Incorporating Explanatory Effects of Neighbour Airports in Forecasting Models for Airline Passenger Volumes

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Abstract: Forecasting airline passenger volumes can be helpful for flight and airport capacity planning. While there are many parameters affecting the passenger volume, to our knowledge no work has directly studied the effect of neighbour airports in modelling of passenger volumes. We develop an integrated model for forecasting the number of passengers arriving/departing an airport, considering the airport's interactions with its neighbour airports. In particular, we analyse the time series of the flights arriving to and departing from two largest airports in Turkey, namely Ankara Esenboga and Istanbul Ataturk Airports, and explore the interactions between these airports by using them as regressors for each other. We also apply independent models based on TBATS which was previously proposed in the literature to handle multiple seasonalities. In our experiments, TBATS performs better than ARIMA for independent modelling, and TBATS with multiple seasonal periods outperforms TBATS with single seasonality in majority of the cases. In several cases, the forecasting accuracy increases when the neighbour airports' traffic data is used in modeling the passenger volumes.

1 INTRODUCTION

Civil aviation authorities and airline companies need short and long term forecasts for effective flight and capacity planning. A wide range of forecasting models are developed including econometric modelling, univariate time series modelling, time series decomposition, non-linear regression models and gravity models (Scarpel, 2013). While it is intuitive that the traffic of an airport is not independent of its neighbour airports, to our knowledge this is not directly taken into consideration in modelling and forecasting airport traffic. Research is needed to investigate how the traffic model of an airport can incorporate its 'neighbours' traffic as they affect each other possibly with a small time shift. In this paper, we consider interactions between neighbour airports in developing time series forecasting models for air traffic volumes. We handle two neighbour airports as a dyad in an airport network and compare independent and neighbour-dependent models to forecast the number of passengers for particular routes.

As a case study, we analyse time series patterns of domestic and international flights arriving to and departing from Ataturk and Esenboga International Airports in Turkey over the course of a year. We propose a neighbour-dependent approach using regression with ARIMA errors and explore explanatory relations by regressor time series. For independent modelling, we consider ARIMA and TBATS models for developing independent forecasting models. TBATS (Trigonometric, Box-Cox transform, ARMA errors, Trend, and Seasonal components) model was proposed to deal over parameterization and handle both non-integer period and dual-calendar effects (De Livera et al., 2011). ARIMA models enable fitting the patterns in data with smallest number of estimated parameters. TBATS handles multiple seasonality which we observe in Turkish flight data. We elaborate accuracy performance of TBATS method and ARIMA models in independent modelling as well. By comparing the accuracy of independent and dependent models we are able to explore contribution of neighbour relations on forecasting performance.

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In our experiments, TBATS performs better than ARIMA for independent modelling. TBATS models with multiple seasonal periods perform better than models with single seasonality. These results verify that TBATS model performs well in airline data with multiple seasonality. Using explanatory time series of neighbours' air passenger volumes is found to be useful in several cases.

The remainder of the paper contains the following sections. First, we present a literature overview on air passenger flow problem and the forecasting methods used in this study. We then present the proposed methodology and empirical results. Finally, we conclude with future research directions.

2 RELATED WORK

Air transportation has achieved a remarkable growth both worldwide and in Turkey, e.g., the total number of passengers in Turkey has risen 14.3% in the last decade (TOBB, 2013). According to EUROCONTROL forecasts, Turkey will be the arrival or departure point for the greatest number of extra flights in the future European airspace by 2035 (EUROCONTROL, 2013). In our study, we generate forecasting models for the number of air travel passengers for different routes between Ankara Esenboga and Istanbul Ataturk Airports.

Several methods have been proposed for forecasting the number of air travel passengers in the context of air travel demand, pax growth and air travel flow. Traditional methods, such as neural networks, exponential smoothing, Box-Jenkins, and Holt-Winters, are commonly applied in this context. Nam et al. use neural networks for predicting international air passenger volume between US and Mexico and compare them with regression and exponential smoothing forecasting models (Nam et al., 1997). Neural network models are also compared with well-known Box-Jenkins and Holt-Winters Methods (Faraway et al., 1998). In an application study, neural networks are shown to outperform the traditional econometric approach for forecasting Brazilian air transport passenger traffic (Alekseev et al., 2009).

