ASSOCIAÇÃO DE POLITÉCNICOS DO NORTE **(APNOR)**

INSTITUTO POLITÉCNICO DE BRAGANÇA

Analysing and Forecasting Tourism Demand in Vietnam with Artificial Neural Networks

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To obtain the Master Degree in Management, Specialisation in Business Management

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Professor Doutor João Paulo Teixeira

Bragança, January, 2022

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Abstract

Vietnam has experienced a tourism boom over the last decade with more than 18 million international tourists in 2019, compared to 1.5 million twenty-five years ago. Tourist spending has translated into rising employment and income for the tourism sector, making it the key driver to the socio-economic development of the country. Facing the COVID-19 pandemic, Vietnam´s tourism has suffered extreme economic losses. However, the number of international tourists is expected to reach the pre-pandemic levels in the next few years after the COVID-19 pandemic subsides.

Forecasting tourism demand plays an essential role in predicting future economic development. Accurate predictions of tourism volume would facilitate decision-makers and managers to optimize resource allocation as well as to balance environmental and economic aspects. Various methods to predict tourism demand have been introduced over the years. One of the most prominent approaches is Artificial Neural Network (ANN) thanks to its capability to handle highly volatile and non-linear data. Given the significance of tourism to the economy, a precise forecast of tourism demand would help to foresee the potential economic growth of Vietnam.

First, the research aims to analyse Vietnam´s tourism sector with a special focus on international tourists. Next, several ANN architectures are experimented with the datasets from 2008 to 2020, to predict the monthly number of international tourists traveling to Vietnam including COVID-19 lockdown periods. The results showed that with the correct selection of ANN architectures and data from the previous 12 months, the best ANN models can forecast the number of international tourists for next month with a MAPE between 7.9% and 9.2%. As the method proves its forecasting accuracy, it would serve as a valuable tool for Vietnam´s policymakers and firm managers to make better investment and strategic decisions to promote tourism after the COVID-19 situation.

Keywords: Artificial Neural Networks, International Tourists, Tourism Forecasting, Tourism Demand, Vietnam.

Resumo

O Vietname conheceu um boom turístico na última década com mais de 18 milhões de turistas internacionais em 2019, em comparação com 1,5 milhões há vinte e cinco anos. As despesas turísticas traduziram-se num aumento do emprego e de receitas no sector do turismo, tornando-o no principal motor do desenvolvimento socioeconómico do país. Perante a pandemia da COVID-19, o turismo no Vietname sofreu perdas económicas extremas. Porém, espera-se que o número de turistas internacionais, pós pandemia da COVID-19, atinja os níveis pré-pandémicos nos próximos anos.

A previsão da procura turística desempenha um papel essencial na previsão do desenvolvimento económico futuro. Previsões precisas facilitariam os decisores e gestores a otimizar a afetação de recursos, bem como o equilíbrio entre os aspetos ambientais e económicos. Vários métodos para prever a procura turística têm sido introduzidos ao longo dos anos. Uma das abordagens mais proeminentes assenta na metodologia das Redes Neuronais Artificiais (ANN) dada a sua capacidade de lidar com dados voláteis e não lineares. Dada a importância do turismo para a economia, uma previsão precisa da procura turística ajudaria a prever o crescimento económico potencial do Vietname.

Em primeiro lugar, a investigação tem por objetivo analisar o sector turístico do Vietname com especial incidência nos turistas internacionais. Em seguida, várias arquiteturas de ANN são experimentadas com um conjunto de dados de 2008 a 2020, para prever o número mensal de turistas internacionais que se deslocam ao Vietname, incluindo os períodos de confinamento relacionados com a COVID-19. Os resultados mostraram, com a correta seleção de arquiteturas ANN e dados dos 12 meses anteriores, os melhores modelos ANN podem prever o número de turistas internacionais para o próximo mês com uma MAPE entre 7,9% e 9,2%. Como o método evidenciou a sua precisão de previsão, o mesmo pode servir como uma ferramenta valiosa para os decisores políticos e gestores de empresas do Vietname, pois irá permitir fazer melhores investimentos e tomarem decisões estratégicas para promover o turismo pós situação da COVID-19.

Palavras-chave: Redes Neuronais Artificiais, Turistas Internacionais, Previsão Turística, Procura Turística, Vietname.

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Abbreviations and Acronyms

ADLM	Auto-Regressive Distributed Lag Model
AI	Artificial Intelligence
AIDS	Almost Ideal Demand System
ANN	Artificial Neural Network
AR	Autoregressive
ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARIMA	Autoregressive Integrated Moving Average
ARIMA-GARCH	Generalized Autoregressive Conditional Heteroskedastic
ARIMAX	Extended version of the ARIMA model
ARMA	Autoregressive Moving Average
AR-MIDAS	Autoregressive Mixed-data Sampling
ASEAN	The Association of Southeast Asian Nations
BGVAR	Bayesian Estimation Techniques
BVAR	Bayesian VAR Model
CI	Cointegration Analysis
DL	Distributed Lag Model
ECM	Error Correction Model
Elliotsig	Elliot symmetric sigmoid transfer function
Elman NN	Elman Neural Network
ES	Single Exponential Smoothing
GA	Genetic Algorithm
GRNN	Generalized Regression Neural Network
GSO	General Statistics Office of Vietnam
HA	Historical Average
IATA	The International Air Transport Association
iDEA	Vietnam E-commerce and Digital Economy Agency
Logsig	Logarithmic sigmoid transfer function

MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MIDAS	Mixed-data Sampling
MLP	Multilayer Perceptron
NAR	Non-linear Autoregressive Neural Network
Purelin	Linear transfer function
RBF	Radial Basis Function Network
SARIMA	Seasonal Autoregressive Integrated Moving Average
SOM	Self-organizing Maps
STSM	Structural Time-series Model
SVM	Support Vector Machines
SVR	Support Vector Regression
Tansig	Tangent-hyperbolic transfer function
Trainbr	Bayesian Regularization backpropagation algorithm
Traincgf	Conjugate gradient backpropagation with Fletcher-Reeves updates
Trainlm	Levenberg-Marquardt algorithm
Trainrp	Resilient Backpropagation algorithm
TVP	Time Varying Parameter
UNESCO	The United Nations Educational, Scientific and Cultural Organization
UNWTO	The United Nations World Tourism Organization
VAR	Vector Autoregressive
VECM	Vector Error Correction Model
VNAT	Vietnam National Administration of Tourism
VP	Static Varying Parameters
WEF	World Economic Forum

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Introduction

Vietnam, a strip of land in the eastern part of Southeast Asia, is one of the most attractive destinations for tourists all over the world. With over 3000 kilometers of coastline, pristine beaches including the best bays in the world, 7 World Heritage Sites, dynamic growing cities, mountainous highlands, and diverse culture and history, Vietnam has favourable conditions for tourism development.

Tourism is one of the fastest-growing sectors and the most important driving forces to the economic development of Vietnam. The sector has seen dramatic growth, ranging from 10 to 25% during the last 10 years. For 2015-2018, the average growth rate was 25%, ranking as one of the highest growth rates in tourism in the world (The World Bank, 2019). Vietnam has been highly successful at attracting tourists and reaping the economic benefits from this booming tourism activity. In 2019, the country received 18 million international tourists, up 2.5 million compared to that of 2018 (Vietnam National Administration of Tourism, 2019). Tourism revenues contributed from 4 to 10% to the national GDP (Vietnam National Administration of Tourism, 2019).

The Vietnamese Government has prioritized tourism as the strategic driver of socio-economic development by introducing a resolution to transform tourism into a leading business and make Vietnam one of the most popular destinations in Southeast Asia. To achieve those ambitious goals, a long-term strategy and action plan for the sector have been made for the period 2018 - 2030 (Government of Vietnam, 2020). A VND30 trillion (US$1.32 billion) program was approved to improve transport infrastructure at major tourist destinations in 2017 (Government of Vietnam, 2017). Further, the government approved the establishment of a VND300 billion (US$12.9 million) tourism development fund for promotional activities in 2018 (Government of Vietnam, 2018). In addition to funding activities, the government has also relaxed immigration policies allowing tourists from 46 countries, including China, Japan, South Korea, Russia, the US, the UK and so on to enter Vietnam for 30 days with a single-entry electronic visa.

Forecasting tourism demand has gained much interest from researchers, managers, and policymakers worldwide (Truong & Le, 2017). According to the UN World Tourism Organization (UNWTO), tourism demand is defined as tourism consumption, tourism gross fixed capital formation and tourism collective consumption (UNWTO, 2021). In forecasting studies, tourism demand is often measured in terms of number of tourist arrivals, tourism expenditure or overnight stays of tourists. Facing an increasingly complicated business environment, tourism needs to rely more on modelling and forecasting techniques to predict demand and optimize the allocation of limited resources (Cortes-Jimenez & Blake, 2011; Baggio & Sainaghi, 2016; Alamsyah & Friscintia, 2019). Accurate predictions are essential for tourist attractions where the decision-makers and business managers try to take advantage of the sector developments and/or to balance their local environmental and economic aspects (Athanasopoulos, Song, & Sun, 2018; Zhang, Li, Muskat, & Law, 2021). For example, governments require precise forecasting methods for informed decision-making on issues such as infrastructure development, and accommodation site planning (Hassani, Silva, Antonakakis, Filis, & Gupta, 2017; Kourentzes & Athanasopoulos, 2019). Organizations need the forecasts to make tactical decisions on tourism promotional activities (Ongan & Gozgor, 2018), and tourism and hospitality practitioners need reliable predictions for operational decisions such as staffing and scheduling (Song & Li, 2008; Fernandes & Teixeira, 2008).

Given the significant role of tourism in socio-economic development, the thesis aims to analyse the characteristics of the tourism sector in Vietnam with a special focus on international tourists – the key target group of customers. Data is obtained from public sources for the period 1995-2020. Next, the forecasting capability of Artificial Neural Network methodology is assessed with the datasets of international tourists to Vietnam from 2008 to 2020. Several ANN architectures are experimented to predict the monthly number of international tourists, considering lockdown periods due to the COVID-19 pandemic. It is expected that the best-performed ANN models in this research will serve as a valuable tool for policymakers and managers in planning tourism activities.

The thesis is structured as follows. After the introduction, a literature review on tourism modelling and forecasting studies is presented in Section 1. Section 2 explains in detail the development of Vietnam´s tourism sector. Section 3 presents ANN methodology and models experimented within the research. Section 4 discusses results generated from the previous part. Conclusions, limitations, and suggestions for further research are presented in the final part.

1. Review of tourism modelling and forecasting studies

1.1. Tourism demand forecasting

According to the UN World Tourism Organization (UNWTO), tourism is defined as «*a social, cultural and economic phenomenon which entails the movement of people to countries or places outside their usual environment for personal or business/professional purposes*» (UNWTO, 2021). Tourism has become one of the most dynamic, resilient, and fastest-growing economic sectors, contributing to GDP, job creation and social and economic development along its value chain, and outpacing the world economy every year over the last decade (UNWTO, 2020a). According to World Tourism Barometer and Statistical Annex in January 2020 (UNWTO, 2020b), international tourists worldwide grew 4% in 2019 to reach 1.5 billion. All regions enjoyed an increase in tourists. The Middle East (+8%) led growth, followed by Asia and the Pacific (+5%). International tourists in Europe and Africa (both +4%) increased in line with the world average, while the Americas saw growth of 2%.

Forecasting tourism demand is a challenging task for both decision-makers and researchers because the seasonal and fragile nature of tourism (Witt & Witt, 1995) especially in the world of increasing uncertainties. Advances in information technologies and better access to large amounts of data provide more possibilities for generating highly accurate forecasting models. New themes and trends in tourism and hotel demand forecasting are comprehensively reviewed by Goh and Law (2011), Wu et al. (2017), Song et al. (2019), Ghalehkhondabi et al. (2019) and Zhang et al. (2020). The existing literature on predicting tourism demand is extensive, ranging from different countries, various statistical techniques, and a different set of data (Silva, Hassani, Heravi, & Huang, 2019). Most recent studies often measured tourism demand in terms of the number of tourists (Gunter & Onder, 2015; Apergis, Mervar, & Payne, 2017; Zhu, Lim, Xie, & Wu, 2018; Alamsyah & Friscintia, 2019; Höpken, Eberle, Fuchs, & Lexhagen, 2021), tourism expenditure (Li, Wong, Song, & Witt, 2006; Cortes-Jimenez & Blake, 2011; Ognjanov, Tang, & Turner, 2018), or overnight stays (Teixeira & Fernandes, 2012; Peng, Song, & Crouch, 2014; Teixeira & Fernandes, 2014; Baggio & Sainaghi, 2016; Constantino, Fernandes, & Teixeira, 2016) as such data is better aggregated (Song, Qiu, & Park, 2019).

