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Improving Accuracy of Tourist Demand Estimation of Asian Countries

Arshin Bakhtiari[1,2], Yuhanis Abdul Aziz[*3], Azmawani Abdul Rahman[4], Rosmah Mohamed[5]

1. *Ph.D. candidate, School of Business and Economics, University Putra Malaysia, Selangor, Malaysia .*
2. *Faculty member, Department of Tourism and Hospitality Management, Faculty of Tourism, Higher Education Complex of Bam, Bam, Iran.*
3. *Prof. Dr. School of Business and Economics, University Putra Malaysia, Selangor, Malaysia*
4. *Prof. Dr. School of Business and Economics, University Putra Malaysia, Selangor, Malaysia*
5. *Senior Lecturer School of Business and Economics, University Putra Malaysia, Selangor, Malaysia*

Abstract

Due to the importance of accurate tourism demand estimation, the evaluation of estimating approaches is still on going. To address this challenge, the current study aimed to present a novel estimation statistical approach for modifying ARIMA to compare with two most prominent soft computing approaches, ANN and SVM. $ARIMA_{adj}$ is the modified ARIMA seasonal adjustment that declares a potential replacement to conventional ARIMA. Current study investigated the accuracy of seasonal adjustment on conventional ARIMA and compared its accuracy with ANN and SVM in estimating tourist demand of Asian countries to South Korea. The results show that the modified ARIMA outperform the soft computing approaches for tourism demand estimation accuracy of five out of six source Asian countries. Therefore, it could be concluded although there is no optimal approach to estimate tourist arrivals with certainty, the findings of this study show that the seasonal adjustment in ARIMA would be a worthwhile model to estimate tourism demand of Asian countries.

Keywords: Asian Countries; ARIMA; Soft computing; South Korea; Tourism demand**.**

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**Corresponding author:*yuhanis@upm.edu.my
http://orcid.org/0000-0001-9839-3305
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1. Introduction

Tourism is a major industry that effects a country's economy in various sectors, such as airlines, hospitality, and restaurant services. Since tourism and hospitality industry include perishable services, the estimation of tourism demand (TD) has received extensive interest from the tourism services providers. Therefore, modeling TD has received considerable attention among researchers worldwide. Moreover, the accurate estimating of TD would facilitate managerial decisions not only in public but also in private sectors. Zhang et al. (2020) described that TD estimation had been a hot topic over the last decade and the estimating model's selection is the substantial criteria that will affect the accuracy of estimates. Several approaches have been used to estimate the TD by different researches over the past decades (Hopken et al., 2020; Jiang et al.,2020; Kulshrestha et al., 2020; Law and Au, 1999; Lim & McAleer, 2002; Wang & Hsu, 2008; Xin Xu et al., 2016; Yao & Cao, 2020).

Generally, tourism demand estimating methods can be divided into two quantitative and qualitative approaches. Some methods, such as Delphi and consensus, which are based on experience or understanding of a specific market, belong to qualitative methods (Kulshrestha et al., 2020; Witt & Witt, 1995). However, most researchers used quantitative approaches to estimate tourist arrivals in various destinations (Li et al. 2005; Song & Li, 2008; Park et al., 2017; Vatsa, 2020; Wu et al., 2017). The quantitative estimating approach is performed in causal econometric and non-causal time-series approaches. Econometric methods are casual and time-series. In the causal econometric approach, any causal relationship between the variables of TD and its influencing factors is identified.

Furthermore, an autoregressive (AR) based model such as moving average (ARMA), integrated moving average (ARIMA), and seasonal autoregressive integrated moving average (SARIMA) time-series models are the most common non-causal approaches (Álvarez-Díaz et al., 2018; Chu, 2009; Kulendran & Shan, 2002; Kumar et al., 2020; Petrevska, 2017;). Cleveland and Tiao (1976) and Butter et al. (1985) investigated the advantage of using modified ARIMA models and showed that by deleting the seasonal component in a time-series, other components could be examined more accurately. However, determining the productivity ability of modified ARIMA models on conventional ARIMA estimation accuracy has been the gap of TD studies. Artificial Intelligence (AI) and soft computing models are also well known in non-causal time-series approaches (Law et al., 2019) and have been advanced in TD estimation (Jiao & Chen, 2019; Kulshrestha et al., 2020). Many researchers in the last decade have focused on using these approaches to estimate time-series of tourism demand due to the greater accuracy of soft computing and data-driven approaches.

Various soft computing approaches in tourism demand estimation applied in the researches, are artificial neural network (ANN) (Berenguer et al., 2015; Claveria et al., 2015; Law et al., 2019), support vector machines (SVMs) (Pai et al., 2006; Mei, 2015), fuzzy time-series models (Aliyev et al., 2019; Huarng et al., 2012) and genetic algorithms (GAs) (Hong et al., 2011). Among the artificial intelligence models, artificial neural networks (ANNs) can be considered as a suitable alternative to conventional statistical methods (Zhang et al., 1998). Whereas, the basis of the SVM algorithm is a statistical learning hypothesis and the principle of structural risk minimization, which had been used for modeling the non-linear system (Vapnik, 1998). Furthermore, the SVM training process is a quadratic programming step whereby a globally perfect solution can be achieved. Therefore, SVMs may obtain more accurate results for tourism estimation than other approaches (Xin Xu et al., 2016). However, by reviewing the existing related literature, considering the monthly frequency of data for estimating TD has been limited.

A review of the tourism demand literature has shown that South Korea as a major tourist destination has received relatively less attention among English-language published articles (Zhang et al., 2020). There have been limited studies on TD of South Korea. However, statistical data from the Korea Tourism Organization (KTO) shows that South Korea had nearly 17.5 million incoming travelers and it displays an increasing trend since the year 2000. Besides, based on Shi and Li (2017) declaration, South Korea has become one of Asia's most popular tourist destinations over the last decades. Korea statistics of tourism in 2020 shows that 78.3% of total of international tourist arrivals were from east Asia and pacific. China with 27.6% and Japan with 17.5% of total arrivals have been the most important countries for tourist inflow into Korea. In addition, Hong Kong, Thailand, Malaysia and Singapore are placed in top ten tourist source countries to South Korea (KTO, 2021). There have been few studies on estimating TD of these six countries to South Korea (Kim, 2002; Park & Jei, 2010, Park et al., 2016, Shi & Li, 2016).

The main objective of this article is to determine if the new modified ARIMA models improve the overall predictive ability of conventional ARIMA estimation accuracy compare with ANN and SVM as soft computing approaches in TD estimation. In addition, this study aims to enhance the accuracy of South Korea inbound TD estimation from the Asian countries and will add to the literature by investigating the optimal accurate structure of ARIMA statistical models and soft computing ANN and SVM models.

2. Literature review

Tourism industry has been placed in the centre of economic growth and tourism demand modeling has played a crucial role in tourism economic researches (Dogru et al., 2019; Zhang et al., 2020). There are TD modeling with different techniques in prior studies. To this effect, Zhang et al. (2020) reviewed the tourism demand forecasting researches and indicated that ARIMA has been the most common prediction approach in tourism demand modeling. The intelligence approaches such as ANN placed in the third position after econometric models. Also, they showed that recent progress in tourism demand modeling researches has concentrated on machine learning-based models. Even though many quantitative forecasting methods have been generally studied, highly precise forecasting models have not been produced (Xin Xu et al., 2016). In recent studies, new approaches have received more attention to improving estimation accuracy.

