Data.

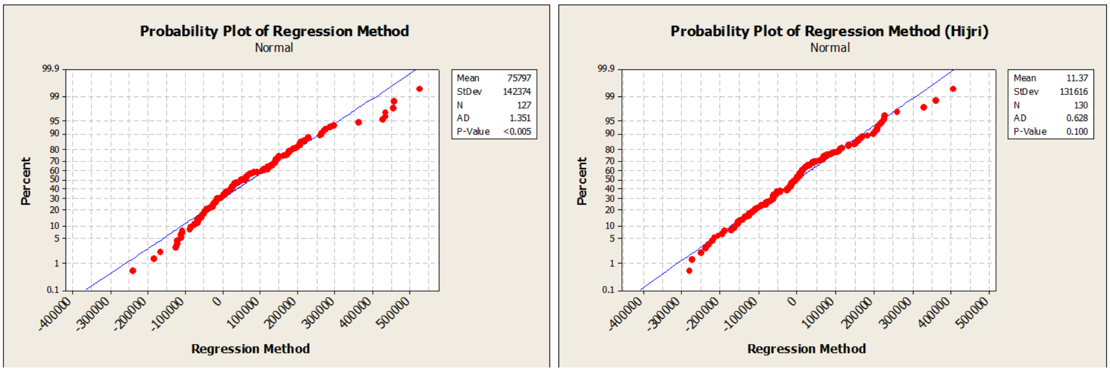


Figure 6: NormalityTestof Residuals For Regression Method For Gregorian And Hijri Data.

Anderson-Darling Normality Test Is Used To Determine If Data Follow A Normal Distribution. If The P-Value Is Lower Than A Pre-Determined Level Of Significance (e.g. < 0.05), The Data Do Not Follow A Normal Distribution [27]. From Figure 6and According To The P-Values, Then The Hijri Data Residuals Are Normally Distributed But That For The Gregorian Data Are Not.

For Randomness, The Sample Autocorrelations Of The Residuals Should All Be Small For All Time Lags k = 1, 2, …,k, k= n/4,Where n Is The Number Of Residuals.

The Number Of Residuals For Gregorian Data Are 127, So k= *n*/4 = 127/4 = 31.75 (Round It Up To Be 32), And For Hijri Data Are 130, So k= n/4 = 130/4 = 32.5 (Rounded It Up To Be 33). The Autocorrelation Functions Of Residuals For Gregorian And Hijri Data Show That Residuals Are Not Random.

Table 3 Represents The Results For Normality And Randomness Tests For Different Regression Methods.

Table 3: Normality And Independence Tests Of Residuals For Different Regression Methods.

Data	Method	Residuals	
		Normality Test	**Independence Test**
Gregorian	**Regression Method**	×	×
	Best Subset	√	×
	Stepwise Regression	√	×
Hijri	**Regression Method**	√	×
	Best Subset	√	×
	Stepwise Regression	√	×

4.7 Using Regression WithNonlinear Expressions Of Time Variable

Since The Trend Equation With Smaller Measures Of Errors Is Curvilinear, Many Alternatives Of The Regression For Seasonal Data Method Are Proposed With Nonlinear Expressions Of The Time Independent Variable. The Nonlinear Expressions Are Different Power Terms And AlsoS-Curve Equation Of The Time Independent Variable. TheNonlinear Expressions T^2, T^3, $\ldots T^{\,6}$ And The S-Curve Equation Are Considered, While The Seasonality Is Handled By Using Dummy Variables In The Regression Function As In The Previous Model. The Proposed Seasonal Model For Monthly Data With A Quadratic Time Trend Will Be As Follows:

$Y_t = B_0 + B_1 t + B_1 t^2 + B_2 S_2 + B_3 S_3 + \ldots\ldots + B_{12} S_{12} + \varepsilon_t$

The Proposed Seasonal Model For Monthly Data With A Time Trend With Power 3 Will Be As Follows:

$Y_t = B_0 + B_1 t + B_1 t^2 + B_1 t^3 + B_2 S_2 + B_3 S_3 + \ldots\ldots + B_{12} S_{12} + \varepsilon_t$

Other Time Trend With t^4, t^5, $t^6$are Also Checked,

Also, A Regression Model With S-Curve Expression Of Time Variable Is Checked, The Equations For The S-Curves For Both The Gregorian And HigriData Are Obtained From The Trend Equations As Follows:

Gregorian: $Y(t) = (10^7) / (0.952042 + 8.09059*(0.991933^t))$

Hijri: $Y(t) = (10^7) / (-2.16360 + 11.3278*(0.995106^t))$.