Samagaio and Wolters propose ARIMA and exponential smoothing models for forecasting the number of passengers for 2008-2020 to help decision making for establishing a new airport (Samagaio et al., 2010). An application of fuzzy regression model is developed to forecast the demand of Rhodes airport (Profillidis, 2000). Grosche et al. propose two gravity models using geo-economic factors as independent variables for estimation of airline passenger volume between city pairs (Grosche et al., 2007). Fildes et al. explore the relations between air traffic flows to different countries by pooled ADL model (Flides et al., 2011). They enhance their models with "world trade" variable and conclude that pooled ADL model with "world trade" variable outperformed the alternatives. Benitez et al. propose a modified Grey Model for airlines routes pax growth for long lead-time (Benitez et al., 2013). ARIMAX and SARIMA based models are recently used to forecast Hong Kong airport's passenger throughput till 2015 (Tsui et al., 2014). Time series involved in our analysis involve multiple seasonal patterns. Hence we use a recent proposal, TBATS, which handles multiple seasonality (De Livera et al., 2011).

3 METHODOLOGY

In this section, we highlight the methods for handling the seasonality from the literature and introduce the details of our methodology to incorporate the interactions of two airports into their forecasting models. In particular, we study Ataturk and Esenboga Airports in Turkey and investigate if they affect each other while forecasting their passenger volumes. The data set of the number of passengers for Ataturk and Esenboga Airports in 2011 is obtained from the General Directorate of State Airports Authority of Turkey. Eight time series of the number of passengers in international and domestic incoming & outgoing flights of these airports are generated. We build models both independently and neighbour-dependently and compare their performance. For independent models, which do not consider the neighbour effects, we investigate the conventional ARIMA and the recently proposed TBATS approach on forecasting airline passenger volumes. We also study a neighbour dependent approach where we use the traditional regression with ARIMA errors approach and incorporate the neighbour effects as a regressor time series.

We now summarize the methods we applied in our independent modelling and present our neighbour dependent modelling approach.

3.1 Independent Modelling with ARIMA and TBATS

We apply ARIMA and TBATS methods for independent modelling and analysis. ARIMA (Auto-Regressive Integrated Moving Average) is a basic approach for analysis and forecasting of equally spaced univariate time series data. Box and Jenkins proposed an entire family of ARIMA models and an analysis to find the smallest number of estimated parameters needed to fit the patterns in the data. Box-Jenkins methodology involves three steps; identification, estimation and diagnostic checking (Pankratz, 1983). As a baseline for comparison, we use automated ARIMA model fitting function in forecast package of R programming.

Our preliminary data analysis reveals that our passenger volume time series involve multiple seasonality. Most commonly used methods for modelling seasonal time series, such as Holt-Winters, exponential smoothing approach, ARIMA models, suffer dealing with double seasonality. Recently, exponentially weighted methods for multiple seasonal time series are proposed (De Livera, 2010). To deal with double seasonality, an extension of Holt-Winter is proposed (Taylor, 2003). In another study, a multiple seasonal method is developed that allows the seasonal cycle to be updated more than once during the period of the cycle (Gould et al, 2007). Also time series may have complex seasonal patterns such as patterns with a non-integer period, have high frequency multiple seasonal patterns or may have dual calendar effects. De Livera et al. propose a new innovations state space model based approach that is capable of dealing over parameterization and tackling with both non-integer period and dual-calendar effects (De Livera et al., 2011). They improve the traditional single seasonal exponential smoothing methods, and introduce two algorithms. They propose TBATS, which stands for Trigonometric, Box-Cox transform, ARMA errors, Trend, and Seasonal components Model.