Although time-series and econometric models have been mostly used in different studies, AI-based models have been used more over the last years (Jiao & Chen, 2019). Yao & Cao (2020) proposed the ANN method for forecasting US inbound traveller and declared that there were few studies which had compared conventional economics models with machine learning-based tourism demand estimation. The advantage of the ANNs approach is that they can model almost any linear or non-linear phenomenon and is powerful in estimating continuous variables (Hornic et al., 1989). According to their learning strategies, ANNs are classified into three types: supervised learning, non-supervised learning, and associative learning. Well-known supervised learning architectures include the multi-layer perceptron (MLP), radial basis function (RBF), and Elman network. Each of these architecture indicates a various learning pattern and therefore handles data in a different set (Claveria et al., 2015). To estimate tourism demand,

ANN architecture is usually used based on supervised learning with MLP architecture (Law, 2000; Tsaur et al., 2002; Claveria and Torra, 2014; Claveria et al., 2015). Another alternative method is RBF architecture. RBF architecture consists of a linear equation of radial basis functions such as kernels centred at several centroids that checks the volume of the input space displayed by a neuron (Bishop, 1995).
Furthermore, Xin Xu et al. (2016) proposed a structure to derive fuzzy rule from SVMs and showed that the SVM approach is a way to improve the accuracy of tourism arrivals estimating. They concluded that the SVM method had better performance for estimating number of tourist arrivals from the US, Australia, Canada, France, Germany, the UK, Japan, Korea, Taiwan, and China to Hong Kong. They also suggested a general future testing of SVM approach in several travel destinations to improve their realization of relationships between SVM, conventional approach, and incoming tourism. The Tsaur and Chan (2014)'s results in applying the SVM to estimate the Chinese TD to Taiwan demonstrated that the proposed approach was performed better than the other methods (regression analysis and exponential smoothing).
During the last two decades, because of the non-linear properties of tourism data, the use of ANNs and SVMs has been considered in a wide range of applications to solve the tourism problems (Mei, 2015; Xin Xu et al., 2016; Ali & Shabri, 2016). Although these approaches are computationally accurate, SVMs and ANN are mainly "black box" approaches with low achievement and understandability. Some articles have cited the ANN as a better approach than the statistical approaches, and some other researchers have argued that the SVMs offer a more reliable performance than ANNs. However, the number of published articles on TD modeling to a specific destination using ANNs and SVMs approaches are limited (Aslanargun et al., 2007). According to the literature review, there is no single AI accurate approach to estimate tourism demand. Also, despite the increasing interest in AI for estimating time-series, evaluating and comparing the training algorithm of different neural network architectures for increasing the accuracy of tourism demand estimating has not been answered.
On the other hand, conventional ARIMA approach has been suggested to estimate tourist arrivals to Australia from Hong Kong, Malaysia, and Singapore (Lim and McAleer, 2002) and it outperformed ANN in forecasting overnight stays in Catalonia (Claveria and Torra, 2014). However, The Palmer et al. (2006), Cho (2003) and Law (2000) study's

results indicated that the ANN outperformed the statistical approaches and Hopken et al. (2020) concluded that the relative superiority of each of these approaches in different researches had given different results. Butter et al. (1985) declared that the ARIMA approach does not always create an individual model for a time-series. They referred to other studies (Bell and Hillmer, 1984; Cleveland and Tiao, 1976) and investigated the sensitivity of the different seasonal adjustment methods to suggest the best ARIMA model. Reviewing the literature indicates that applying the modified ARIMA is the gap of TD studies. China railway passenger traffic in Chinese language (Wang and Wang, 2013) and flight incident (Zhao et al. 2019) are the limited existing researches, whereas employing seasonal adjustment in ARIMA to improve the accuracy of the statistical estimation approach is novel for tourism demand estimation modelling.

3. Research Method

3.1. Data set

This study uses a number of monthly six major Asian source countries (China, Hong Kong, Japan, Malaysian, Singapore, Thailand) to South Korea from January 2003 to December 2019 with a total of 192 observations for each one. These long-term data were collected based on availability and validity and were taken from the Korea Tourism Organization website (https://kto.visitkorea.or.kr/eng.kto). Figure 1 shows the time-series of TD for each of the source countries for the observation period and obviously reveals a strong non-linearity, some monthly fluctuations, and an upward trend of tourist arrivals. The data of this study divided into two parts of training (75% of the data sets) and test (25% of the data) for modeling. In this study, the ANN has been implemented in the Neural Network Toolbox in MATLAB ver. 9.4.0.813654, R2018 software. Similarly, this software was used to write computational codes and develop learning and simulating algorithms for the SVM approach.

Furthermore, for selecting an appropriate ARIMA model for estimating a univariate time-series, the Box–Jenkins method was used. The data were processed using the E-views ver. 9 and SPSS ver. 24. In the time-series modeling framework, we need to consider the proper lag-time of the data series. Figure 2 illustrates the-time series matrix based on monthly tourist arrivals with 3-lagged years. In this matrix, the inputs are shown as $x_{i,t}$ that represents tourist arrivals at i^{th} month $(i = 1.2 \ldots .12)$ in the time t.

Moreover, $x_{i.t-1}$, $x_{i.t-2}$, and $x_{i.t-3}$ are the number of the tourist arrivals at i^{th} month in the time $t-1$, $t-2$, and $t-3$, respectively. The outputs of the matrix $(x_{1.t}\ , x_{2.t}\ , \ldots, x_{12.t})$ are estimated the number of tourist arrivals at the corresponded months of the year in the time t based on $t-1$, $t-2$, and $t-3$.

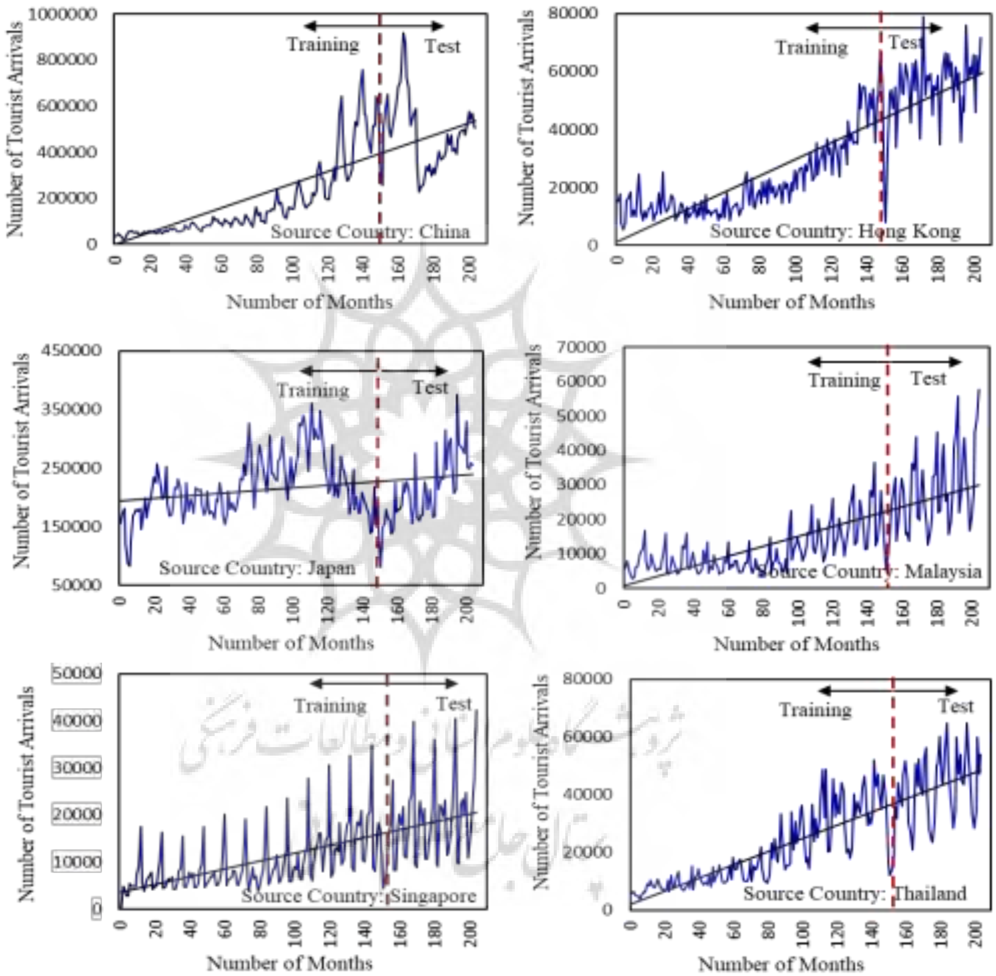


Fig 1. Monthly tourist arrivals from each of the six Asian major source countries to South Korea from 2003 to 2019.