Table 4 Represents The Forecasting Performance Of The Best Regression Equations. From The Table, It Is Shown That The Minimum Measures Of Errors Are Obtained With The Regression Model Having t, t^2 And t^3 For The Gregorian Data, And The Model Having t, t^2, t^3,t^4 Andt^5 For The Hijri Data. Both Models Satisfy The Normality Test But Fail To Satisfy The Independence Test.

4.8 Combining Forecasts

A Developing Branch Of Forecasting Study Involves The Combination Of Two Or More Forecasting Methods To Produce The Final Forecasts. Considerable Literature Has Accumulated Over The Years Regarding The Combination Of Forecasts. The Primary Conclusion Of This Line Of Research Is That Forecast Accuracy Can Be Substantially Improved Through The Combination Of Multiple Individual Forecasts. Furthermore, Simple Combination Methods Often Work Reasonably Well Relative To More Complex Combinations.The Gains In Accuracy From Combining Increased With The Numbers Of Forecasts Used, Especially When These Forecasts Were Based On Different Methods And Different Data, And In Situations Involving High Levels Of Uncertainty [40].

Table 4: Forecasting Performance Of The Best Regression Equations

Expression Of Time T	Best Measurements Of Forecasting Errors									
	Hijri					Gregorian				
	MAPE	MAD	MSE	Normal?	Random?	MAPE	MAD	MSE	Normal?	Random?
T	0.06052	98491	1.68E+10	√	×	0.06022	100190	1.71E10	√	×
T & T^2	0.055983	94681	1.51E+10	√	×	0.056569	97978.25	1.62E10	√	×
T, T^2&T^3	0.042503	74954	9.68E+09	√	×	0.047219	81945	1.19E10	√	×
T, T^2, T^3& T^4	The Same Results As T, T^2 And T^3			√	×	The Same Results As T, T^2 And T^3			√	×
T, T^2, T^3,T^4& T^5	0.043248	74932	9.66E+09	√	×	0.047742	82472	1.24E10	×	×
T, T^2, T^3,T^4,T^5&T^6	0.043316	75028	9.67E+09	√	×	0.050529	82616	1.23E10	×	×
S-Curve	0.058884	100159	1.64E+10	√	×	1.64E10	0.058408	99588	√	×

.In Practice, The Method Most Commonly Used Is The Simple Averaging Of The Forecasts [41]. If $\hat{Y}_{11}, \hat{Y}_{12}, \dots \dots, \hat{Y}_{1m}$ Are One-Step-Ahead Forecasts Produced By *M* Different Methods, Then The One-Step-Ahead Combined Forecast, $\hat{Y}_{1C}$, Obtained By Simple Averaging Is:

$$\hat{Y}_{1C} = \frac{\hat{Y}_{11} + \hat{Y}_{12} + \dots + \hat{Y}_{1m}}{m}$$

The Common Practice, However, Is To Obtain A Weighted Average Of Forecasts, With The Weights Adding Up To Unity. In This Case, Each One-Step-Ahead Forecast, $\hat{Y}_{1i}$, Receives Weight $0 < W_i < 1$ Where $\sum_{i=1}^{m} w_i = 1$.