New methods have been continually developed to gain higher forecasting accuracy (Jiao, Li, & Chen, 2020). Van Doorn (1984) presented four main categories of the methodology include explorative forecasting methods (time series analysis, historical analogy, causal methods, projective scenarios and morphological analysis), speculative forecasting (individual expert opinion, brainstorming, panel consensus and Delphi), normative/explicative forecasting (subjective probabilistic forecasting, Bayesian statistics, pattern identification or prospective scenarios) and integrative methods (input-output analysis, multimethod models and cross-impact analysis).

More recently, the studies on tourism demand forecasting can be categorized generally into qualitative and quantitative approaches (Law, Li, Fong, & Han, 2019). Major groups of methods used to forecast tourism demand include time series models, econometrics models, artificial intelligence techniques and qualitative methods (Sun, Wei, Tsui, & Wang, 2019; Chen, Li, Wu, & Shen, 2019; Fu, Hao, Li, & Hsu, 2019). Time series models, econometric approaches, and artificial intelligence (AI) models are three main categories of quantitative forecasting methods (Peng, Song, & Crouch, 2014). The fourth category is judgmental methods, which can be used for both qualitative and quantitative forecasting (Lin & Song, 2015; Wu, Song, & Shen, 2017). Time series models and econometric models are most frequently used, and artificial intelligence models have started to gain popularity in the past decade (Fernandes & Teixeira, 2008; Jiao & Chen, 2019) thanks to their capability to deal with non-linear behaviour (Teixeira, Santos, & Fernandes, 2014). In general, time-series and econometrics models rely on the stability of historical patterns and economic structure, while artificial intelligence models are dependent on the quality and size of available training data (Law, Li, Fong, & Han, 2019). Scholars have generally agreed that no single method can consistently outperform other methods on all occasions (Li, Hu, & Li, 2020).

Extensive review papers captured tourism demand forecasting methods developed during certain periods. Witt and Witt (1995) reviewed empirical research on tourism demand forecasting from the 1960s to the 1990s. The authors classified the research into two main groups: quantitative forecasting (econometric models, spatial models, and time-series methods) and qualitative forecasting (Delphi method). According to Witt and Witt (1995), when accuracy is measured in terms of error magnitude, the no-change model and autoregression outperformed exponential smoothing, trend curve analysis, Gompertz and econometrics. When measuring accuracy in terms of the direction of change error, econometrics was possible to forecast the direction of change of tourism demand with higher accuracy than the no-change model.

Li, Song, and Witt (2005) reviewed eighty-four post-1990 empirical studies of international tourism demand modelling and forecasting using econometric approaches. Compared to the studies between the 1960s and 1980s, more advanced econometric techniques, such as the Cointegration Analysis model (CI) and Error Correction Model (ECM), Vector Autoregressive approach (VAR), Time-Varying-Parameter (TVP), and Almost Ideal Demand Systems (AIDAS) models have been applied to tourism demand studies in the 1990s and early 2000s. These methods contribute to improvements in the understanding of international tourism demand. In particular, the CI/ECM approaches identify the differences between the long-run and short-run demand elasticities, and the time-varying-parameter model demonstrates the evolution of elasticities throughout time. A further review of 23 tourism demand forecasting studies suggested that there is no single model that outperforms the others in all cases. The performance of alternative models was situation-specific, and many factors may influence their forecasting accuracy. In general, the TVP model and the structural time-series model (STSM) performed relatively well, especially for short-run forecasting. When advanced econometric models compete with their univariate time-series counterparts or the conventional benchmark no-change model, the econometric models were likely to outperform the others, especially as far as annual data are concerned.

Goh and Law (2011) reviewed 155 research papers published between 1995 and 2009 on modelling the estimation and forecasting of tourism demand. The models were classified into three main groups according to the methods and techniques adopted—an econometric-based approach, time-series techniques, and artificial intelligence (AI)-based methods. It appears that the more advanced econometric (and time series analysis) methods such as cointegration, ECM, and TVP produce better results in terms of forecasting accuracy. Moreover, the combined use of these advanced methods seemed to have outperformed the fixed-parameter models. Among the 384 models established in the 155 papers, 45% and 50% were correspondingly based on econometric and time series techniques, whereas only 5% adopts AI-based techniques. Although AI-based methods were found at almost all times to outperform their econometric counterparts, the forecasting performance of these techniques cannot be generalized, as it remains largely unknown whether the techniques can outperform advanced econometric techniques.

Song and Li (2008) reviewed 121 post-2000 empirical studies. The latest developments of quantitative forecasting techniques are summarized in three categories: time-series models, the econometric approach, and AI techniques. Although the studies showed that the newer and more advanced forecasting techniques were likely to generate higher forecasting accuracy under certain circumstances, no clear-cut evidence showed that any one model could consistently outperform other models in the forecasting competition.

Peng, Song, and Crouch (2014) reviewed 65 studies published during the period 1980–2011, the meta-regression analysis showed that the origins of tourists, destination, time period, modelling method, data frequency, number of variables and their measures and sample size all significantly influenced the accuracy of forecasting models. This study was the first attempt to pair forecasting models with the data characteristics and the tourism forecasting context.

Wu, Song, and Shen (2017) reviewed studies published from 2007 to 2015 on tourism and hotel demand modelling and forecasting. This review finds that the studies focused on hotel demand are relatively less than those on tourism demand. It is also observed that more and more studies have moved away from the aggregate tourism demand analysis, whereas disaggregate markets and niche products have attracted increasing attention. Some studies have gone beyond neoclassical economic theory to seek additional explanations of the dynamics of tourism and hotel demand, such as environmental factors, tourist online behaviour and consumer confidence indicators, among others. More sophisticated techniques such as nonlinear smooth transition regression, mixed-frequency modelling technique and nonparametric singular spectrum analysis have also been introduced to this research area. Several techniques such as Delphi (Lin & Song, 2015) or specific econometric models (Li, Song, & Witt, 2005) or the literature on uncertainty in travel demand (Rasouli & Timmermans, 2012) have also been examined.

Jiao and Chen (2019) reviewed 72 studies in tourism demand forecasting during the period from 2008 to 2017. Forecasting models were examined in three categories: econometric, time series and AI models. Econometric and time series models are popular models as these two models are often used as benchmarks for forecasting capability and comparison concerning new models. AI models have been rapidly developed in the past decade and hybrid AI models have become a new trend. Time series, econometric, AI and combination models continue to dominate tourism demand forecasting, whereas some new trends have emerged from 2008 to 2017. Regarding the capability of forecasting as a benchmarking, research shows that hybrid models often outperform individual standard models. However, there is no single model that outperforms the others in every circumstance, which is consistent with the conclusions in the literature review by Li, Song, and Witt (2005). Most recently, Song, Qiu, and Park (2019) conducted an extensive review on a wide range of forecasting methods applied over the period from the 1960s to 2018, from judgmental approaches to various kinds of quantitative methods, including time series, econometric and AI-based models.

1.2. Time series models

A time series is an ordered sequence of values of a random variable, which is documented on constant time intervals (Ghalehkhondabi, Ardjmand, Young, & Weckman, 2019). For example, the number of tourists to Vietnam every day, month or year is time series. Based on successive values that represent consecutive measurements taken at regularly spaced intervals (such as monthly, quarterly, or annual measurements) (Song, Qiu, & Park, 2019), time series models try to recognize the trends, establish historical patterns and use the patterns to predict the future value for the next coming time series. Peng, Song, and Crouch (2014) divided time series models into basic and advanced time series techniques.

According to Song, Qiu, and Park (2019), the most common types of time series models included the Naïve, autoregressive (AR), single exponential smoothing (ES), moving average (MA) and historical average (HA) models. Naïve 1 and Naïve 2 are undoubtedly the most easily adopted and the most popular methods used in the tourism forecasting literature. Time series models have been extensively employed in forecasting tourism demand thanks to their simple operation and practical ability to establish historical patterns. Based on the conclusions from (Athanasopoulos, Hyndman, Song, & Wu, 2011; Claveria, Monte, & Torra, 2015a), Naïve 1 model was able to provide forecasting accuracy, particularly for short predicting horizons.

The main difference between the basic and advanced time series models is the ability of the advanced method to capture trends and seasonality of the time series. The Autoregressive Moving Average (ARMA) models are a type of stationary stochastic models that comprise two models of autoregressive and moving average models to achieve greater flexibility in the fitting of actual time series (Box, 2015). Based on the traditional ARMA models, various models have been developed such as autoregressive integrated moving average (ARIMA) and seasonal ARIMA (SARIMA). ARIMA models could be applied when the data is not stationary while SARIMA models could show better forecasting accuracy in the case of univariate time series data with a seasonal component. ARIMA models consider both current and lagged observations (AR components), both current and lagged random shocks (MA components), the degrees of integration (I). SARIMA models consider both non-seasonal and seasonal factors (S components). Among the models, ARIMA methods are more popular thanks to their flexibility in modelling tourism demand (Lim & McAleer, 2002; Gounopoulos & Petmezas, 2012). Several recent developments in time series techniques are based on ARIMA-type models. Chu (2008) applied the autoregressive fractionally integrated moving average (ARFIMA) approach to forecasting the tourism demand in Singapore. Chan, Lim, and McAleer (2005) applied the generalized autoregressive conditional heteroskedastic (model ARIMA-GARCH) to forecast international tourists in Singapore. Many other studies used the Autoregressive fractionally integrated moving average (ARFIMA) as a benchmark for the time series model (Nowman & Van Dellen, 2012; Apergis, Mervar, & Payne, 2017).

Various studies have acknowledged that seasonality is the core nature of tourism. As a result, literature on forecasting tourism demand has considered seasonality as the key predictor in modelling. Loganathan and Ibrahim (2010) used the Box-Jenkins SARIMA model to forecast the number of international tourists to Malaysia. Nanthakumar (2012) applied the SARIMA method to forecast the tourists from ASEAN countries to Malaysia. The study found that SARIMA did not out-performance ARIMA in forecasting tourism demand. Bigovic (2012) used Box-Jenkins-based SARIMA models to forecast the Montenegrin tourists. In a more recent study, the Box-Jenkins ARIMA model was developed by Anvari, Tuna, Canci, and Turkay (2016) to predict the tourism demand to Turkey. Gil-Alana (2010) used seasonal-AR to analyse international tourists in the Canary Islands. The ARIMA-seasonal decomposition model was used to investigate Turkish inbound tourism by Koc and Altinay (2007). Seasonal fractional-ARIMA was employed to estimate Spanish tourism demand by Gil-Alana et al. (2004)

1.3. Econometric models

For the last decades, researchers have shown increasing interest in econometric forecasting approaches that focused on searching the causal relationships between economic factors and tourism demand in diverse practical circumstances (Song, Qiu, & Park, 2019). The most distinctive difference between econometric methods and non-causal time series is the ability of econometric models to use explanatory variables to predict tourism demand (Jiao & Chen, 2019). Econometric models attempt to find a causal relationship between the output variable (tourism demand) and the input variables (economic, social, demographic, etc.) (Ghalehkhondabi, Ardjmand, Young, & Weckman, 2019). As such, the focus of economic models is to establish the cause-and-effect between input and output variables. Then, define how significantly a variety of explanatory variables influence future tourism demand and identify the most influential variables by removing uncorrelated ones.

The most prevalent econometric methods include distributed lag (DL) models (Wan & Song, 2018), the error correction models (Lee, 2011; Vanegas, 2013, Gunter & Onder, 2015), autoregressive distributed lag models (Ayeh & Lin, 2011; Tukamushaba, Lin, & Bwire, 2013; Huang, Zhang, & Ding, 2017), vector autoregressive models (Gunter & Onder, 2016) and time-varying parameter models (Song, Li, Witt, & Athanasopoulos, 2011).