$$\begin{array}{c}
\xleftrightarrow{\qquad\qquad\qquad\qquad\text{Input}\qquad\qquad\qquad\qquad} \qquad \xleftrightarrow{\text{Output}} \\
\begin{bmatrix}
X_{1,1} & X_{1,2} & X_{1,3} & X_{1,4} & \cdots & X_{1,t-3} & X_{1,t-2} & X_{1,t-1} & X_{1,t} \\
X_{2,1} & X_{2,2} & X_{2,3} & X_{2,4} & \cdots & X_{2,t-3} & X_{2,t-2} & X_{2,t-1} & X_{2,t} \\
X_{3,1} & X_{3,2} & X_{3,3} & X_{3,4} & \cdots & X_{3,t-3} & X_{3,t-2} & X_{3,t-1} & X_{3,t} \\
\vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\
X_{12,1} & X_{12,2} & X_{12,3} & X_{12,4} & \cdots & X_{12,t-3} & X_{12,t-2} & X_{12,t-1} & X_{12,t}
\end{bmatrix}
\end{array}$$

Fig 2. Structure of the inputs and outputs matrix corresponding to the applied AI approaches

3.2. Data normalization

To use understudy approaches, the normality test based on Kolmogorov and Shapiro test was conducted for each of the source country series, separately. At a significant level α=0.05, the null hypothesis that the series is normally distributed was tested for each series. The hypothesis of the normal distribution is not rejected (p values >0.05). It is also required to scale the data between zero and 1 for preventing the problem associated with extreme values in the applied models. All the data were normalized using equation 1 to improve the models during the training phase.

$$x_i = 0.8\left(\frac{x - x_{min}}{x_{max} - x_{min}}\right) + 0.1 \quad (1)$$

where x_i is the normalized value of each variables for each sample i; x is the actual value of each variables and x_{min}, x_{max} are the minimum and maximum rates of the observed values, respectively. All the input and output variables were normalized to have zero mean and unit variance.

3.3. Explanation of chosen approaches

Two soft-computing approaches, ANN and SVM, and one of the most common statistical non-casual approaches, ARIMA, were used in this study to model South Korea tourist arrivals. So, a summary of these approaches is provided below.

3.4. ANN approach

All ANNs utilize mathematical and statistical simulation that structures are inspired by biological neurons systems of the human brain. The main features of these approaches are parallel processing and distributed memory, which result in robustness and tolerance to error and noise. The development of ANN approaches was based on investigating the interrelation between input and target variables. As a rule, the structure of an ANN is composed of numerous neurons that are structured in different layers, i.e., input layer, hidden layer, and an output layer (Figure 3).

Since there is no defined method for determining the optimal number of hidden layers or hidden neurons, so their determination is usually troublesome. A neuron contains multiple inputs and a single output. However, the number of neurons in the output layer is equivalent to the number of estimated values. In order to communicate between each layer and neuron a communication link is used, each of which is assigned a 'synaptic weight'. Each of these weights is independent and contains the knowledge or data that the ANN has about a particular problem. ANNs learn from the training data by adjusting the connection weights. The task of a neuron in the hidden layer is to receive the input signals (x_i) from neighboring neurons. The input signals are weighted by the interconnection weights (ω_{ij}). By summing these weights, the net input values for the neuron in the hidden layer are obtained. Then, the activation threshold of the neuron (j) which shown by (θ_j) is added to the net input values. Then, by applying a non-linear activation function (usually a sigmoid function) (equation 2) to the net input, the output value (y_j) is computed and sent to subsequent neurons (Haykin, 1998).

$$y_j = f\left(\sum(\omega_{ij}.x_i)\right) = \frac{1}{1+e^{-\left(\sum \omega_{ij}.x_i\right)}}$$

(2)

where ω_{ij} is the connection weight joining the i^{th} neuron in the input layer with the jth neuron in the hidden layer, x_i is the value of the i^{th} neuron in the input layer, and $f(.)$ is an activation function.

There is a range of ANN architectures designed and applied in various fields of the tourism industry. Among different them, feed-forward network with the BP training is widely used, which is able to detect the nonlinear pattern (Burger et al., 2001). A comprehensive description of neural networks and their algorithm was provided by numerous researchers, providing valuable information (Haykin, 1998). Therefore, in the next section, only the methods and algorithms used in this study are described.

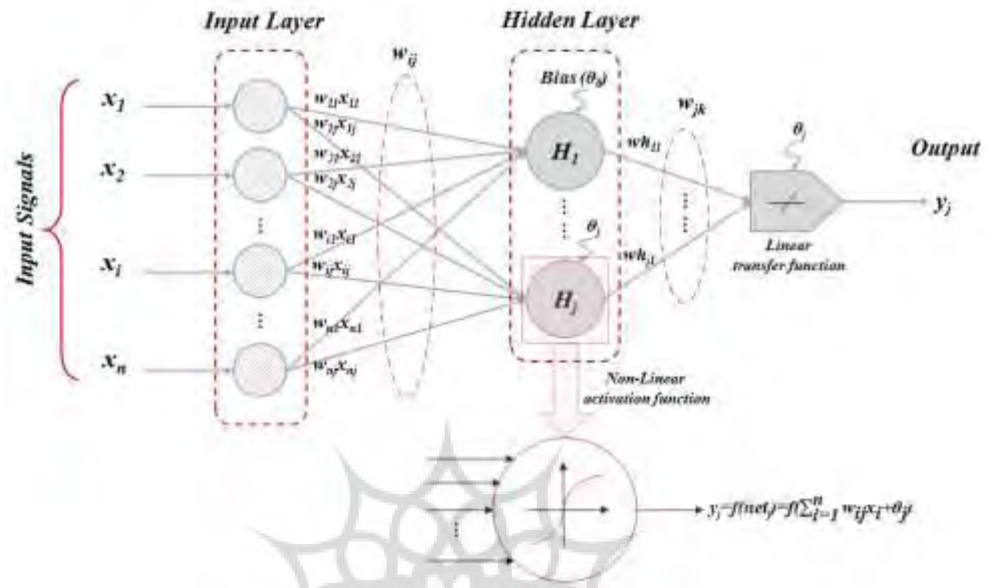


Fig 3. The architecture of a feed-forward three-layer neural network of time-series modelling

3.5. Multi-layer perceptron (MLP)

The multi-layer perceptron (MLP) architecture is the neuronal network model most commonly applied in time-series analysis related to tourism (Law, 2000; Palmer et al., 2006; Claveria, et al., 2015). The MLP uses a simple perceptron model as a supervised neural network. This architecture is built from an input layer, one or more hidden layers, and an output layer. In this type of network, data are always passed from the input layer to the output layer. Each input neuron indicates one of the independent parameters, whilst the output neurons indicate dependent and estimating variables. The capacity of the MLP network to achieve an appropriate approximation of output is determined by the number of neurons used in the hidden layer. The MLP network usually consists of two phases of running and training (learning). In the first phase, the input pattern is presented to the trained network, and this is done through various layers and neurons until getting an output.