Therefore, With *M* One-Step-Ahead Forecasts Produced By *M* Different Methods, The Combined Forecast,$\hat{Y}_{1C}$ Is:

$$\hat{Y}_{1C} = w_1\hat{Y}_{11} + w_2\hat{Y}_{12} + \dots + w_m\hat{Y}_{1m} \text{ , Where: } \sum_{i=1}^{m} w_i = 1$$

Past Errors Of Each Of The Original Forecasts Are Used To Determine The Weights To Attach To These Two Original Forecasts In Forming The Combined Forecasts, One Would Wish To Give Greater Weight To The Set Of Forecasts Which Seemed To Contain The Lower (Mean-Square) Errors, I.E. Set Weights Proportional To The Inverse Of The Models' MSE-Values [42]:

$$w_i = \frac{MSE_i^{-1}}{\sum_{i=1}^{m} MSE_i^{-1}}$$

This Method Is Applied To The Problem By Combining The Two Most Promising Forecasting Methods. Those Methods Are: ARIMA(1,1,1)(1,0,3) For Hijri Data (Which Is The Only Method Having Random Residuals) With The Regression Method With Nonlinear Expressions Of Time Variable T, T^2, T^3,T^4& T^5 (Which Has The Smallest Measures Of Errors For Hijri Data, But Errors Are Not Random). The Combination Is Done By Considering Different Weights As Shown In Table 5. From The Table, Measures Of Errors In The Best Combining Forecasts With Equal Weights Are Smaller Than Both Combined Methods, But Residuals Of That Method Are Not Random, Moreover, The Residuals For All The Combined Models Are Correlated.

Table 5: Measures Of Errors For The Combining Forecasts Method.

Forecasting Methods		Hijri Data			
		Measures Of Errors			
ARIMA	Regression Seasonal Data	MAPE	MAD	MSE	Random ?
0.1	0.9	0.041999	73106.71	9.47E9	No
0.2	0.8	0.041114	71658	9.32E9	No
0.3	0.7	0.040486	70589	9.25E9	No
0.32	0.68	0.040416	70478	9.24E9	No
0.34	0.66	0.040352	70375	9.24E9	No
0.36	0.64	0.040288	70274	9.24E9	No
0.38	0.62	0.040229	70181	9.24E9	No
0.4	0.6	0.04017	70088	9.25E9	No
0.42	0.58	0.040113	70000	9.26E9	No
0.44	0.56	0.040071	69932	9.28E9	No
0.46	0.54	0.040045	69892	9.29E9	No
0.47	0.53	0.04004	69883	9.3E9	No
0.48	0.52	0.040036	69874	9.31E9	No
0.5	0.5	0.040028	69858	9.34E9	No
0.6	0.4	0.040281	70210	9.5E9	No
0.7	0.3	0.040805	71008	9.75E9	No
0.8	0.2	0.041457	71998	1.01E10	No
0.9	0.1	0.042456	73578	1.05E10	No
0.46757	0.53243	0.040042	69885	9.3E9	No
= Proportional To Inverse Of MSE					

V. Results

A Comparison Between Measures Of Forecasting Errors For The Used Forecasting Methods Is Presented In Table 6. From The Measurement Of Forecasting Errors, It Can Be Seen That Methods With Minimum Measures Of Errors And Uncorrelated Residuals Are ARIMA(1,1,3)(1,0,3) For Gregorian Data And ARIMA(1,1,1)(1,0,3) For Hijri Data. These Two Methods Will Be Used For Long-Term Forecasting Of The Number Of Passengers In Saudi Arabian Airlines. It Can Be Seen Also That All Measures Of Error In The Gregorian Data Are Smaller Than That Measures In The Hijri Data.

6. LONG TERM FORECASTING OF PASSENGER NUMBERS

Forecasting Using Gregorian Data Is More Suitable Than Forecasting With HigriData For These Reasons:

A) The Gregorian Data Are Actual Observations, While The Hijri Data Are Calculated Using The Daily Average Number Of Passengers For The Missing Part Of The Data.

Table 6:Performance Of The Forecasting Methods.