The Box-Cox transformation, ARMA errors, Trend and Seasonal components (BATS) are defined by;

$$y_t^{(\omega)} = \begin{cases} (Y_t^{\omega} - 1)/\omega & when\ \omega \neq 0 \\ logY_t & when\ \omega = 0 \end{cases},$$

$$y_t^{(\omega)} = l_{t-1} + \phi b_{t-1} + \sum_{i=1}^{n} s_{t-m_i}^{i} + d_t \tag{3.1}$$

$$l_t = l_{t-1} + \phi b_{t-1} + \alpha d_t \tag{3.2}$$

$$b_t = (1-\phi)b + \phi b_{t-1} + \beta d_t \tag{3.3}$$

$$s_t^{(i)} = s_{t-m_i}^{(i)} + \Upsilon_i d_t \tag{3.4}$$

where $\omega \in R$ is the Box-Cox transformation parameter, $m_1 \dots\dots m_n$ denote the constant periods of the n seasonal components, b is the long run trend, $\{d_t\}$ is an $ARMA(p,q)$ process with Gaussian white noise innovations having zero mean and constant variance, and for $t = 1, \dots., T$, l_t is the local stochastic level, b_t is the short term trend and $s_t^{(i)}$ is the stochastic level of the $i-th$ seasonal component.

De Livera et al. proposed a new trigonometric representation of seasonal components based on Fourier series.

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)} \tag{3.5}$$

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} cos\lambda_j^{(i)} + s_{j,t-1}^{*(i)} sin\lambda_j^{(i)} + \Upsilon_1^{(i)} d_t \tag{3.6}$$

$$s_{j,t}^{*(i)} = -s_{j,t-1} sin\lambda_j^{(i)} + s_{j,t-1}^{*(i)} cos\lambda_j^{(i)} + \Upsilon_2^{(i)} d_t \tag{3.7}$$

Where $\Upsilon_1^{(i)}$ and $\Upsilon_2^{(i)}$ are smoothing parameters, $\lambda_j^{(i)} = 2\pi j/m_i$. $s_{j,t}^{(i)}$ describe the stochastic level of the i^{th} seasonal component, and the stochastic growth in the level of the i^{th} component that is needed to describe the change in the seasonal component over time is described by $s_{j,t-1}^{*(i)}$. The number of harmonics required for the i^{th} seasonal component is denoted by k_i (De Livera et al., 2011). The performance of these approaches on forecasting passenger volumes is presented in the experimental section.

3.2 Neighbour Dependent Modelling

In neighbour-dependent analysis, we incorporate the explanatory effects of regressor time series of neighbour airports using regression with ARIMA errors method.

$$Y_t = b_0 + b_1 X_{1,t} + \dots + b_k X_{k,t} + N_t \tag{3.8}$$

One of the key assumptions of multiple regression is that N_t is an uncorrelated series. For regression with ARIMA, it is considered that N_t contains autocorrelations. The resulting model is now a regression model with ARIMA errors. Equation 3.8 still holds but N_t is modeled as an ARIMA process. We follow the notations of Makridakis et al. (1998) for stating regression with ARIMA model. For example, if N_t is an ARIMA (1, 1, 1) model, 3.8 can be written

$$Y_t = b_0 + b_1 X_{1,t} + \dots + b_k X_{k,t} + N_t \tag{3.9}$$

where $(1 - \phi_1 B)(1 - B)N_t = (1 - \phi_1 B)e_t$ and e_t is a white-noise series.

For identification of regressor time series, we analyse the cross correlation between time series and consider highly correlated and weakly correlated series for building significant explanatory relations. Initially we build regression with ARIMA models in line with the correlation between Ataturk and Esenboga series and we add regressor variables into the model individually. Then we check the internal cross correlation in Ataturk and Esenboga series in order to identify regressor pairs. In this analysis it is revealed that all series in Ataturk dataset are highly correlated, hence we do not use any pairs while building explanatory models for Esenboga series with Ataturk data. In Esenboga dataset, we find out that Esenboga International Incoming Passengers data is weakly correlated with the rest of the series and this result enables us to use pairs as regressors while building explanatory models for Ataturk data.

