FORECASTING REVENUE PASSENGER ENPLANEMENTS USING WAVELET-SUPPORT VECTOR MACHINE

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This thesis is the final will that a father left for his son during his dying moment

To my late father,
Haji Zainuddin Bin Embong
(March 5th, 2014, Makkah)
may you rest in peace.

To the Dean family,
Lea, Jimmy, Annie & Ella
thank you for being strong.

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Although volleyball that connects us, is our friendship that actually keep us going.
Keep the volleyball flying.

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ABSTRACT

Forecasting is an important element in an airline industry due to its capability in projecting airport activities that will reflect the relationship that drives aviation activities. A wavelet-support vector machine (WSVM) conjunction model for revenue passenger enplanements forecast is proposed in this study. The conjunction model is the combination of two models which are Discrete Wavelet Transform (DWT) and Support Vector Machine (SVM). The method is then compared with single SVM and Seasonal Decomposition-Support Vector Machine (SDSVM) conjunctions. Seasonal Decomposition (SD) readings are obtained through X-12-ARIMA. The monthly domestic and international revenue passenger enplanements data dated from January 1996 to December 2012 are used. The performances of the three models are then compared utilizing mean absolute error (MAE), mean square error (MSE) and mean absolute percentage error (MAPE). The results indicate that WSVM conjunction model has higher accuracy and performs better than both basic single SVM and SDSVM conjunctions.

ABSTRAK

Proses ramalan merupakan elemen penting dalam industri penerbangan kerana melalui proses ini, segala hubungkait antara aktiviti di lapangan terbang yang mempengaruhi aktiviti penerbangan dapat dilihat. Model gabungan gelombang-mesin vektor sokongan (WSVM) bagi meramal pendapatan daripada bilangan penumpang yang menaiki pesawat dicadangkan dalam kajian ini. Gabungan tersebut adalah daripada dua model iaitu gelombang singkat diskrit (DWT) dan mesin vektor sokongan (SVM). Model yang dicadangkan kemudiannya dibandingkan dengan model SVM tunggal dan penguraian piawai – mesin vektor sokongan (SDSVM). Bacaan daripada penguraian bermusim (SD) diperoleh dengan menggunakan kaedah X-12-ARIMA. Dalam kajian ini, data bulanan yang digunakan untuk meramal pendapatan daripada bilangan penumpang yang menaiki pesawat adalah jumlah pendapatan daripada penumpang yang menaiki pesawat bagi penerbangan domestik dan antarabangsa masing-masing dengan julat masa dari Januari 1996 hingga Disember 2012. Prestasi setiap model dinilai berdasarkan bacaan purata ralat mutlak (MAE), purata ralat kuasa dua (MSE) dan purata peratusan ralat mutlak (MAPE). Keputusan perbandingan antara semua model menunjukkan bahawa model WSVM mempunyai prestasi yang baik berbanding model SVM tunggal dan model gabungan SDSVM.

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LIST OF SYMBOLS

FAA	-	Federal Aviation Administration
U.S.A.	-	United States of America
SVM	-	Support Vector Machine
EEMD	-	Ensemble Empirical Mode Decomposition
CAA	-	Civil Aviation Authority
DETR	-	Department of the Environment, Transportation and Regions
UK	-	United Kingdom
ANN	-	Artificial Neural Network
GP	-	Genetic Programming
EMD	-	Empirical Mode Decomposition
SD	-	Seasonal Decomposition
LSSVR	-	Least Squares Support Vector Regression
SRM	-	Structural Risk Minimization
DWT	-	Discrete Wavelet Transform
WSVM	-	Wavelet-Support Vector Machine conjunction
ARIMA	-	Autoregressive Integrated Moving Average
RM	-	Revenue Management
WTP	-	Willingness-To-Pay