DL models could include previous values of the influential factors to tourism demand. Guizzardi and Mazzocchi (2010), Wan and Song (2018) used the DL models used as the benchmarks in assessing and comparing forecasting capability. As a more advanced model, Auto-Regressive Distributed Lag

Model (ADLM) has gained more attention than DL. The model could not only evaluate the impact of influential variables but also the effect of lagged demand factors. The ADLM and the ECM methods show remarkable ability in assessing tourism demand. Thanks to its flexibility, the ADLM can be integrated with other methods to improve its performance in tourism modelling and forecasting. For instance, the time-varying parameter was found to work well with both the ADLM and the ECM for describing structural variations (Li, Wong, Song, & Witt, 2006).

Based on those models, many researchers have presented improved and integrated approaches. The TVP structural time-series model (TVP-STSM) was introduced by Song, Li, Witt, and Athanasopoulos (2011). TVP and STSM were combined to take advantage of the ability of STSM to capture seasonality, trends and cycles while TVP was used to identify coefficients of the explanatory variables. Gunter and Onder (2016) have combined Bayesian estimation with VAR methods while considering big data as explanatory variables. ECM models have been improved based on ADLM methods. ECM examines the long-term relationship between tourism demand and its influential variables as well as the short-term error correction process in deciding tourism demand. Both the ADLM and ECM underline the magnitude of the causal relationships between influential factors and tourism demand (Song, Qiu, & Park, 2019). Mixed-data sampling (MIDAS) is integrated with a reduced form of ADLM for using mixed-frequency data to estimate tourists in the Caribbean (Bangwayo-Skeete & Skeete, 2015). The term 'AR-MIDAS' means that the functional form of the applied model is a partial adjustment model, or a reduced ADLM (Song, Qiu, & Park, 2019).

The ARIMAX is an extended version of the ARIMA model, aiming at distinguishing the dynamics of tourism demand. X in the ARIMAX models signifies the exogenous variables. An autoregressive term with exogenous variables method was implemented by Li, Goh, Hung, and Chen (2018) to explore the impact of climate change on tourism. Tsui, Balli, Gilbey, and Gow (2014) found that the ARIMAX model performed better in the long run than the SARIMA model in predicting air passengers to Hong Kong. In a study of forecasting demand for hotels (Pan & Yang, 2017) concluded that the ARMAX model showed better performance compared to the ARMA model in forecasting hotel occupancies. To forecast the number of Japanese tourists to Korea, Park, Lee, and Song (2017) used the SARIMAX model and the result showed that this model outperformed standard time series models, such as the SARIMA or the Holt-Winters ES. Also, the ARIMAX-type models have been integrated with static varying parameters (VP) and MIDAS and showed promising results in predicting tourism demand (Pan & Yang, 2017).

The STSM considers the impact of seasonal factors as exogenous variables. Some applications of the STSM in tourism demand modelling and forecasting can be the vector autoregressive model and the vector error correction model (VECM). These extension models can capture the interdependency of multiple time series. Within a VAR framework, all the explanatory variables are treated as endogenous, with an assumption that all of the variables affect each other intertemporally (Guizzardi & Stacchini, 2015; Ognjanov, Tang, & Turner, 2018).

Bayesian VAR (BVAR) model is an improved model of classical VAR in which informative restrictions were included in the modelling process. Wong, Song, and Chon (2006) found that BVAR considerably outperformed non-Bayesian models. The classical VAR model has been further expanded into a global VAR (GVAR) framework by Pesaran, Schuermann, and Weiner (2004). Based on the approach, Assaf, Li, Song, and Tsionas (2018) presented Bayesian estimation techniques (BGVAR) to forecast international traveling demand in Southeast Asian countries. Another rare type of method to forecast tourism demand is the panel data regression which incorporates information on both the intertemporal movements and the cross-sectional heterogeneity of the tourism demand data (Long, Liu, & Song, 2019). In many cases, econometric techniques outperformed the classical VAR (Song & Li, 2008).

The most influential factors in forecasting tourism demand are tourist´s income level and relative price (comparing tourism price in the destinations with such in the origins), substitute price (comparing prices of tourism between rival destinations) (Ayeh & Lin, 2011; Gunter & Onder, 2015), the exchange rate of origin and destinations (Li, Song, & Witt, 2005; Song & Li, 2008). Many other variables such as financial crises (Song & Lin, 2010), terrorist attacks (Bonham, Edmonds, & Mak, 2006), economic crisis and swine flu (Page, Song, & Wu, 2012), climate change (Moore, 2010), and political instability and terrorism (Saha & Yap, 2014) have also been considered in the length of tourism forecasting literature.

1.4. AI-based models

The success of AI-based techniques which are widely applied in various scientific areas has supported tourism researchers to use the techniques in forecasting tourism demand (Díaz & Sbert, 2011). AI models can capture nonlinear relationships and patterns among time series and exogenous variables and AI’s potential to improve forecasting performance. Palmer, Montaño, and Sesé (2006) suggested that time series and econometric models are limited in a way that the model must be formally specified and a probability distribution for data must be assumed before implementation. According to Hansen, McDonald, and Nelson (1999) AI-based techniques do not require a formally specified model and data probability distribution, making it a more advantageous method compared to time series and econometric models, especially in the case of non-normal and nonlinear data.

According to Goh and Law (2011) ANN-based models to forecast tourism demand can be categorized into two groups: AI-based time series methods and AI-based casual methods. AI-based models also can be classified into five main categories: artificial neural network (ANN), rough sets approach (Pai, Hong, & Lin, 2005; Pa, Hong, Chang, & Chen, 2006), fuzzy time series (Tsaur & Kuo, 2011; Lee, Nor, & Sadaei, 2012; Huarng, Yu, Moutinho, & Wang, 2012), and grey theory (Sun, Sun, Wang, Zhang, & Gao, 2016; Ma, 2021; Hu, 2021).

Rough set modelling is a good technique to handle vague data and identify relationships and patterns in hybrid data, with both quantitative and qualitative information (Jiao & Chen 2019). Goh et al. (2008) used a rough set approach to the long-haul United States´ and United Kingdom´s tourism demand for Hong Kong by incorporating two non-economic variables, a leisure time index, and a climate index into the traditional regression framework. The study found that the rough sets method with non-economic variables outperforms the regression models with the same datasets. Tourism data are believed to be affected by both qualitative and quantitative data and thus are suitable to use a rough set approach for tourism forecasting. Another study on the rough set approach could be found in the study of Celotto, Ellero, and Ferretti (2012)

Fuzzy models have fewer observations than other forecasting methods because the models do not require the presumption of data distribution and model formulation. There are different types of fuzzy system models applied in tourism demand forecasting. Chen, Ying, and Pan (2010) applied an adaptive network-based fuzzy inference system on forecasting annual tourists to Taiwan and later on (Hadavandi, Ghanbari, Shahanaghi, & Abbasian-Naghneh, 2011; Shahrabi, Hadavandi, & Asadi, 2013) developed a new hybrid intelligence model that incorporates genetic algorithm (GA) into the fuzzy system. Genetic algorithm is another AI technique that has been used in forecasting tourism demand, often combined with other AI models such as support vector regression (Chen & Wang, 2007; Cai, Lu, & Zhang, 2009; Chen, Liang, Hong, & Gu, 2015).

ANNs have been the most frequently used AI-based models (Fernandes & Teixeira, 2008; Teixeira & Fernandes, 2012; Fernandes, Teixeira, Ferreira, & Azevedo, 2013; Constantino, Fernandes, & Teixeira, 2016; Srisaeng & Baxter, 2017; Silva, Hassani, Heravi, & Huang, 2019). Various studies compare the forecasting performance of ANN models to that of other methods, for example Law (2000) presents a neural network model that incorporates the back-propagation learning process to forecast the nonlinearly separable tourists. The results show that the ANN outperforms the multiple regression models. Fernandes, Teixeira, Ferreira, and Azevedo (2008) examined the ANN models as an alternative to the Box-Jenkins methodology in forecasting tourism demand in Portugal. The results showed that the ANN models produced satisfactory statistical and adjustment qualities, suggesting that it is suitable for modelling and forecasting the tourism demand. Among three different ANN techniques for tourist demand forecasting, a multi-layer perceptron and a radial basis function showed better predictive performance than the Elman network (Claveria, Monte, & Torra, 2015a).

Although the satisfying forecasting performance generated by AI models facilitates the development of AI models, it is not common to construct entirely new models to forecast tourism demand. Instead, hybrid models are frequently developed, aiming to take advantage of different aspects of the AI single models involved and minimize the limitations on tourism demand forecasting, by combining the modelling process systematically (Jiao & Chen, 2019).

Different AI models described above have their advantages and disadvantages. Hence, a simple solution is to integrate different AI models aiming to combine their advantages and minimize their limitations by generating hybrid models upon single AI models (Hadavandi, Ghanbari, Shahanaghi, & Abbasian-Naghneh, 2011). After 2010, hybrid models become a new trend in tourism forecasting, especially AI-based hybrid models (Pai, Hung, & Lin, 2014). AI-based models under different classifications including SVR, ANN and GA are combined systematically to improve forecasting accuracy (Hong, 2011; Abellana, Rivero, Aparente, & Rivero, 2021).

A combination of SVR methods with GA suggested a hybrid approach known as the GA-SVR. Pai, Hong, Chang, and Chen (2006); Chen and Wang (2007) used the approach for tourism demand modelling and forecasting. Chen, Liang, and Hong (2015) proposed a model of support vector regression with an adaptive genetic algorithm and the seasonal mechanism. Next, a combination of seasonal SVR with a new algorithm fruit fly optimization algorithm, based on the fly food-finding process was introduced by Lijuan and Guohua (2016).

Fuzzy system models were also combined with other AI models to construct hybrid models as well. Hadavandi et al. (2011) presented the hybrid model using a genetic algorithm for learning rule base and tuning database of fuzzy system. The proposed model showed successful forecasting capability for tourist demand to Taiwan from different source markets including Hong Kong, the US and Germany. Shahrabi, Hadavandi, and Asadi (2013) developed a new modular genetic-fuzzy forecasting system by combining genetic fuzzy expert systems and data pre-processing to forecast monthly tourists to Japan.

Hybrid models are also combined with linear and nonlinear models, for example Purwanto, Sunardi, Julfia, and Paramananda (2019) proposed a hybrid model combining ARIMA and linear trend model to predict tourist arrivals in Indonesia. The results showed that the hybrid model produced better prediction performance compared to ARIMA, linear trend and Holt-Winter triple exponential smoothing models. Chen (2011) combined the linear and nonlinear statistical models to forecast real-time series data sets of Taiwanese outbound tourism demand with possibly nonlinear characteristics. The paper suggested that a combination of forecasting methods can show promising predictive performance in the tourism context.

With the rapid expansion of the internet, people depend more on the Internet in the decision-making process in various aspects of life including traveling. Therefore, big data has become an important driver in the development of AI-based forecasting approaches. As a result, using online big data becomes a new trend in predicting traveling decisions. The search engine data from sources such as the Google Trends, Google Analytics and Baidu indices have shown the promising predictive ability of tourism demand (Dergiades, Mavragani, & Pan, 2018; Sun, Wei, Tsui, & Wang, 2019; Huarng & Yu, 2019; Feng, Li, Sun, & Li, 2019; Li, Hu, & Li, 2020; Li & Law, 2020; Höpken, Eberle, Fuchs, & Lexhagen, 2021). However, many challenging questions remain such as interpretation of the empirical results (Song & Liu, 2017), unavailable time series data for search volume index, keyword threshold selection (Park, Lee, & Song, 2017) or over-parameterization (Gunter & Onder, 2016).

1.5. Judgmental methods

Lin and Song (2015) suggested that judgmental techniques in forecasting referred to the techniques of ‘asking’ the experts, stakeholders, and the public, plus using judgment-aided methods for developing scenarios. It is believed that the approach could provide a comprehensive and conclusive description of future developments by using the accumulated experience and insights of experts or public groups (Song, Qiu, & Park, 2019). Uysal and Crompton (1985) presented two most used judgmental methods in forecasting tourism demand, i.e., Delphi techniques and scenario-building.