In the second phase, the network synaptic weights are frequently modified based on a training set. In this phase, the error between the output generated

by the network and the expected output is minimized. In this study we used the MLP description proposed by Bishop (1995):
$$y_j = \theta_0 + \sum_{j=1}^{k} \omega_{jk} \times f(net_j) \times \left[\sum_{i=1}^{n} \omega_{ij} x_{t-i} + \theta_j\right]$$
(3)
where y_j is the output vector of the MLP at time$t$, $f(net_j)$ is the non-linear activation function in the hidden layer, x_{t-i} are the input values at time $t-i$, which i is the number of lags for introducing the context of the original observation, n is the number of neurons in the hidden layer, ω_{ij} are the weights of neuron j connecting the input with the hidden layer, and ω_{jk} are the weights connecting the output of the neuron j at the hidden layer with the output neuron.
The estimation of the parameters of the network (ω_{ij} and ω_{jk}) can be done using different numeric algorithms, such as Quasi-Newton search or line search, which can be obtained from Bishop (1995). In the MLP network, a well-known algorithm used for training is BP algorithm, which is the supervised learning algorithm for the training phase base on the Widrow-Hoff training rule, as suggested by Rumelhart et al. (1986). The purpose of applying this algorithm is to minimize the sum of square errors by the weights and biases adjustment, which is done by propagating the error back at each step. To do this, various researchers have proposed using different BP algorithms based on different optimization algorithms. In this paper, two algorithms of Levenberg-Marquardt (LM) and Bayesian-regularization (Br) have been used to speed up the training phase. These algorithms have the best convergence to a minimum of mean square error and are suitable for neural network training with time series of small and medium data sets.

3.6. Support Vector Machine (SVM)
As a machine learning approach, SVM developed to resolve both classification and regression issues and different from the conventional regression analysis. This approach was first presented by Vapnik (1995) based on the classification technique, which was used as a linear model to divide the original data into a feature space through a non-linear mapping function. In other words, this approach is mapping the main sample space to a high-dimensional linear space through a non-linear transformation in this new space to seek the optimal linear classification surface. To eliminate classification problems, the boundary between two opposing classes and the risk of a structure maximized and minimized, respectively. On the other

hand, to use SVM in the regression equations, we should reduce the number of errors in the training phase. For this purpose, this approach uses non-linear systems to find the most suitable hyperplane. Consider a training set of data $D = \{x_i . y_i\}_{i=1}^{n}$ with input vectors X_I=$\{X_I^1 . \dots . X_I^n\} \in R^n$and target labels $y_i \in \{-1. +1\}$. The generic linear function which was used to formalize SVM is as equation 4.

$$f(x) = \omega . \phi(x) + b$$

(4)

The SVM binary classifier should satisfies the following condition:

$$y_i[\omega^T . \phi(x_i) + b \geq 1]. \quad i = 1. \dots . n$$

(5)

where ω is weighting factor, b represents the bias, which is constant, $\phi(x)$ indicates the non-linear function maps the input vectors into a high-dimensional feature space. The target is to estimate the values of ω and b. These coefficients can be estimated by regularization risk function:

$$R_{SVM}(f) = c \times \frac{1}{n} \sum_{i=1}^{n} L_\varepsilon(f(x_i). y_i) + \frac{1}{2} \|\omega\|^2$$

(6)

$$L_\varepsilon[f(x) - y] = \begin{cases} |f(x) - y| - \varepsilon. & |f(x) - y| \geq \varepsilon \\ 0 & . others \end{cases}$$

(7)

By combining equations 5 and 6:

$$R_{SVM}(f) = c \times \frac{1}{n} \sum_{i=1}^{n} (y_i \times \omega^T \times \phi(x_i) + b) + \frac{1}{2} \|\omega\|^2$$

(8)

The equation 6 is divided in to two terms. The first term, $\left\{c \frac{1}{n} \sum_{i=1}^{n} L_\varepsilon(f(x_i). y_i)\right\}$ indicates the empirical risk and the second term, $\left\{\frac{1}{2} \|\omega\|^2\right\}$ indicates regularization which measures the smoothness of the function. The empirical risk measured by Vapnik's ε-insensitive loss function $[L_\varepsilon(f(x_i). y_i]$ which indicates the empirical error (Vapnic, 1995). This function represents the decision function of the sparse points. In other words, the loss function illustrated that errors below ε are not penalized. The constant of c is the penalty parameter of the error term, which evaluates the balance between the empirical risk function and the regularization term. In order to find the coefficients of ω and b, the positive slack variables ξ_i and ξ_i^* should be used to minimize the equation 9. These variables represent the distance of the observed values from the boundary values.

$$R_{SVM} = \frac{1}{2}\|\omega\|^2 + c\sum_{i=1}^{n}(\xi_i + \xi_i^*)$$
(9)

The constraint condition is as follows:

$$f(x) = \begin{cases} \omega^T \times \phi(x_i) + b - y_i \leq \varepsilon + \xi_i \,.\ \xi_i \geq 0 \\ y_i - \omega^T \times \phi(x_i) - b \leq \varepsilon + \xi_i^* \,.\ \ \xi_i^* \geq 0 \end{cases}$$
(10)

Finally, after applying the Lagrangian and optimal conditions, the above problem can be transformed into a non-linear regression function.

$$f(x) = \sum_{i=1}^{n}(\alpha_{i-}\alpha_i^*)(\phi(x_i).\phi(x)) + b = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\, k(x_i.x) + b$$
(11)

where α_i and α_i^* are the Lagrange multiplier, $k(x_i.x)$ is a kernel function that satisfies Mercer's theorem (Haykin, 1999), introducing an inner product in some transformed space. One of the common kernel functions widely used in the different researches is the Radial Basis Function (RBF) (Shawe-Taylor & Cristianini, 2000):

$$k(x_i.x) = exp[-\gamma|x - x_i|^2]$$
(12)

where γ is a kernel's parameter. The general performance of SVM models depends on a proper setting of γ and c.

3.7. Autoregressive Integrated Moving Average (ARIMA) Model

Autoregressive approaches are considered a popular type of model for analysing time-series (Box et al., 1994). These approaches presented the numerical transformation of the non-stationary into stationary time-series by a differentiation procedure determined by order of integration parameter. A random variable with a time-series nature is assumed to be stationary if its statistical characteristics as average and variance are stable over time. A stationary series is considered to have no pattern, which means its variations around the average will have a steady amplitude. The equation of time-series is a linear equation for stationary time-series data. One of the well-known equations proposed by Box and Jenkins (1970) is the Autoregressive moving average (ARMA) method. The ARMA methods combine two autoregressive (AR) and moving average (MA) models.

In the autoregressive models [AR(p)], p indicates the number of autoregressive values (number of autoregressive delays) $(x_{t-1}.x_{t-2}.\dots.x_{t-p})$ for estimating the values of a variable (x_t), and include a random disturbance (ε_t). In the moving average models [MA(q)], q denotes the number of moving average values and the model estimates the variable (x_t) based on a number (q) of prediction errors of past values ($\varepsilon_{t-1}.\varepsilon_{t-2}.\dots.\varepsilon_{t-q}$) . The combination of the AR(p) and MA(q) obtains more flexible models that defined ARMA (p, q) models. The stationarity of the data series is necessary for the application of all these models. Box and Jenkins (1976) devised the numerical transformation of the non-stationary time-series into a stationary one. They proposed a differentiation procedure distinguished by order of integration parameter [number of times of differentiation (d)].

In other words, parameter d represents the number of times needed to bring the series to a statistical balance form. This transformation led to the creation of Auto-Regressive Integrated Moving Average (ARIMA) methods, being called the (p, d, q) model, too. The (p, d, q) is called the non-seasonal part of the model, with its regular autoregressive terms (p), moving average (q), and the number of non-seasonal differences needed for stationarity (d) components. The general format of a stationary ARIMA (p, d, q) model for observed data series (x_t), represented by equation 13.

$$x_t = \sum_{j=1}^{p} \phi_j x_{t-j} + \varepsilon_t - \sum_{k=1}^{q} \theta_k \varepsilon_{t-k} \quad (13)$$

Where $\phi_1.\phi_2.\dots.\phi_p$ are the AR coefficients, $\theta_1.\theta_2.\dots.\theta_q$ are the MA coefficients, and ε_i is the residual series.