SDSVM	-	Seasonal Decomposition-Support Vector Machine conjunction
MAE	-	Mean Absolute Error
MSE	-	Mean Square Error
MAPE	-	Mean Absolute Percentage Error
RITA	-	Research and Innovative Technology Administration
SVM-n	-	SVM model with nth input
NMSE	-	Normalize Mean Square Error
RMSE	-	Root Mean Square Error
MAPE	-	Mean Absolute Percentage Error
GMRAE	-	Geometric Mean Relative Absolute Error
DS	-	Dynamical System
SARIMA	-	Seasonal Autoregressive Integrated Moving Average
CSD	-	Core Standard
LESA	-	Line Extrapolation with Seasonal Adjustment
R	-	Correlation coefficient
MRA	-	Multiresolution Analysis
SRC	-	Sediment Rating Curve
SW	-	SARIMA-wavelet conjunction
Y_t	-	Original data
C_t	-	Trend-cycle
S_t	-	Seasonal component
I_t	-	Irregular component
D_t	-	De-trend component

$\hat{C}_t$	-	Estimated trend-cycle
MA, M_t	-	Moving Average
a_j	-	Weight
R_t	-	Ratio of actual moving average
$\hat{S}_t$	-	Seasonal index
$\hat{I}_t$	-	Estimated irregular component
$\psi(t)$	-	Wavelet function
a	-	Scaling parameter
b	-	Location parameter
$\Re$	-	Real numbers
$f(t)$	-	Function at t
$\varphi(t)$	-	Sets of real valued function at t
l	-	Integer index
m	-	Valued expansion coefficient
j	-	Discrete translation
k	-	Discrete scaling
$W_{\psi}f(j,k)$	-	Wavelet coefficient for discrete wavelet
DB-n	-	Daubechies-n-wavelet
x_i	-	Independent variable
y_i	-	Dependent variable
ξ_i , $\xi_i{}^*$	-	Slack variables
C	-	Capacity constant

w	-	Vector of coefficient
ε	-	Width of tube
RBF	-	Radial Basis Function
K	-	Kernel
Ds, D_t	-	Detail component
X_t	-	Normalize data at time t
y_{max}	-	Maximum value in the original data set
$\hat{X}_t$	-	Normalized forecasted data at time t
$\hat{y}_t$	-	Value of forecasted data at time t
x_{t+n}	-	Predicted value t
s_i	-	Lag period
$\frac{\partial}{\partial x}$	-	Derivative
Σ	-	Summation
α_i	-	Lagrange multiplier
$\mathcal{L}$	-	Langrangian
SV, w	-	Support Vector
z	-	Sample data
$K(x_i, x_j)$	-	Kernel function
e_t	-	Error at time t
A_t	-	Approximate component
$\hat{A}_t$	-	Predicted approximate component
$\hat{D}_t$	-	Predicted detail component

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Forecasting is an important element in airline industry due to its capability in projecting airport activity that will then reflect the underlying causal relationship that drives aviation activity. Aviation activity levels are resulted from the interaction of demand and supply factors. The demand for aviation is mostly a function of demographic and economic activity. Activity levels are influenced by supply factors such as cost, competition and regulations.

Normally, passenger enplanements can be modelled as a function of variables such as real personal income and real yield. The number of commercial operations, in turn, is a function of passenger enplanements as well as operational factors including average load factors and average seats per aircraft. Thus, local population and income levels, the cost of flying, and the number of based aircraft at the airport are examples of elements that can determine a general aviation activity.

Generally, forecasters evaluate the projections of aviation activity that result from applying appropriate forecasting methods and its relationships before they are finalized. Other than providing a means for developing quantifiable results, aviation forecasters use forecasting methods and their professional judgement to determine what is reasonable. Thus, making the evaluation forecast results an essential part of the forecasting process (GRA Inc., 2001).