According to Vanhove (1980), the Delphi model is a well-established judgmental method for long-term demand forecasting. This method aims to generate debate and build consensus rather than test hypotheses, to map out a field rather than to test relationships within it (Kaynak & Macaulay, 1984). Kaynak, Bloom and Leibold (1994) suggested that the technique was suitable to use when dealing with uncertainty in the tourism context where our understanding of tourism demand and its determinants is limited. According to Briedenhann and Butts (2006), the Delphi technique is a unique method that could stimulate straightforward responses and indirect interactions between anonymous experts, while concurrently exposing arguments. However, this approach has been criticized for its biased interpretation because the collective judgment of experts often contains subjective opinions.

Several studies applied the Delphi method along with some quantitative forecasting models. Tideswell, Mules, and Faulkner (2001) combined statistical techniques with expert opinions in a quasi-Delphi process in developing the forecasts of tourism in South Australia. Lin and Song (2015) confirmed that the incorporation of the Delphi methods and quantitative approaches could be very valuable for achieving convergent validity. Song, Gao, and Lin (2013) suggested a forecasting model for tourism demand with both quantitative and judgmental forecasting components. The study applied scenario analysis and dynamic Delphi surveys by users and experts to adjust the predictions of ADLM models.

The limitations of Delphi methods might be improved through discussions of experts who exchange views on forecasting tourism development. The approach to scenario construction which has been used in policy formulation and societal studies and climate change has been one of the key components entrenched in the scenario studies (Song, Qiu, & Park, 2019). The study by Moutinho and Witt (1995) proposed a non-Delphi consensus forecasting approach to analyse selected scenarios through applying scientific and technological developments. The results showed that the tourism experts expected scientific and technological developments would have major impacts on tourism up to 2030. Yeoman et al. (2007) studied the long-term implications of increasing oil prices on Scottish Tourism with 2 scenarios, i.e., energy inflation and carbon tax. The study proposed economic assumptions for each scenario regarding variability in energy prices, value-added tax rate and petroleum capacity in Scotland. Peeters and Dubois (2010) presented a set of 70 scenarios using a linear growth (i.e., constant growth rates) model for tourist trips, tourist nights, and differential growth of the transport volume for three transport modes (air, car, and others) to achieve the target emission reduction.

1.6. Tourism modelling and forecasting using ANN methodology

AI-based models have been applied widely in forecasting tourism demand thanks to its capability to explain non-linear data without a priori information about the associations between inputs and outputs The artificial neural network (ANN) approach is the most frequently used AI-based method because it shows strong flexibility in processing imperfect data and nonlinearity. These data-driven and model-free approaches have played an important role in forecasting studies in the tourism context.

The first neural networks were introduced in 1943 by neurophysiologist Warren McCulloch and mathematician Walter Pitts. They used electrical circuits and a basic algorithm-based system to model how neurons in the brain might work. With more advanced computers, in 1958, Frank Rosenblatt, a psychologist at Cornell University, proposed the idea of a system with a simple input-output relationship as known as Perceptron. Perceptron used a ground-breaking algorithm to handle complicated tasks. Thanks to the advancements of computers and the availability of large data from the 2000s, ANNs have gained the enormous interest of researchers worldwide.

ANN approach is a modelling technique imitating the human nervous system that allows learning by example from representative data. The method is unique in a way that it can establish empirical relationships between multi-inputs and multi-outputs, then extract subtle knowledge from representative data (Mehrotra, Mohan, & Ranka, 1997). ANNs comprise an input layer and output layer which are connected by one or more layers of hidden nodes (Haykin, 2009) (see Fig.1). All nodes in an ANN model are interconnected and have an impact on each other. Nodes in the input layer represent independent parameters of the system. The hidden layer is used to add an internal representation handling non-linear data. The output of the neural network is the solution for the problem (Fernandes & Teixeira, 2008). By using activation functions, input layer nodes send information to hidden layer nodes and the result generated in the hidden layer will be sent to output nodes by firing output activation functions. The weight of links between layers which is a numerical measure, randomly allocated, and changes through the training process determines ANNs learning ability. Activation functions are mathematical equations to calculate the value of ANNs.

ANNs require a sufficiently large amount of data to produce meaningful trainings. Assumptions about the mathematical representation of the datasets are not required to identify the relationships between inputs and outputs. ANNs can recognize complex patterns of enormous data thanks to the ability to distinguish every element of the tested data and combine ambiguities by estimating the likelihood of each output node.

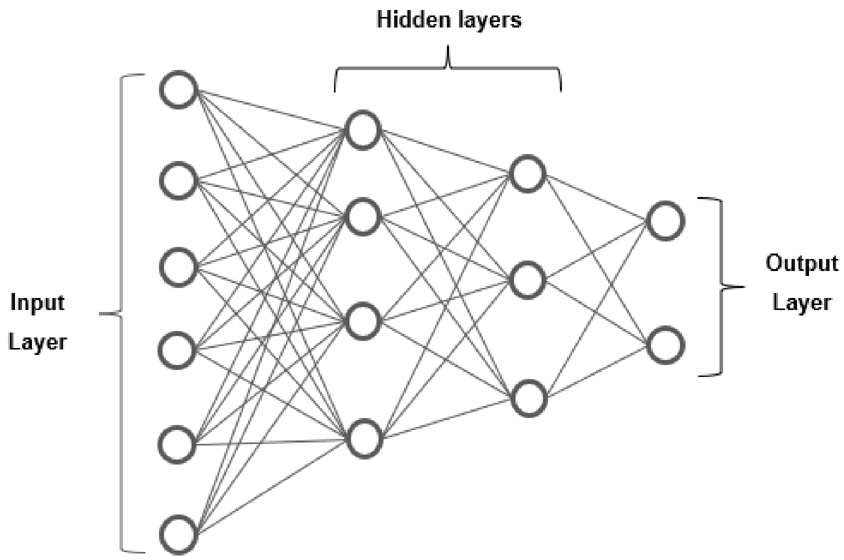


Figure 1. Structure of Artificial Neural Networks.

Source: Author's own elaboration based on Haykin (2009, p.124).

According to Haykin (2009), ANNs have the following properties and capabilities:

- Nonlinearity: A neural network, made up of an interconnection of nonlinear neurons, is itself nonlinear. The nonlinearity is of a special kind in the sense that it is distributed throughout the network.
- Input-Output Mapping: the network learns from the examples by constructing an input-output mapping for the problem at hand. A supervised learning involves modification of the synaptic weights of a neural network by applying a set of labelled training examples, or task examples. Each example consists of a unique input signal and a corresponding desired (target) response. The network is presented with an example picked at random from the set, and the synaptic weights (free parameters) of the network are modified to minimize the difference between the desired response and the actual response of the network produced by the input signal following an appropriate statistical criterion. The training of the network is repeated for many examples in the set until the network reaches a steady state where there are no further significant changes in the synaptic weights.
- Adaptive Learning: Neural networks have a built-in capability to adapt their synaptic weights to changes in the surrounding environment. A neural network trained to operate in a specific environment can be easily retrained to deal with minor changes in the operating environmental conditions.
- Evidential Response: In the context of pattern classification, a neural network can be designed to provide information not only about which particular pattern to select, but also about the confidence in the decision made. This latter information may be used to reject ambiguous patterns, should they arise, and thereby improve the classification performance of the network.
- Contextual Information: Knowledge is represented by the very structure and activation state of a neural network. Every neuron in the network is potentially affected by the global activity of all other neurons in the network. Consequently, contextual information is dealt with naturally by a neural network.
- Fault Tolerance: A neural network, implemented in hardware form, has the potential to be inherently fault tolerant, or capable of robust computation, in the sense that its performance degrades gracefully under adverse operating conditions. For example, if a neuron or its connecting links are damaged, recall of a stored pattern is impaired in quality.

In terms of connecting patterns of different layers, Claveria, Monte, and Torra (2015b) divided ANNs into two architecture groups: feed-forward networks and feedback networks (or recurrent networks). Feed-forward networks have one input layer and a single output layer in which input nodes send information to output nodes in one direction. Feedback networks or interactive networks use their memory to deal with a series of inputs with feedback connections from outer layers to lower layers of nodes considering the data´s temporal structure. Unlike feed-forward networks, signals of recurrent networks can go in both ways through hidden layers. The architectures are commonly utilized to handle a sequence of events happening in a certain order. There are many recurrent architectures: fully recurrent, simple recurrent, bidirectional recurrent, and Elman networks (a special case of recurrent networks) and so on.

Relate to learning strategy, ANNs can also be categorized into two groups: supervised and unsupervised learning networks. In supervised learning networks, weights are varied to estimate the target outputs for each experimented pattern. Support vector machines (SVM) and Multilayer perceptron (MLP) networks are among the most used supervised learning models. On contrary, during the training under unsupervised learning, ANNs have no target outputs and depending on the input values, the networks group similar weight values in a certain range. In other words, data patterns are examined and organized according to their correlations. Based on 10 time series of monthly tourist arrivals to Turkey between 2001 and 2011, Akın (2015) compared the forecasting performances of SARIMA, SVR and Multilayer Perceptron (MLP) and confirmed that there is no single best model for all the cases.

Self-organizing maps (SOM) of Kohonen are among the most popular non-supervised models (Kohonen, 1982). According to Claveria, Monte, and Torra (2015b), ANN hybrid learning is a combination of both learning methods in which some weights are determined by a supervised process while the others are determined by unsupervised procedure. Radial basis function (RBF) network, an example of the hybrid model, combines supervised and unsupervised learning strategy with three layers such as input layer, the hidden layer including nodes computing a radial symmetric activation function and output layer including nodes that linearly combine outputs from hidden layers.

Following are some common types of ANNs:

- Feedforward Neural Network – is one of the most basic forms of ANNs. Data in the network is sent through the different input nodes until it reaches output nodes. The process is considered as front propagating wave because data pass in one direction from the first layer to the output node. The network determines the sum of values of inputs and their weights which are later sent to the output layer. Applications of feed-forward networks can be found in the studies of Fernandes, Teixeira, Ferreira, and Azevedo (2008), Teixeira and Fernandes (2012), Fernandes, Teixeira, Ferreira, and Azevedo (2013), Teixeira, Santos, and Fernandes (2014), Teixeira and Fernandes (2015), Constantino, Fernandes, and Teixeira (2016). Multilayer Perceptron (MLP) is the same as Feedforward Neural Network which is made up of three or more layers. It is employed in the classification of data that cannot be separated linearly. It is a form of a fully connected ANN. The studies of Claveria, Monte, and Torra (2013), Cuhadar, Cogurcu, and Kukrer (2014) are among numerous experiments using MLP to forecast tourist volume.
- Radial Basis Function Neural Network: considers the distance of any point from the centre. These neural networks are composed of two layers. The characteristics are merged with the radial basis function in the inner layer. The output of these characteristics is then used to calculate the identical result in the following time step. Studies by Zhang and Li (2012), Cuhadar, Cogurcu, and Kukrer

(2014), Claveria, Monte, and Torra (2017) applied these networks to forecast tourism demand in different contexts.

- Modular Neural Network: consists of independent networks which operate individually to get target outputs. The task is divided into small components which are processed separately, increasing the speed of the computational process for a large set of data (Happel & Murre, 1994).

Although ANNS have been shown the highly predictive capability for tourism data, ANNs are questioned as a theoretical background for the approach is unidentified (Zhang, Patuwo, & Hu, 1998). The methods have black boxes due to the unknown assumptions under each input and output node. The independent variables in forecasting the desired output values are difficult to extract within the network, and the weight adjusting process is often insufficiently examined. Besides, in case of rare distress events application of ANN is limited as the data is often insufficient to train the model. ANN models are not able to combine judgmental approaches in the modelling process.