4 EMPIRICAL ANALYSIS

To evaluate the performance of the presented methods for forecasting the number of passengers for an airport, we collected a list of real time series as presented in Table 1. We adjusted our dataset by forming equal time intervals for all time series. Volumes of passengers are quarterly aggregated by six-hour time periods for each day that helps to detect seasonal patterns inherent in data. Following the data adjustment, we divided the available one-year data into training and test sets. We built models with a training set involving 1092 data points and tested the models with 124 data points.

Table 1: List of analysed time series.

Ataturk A. Domestic Flights Incoming Number of Passengers **(ADI)**
Ataturk A. Domestic Flights Outgoing Number of Passengers **(ADO)**
Ataturk A. International Flights Incoming Number of Passengers **(AII)**
Ataturk A. International Flights Outgoing Number of Passengers **(AIO)**
Esenboga A. Domestic Flights Incoming Number of Passengers **(EDI)**
Esenboga A. Domestic Flights Outgoing Number of Passengers **(EDO)**
Esenboga A. International Flights Incoming Number of Passengers **(EII)**
Esenboga A. International Flights Outgoing Number of Passengers **(EIO)**

All series have multiple seasonal patterns and high frequency seasonality. For each set of data, four independent models are fit: **(I)** ARIMA model with frequency=4,**(II)** ARIMA model with frequency=28, **(III)** TBATS Model with frequency=28 and **(IV)** TBATS Model with double seasonality. For neighbour-dependent analysis, we build regression with ARIMA models with convenient regressor time series. MAPE (Mean Absolute Percentage Error) is the preferred forecasting accuracy measure for simplicity when all data are positive and much greater than zero (Hyndman and Koehler, 2006). We also report MAE (Mean Absolute Percentage Error) and MASE (Mean Absolute Scaled Error) based results of our experiments (Hyndman and Koehler, 2006).

4.1 Independent Analysis with ARIMA and TBATS Models

We first analyse the time-series, ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots for all data sets. For brevity, we present the models for one representative data set (i.e., ADI) in detail and for the rest of the series we present the model results.

The ACF and PACF plots illustrate two seasonal periods (Figure 1). The first seasonality arises from aggregating daily data quarterly by 6 hour time periods and the seasonal period is four. The second seasonality is observed with the help of PACF plot, 28 periods indicates the weekly seasonality in the training data set.

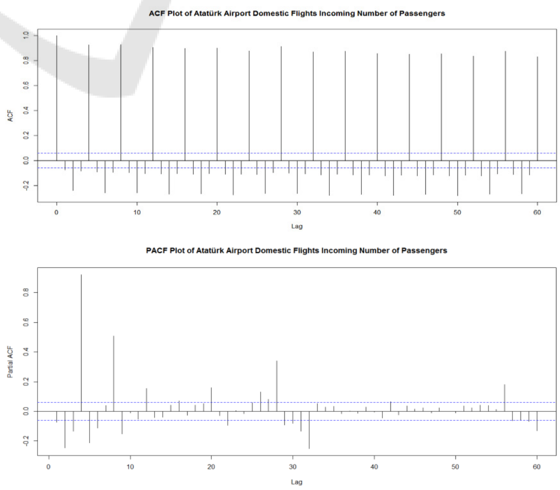

Figure 1: ACF and PACF plots of ADI data.

Based on these results, we fit four independent models. **(I)** ARIMA model with frequency=4, **(II)**

ARIMA model with frequency=28, **(III)** TBATS Model with frequency=28 and **(IV)** TBATS Model with double seasonality for each dataset. We developed these four independent models for each of the eight time series and according to MAPE (Mean Absolute Percentage Error) measure we present the best independent models for each of the time series in Table 3.

Table 2: Forecasting Accuracy of Independent Models for ADI.