The level and type of aviation activity expected at the airport, as well as the nature of planning being done determine the parameters that needed to be forecast. The level and type of aviation demand generated at the airport that are measured by aircraft operations is mainly the most important activity forecast for airfield planning. This is due to this demand that defines the runway and taxiway requirements. Runway and taxiway improvements are one of the dominant categories of airport improvement funding provided through the Federal Aviation Administration (FAA). For airport that is served by commercial air carriers, another important activity measure is the level of commercial passenger enplanements because it assists in determining the size of the terminal, the number of gates, and other important elements of airport infrastructures. A number of aviation planning is conducted on a regional basis and would include both regional demand and the distribution of demand among airports in the region. Other planning requires detailed analysis of enplanements and aircraft movements by city-pair. In planning a hub airport, detailed network analysis of the hub and spoke system of service may be involved.

Developing forecast of commercial activity is represented by passenger enplanements, operational factors and operations. Although primary forecast need may be aircraft operations, the forecast for commercial airports should begin with projecting air carrier and commuter enplanements and then apply forecast of average seats per aircraft and average load factor by category in order to develop air carrier and commuter operations.

FAA Aerospace Forecasts done by FAA is a forecast of national level U.S.A. aviation demand. The study provides a 12-year outlook and is updated each year in March (FAA, 2001). It is classified as the official FAA view of the immediate future aviation. Aggregate level forecast of passenger enplanements, revenue passenger miles, fleet, and hours flown for large air carriers and regional/commuters are also included. Another study done by FAA is the *FAA Long Range Aerospace Forecasts* which is a long-range forecast that extends the 12-year forecast to a longer time horizon for a period of 25 years (FAA, 2000). The forecast contains projections of aircraft fleet and hours, air carrier and regional/commuter passenger enplanements, air cargo freight revenue ton-miles, pilots, and FAA workload measures.

GRA Inc. (2001) stated that forecasting method used is not the main concern in forecasting aviation demand due to the behaviour of data used. Different types of data require suitable forecasting methods that can satisfy every criteria and its behaviour. When the variables are finalized, only then appropriate methods is selected to develop the forecast for the airport's forecasting. Incorporating an analysis of local and regional socioeconomic is very useful. This includes historical and forecast data on variables such as population, revenue, and employment.

In forecasting, trend analysis is also a part of the process. Trend analysis relies on projecting historic trends into the future. A regression is used with time as the independent variable in trend analysis. This is one of the fundamental techniques used to analyse and forecast aviation activity. It is often used as a back-up or expedient technique but it is highly valuable because of its simplicity when applying. In certain time, trend analysis is used as a reasonable method of projecting variables that would be very complicated and costly to project by other means.

After the list of forecast elements has been identified, appropriate forecasting methods is then selected with gathered data, the methods then need to be applied in order to obtain the forecast of aviation activity. The results evaluation process is essential. A useful step in evaluating the results is to graph key forecast results against historic data trends. This is to determine whether the forecast appear reasonable.

Air passenger traffic forecast provides a concrete basis for planning decisions in air transport infrastructure for civil aviation authorities. For example, the Civil Aviation Authority (CAA) in United Kingdom has the responsibility for regulating the air transport industry in the UK and advising the government's Department of the Environment, Transport and Regions (DETR) on air transport matters (Grubb and Mason, 2001) DETR is then presented the national forecasts periodically for the future demand for air travel, by passenger numbers, at UK airports as a whole since 1980s.

The quantitative forecasting models falls into two categories which are econometric modelling and forecasting but little attention has been paid on time series models in air passenger traffic forecasting. Recent research on modelling time series with complex nonlinearity, dynamic variation, and high irregularity provided two promising directions. Firstly is to establish emerging artificial intelligence models such as artificial neural networks (ANN), support vector machine (SVM) and genetic programming (GP). Secondly is to integrate data decomposition techniques such as empirical model decomposition (EMD) or ensemble empirical mode decomposition (EEMD) into a unified modelling framework to forecast complex nonlinear time series with great fluctuation and irregularity. Xie, Wang and Kin (2013) also did a study on air passenger forecasting using hybrid seasonal decomposition (SD) and least squares support vector regression (LSSVR) approach.