1.7. ANN-based models proposed in the research

The Artificial neural network (ANNs) model is one of the most frequently used AI-based models. A neural network is a machine that is designed to model how the brain performs a particular task or function of interest (Ghalehkhondabi, Ardjmand, Young, & Weckman, 2019). A neural network is composed of a set of interconnected artificial neurons, or a group of processing units, which process and transmit information through activation functions (Teixeira, Santos, & Fernandes, 2014). Various studies show empirical evidence in favour of ANNs (Fernandes, Teixeira, Ferreira, & Azevedo, 2008; Teixeira & Fernandes, 2015; Law, Li, Fong, & Han, 2019; Álvarez-Díaz, González-Gómez, & Otero-Giráldez, 2019). Fernandes, Teixeira, Ferreira, and Azevedo (2013) used ANN to forecast tourism demand in the North and Centre of Portugal. The study found that ANN was suitable for modelling and predicting the reference data. Srisaeng and Baxter (2017) used ANN to predict passenger demand for international airlines in Australia and the result showed that ANN using MLP architecture provided highly predictive capability. Also, according to Alamsyah and Friscintia (2019), ANN was able to accurately predict the monthly tourists in Indonesia. Álvarez-Díaz et al. (2019) found that a non-linear autoregressive neural (NAR) network shows slightly better performance than SARIMA in the case of forecasting international overnight stays and international tourists. While comparing ARIMA models and ANNs in forecasting tourism demand in Sweden, Höpken, Eberle, Fuchs, and Lexhagen (2021) confirmed that ANNs tend to outperform the ARIMA model when using a big data-based approach.

The advantages of ANNs are (i) capability to map linear or nonlinear function without any assumption imposed by the modelling process (Wu, Song & Shen, 2017); (ii) having been proved to have strong practicality and flexibility for treating imperfect data, or handling almost any kind of nonlinearity (Song, Qiu, & Park, 2019); (iii) the neural network methods can perform well for shorter records of tourism demand under unstable tourism conditions (Kon & Turner, 2005).

Different ANN models have been applied to tourism and hotel forecasting practice, including multi-layer perceptron (MLP), radial basis function (RBF), generalized regression neural network (GRNN) and Elman neural network (Elman NN) in which MLP is the most widely used (Song, Qiu, & Park, 2019). According to Haykin (2009) a multilayer perceptron is a neural network structure containing one or more layers that are hidden from both the input and output nodes. The model of each neuron in the network includes a nonlinear activation function that can be differentiable between layers. The nodes of adjacent layers of an MLP ANN are fully connected by the synaptic weights of the network.

The ANN is submitted to a training stage using a training dataset, and later the ANN is ready to perform classification or prediction using new data in its input. The training process is carried out through the adjustment of the weights of the connections between the nodes of successive layers in a sequence of iterations or epochs using a back-propagation algorithm to reduce the error between the output of the ANN and the target of the training dataset (Teixeira, Santos, & Fernandes, 2014). Figure 2 shows one architecture example of a multiplayer perceptron with one hidden layer and an output layer. Given the available dataset and the objectives, MLP ANN is employed to predict International Tourists to Vietnam in this work.

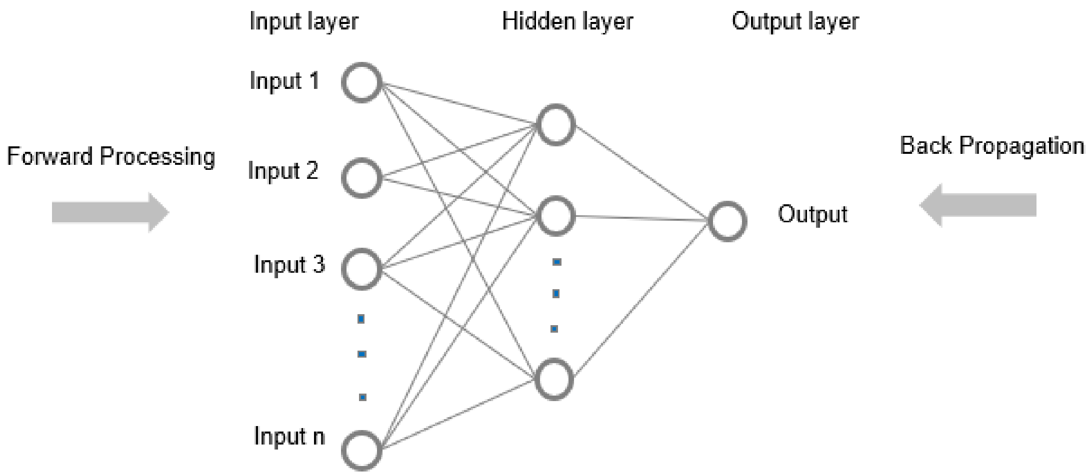


Figure 2. Architectural graph of a MLP ANN with one hidden layer.

Source: Author's own elaboration based on Haykin (2009, p.124).

2. Development of tourism sector in Vietnam

The tourism sector plays an important role in the economy thanks to its ability to create jobs, attract foreign investments, contribute to tax revenues, foster economic growth, and spread prosperity. The service sector seems to create more job opportunities for women and young people than others. As a labour-intensive sector, the blossom of tourism provides significant prospects for small and medium enterprises – key players of the economy – to flourish. The sector also creates linkages with various sectors transportation, food and beverage, real estate. Therefore, it has strong multiplier effects on the rest of the economy, generating jobs and income opportunities along its value chain (The World Bank, 2019). Furthermore, one way to share prosperity between prosperous and underprivileged areas is to facilitate tourism development to boost up local economies.

With beautiful landscape, pristine nature and diverse culture, Vietnam has been benefited from the development of the tourism sector. According to the World Economic Forum's (WEF) Travel and Tourism Competitiveness Index in 2019, Vietnam ranks the 35th globally (out of 140 countries) and the 3rd within the Southeast Asia region in terms of its natural and cultural resources and the 29th in terms of cultural resources and business travel (World Economic Forum, 2019). Remarkably, Vietnam has eight UNESCO World Heritage sites - the highest number compared to other countries in Southeast Asia.

Considering this setting, the Government of Vietnam is prioritizing tourism as a strategic sector and driver of socio-economic development. In January 2020, the Government approved a long-term strategic plan for the development of the tourism sector until 2030 with specific goals for the next period 2020-2025 and 2026-2030 (Government of Vietnam, 2020). Until 2025, the government expects that Vietnam´s tourism sector will become one of the leading industries, making Vietnam into the top 50 countries in terms of the Travel and Tourism Competitiveness Index.

Table 1. Targets for the tourism sector toward 2030.

Indicators	Unit	2019	Target 2025	Annual growth rate	Target 2030	Annual growth rate
Number of international tourists	Million	18	35	12-14%	50	8-10%
Number of domestic tourists	Million	85	120	6-7%	160	5-6%
Total revenue	US$ billion		77-80	13-14%	130-135	11-12%
Number of jobs created	Million		5.5-6	12-14%	8.5	8-9%
Contribution to GDP	Percent	9.2	12-14		15-17	

Source: Government´s Decision No. 147/QD-TTg (January 2020).

To transfer such an ambitious plan into reality, the following solutions will become the key focus of Vietnam´s government and the sector over the coming decade: (i) transform the mind-set of state management on tourism, (ii) improve and refine policies on tourism development, (iii) develop tourism infrastructure, (iv) enhance tourism human resources, (v) diversify target groups of tourists, (vi) develop tourism products, (vii) improve tourism promotion, (viii) apply new technologies, (ix) strengthen state management of the tourism sector.

2.1. Tourism demand

Thanks to the economic reforms since the 1980s, Vietnam has witnessed remarkable transformations in all aspects of the country. Vietnam´s government has considered the tourism sector a spearhead industry for economic development. The tourism sector has experienced an incredible surge in the number of international and domestic tourists. For two and a half decades, the number of international tourists to Vietnam in 2019 has multiplied 13 times compared to 2000. Domestic tourists have also experienced a similar boom - a nearly eight-fold increase, from 11.2 million in 2000 to 85 million in 2019, reflecting rising income and the increase of middle class who have a strong desire for travel, and higher affordability of air transport thanks to the rapid growth of low-cost domestic air carriers (Fig. 3).

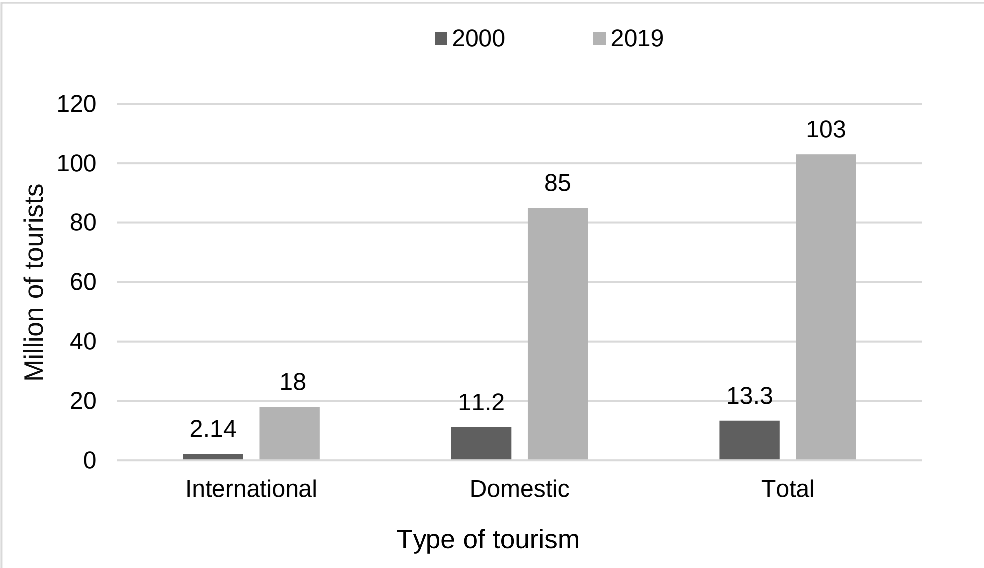


Figure 3. Tourism demand in Vietnam between 2000 and 2019.

Source: GSO (2020).

Although domestic tourists outnumbered international tourists, the contribution of inbound tourism accounted for a larger part of total tourism revenues. It is important to focus on the target group of customers as forecasting accurately demands of this group will be beneficial to the local economy.

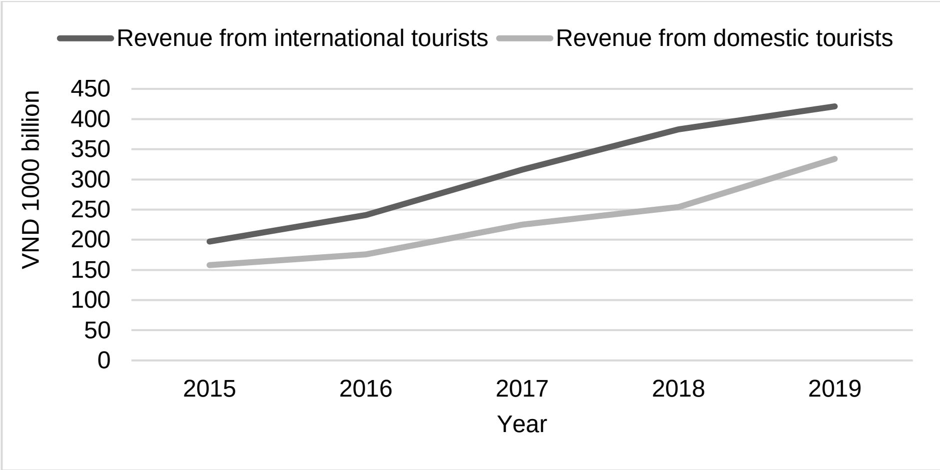


Figure 4. Tourism revenues by groups of tourists (VND 1000 billion).

Source: VNAT (2019).

2.1.1 International tourists

During the period 1995-2019, Vietnam has experienced a boom in inbound tourism. Compared to other competitors in Southeast Asia, the strong increase of the tourist group has enabled Vietnam to seize the increasing tourism market share in the region where Vietnam ranked second. In terms of the overall number of international tourists, Vietnam has passed Indonesia and the Philippines and gradually reached Singapore (Fig.5). The gap between Vietnam and the top performers - Thailand and Malaysia - has also been narrowed down with an increasing share of total tourists. In terms of country size, Vietnam still has more room to grow as the tourists to Vietnam per capita accounted for around 30% while the percentage in Malaysia and Thailand were 55% and 80% correspondingly (The World Bank, 2019).