Model	MAE	MAPE	MASE
ARIMA(0,1,2)(2,0,0)[4]	727.15	19.81	1.24
ARIMA(4,0,0)(0,1,1)[28]	513.41	12.45	1.05
TBATS(0.71, {2,1}, 0.809, {<28,7>})	455.22	11.69	0.93
TBATS(0.684, {2,1}, 0.861, {<4,1>, <28,6>})	441.30	11.07	0.90

Table 3: Best Independent Models for All Time Series.

Data	The Best Model	MAPE
ADO	TBATS(1, {2,1}, -, {<28,8>})	12.03
AII	ARIMA(4,0,0)(0,1,1)[28]	9.24
AIO	TBATS(0.998, {5,4}, -, {<4,1>, <28,5>})	9.70
EDI	TBATS(0.999, {4,5}, -, {<28,8>})	11.94
EDO	ARIMA(4,0,0)(0,1,1)[28]	7.85
EII	TBATS(0.327, {4,4}, -, {<28,7>})	52.02
EIO	TBATS(0.095, {0,0}, -, {<4,1>, <28,5>})	56.58

In half of the independent models, TBATS model with multiple seasonality outperformed other models according to MAPE measure. In the second half of the independent models, TBATS and ARIMA models with weekly seasonality outperform other models. These results show that TBATS successfully handles multiple seasonality in our airline passenger volume time series, and it yields better forecasting accuracies than the traditional ARIMA approach.

4.2 Neighbour-dependent Analysis with Regression with ARIMA Errors

We generated a cross correlation matrix for time series in the preliminary analysis phase. Table 4 depicts the cross correlation in all series. According to correlation values in this matrix, we establish the explanatory relations between time series and we build regression with ARIMA models with regressor time series. While building regression with ARIMA models for Ataturk Airport time series data, initially we analysed cross correlation with Esenboga Airport data. For example, ADI data can be paired with data of EIO, EDI and EDO data as explanatory Regressor variables.

Table 4: Cross Correlation between All Series.

	ADI	ADO	AII	AIO	EDI	EDO	EII	EIO
ADI	1.00	0.53	0.44	0.88	0.72	0.87	0.16	0.57
ADO	0.53	1.00	0.83	0.50	0.53	0.55	0.51	0.40
AII	0.44	0.83	1.00	0.46	0.42	0.39	0.62	0.31
AIO	0.88	0.50	0.46	1.00	0.64	0.79	0.21	0.59
EDI	0.72	0.53	0.42	0.64	1.00	0.74	0.26	0.34
EDO	0.87	0.55	0.39	0.79	0.74	1.00	0.20	0.53
EII	0.16	0.51	0.62	0.21	0.26	0.20	1.00	0.27
EIO	0.57	0.40	0.31	0.59	0.34	0.53	0.27	1.00

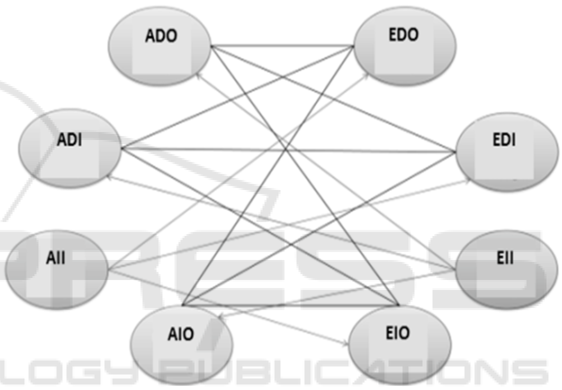

Figure 2: Explanatory Relations between Time Series.

Taking into account all possible routes and connections we consider the explanatory relations in Figure 2. In this figure, black undirected edges represent the mutual interactions, the gray directed edges represent the single sided influence. According to these relations, it is clear that the volume of passengers in international incoming flights cannot be explained by neighbour effects. This observation also makes sense in practice. Hence we do not build regression with ARIMA models for international incoming passengers data. But we consider these series as explanatory variables in other models.