In the literatures, an ARIMA model is registered using different symbols. For instance, for the first-order autoregressive model, ARIMA (1, 0, 0): $x_i = \mu + \phi_1 x_{t-1} + \varepsilon_t$ or $(1 - \phi_1 B)x_t = \mu + \varepsilon_t$ where μ is the model constant, and B is the backshift operator. Managing the missing values in the observed data is one of the main advantages of the ARIMA model. Although the normal distribution of data is one of the main assumptions, the data may be stationary or non-stationary. In non-stationary series, the differencing method is used for the transformation process (Box et al. 1994). On the other hand, sometimes in the ARIMA time-series approach, a seasonal component prevents accurate analysis. The literature shows that it is possible to separate an ARIMA time-series into a seasonal and non-seasonal component (Butter et al., 1985). Therefore, the desired series can be examined by ignoring the seasonal component. A modified method called ARIMA seasonal adjustment ($ARIMA_{adj}$) has been used to remove the seasonal property (Cleveland & Tiao, 1976). Since the conventional ARIMA models include the seasonal parts in our time-series data, we can use the modified models. The modifying process of the ARIMA seasonal adjustment in this study is illustrated in figure 4.

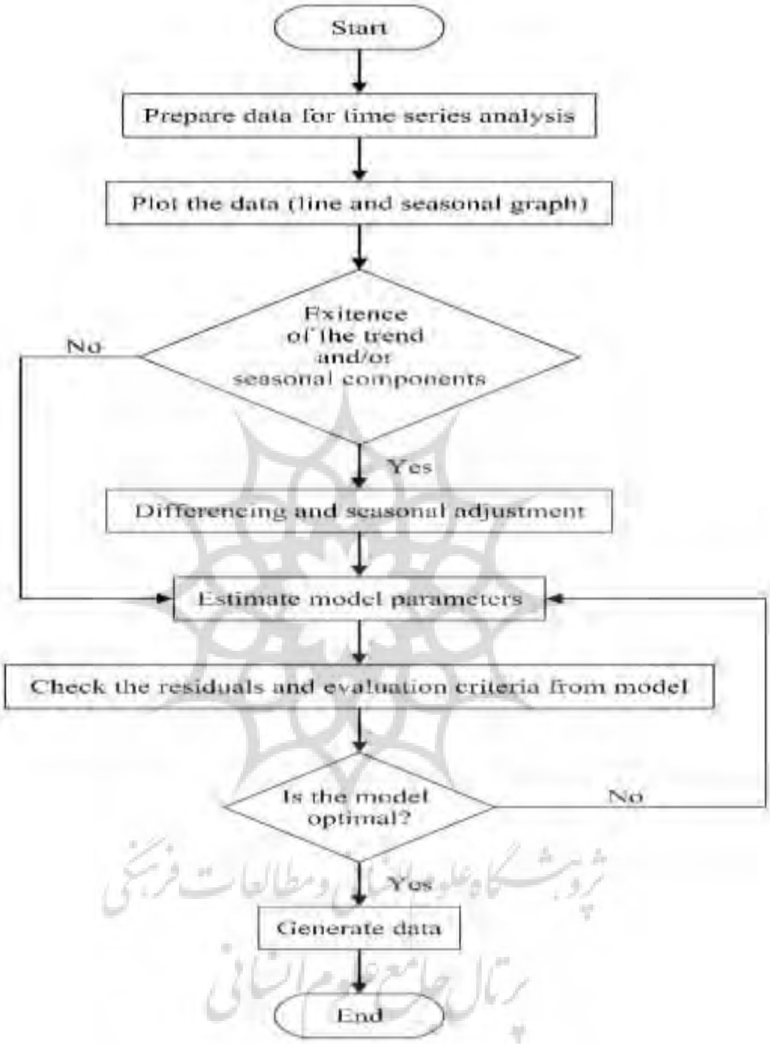


Fig 4. A brief flowchart of the ARIMA seasonal adjustment algorithm used in this study (Own elaboration)

3.8. Models Evaluation

Since there are uncertainties in the estimates, the models' tourist arrival may not exactly correspond to reality. Different indices are recommended to assess the performance of the models in the training and testing phases, which is generally considered as a goodness of fit (Shcherbakov et al., 2013). Therefore, the comparison between ANN and SVM approaches was made by considering three statistical indices including the coefficient of determination (R^2), root mean square error ($RMSE$), and mean absolute error (MAE), which are defined as equations 14 to 16.

$$R^2 = \left[\frac{\sum_{t=1}^{n}(y_t - \bar{y})(\hat{y}_t - \bar{\hat{y}})}{\sum_{t=1}^{n}(y_t - \bar{y})^2 . \sum_{t=1}^{n}(\hat{y}_t - \bar{\hat{y}})^2}\right]^{\frac{1}{2}}$$
(14)

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y_t})^2}$$
(15)

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y_t}|$$
(16)

where y_t and $\hat{y_t}$denote the observed and modeled values at time point t, respectively; $\bar{y}$ and $\bar{\hat{y}}$ are the means of observed and modeled values; respectively, and n is the number of observations.

Given the performance and application of each of these indices, R^2 indicates the percentage of the total variance in the observed tourist arrivals explained by the estimated tourist arrivals. For a perfect model, this coefficient is close to one. However, this coefficient is insufficient because it is obtained based on linear regression and is sensitive to outliers. Therefore, other performance indices such as $RMSE$ and MAE have been employed to understand better the efficiency of the models used.

4. Results

The empirical results from the performance of the three estimation approaches, ANN, SVM, ARIMA and modified ARIMA, were learned for the TD from the major Asian source countries to South Korea.

4.1. ANN and SVM results

Different models and activation functions (log-sigmoid and tan-sigmoid) with various neuron structures were tested to achieve ANN's optimum model. The training and test data were used to evaluate and compare the performance of the networks. The neurons effect number in the hidden layer and the type of training algorithm was considered for each of the six source countries. The number of neurons in the hidden layer differed between 2 and 15. Eventually, the optimal number of the hidden neurons was selected during the training phase based on the lowest performance criteria of the RMSE value. The LM and Br algorithm results in the training phase were presented in figure 5 separately. As shown, the LM algorithm had the lowest RMSE value in the different number of hidden neurons for each of the six understudy countries.

Fig. 5. Levenberg-Marquardt (LM) and Bayesian-regularization (Br)algorithms on the ANN training phase for the understudy source countries to South Korea