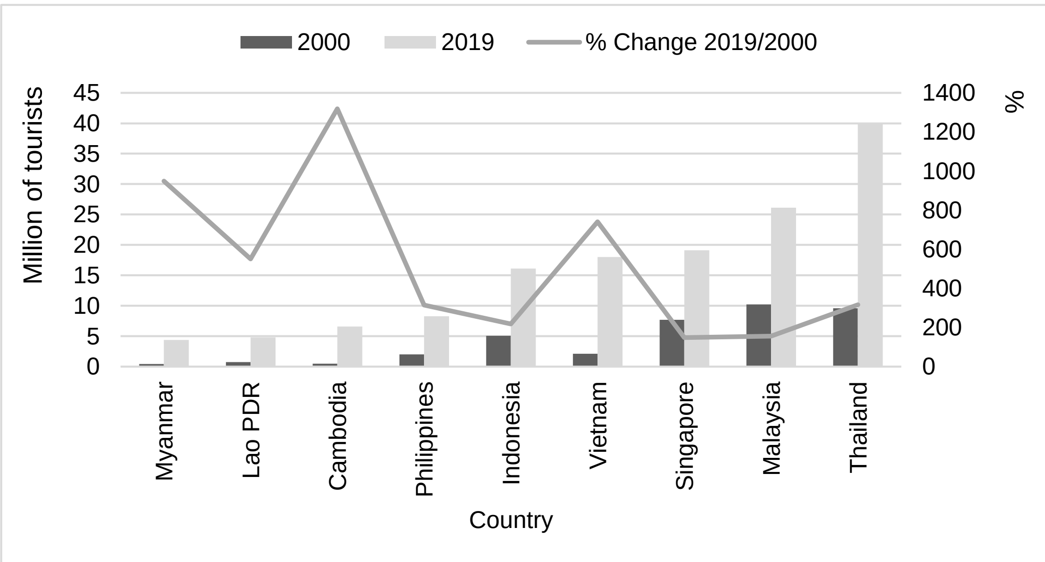


Figure 5. International tourists to Southeast Asia in 2019.

Source: The World Bank (2019).

The number of international tourists to Vietnam has increased more than 13 times during 1995-2019, from 1.35 million in 1995 to 18 million in 2019 (Fig.6). The average growth rate of the 1996-2015 period was almost 10%. The 2016-2019 period saw a remarkable acceleration in international tourists with the average growth rate of 23%. The number of international tourists reached 18 million in 2019, the highest peak in the last 25 years.

Figure 6. Number of international tourist arrivals to Vietnam and annual change rates in arrivals (1995–2020).

Source: GSO (2020).

Although the graph shows increasing numbers of international tourists to Vietnam through the years, there are remarkable drops in tourism demand during 2003, 2008-2009, 2014-2015 and 2020. In 2003, world tourism faced many distressing events: the Iraq war, the SARS pandemic in 32 countries and regions including Vietnam, terrorist attacks in many parts of the world such as Indonesia, Turkey, Russia, Columbia, Saudi Arabia etc. According to UNWTO´s Tourism Highlights Report (World Tourism Organization, 2004), international arrivals to Southeast Asia decreased by 14% in 2003. Vietnam´s tourism also suffered certain losses due to the outbreak of SARS, making international tourists decline by nearly 8%.

The global financial crisis in 2008 – 2009 and the epidemic influenza A/H1N1 at the same time were the major hit to Vietnam's tourism industry, leading to a lower low of foreign tourist volume than the previous years. According to a report on Vietnam´s socio-economic situation in 2009 by the General Statistics Office (General Statistic Office of Vietnam, 2009), tourists from major markets continued to decrease in which those from China and South Korea recorded a double-digit decline by 18% and

19,4% respectively. Other top source markets also saw a significant decrease, for example, Japan (8,6%), Taiwan (10.4%), Australia (6.9%) and so on.

The number of international tourists to Vietnam in 2015 only increased by nearly 0.9% compared to 2014, making it the lowest growth rate among the last six years. Such a low rate was largely attributed to the 2014 China – Vietnam oil rig crisis and the devaluation of the Russian currency (Truong & Le, 2017). China's deployment of an oil rig together with civilian, coast guard and Army Navy vessels in disputed waters (as known as the South China Sea or East Sea in Vietnam) triggered anti-China protests in Vietnam, resulting in a significant decline by 8.5% in the number of international tourists mainly from Chinese-speaking markets from May 2014 to the end 2015 (Vietnam National Administration of Tourism, 2015). However, the number of Chinese tourists to Vietnam in the following year increased again, marking a growth of nearly 51.4% year-on-year (Vietnam National Administration of Tourism, 2016). On the other hand, in 2015, the number of tourists from Russia – an important market to Vietnam´s tourism thanks to visa relaxation policy for Russian tourists since 2009 – declined by 7.1% compared to 2014 due to the continuous weakening of the Russian rouble as a result of Ukraine incident (Truong & Le, 2017) (Vietnam National Administration of Tourism, 2015).

Having been hit by the COVID-19 crisis in early 2020, Vietnam has faced severe economic consequences. Tourism is among the most affected. Border closing and the ban on international tourists immediately led to an abrupt decline of international arrivals, causing a significant decrease in total tourism revenue in 2020 by 48.4% compared to that of 2019 (General Statistics Office, 2021).

Even though yearly data show a consistently increasing trend of international tourists to Vietnam, monthly statistics of international tourists reveal fluctuations that could be attributed to the seasonality nature of tourism. November to March of the next year and July-August are usually the highest seasons for international tourists to Vietnam. It is understandable as in these months most people in the world have long holidays which enable them to take a lengthy vacation abroad. The period from September to November every year is considered the low season for Vietnam's tourism when the new school year and rainy season start, resulting in a sharp decrease in tourism demand. The number of international tourists hit the bottom in September 2009 and October 2011 but bounced back to a higher level in the next coming months.

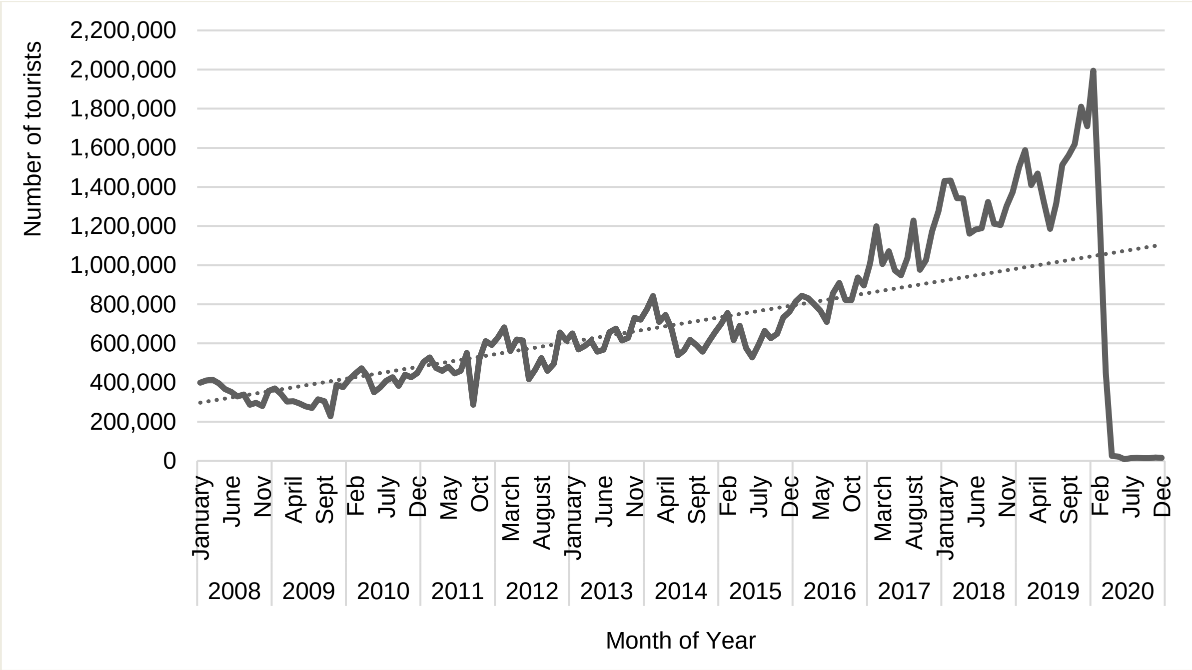


Figure 7. Monthly number of international tourist arrivals in Vietnam and its trend (2008:01 to 2020:12).

Source: GSO (2020).

At the beginning of 2020, the tourism sector in Vietnam witnessed robust growth in the number of both international and domestic tourists (up by 33% compared to the same period of 2019). However, at the end of January 2020, these numbers quickly plummeted due to the outbreak of the COVID-19 pandemic. In April 2020, the tourism demand hit rock bottom as social distancing and border closure were put into practice (Fig.7). Domestic tourism was encouraged from May onwards, but a new COVID-19 outbreak in Da Nang (one of the most popular tourist attractions in Vietnam) in July 2020 and April 2021 ruined local tourism recovery. According to the statistical yearbook 2020 by GSO international arrivals to Vietnam decreased by 78.7% compared to that of 2019 (General Statistics Office, 2021).

In terms of international tourists by region, most tourists come from Asia (79.9%), of which Northeast Asia accounted for 66.8% and Southeast Asia had a share of 11.3%; the remaining Asian markets accounted for 1.8%. Those from Europe comprised 12%, while the Americas and Australia followed with 5.4% and 2.4% respectively (Fig. 8). The key source markets for Vietnam´s tourism are countries from Northeast Asia particularly China, South Korea, and Japan. Together, the three countries accounted for 61.4% of Vietnam’s international tourists in 2019.

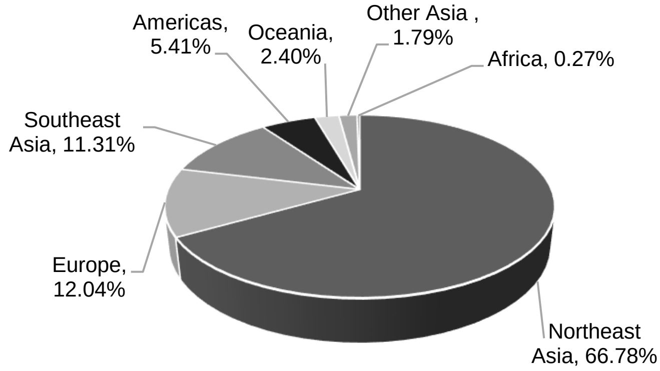


Figure 8. International tourists to Vietnam by region in 2019.

Source: VNAT (2019).

Most top source markets saw robust double-digit growth rates from 10 to 20% in 2019 (Fig.9). The strong annual growth of tourists from China (19.9%) and South Korea (23.1%) made the share of these markets surge from 31% in 2012 to 56% in 2019. Tourists from USA and Russia continued to stand in the top 10 key source markets for Vietnam´s tourism thanks to their strong historical connections to Vietnam during the Cold War. In 2019, American and Russian tourists were 746 thousand and 647 thousand people, accounting for 4.1% and for 3.6% respectively of total international tourists to Vietnam (Vietnam National Administration of Tourism, 2019).