When we consider all possible routes and connections that may affect ADI data, we may expect ADI data to be correlated with all series in Esenboga data. We build seven neighbour-dependent models for ADI dataset and compare contribution of regression variables in forecasting performance. Regression with ARIMA models for ADI data is presented in Table 5. We find out that the best model in neighbour-dependent models is regression with ARIMA model including EDO data as regressor variable, and it performs better than an independent ARIMA model (seasonal period: 4). We compare these neighbour dependent model results with the independent model results in Table 6 by MAPE accuracy measure. For this data set, the best model out of all models is the independent TBATS model with multiple seasonality.

Table 5: Regression with ARIMA models for ADI Data (Neighbour dependent models).

Model	MAE	MAPE	MASE
ARIMA(0,1,2)(2,0,0)[4] REG. with EDI	721.32	18.80	1.23
ARIMA(0,1,3)(2,0,0)[4] REG. with EDO	632.39	16.36	1.08
ARIMA(1,1,1)(2,0,0)[4] REG. with EII	1063.30	32.13	1.82
ARIMA(3,1,1)(0,0,1)[4] REG. with EIO	778.20	21.99	1.33
ARIMA(0,1,3)(2,0,0)[4] REG. with EII and EIO	1020.09	30.04	1.74
ARIMA(1,1,1)(2,0,0)[4] REG. with EII and EDI	690.17	17.71	1.18
ARIMA(0,1,3)(2,0,0)[4] REG. with EII and EDO	619.53	15.88	1.06

Table 6: Forecasting Accuracy of Independent Models for ADI.

Model	MAE	MAPE	MASE
ARIMA(0,1,2)(2,0,0)[4]	727.15	19.81	1.24
ARIMA(4,0,0)(0,1,1)[28]	513.41	12.45	1.05
TBATS(0.71, {2,1}, 0.809, {<28,7>})	455.22	11.69	0.93
TBATS(0.684, {2,1}, 0.861, {<4,1>, <28,6>})	441.30	11.07	0.90

Ataturk Airport Domestic and International Outgoing Passengers data are correlated with all series in Esenboga data. For this reason, we add all series as regressor variables individually and we also consider the weakly interrelated Esenboga time series pairs as regressor variables. Regression with ARIMA models with the best test results are presented in Table 7.

The best model for ADO data in the neighbour-dependent approach is when EDI is used as a regressor variable. It outperforms the worst model, ARIMA (seasonal period: 4) in independent models. For ADO data, the best model out of all models is the independent TBATS model with single seasonality. The comparison of the best performing dependent and independent models is presented in Table 8.

For AIO data, the best neighbour-dependent model is the regression with ARIMA model including EDO data. The best model out of all models is the independent TBATS model with multiple seasonality. The comparison of the best performing dependent and independent models is presented in Table 9.

Table 7: The Best Regression with ARIMA models for ADO and AIO Data.

Data	The Best Neighbour Dependent Models	MAPE
ADO	ARIMA(3,1,0)(0,0,1)[4] REG. with EDI	16.59
AIO	ARIMA(0,1,1)(2,0,1)[4 REG. with EDI	11.48

Table 8: Comparison of Models for ADO Data.

Data	Models	MAPE
ADO	ARIMA(3,1,0)(0,0,1)[4] REG. with EDI	16.59
	TBATS(1, {2,1}, -, {<28,8>})	12.03

In regression with ARIMA models for Esenboga Airport, due to the strong cross correlation in Ataturk Airport time series data, each regression with ARIMA model built for Esenboga Airport routes involves one of the Ataturk Airport time series. The accuracy performance of regression with ARIMA models is demonstrated in Tables 10-11.

Table 9: Comparison of Neighbour Dependent and Independent Models for AIO Data.

Data	Models	MAPE
AIO	ARIMA(0,1,1)(2,0,1)[4] REG. with EDI	11.48
	TBATS(0.998, {5,4}, -, {<4,1>, <28,5>})	9.70

Table 10: Regression with ARIMA models for EDI Data (Neighbour Dependent Models).