Forecasting Methods		Measurements Of Forecasting Errors							
		Hijri				Gregorian			
		MAPE	MAD	MSE	Random ?	MAPE	MAD	MSE	Random ?
Naïve For Trend And Seasonality		0.07364	131710	2.8E10	×	0.07294	135878	2.73E10	×
Double Exp. Smoothing		6.26151	1.0671E5	2.07307E10	×	7.13798	127513	2.70174E1	×
Seasonal Exp. Smoothing		4.56101	7.9016E4	1.23716E10	×	4.92557	854176	1.46527E1	×
Decomposition		6.09646	98804	1.73898E10	×	6.02587	101961	1.73642E1	×
Trend	Quadratic	7.68115	125341	2.4929E10	×	7.81780	130828	2.7699E10	×
	S-Curve	7.66434	128221	2.6917E10	×	7.67063	130744	2.8416E10	×
ARIMA	(1,1,3)(1,0,3)	Model Cannot Be Estimated				0.037788	68115	9.85E09	√
	(1,1,1)(1,0,3)	0.04352	75248	1.1E10	√	0.03845	69160	1.02E10	×
Regression on Seasonal Data	$T, T^2 \& T^3$	0.04250	74954	9.68E09	×	0.047219	81945	1.19E10	×
	$T, T^2, T^3, T^4 \& T^5$	0.04325	74932	9.66E09	×	0.047742	82472	1.24E10	×
Combining Forecasts		0.0400	69885	9.3E+09	×				

B) The Residuals Of The Gregorian Data For The Used Forecasting Method Are Clearly Random, But Those For The Hijri Data Are Not.

C) All The Three Measures Of Errors For The Forecasting Method In Gregorian Data Are Slightly Smaller Than Those Of The Hijri Data.

D) Saudi Arabian Airlines Already Uses The Gregorian Calendar For All The Reservation, Which Is Standard Calendar Around The World.

Minitab Software Is Used To Long-Term Forecast The Expected Number Of Passengers In Saudi Arabian Airlines For The Upcoming 5-Years (60 Months) For The Gregorian Calendar. Figures 7 And 8 Represent The Original Observations And Fitted Values And The 5 Years Forecasts Respectively.

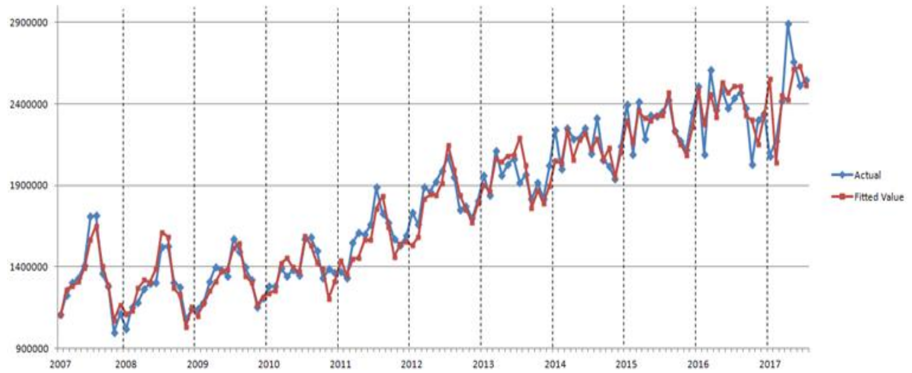


Figure 7: Graph For The Original Observations And Fitted Values For The Gregorian Data.

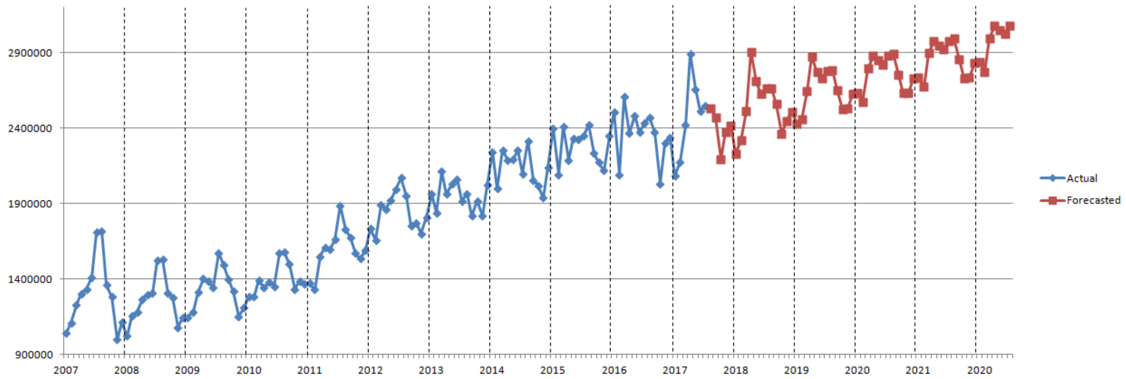


Figure 8: Graph For The 5 Years Forecasts For The Gregorian Data.