Air transportation has grown considerably around the world due to increment of revenues and populations, and the change of the industry's structure. An example is the competition between high-speed railroad service and air transport (Park and Ha, 2006). Therefore, air passenger forecasting can provide a key input into decision of daily operation management and infrastructure planning of airports and navigation services, and for aircraft ordering and design (Scarpel, 2013). Thus, enhanced forecasting tools are to be used to satisfy the new conditions of airlines and airports. SVM has been proven to possess excellent capability for classification and prediction by minimizing an upper bound of the generalization error (Vapnik, 1995).

For this present study, a similar case of passenger enplanements forecasting is studied but in term for its monthly revenue. The data are distributed by months for each year involved. It second the above statement stating that the need of revenue passenger enplanements forecasting is to assist the aviation activity for it being able to optimize its system or to plan for future expansion or reduction. Thus, makes it a major importance in planning an aviation activity.

The application of wavelet transform for analyzing variations, periodicities, trends in time series has received much attention in recent years (Smith *et al*., 1998). Discrete Wavelet Transform (DWT), a technique with a mathematical origin, is very appropriate for noise filtering, data reduction and singularity detection which makes it a good choice for time series data processing. DWT is a powerful tool for a time-scale multiresolution analysis on time series and has been used to break down an original time series into different components, each of which may carry meaningful signals of the time series (Chaovalit *et al*., 2011). For example, a time series with a frequency of five event occurrences per minute represents an interval (scale) of 12s between events. Since DWT is a data transformation technique that produces a new data representation which can be dispersed to multiple scales, the analysis of the transformed data can also be performed at multiple resolution level. Partal and Kucuk (2006) used a DWT for determining the possible trends in annual total precipitation series.

In this study, an attempt to use a Wavelet-Support Vector Machine (WSVM) conjunction model to forecast the revenue passenger enplanements time series data. SVM offers remarkable generalization performance in many areas such as pattern recognition, text classification and regression estimation (Asefa *et al*., 2006). Feng *et al*., (2010) stated that SVM has become a popular tool in recent years in pattern recognition and machine learning. SVM is used for classification problems and its goal is to optimize "generalization" (Cristianini and John, 2000). Fernandez (2007) used Wavelet-and-SVM-based forecasts to analyse U.S. metal and materials manufacturing industry. Turkoglu and Avci (2008) used the same approach, WSVM, but it was applied towards fuzzy inference system for texture classification. Both studies compared their WSVM model with other benchmark models based on their performance criteria and the outcomes are the same; where WSVM won against other benchmark model such as ARIMA (Fernandez, 2007; Turkoglu and Avci, 2007).

1.2 Problem Statement

In the nascent years of airline Revenue Management (RM) system, American Airlines once simplistically described the developing practice as "selling the right seats to the right customers at the right prices" (Smith *et al*., 1992). This was and still is the goal of Revenue Management. A generation ago, RM could have been considered a narrow area of interest to academics and airline operations enthusiasts; it was somewhat of a curiosity in the heavily regulated industry where airlines had minimal control over fares and booking methods. Today, RM is an indispensable tool, as nearly every carrier in the world seeks to maximize passenger revenue by extracting fares at customers' highest willingness-to-pay (WTP). Following deregulation of the US airline industry in 1978, airlines faced two choices: either adaptation to a new business environment – one without artificial limits on competition – or obsolescence. And just as the nimble airlines once developed creative new RM approaches to confront wholesale changes in the business of a new competitive environment – one where the assumptions previously made about customers' booking habits have been invalidated. The simplification of traditional fare structures is common in today's air transportation marketplace. The crucial question that in RM: what kind of demand can be expected for this flight? Forecasting is the process of quantitatively estimating the expected demand for a particular service and relies on bookings for previous or current similar services (Reyes, 2006).