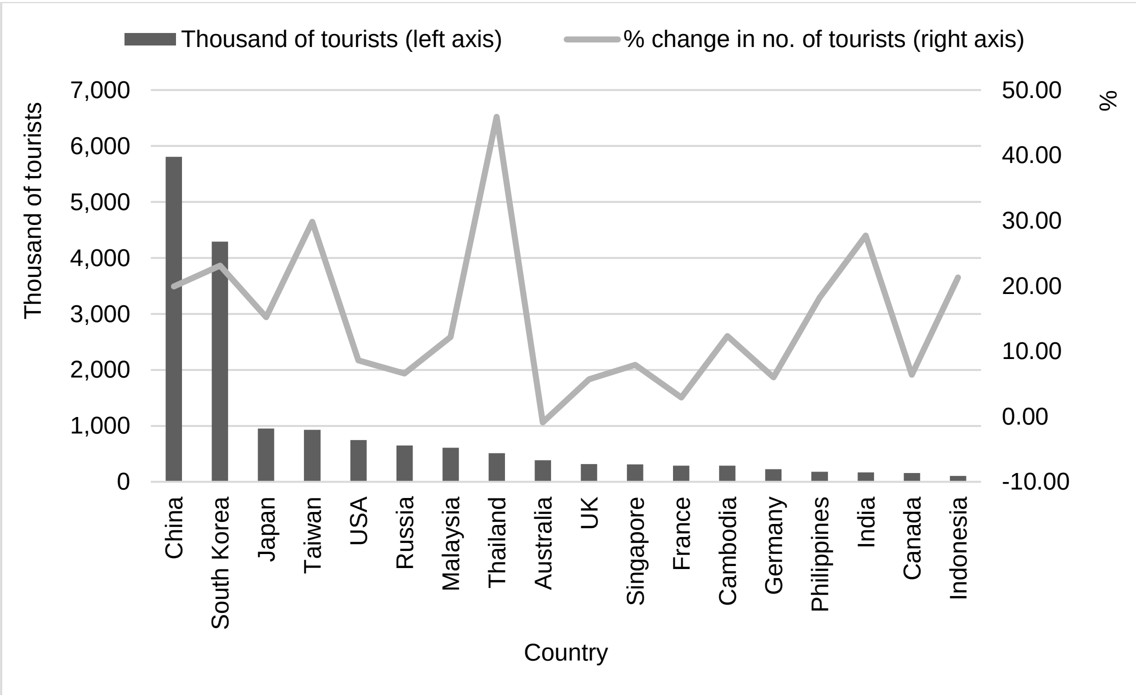


Figure 9. International tourists to Vietnam by country in 2019.

Source: VNAT (2019).

European markets also play an important role in Vietnam´s tourism thanks to their high spending and longer stay. Tourists from 5 Western European countries (UK, France, Germany, Spain, and Italy) to Vietnam saw a continuously significant growth rate through 2015-2019 (Fig.10).

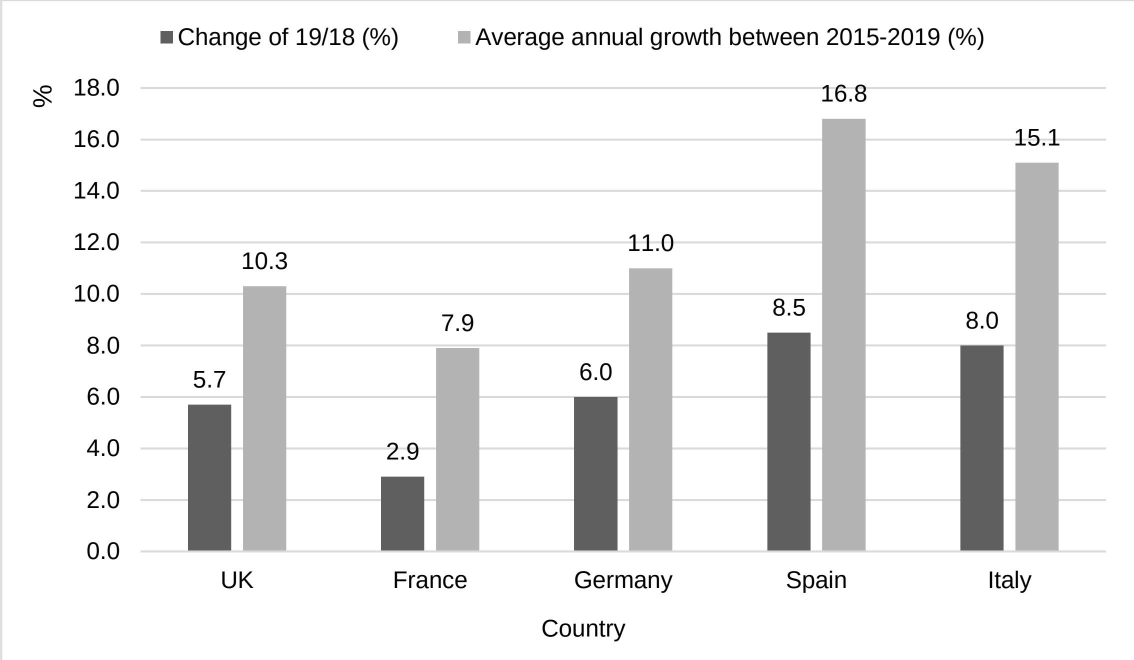


Figure 10. Growth of international tourists from 5 Western European countries.

Source: VNAT (2019).

International tourists to Vietnam by air accounted for 79.8%, 18.7% by land and 1.5% by sea in 2019 (Fig.11). Especially, those traveling to Vietnam by air took up a considerably larger part in comparison to the average rate of global tourism. According to UNWTO (2019), 58% of international tourists in the world travel by air 38% by land and 4% by the sea in 2019.

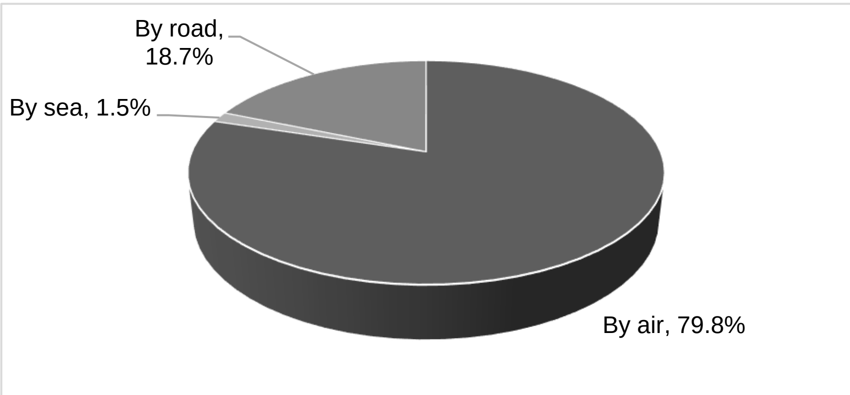


Figure 11. International tourists by mode of transport.

Source: VNAT (2019).

In 2019, on average an international tourist stays at commercial accommodations 8.02 days while the average overnight stay at non-commercial accommodations is 11.92 days. International tourists staying at commercial accommodations spend an average of USD 1,083.36 while tourists staying at non-commercial accommodations (e.g., homes of friends, relatives…) spent an average of USD 622.71 (Fig. 12). As the cost for accommodation accounts for the major part of tourism expenditure, it is reasonable that although the longer days foreign tourists spend at non-commercial accommodations, the lower spending they make compared to ones staying at commercial accommodations.

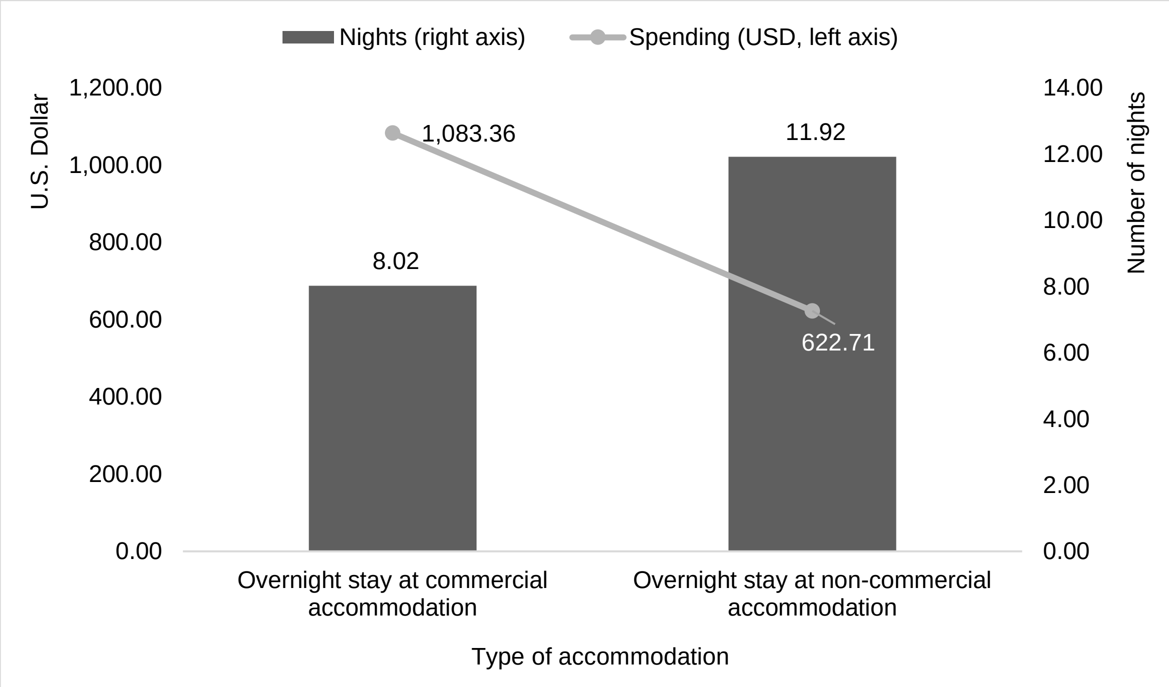


Figure 12. Average overnight stays and spending of international tourists in 2019.

Source: VNAT (2019).

Although the share of short-haul markets comprised a major part of the total market share, yielding from the tourist group is relatively low. For example, China has the biggest change in the share of total tourists to Vietnam, but their daily spending is much lower than average. International tourists from long-haul markets tend to spend higher than those from short-haul markets due to their long trips. Tourists from Russia ranked 1st with USD 1,830.10 for 15.33 days. Followings were the UK (USD 1,715.82 for 14.46 days), USA (USD 1,570.77 for 12.02 days), Australia (USD 1,541 for 12.25 days) and France (USD 1,443.28 for 12.76 days) (Fig. 13).

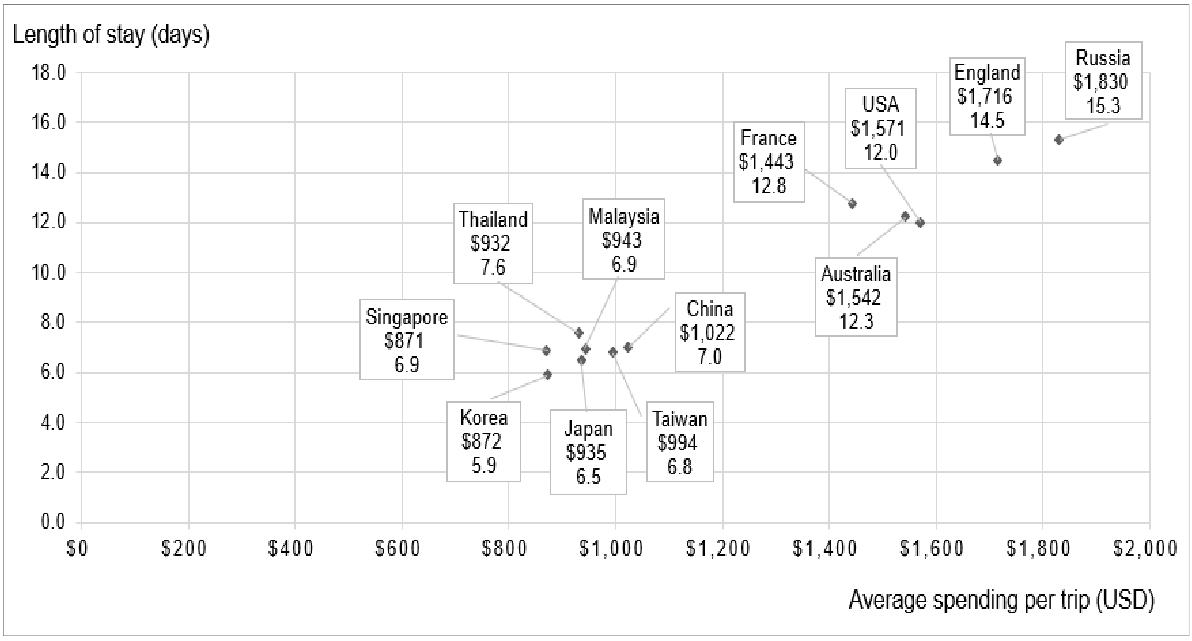


Figure 13. Length of stay and average spending by major markets in 2019.