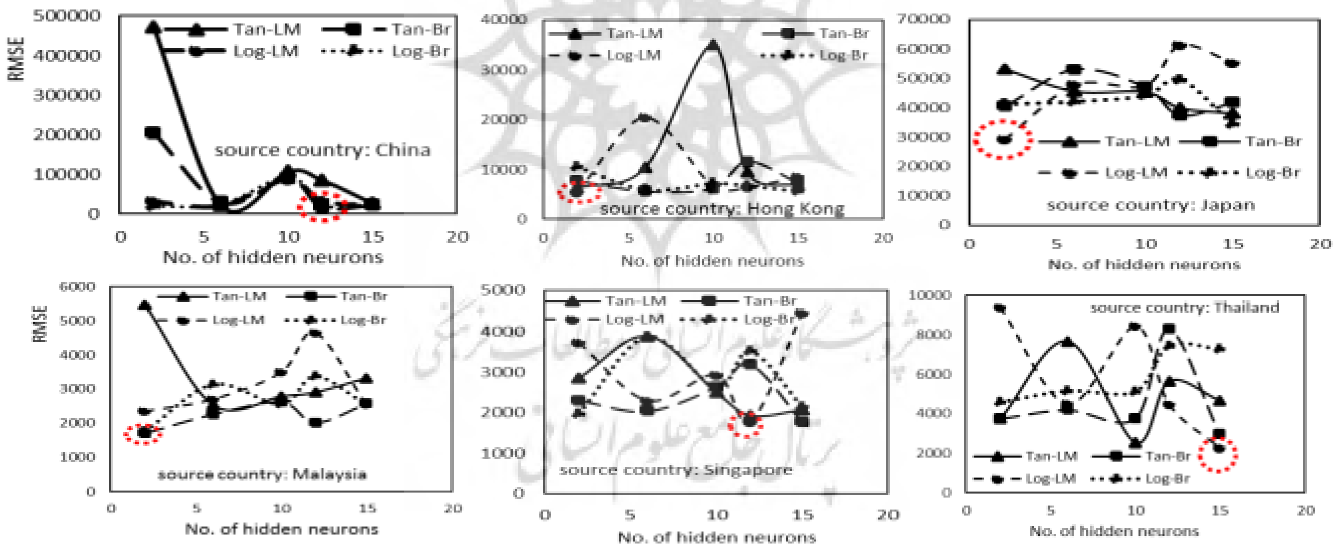


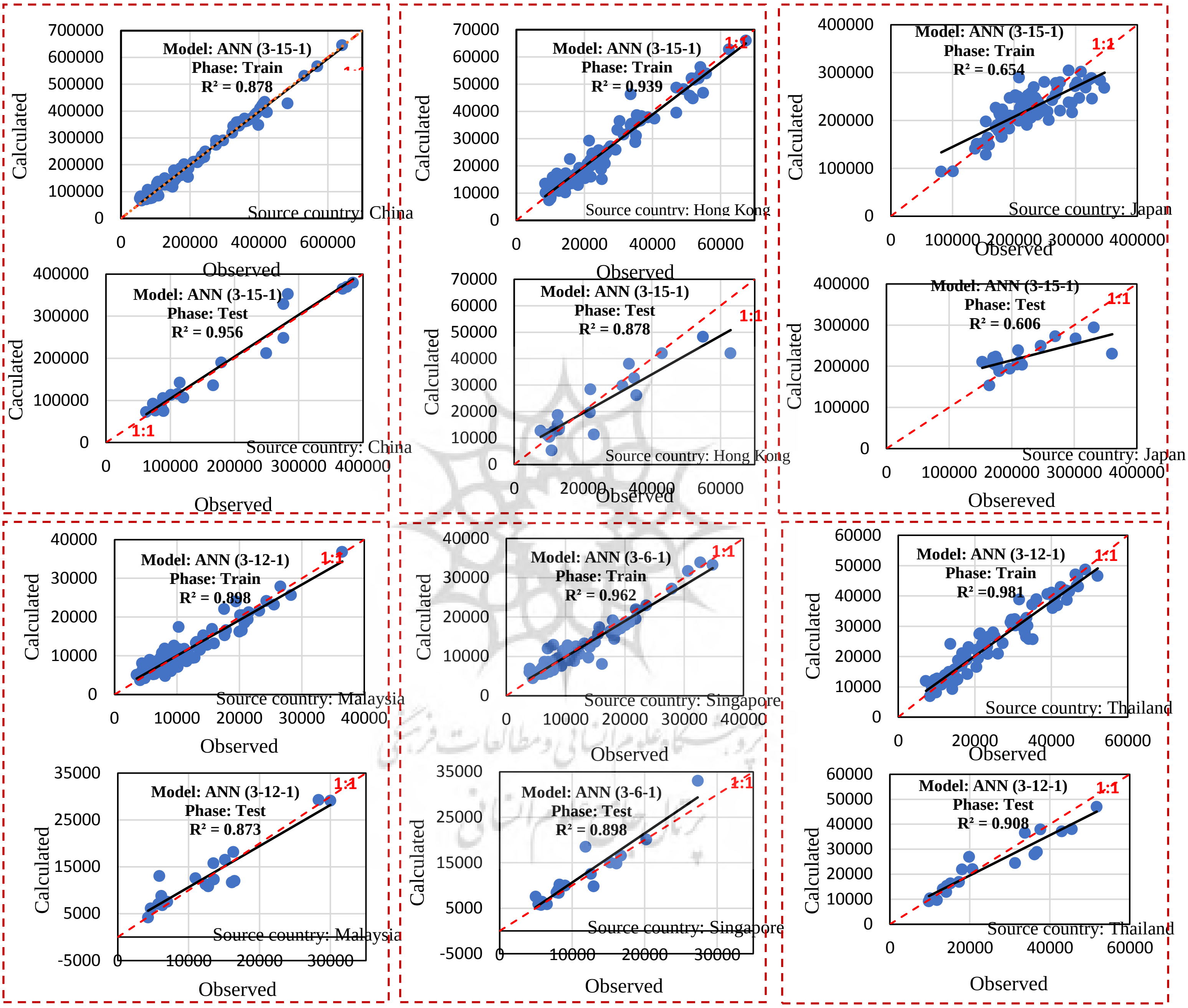
Table 1 demonstrates the structure of the neurons with higher accuracy for all the six source countries separately. Since an ANN with a hidden layer seems enough to explain a non-linear relationship between the TD time-series of prior and future times, this study employed one hidden layer with the number of hidden neurons. Table 1 shows the ANN's optimum models, with different activation functions (log-sigmoid and tan-sigmoid). The training and test data were used to evaluate and compare the performance of the networks. According to the results, the ANN (3-15-1) with the LM training algorithm was determined as the optimal network algorithm for China, Hong Kong, and Japan and displays the same activation functions for China and Hong Kong. Furthermore, the ANN (3-12-1) with the LM algorithm, with different activation functions, appears the least errors for Malaysia and Thailand. The LM logarithm, ANN (3-6-1) and log-sig activation function for Singapore shows dissimilar results comparing to the other five source countries. Based on the overall ANN results, China, Singapore, and Thailand show higher than 90 percent value of the R^2 for both in the training and testing phases. However, among these three source countries, the least RMSE and MAE for both phases belong to China and Singapore. It is also clear that the least accuracy of the ANN estimation models belonged to Japan. Additionally, after 43 times algorithm running, the parameters of γ and c were optimized in the SVM approach. We started with $\varepsilon = 0.1$ and used a grid search to select optimal values for c and γ and chose the pair (γ, c) that obtained the best performance on the testing data. This procedure continued for a few cycles until the optimum values of the parameters were selected. Next, we tried several values in the range of 0.1-0.4 and determined the amount that made SVM perform the best on the testing data. Table 1 also shows the overall optimized results of SVM estimation models. As it has shown, the optimal parameters determined were $c = 500$, γ=1.0, and $\varepsilon = 0.1$ for China, Malaysia, Singapore, and Thailand. However, $c = 600$, γ=1.0, and $\varepsilon = 0.1$ were satisfactory results for Hong Kong and also Singapore. Finding demonstrates that Japan's optimal parameters differed from other source countries ($c = 600$, γ=1.0 and $\varepsilon = 0.1$). After the user-defined parameters were selected, the SVM was trained on the data. The values obtained were underestimated in both the training and testing phases. Overall, there were lower accuracy and higher estimation errors for the SVM models than the ANN models in TD estimation of each understudy country. Moreover, both ANN and SVM have the least accuracy for estimating TD from Japan to South Korea.