In this study, an attempt in applying SVM on revenue passenger enplanements forecasting is done. Support vector machine (SVM) is considered one of the soft computational techniques that have been successfully used in various research areas (Vapnik *et al.*, 1996; Yoon *et al*., 2004; McNamara *et al*., 2005; Awad *et al*., 2007; Kaheil *et al*., 2008; Gao *et al*., 2010). This was brought about by the remarkable characteristics of SVM such as good generalization performance, the absence of local minima and sparse representation of solution. Another key characteristic of SVM is that training SVM is equivalent to solving a linearly constrained quadratic programming problem so that the solution of SVM is always unique and globally optimal, unlike other networks' training SVM which requires nonlinear optimization with the danger of getting stuck into local minima. In SVM, the solution to the problem is only dependent on a subset of training data points which are referred to as support vectors. Using only support vectors, the same solution can be obtained as using all the training data points. Although SVMs have good generalization performance, they can be abysmally slow in test phase (Burges, 1996; Osuna and Girosi, 1998). From a practical point of view, the most serious problem with SVM is the high algorithmic complexity and extensive memory requirements of the required quadratic programming in large-scale tasks (Horváth, 2003).

Recently, wavelet transform is widely known for its capability in analyzing variations, periodicities trends in time series. It also allows decomposition of a signal into different levels of resolution scales where required data components can be extracted. Choi, Yu and Au (2011) used DWT to decompose time series data into several scales, where both the coarse and fine parts of the data are obtained. The coarse scales (approximated) reveal the trend, while the fine (detailed) scales tend to be related to seasonal influences and exogenous variables. Usually, the extracted data gain from wavelet transform become input to the model applied. Thus, the ability wavelet transform has become a major reason in improving the ability of model applied predictions.

The term conjunction or hybridization of at least two forecasting models is the trend nowadays. The reason is that it improves the performance of singular forecasting method. Thus, in this study, a conjunction model between Discrete Wavelet Transform (DWT) and SVM is proposed to model the revenue passenger enplanements forecasting. The goal of this thesis is to answer the following question: Does hybrid forecasting lead to revenue passenger enplanements improvement over singular forecasting?

1.3 Objectives of the Study

In view of the problems mentioned, this study is intended to propose a WSVM revenue passenger enplanements estimation for U.S.A. airports for domestic and international flights. The objectives of the study are as follows:

i. To explore the potential application of SVM model for revenue passenger enplanements forecasting

ii. To propose a conjunction model for revenue passenger enplanements by combining DWT and SVM

iii. To compare the performance of the proposed conjunction model with other forecasting models such as singular SVM and SDSVM in terms of MAE, MSE and MAPE.

1.4 Scope of Study

In this study, the data used are secondary data that was obtained from Research and Innovative Technology Administration (RITA), Bureau of Transportation Statistics, T-100 Market and Segment, U.S. Air Carrier Traffic Statistics (www.rita.dot.gov/bts/acts). There are two data sets where one is the domestic flight and the other one is the international flight for revenue passenger enplanements. Both data sets are monthly data dated from January 1996 to December 2012 which total to 204 data for each set.

The SVM models applied in this study are SVM2, SVM4, SVM6, SVM8, SVM10 and SVM12 before each performance is evaluated. For SDSVM, an application of X-12-ARIMA additive decomposition is used for data decomposition before it is combined with SVM. The DWT Daubechies wavelet was chosen as mother wavelet and DWT is decomposed using Mallat algorithm. One, two and three level decomposition of DWT were applied in this study. DWT is later combined with SVM forming a WSVM model. SVM and SDSVM are then used to compare their performance with WSVM. At the final stage, each model's performance in estimating revenue passenger enplanements forecasting is evaluated by its mean absolute error (MAE), mean squared error (MSE) and mean absolute percentage error (MAPE).

1.5 Significance of the Study

This research is to expect that the proposed model WSVM can be used as an alternative model compared to singular SVM and SDSVM because WSVM is an improvement of SVM model and due to its conjunction; it is supposed to outperform

SDSVM because wavelet decomposition is known to be better than seasonal decomposition (SD).

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