Model	MAE	MAPE	MASE
ARIMA(3,1,1)(0,0,1)[4] REG.with ADI	257.95	12.12	0.70
ARIMA(3,1,0)(2,0,0)[4] REG.with ADO	372.63	15.94	1.02
ARIMA(0,1,3)(1,0,1)[4] with drift REG. with AII	254.69	12.93	0.70
ARIMA(0,1,3)(1,0,1)[4] with drift REG. with AIO	277.25	14.20	0.76

For EDI data, the best model out of all models is the independent TBATS model with single seasonality. The second best model is the neighbour-dependent model, i.e., regression with ARIMA model involving ADI data as regressor variable. The comparison is presented in Table 11.

Regression with ARIMA models with best forecasting accuracy for Esenboga Outgoing (Domestic and International) Passengers data are presented in Table 12.

Table 11: Comparison of Neighbour Dependent and Independent Model for EDI Data.

Data	Models	MAPE
EDI	TBATS(0.999,{4,5},-, {<28,8>})	11.94
	ARIMA(3,1,1)(0,0,1)[4] REG. with ADI	12.12

Table 12: The Best Regression with ARIMA models for EDO and EIO Data.

Data	The Best Neighbour Dependent Models	MAPE
EDO	ARIMA(3,1,0)(2,0,0)[4] REG. with ADI	20.99
EIO	ARIMA(3,1,0)(0,0,1)[4] REG. with AII	64.33

For EDO data, the best model out of all models is the independent ARIMA model with seasonal period 28. For EIO data, the best model out of all models is the independent TBATS model with multiple seasonalities. The comparisons are presented in Table 13 and Table 14.

Table 13: Comparison of Neighbour Dependent and Independent Model for EDO Data.

Data	Models	MAPE
EDO	ARIMA(3,1,0)(2,0,0)[4] REG. with ADI	20.99
	ARIMA(4,0,0)(0,1,1)[28]	7.85

Table 14: Comparison of Neighbour Dependent and Independent Model for EIO Data.

Data	Models	MAPE
EIO	ARIMA(3,1,0)(0,0,1)[4] REG. with AII	64.33
	TBATS(0.095, {0,0}, -, {<4,1>, <28,5>})	56.58

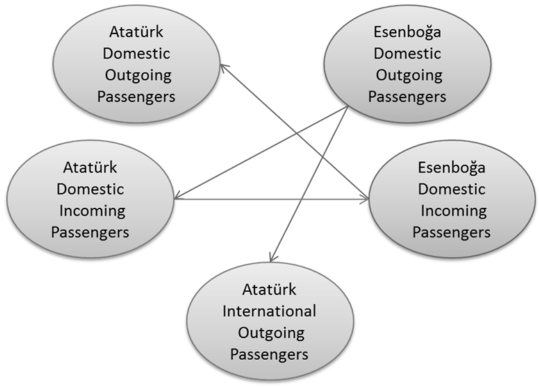

Figure 3: Resulting Explanatory Relations.

The experimental results illustrate some improvements using the explanatory regression with ARIMA models. Figure 3 summarizes the observed explanatory relationships between the data sets that showed considerable improvements in accuracies of the forecasting models. The head of the arrow shows the dependent time series while the tail shows the regressor time series.

5 CONCLUSIONS

In this paper, we investigate incorporation of the data of the neighbour airports in forecasting the traffic volume of an airport. To analyse the contribution of neighbour effects, we report on forecasting accuracies of independent and neighbour-dependent models for a variety of real time series data sets. In several cases, we observe improvement on forecasting performance when neighbour-dependent models are used. We also compared the performance of independent models based on TBATS vs. ARIMA. In half of the series, TBATS model with multiple seasonality outperforms the other models. For the rest, TBATS with single seasonality and ARIMA models provide comparable results. For future work, we are planning to observe the performance of TBATS model on long term airline passenger data involving dual calendar based seasonality. Dual calendar effects were studied for demand cash (Du Toit, 2011) and European tourist arrivals (Hassani et al., 2015) in the literature.

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