Table 1. The comparison of the ANN and SVM models in the training and testing phases to estimate tourist arrivals from the major Asian source countries to South Korea

Source Country Model	Training algorithm	Activation function	Training			Testing		
			R^2	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**
China								
ANN (3-6-1)	Br	tan-sig	0.982	16663	13039	0.958	28123	20402
ANN (3-15-1)	LM	log-sig	0.980	19728	14784	0.955	22081	17671
ANN (3-15-1)	**LM**	**tan-sig**	**0.987**	**15728**	**11688**	**0.956**	**22032**	**19103**
SVM (500, 1.0, 0.1)	---	---	0.918	67633	57680	0.652	95095	80244
Hong Kong								
ANN (3-10-1)	LM	tan-sig	0.913	4445	3288	0.879	34961	12192
ANN (3-15-1)	LM	log-sig	0.787	7064	4524	0.786	8550	5882
ANN (3-15-1)	**LM**	**tan-sig**	**0.939**	**3651**	**2744**	**0.878**	**6837**	**4733**
SVM (600, 1.0, 0.1)	---	---	0.765	7442	5209	0.232	35259	27073
Japan								
ANN (3-6-1)	LM	log-sig	0.512	35088	27540	0.432	47804	40417
ANN (3-12-1)	LM	log-sig	0.637	35347	27279	0.518	61320	47541
ANN (3-15-1)	**LM**	**log-sig**	**0.654**	**31905**	**24769**	**0.606**	**55401**	**37822**
SVM (600, 2.0, 0.01)	---	---	0.649	30937	21168	0.537	56792	37398
Malaysia								
ANN (3-6-1)	LM	tan-sig	0.893	2192	1699	0.869	2538	1918
ANN (3-10-1)	LM	log-sig	0.887	2195	1702	0.842	2497	1954
ANN (3-12-1)	**LM**	**tan-sig**	**0.898**	**2104**	**1582**	**0.873**	**2147**	**1590**
SVM (500, 1.0, 0.1)	---	---	0.815	2242	1625	0.801	2582	1925
Singapore								
ANN (3-6-1)	**LM**	**log-sig**	**0.962**	**1264**	**1228**	**0.901**	**2290**	**1378**
ANN (3-6-1)	Br	tan-sig	0.921	1792	1122	0.839	2038	1663
ANN (3-10-1)	LM	log-sig	0.960	1775	860	0.835	2930	1916
SVM (500, 1.0, 0.1)	---	---	0.840	2707	2183	0.809	4629	2983
SVM (600, 1.0, 0.1)	---	---	0.842	2694	2167	0.805	4598	2868
Thailand								
ANN (3-6-1)	LM	log-sig	0.855	4683	3012	0.851	4499	3383
ANN (3-10-1)	Br	log-sig	0.916	4521	2944	0.872	5120	3477
ANN (3-12-1)	**LM**	**log-sig**	**0.981**	**4324**	**3164**	**0.908**	**4478**	**3356**
SVM (500, 1.0, 0.01)	---	---	0.875	4430	2629	0.588	9231	6811
SVM (500, 1.0, 0. 1)	---	---	0.850	4887	3852	0.672	9816	7276

The scatter plot and the correlation between the TD values estimated with the optimum ANN and the observed values in the training and testing phases are shown in figure 6. The greater agreement of the regression line with the 1:1 line and the smaller amount of intercept indicates the superiority of the ANN model results for the all source countries except Japan. For Japan, this method overestimated TD for values less than 200000 and underestimated more than 200000 observed values for both the training and testing phase.

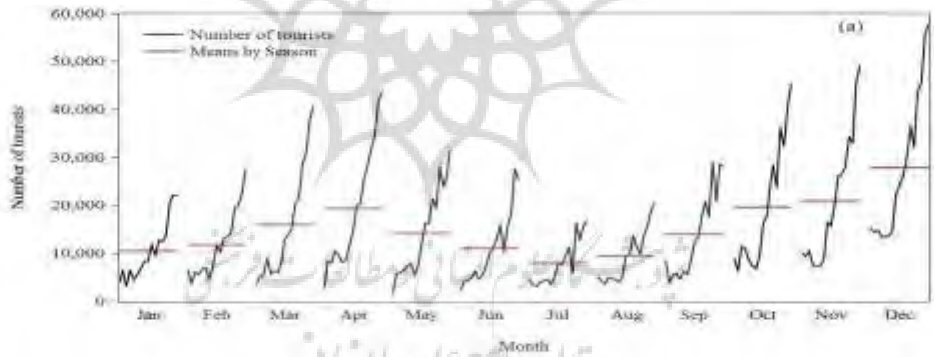
Fig. 6. The correlation between observed and calculated tourist arrivals at the training



and testing phases based on the optimal ANN models.

4.2. ARIMA and modified ARIMA results

For using ARIMA approaches, the series should be stationary. The normality test based on Kolmogorov and Shapiro test was conducted for each source country data series to check the stationary. The results indicated that ARIMA could fit the data for all the six understudy countries. The results showed that the data series follows a trend, and they also have a seasonal effect. Figure 7 illustrates the seasonal variations of the Malaysia TD as an example, to South Korea before and after seasonal adjustment. In this part, we employed conventional ARIMA and seasonal adjustment ARIMA ($ARIMA_{adj}$) to compare. Table 2 presents the optimized structural models of ARIMA and $ARIMA_{adj}$ for each of the source countries. It indicates the optimized model structure is not the same for the ARIMA and $ARIMA_{adj}$. Thus, there are differences between ARIMA and $ARIMA_{adj}$ model structure to determine optimal TD estimation of each understudy countries. Although the R^2 values of China, Hong Kong, Malaysia, Singapore and Thailand in ARIMA and the modified ARIMA are close to each other, Japan R^2 value declares significant difference between the two models.



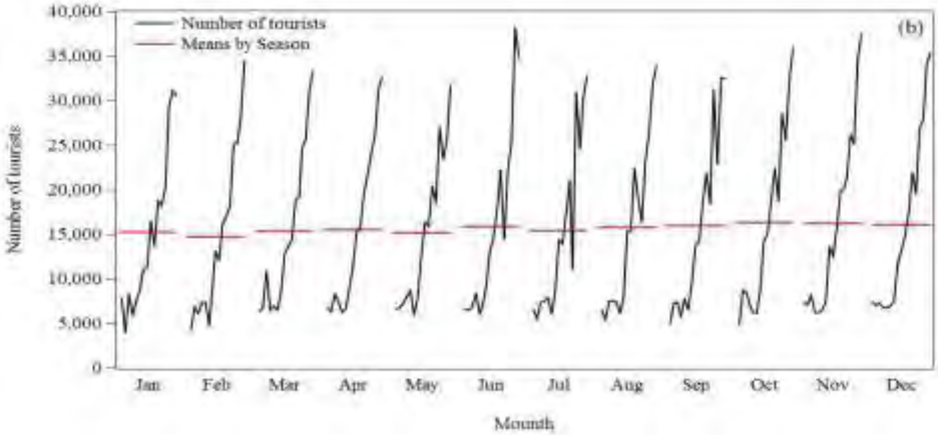


Fig 7. Number of tourist arrivals from Malaysia to South Korea, a) before seasonal adjustment, b) after seasonal adjustment

Table 2. The optimized structural models of the ARIMA and the modified ARIMA for the six major Asian source countries to South Korea

Source Country	Model Structure	ARIMA			Model Structure	$ARIMA_{adj}$		
		R^2	RMSE	MAE		R^2	RMSE	MAE
China	(0, 1, 3)	0.938	52551	31635	(0, 1, 2)	0.956	42669	20233
	(7, 1, 11)	0.948	44994	30439	(8, 1, 11)	0.968	28150	19986
Hong Kong	(1, 1, 3)	0.880	6726	4698	(0, 1, 2)	0.890	6225	3545
Japan	(1, 1, 12)	0.661	30855	23882	(6, 0, 3)	0.870	10146	6070
	(9, 0, 8)	0.828	22960	16689				
Malaysia	(12, 1, 10)	0.946	2810	2054	(0, 1, 1)	0.948	2145	1483
					(4, 1, 2)	0.952	2090	1412
Singapore	(11, 1, 9)	0.910	2418	1480	(1, 1, 2)	0.912	1549	828
Thailand	(11, 1, 11)	0.960	3226	2213	(11, 1, 7)	0.970	2368	1606

Furthermore, the results in terms of measure of RMSE and MAE values show that the $ARIMA_{adj}$ outperform the conventional ARIMA for all the six understudy countries.