VI. Conclusions

The Main Purpose Of This Paper Is To Long-Term Forecast The Number Of Passenger In Saudi Arabian Airline Flights. The Collected Data Were Monthly For Ten Years From January 2007G To July 2017G In Gregorian, However, Hijri Data Were Only From Muharram 1435H To Shawal 1438H. The Gregorian Data Are Converted To Hijri To Complete The Missing Gab Using A Special Average Daily Number Of Passengers.

The Data For Both Calendars Are Of Trend Pattern And Moderate Seasonality. Nine Candidate Time Series Forecasting Models Available In Minitab And Excel Software Are Selected To Apply For Both The Gregorian And Hijri Data Of The Number Of Passengers In Saudi Airlines. These Time Series Forecasting Models Are:Naïve For Trend And Seasonality, Double Exponential Smoothing, Seasonal Exponential Smoothing, Decomposition, Trend Models,ARIMA, Regression For Seasonal Data And Combining Forecasts.
The Main Conclusions From This Research Cab Be Summarized As Follows:

1. The Autocorrelation Functions Indicate That Residuals Are Not Random For All The Used Forecasting Models Except For One Model Of ARIMAMethod For Each Of The Gregorian And Hijri Data.
2. Measures Of Errors Vary Considerably For Each Of The Proposed Forecasting Methods, And There Is No Preference Between Methods For Trend Data Patterns And Those For Trend And Seasonality In The Measures For Errors.
3. Some Forecasting Methods Give Smaller Measures Of Errors For The Gregorian Data, While Others Give Smaller Measures For The Hijri Data.
4. The Forecasting Method Having The Smallest Measures Errors And Random Residuals Is ARIMA(1,1,3)(1,0,3) For The Gregorian Data And ARIMA(1,1,1)(1,0,3) For The Hijri Data.
5. The Regression Method With Nonlinear Expressions Of Time Variable t, t^2, t^3,t^4&t^5 For Hijri Data Has The Smallest Measures Of Errors, But Errors Are Not Random. This Method Is Combined With ARIMA(1,1,1)(1,0,3) By Considering Different Weights. Although The Measures Of Errors For The Resulted Combining Forecasts Are Smaller Than Measures Of Each Of The Combined Methods, But The Errors Are Not Random.
6. All The Three Measures Of Errors For The Best Forecasting Method In GregorianData Are Slightly Smaller Than Those Of The Hijri Data.
7. A Regression Model Can Be Used In Order To Forecast The Seasonal Data. In This Model, The Trend Is Handled By Adding An Independent Variable *T* Representing The Time And The Seasonality Is Handled By Using Dummy Variables In The Regression Function.
8. Since The Trend Equation With The Smallest Measures Of Errors Is Curvilinear, Many Alternatives Are Proposed With Nonlinear Expressions Of The Time Independent Variable. The Nonlinear Expressions Are Different Power Terms And AlsotheS-Curve Equation Of The Time Independent Variable. The Nonlinear Expressions t^2, t^3, …t^6 And The S-CurveEquation Are Considered.
9. Long-Term Forecasting For 5 Years (60 Months) Is Done Using ARIMA(1,1,3)(1,0,3) For The Gregorian Data And ARIMA(1,1,1)(1,0,3) For The Hijri Data. The Graph For The Fitted Values Showsa Good Match Between The Predicted And The Real Data, Which Reassure The Results Of The Future Forecasts.
10. Forecasting Using Gregorian Data Is More Suitable Than Forecasting With HigriData.

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