As an example, Figure 8 shows the comparison of adjusted actual TD of $ARIMA_{adj}$ (0, 1, 1) and $ARIMA_{adj}$ (4, 1, 2) models of tourist arrivals from

Malaysia to South Korea. The fitted values are sufficiently close to the actual values using the adjusted ARIMA models for TD from Malaysia. Nevertheless, the calculated values from the conventional ARIMA models are not fitted to the actual values as well as adjusted ARIMA. We achieved similar results for the other source countries. Due to the limited number of article pages, the other figures are available on request.

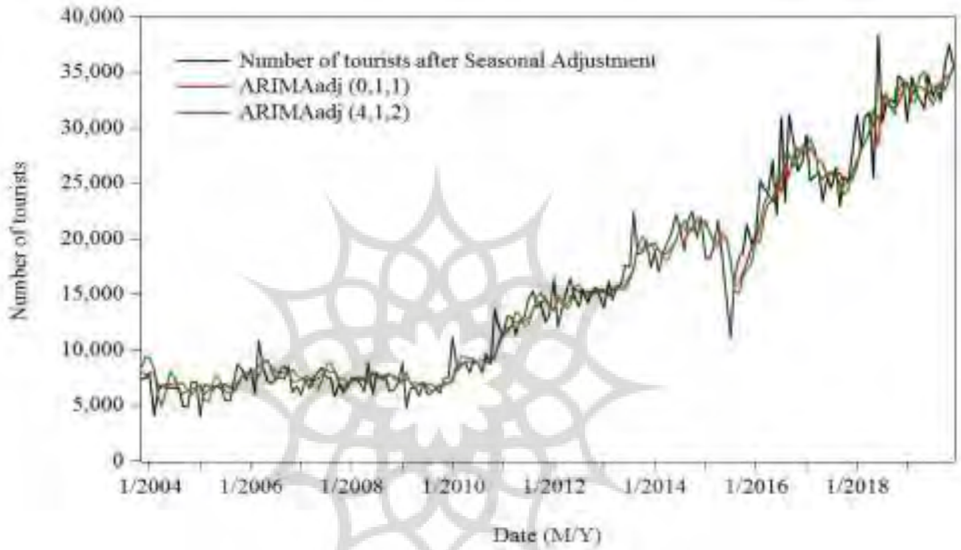


Fig 8. Comparison between observed values and calculated $ARIMA_{adj}$ models for Malaysia tourist arrivals to South Korea

4.3 comparison between ANN and the modified ARIMA results

The results depict the comparison of the accuracy of the ANN, SVM, ARIMA and seasonal adjusted ARIMA approaches. From the Table 1 it can be seen that in terms of measure of R^2 and RMSE and MAE values, ANN performs better compared to the SVM models for all the six source countries. According to the outcomes presented in Table 2, $ARIMA_{adj}$ models shows lower estimation errors than conventional ARIMA models for the understudy countries.

We can observe that the modified models outperform the other estimation models, namely ANN, SVM and conventional ARIMA for Hong Kong, Malaysia, Singapore and Thailand's TD to South Korea. $ARIMA_{adj}$ (0 1 2) for Hong Kong, $ARIMA_{adj}$ (4 1 2) for Malaysia, $ARIMA_{adj}$ (1 1 2) for

Singapore and $ARIMA_{adj}$ (11 1 7) for Thailand are determined as the optimal estimation models of TD to South Korea. In the case of Japan tourist arrivals to South Korea, the results depict the differences between the estimation errors of the proposed models, the ANN and the ARIMA. Among the proposed models, $ARIMA_{adj}$ (6 0 3) algorithm found to be the best configuration for estimation of Japanese tourist arrivals. Therefore it was found out that $ARIMA_{adj}$ model produce better results for estimating TD of the understudy countries except for China to South Korea. In the case of the Chinese tourist arrivals, ANN outperforms the optimum $ARIMA_{adj}$ algorithm.

Based on R^2 and RMSE and MAE criterion, we can observe close R^2 values among ANN (3 15 1) and the $ARIMA_{adj}$ (8 1 11) algorithm in China. However, RMSE and MAE values for artificial neural network technique is found to be lesser than the seasonal adjusted ARIMA benchmark model. From the above results, the $ARIMA_{adj}$ algorithms show better performance in estimating Asian understudy countries TD to south Korea. However, China is the only source country that seasonal adjusted ARIMA placed in the next priority after ANN. Thus, we conclude that the modified ARIMA algorithms compared with conventional ARIMA results have had closer accuracy to ANN as a soft computing approach. In addition, there is not a certain approach between ANN and $ARIMA_{adj}$ to recommend to estimate tourist arrivals from the Asian source countries to South Korea.

5. Discussion and Conclusion

Correct estimation of tourism demand is essential for superior operational travel planning and management. Obtaining a more accurate estimation is a prerequisite for those businesses involved in the tourism and hospitality industry. In this paper, the performance of two soft computing approaches and a statistical approach has been compared tourist demand time-series modelling of the six selected Asian countries. The three approaches have been employed in estimating the number of tourism arrivals from the major Asian source countries to South Korea. Although each approach has its strong and weak points, this study aims to determine the accuracy of the novel modified ARIMA models. Studying the overall predictive ability of the seasonal adjusted ARIMA models and comparing with conventional ARIMA, ANN and SVM estimation accuracy in TD estimation of Asian source countries are the main objectives of this paper. This study investigates the productivity of ANN, SVM, and ARIMA approaches and determines the accuracy of their patterns for optimizing the estimated models for each of the Asian source countries to South Korea. While ANN and SVM are sufficient to solve non-linear and complex problems as universal function approximators, the ARIMA approach has been used to estimate the time-series of monthly tourism demand conventionally. The results of this study contribute to the tourism and hospitality literature by applying deep learning to determine the better performance of ANN, SVM, and ARIMA. The results indicate that the determined models of the three approaches have different accuracy in estimating tourist arrivals.

The results were presented in terms of R^2 and RMSE and MAE and determined the optimal model structure of each approach for estimating TD from China, Hong Kong, Japan, Malaysia, Singapore and Thailand, separately. The experimental findings suggested that the LM algorithm in ANN approach with different activation functions, provides higher estimation accuracy. The outcomes also showed that the estimation errors for the SVM models are higher than the ANN models for all of the understudy countries. However, both ANN and SVM models do not show adequate accuracy for estimating TD from Japan to South Korea. Results also establish that the modified ARIMA model, $ARIMA_{adj}$, leads to better model performance comparing with the conventional ARIMA for TD estimation from the all six understudy countries. Thus, the $ARIMA_{adj}$ declares more satisfying results to compare with ANN and SVM as soft computing approaches in the selected Asian countries.

The outcomes point out that $ARIMA_{adj}$ model has performed better for Hong Kong, Malaysia, Singapore and Thailand source countries and ANN placed in the second rank of the accuracy for these countries. However, the estimation of Japanese tourist arrivals to South Korea by a significant difference to ANN and conventional ARIMA, is satisfied by the modified ARIMA algorithm. On the other hand, in the case of the Chinese TD estimation, ANN outperforms the optimum $ARIMA_{adj}$ algorithm.

Therefore, based on the results of this study, the $ARIMA_{adj}$ algorithms show better performance in estimating tourism demand of the source Asian countries to South Korea, whereas China is the understudy country that seasonal adjusted ARIMA placed in the next priority after artificial neural network. Hence, it is concluded that although there is no optimal approach to estimate tourist arrivals from the Asian source countries to South Korea with certainty, in particular the findings of this study show that seasonal adjusted ARIMA models would be an accepted model to estimate tourism demand. Thus, even if Zhang et al. (1998), Jiao & Chen (2019) and Kulshrestha et al. (2020) are correct in the observation that "ANNs are advanced in tourist demand estimation, and provide a potential replacement to conventional linear statistical methods", this study illustrates that the ARIMA conventional statistical approach is flexible, and its modified models should be especially considered in terms of TD estimation of Asian countries. For a better generalization, we suggest studying more Asian source and destination countries in future researches. More studies may be addressed to extend our findings for determining tourism demand estimation optimal models for tourism arrivals estimating from Asian source countries.

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