Source: VNAT's Survey of International Tourists 2019.

Compared to the daily spending of tourists in other tourist attractions in the same region of Southeast Asia, such spending amount in Vietnam is below that of Singapore (286 USD), Philippines ($128.3), Indonesia ($129), Malaysia ($134), Phuket (Thailand) 239 USD, Bangkok (Thailand) 173 USD etc. There are many reasons for this low number in Vietnam, i.e.: lack of entertainment and recreation centers and large scale of shopping malls, the weak link between travel agencies and shopping chains, low value-added goods for tourists, pollution and bad traffic, low quality of human resources etc. Figure 14 shows the average spending per day of international tourists in Vietnam through the years.

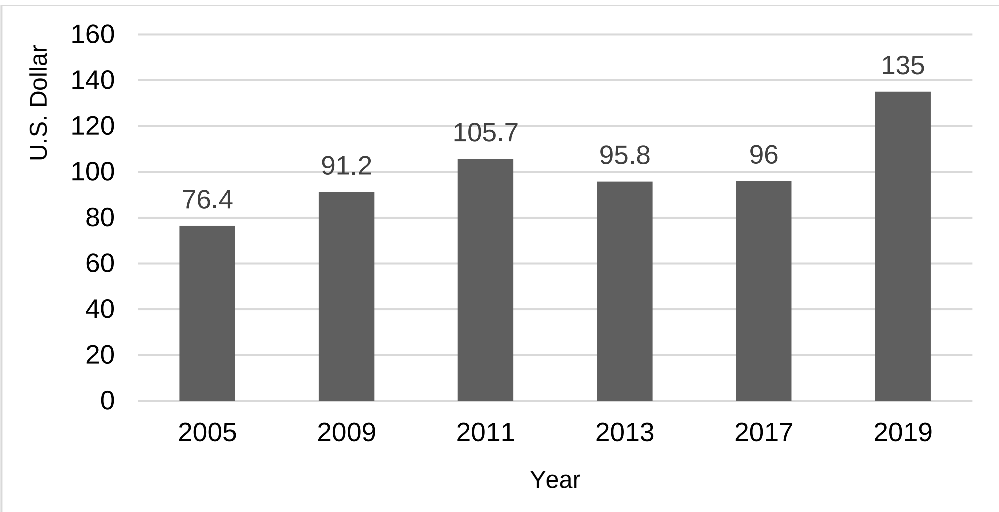


Figure 14. Average spending per day of international tourists (USD).

Source: VNAT (2019).

Figure 15 presents the spending of international tourists by purpose. Accommodation cost accounts for the larger part of tourist expenditure (from 25.1% to 32.96%). Spending on food and beverage comprised from 18.3% to 23.78% of the total cost. Expenditure on transport decreased from 18.7% to 15.01%. Spending on shopping saw a continual decrease through the years (from 16.6% in 2005 to 15.45 in 2019), implying the lack of high value-added goods for tourists.

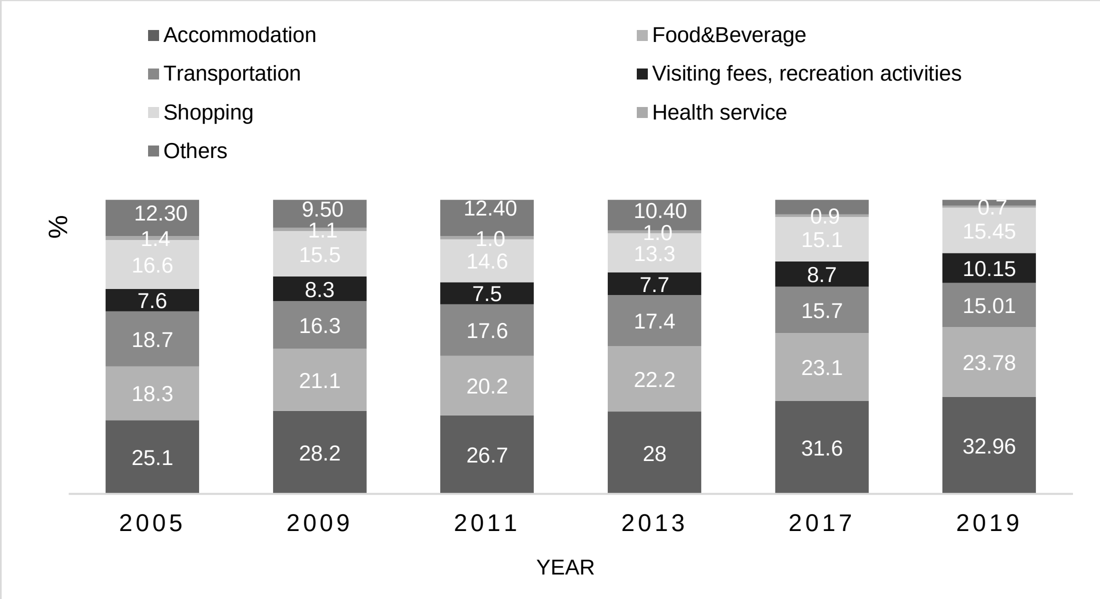


Figure 15. Spending purposes of international tourists (%).

Source: VNAT (2019).

Simultaneously as the nationality structure of international tourists has not significantly changed, the purpose of visit and destination have continued stable. More than two-thirds of international tourists come to Vietnam largely for holidays and leisure, and business or meetings, incentives, conferences, and events purposes. In general, international tourists have continued to be attracted to the same popular local destinations. Figure 16 shows the top 10 most-visited cities/provinces by international tourists.

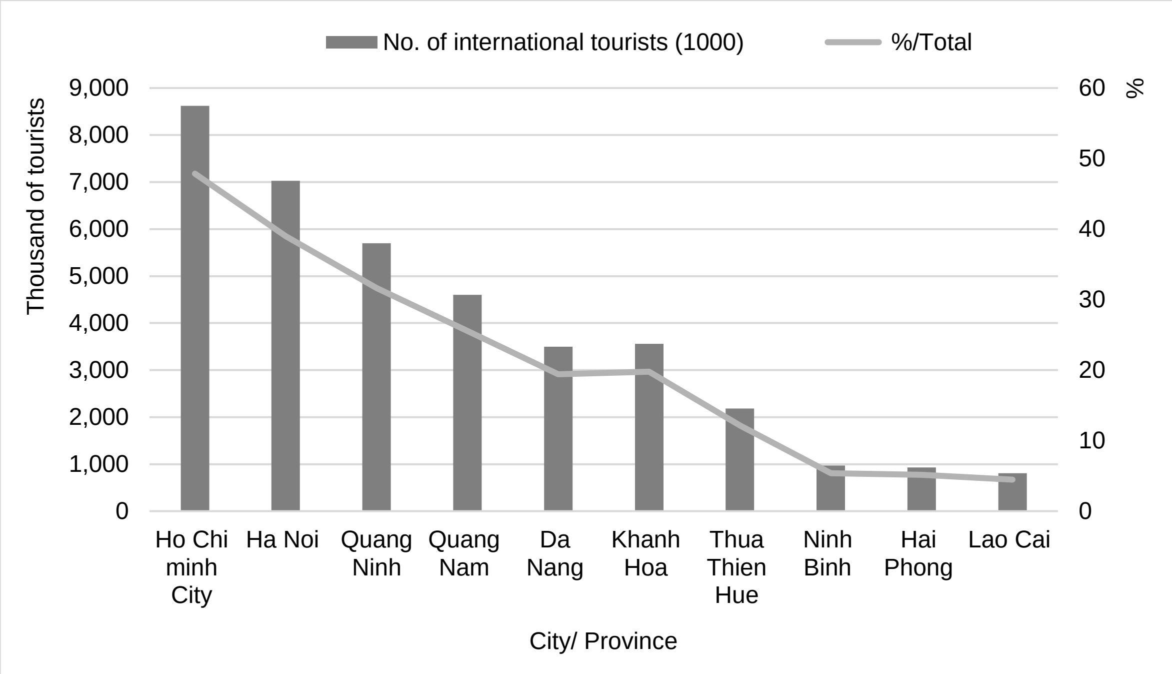


Figure 16. Key destinations for international tourists in Vietnam in 2019.

Source: VNAT (2019).

2.1.2. Domestic tourists

Domestic tourists in Vietnam, which outnumbered international tourists, have surged from more than 10 million in 2000 to 85 million domestic tourists in 2019 (Vietnam National Administration of Tourism, 2019). The volume of domestic tourists increased 8.5 times after nearly two decades thanks to the significant increase of income per capita, improved infrastructure as well as the rapid growth of low-cost airlines enabling tourism more affordable and easily accessible for most of the citizens.

For the last two decades, domestic tourists have experienced a quite steady growth rate with the exceptional surge in 2009, 2015 and 2017 (more than 20%). However, the big change between 2014 -2015 was attributed to the altering of statistical methodology for measuring domestic tourists especially in terms of the measurement of same-day tourists in 2015. The number of domestic tourists increased significantly in 2009 thanks to a nationwide tourism promotion including remarkable discounts for hotels, tours, and airline tickets (Fig.17).

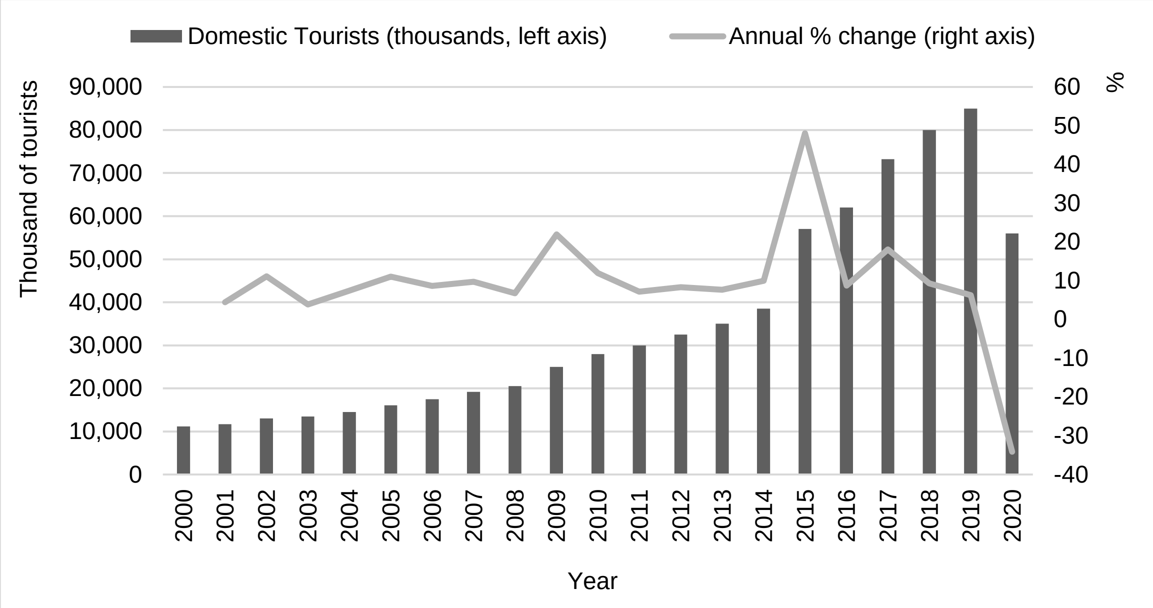


Figure 17. Domestic Tourists.

Source: VNAT and GSO (2020).

Spending of domestic tourists considerably contributed to the total tourism revenues of Vietnam. From 2015 to 2019, tourism revenue from domestic tourists rose by 2.1 times, while the number of domestic tourists increased only by 1.5 times in the same period. Domestic tourists spent an average of US$ 250 for the trip of 3.62 days. Same-day tourists had an average expenditure of US$49. Overnight tourists staying at commercial accommodations had an average expenditure of US$266 for the trip duration of 3.57 days. Overnight tourists staying at non-commercial accommodations (like homes of friends, relatives…) had an average expenditure of US$171 for the trip of 3.96 days (Fig.18).

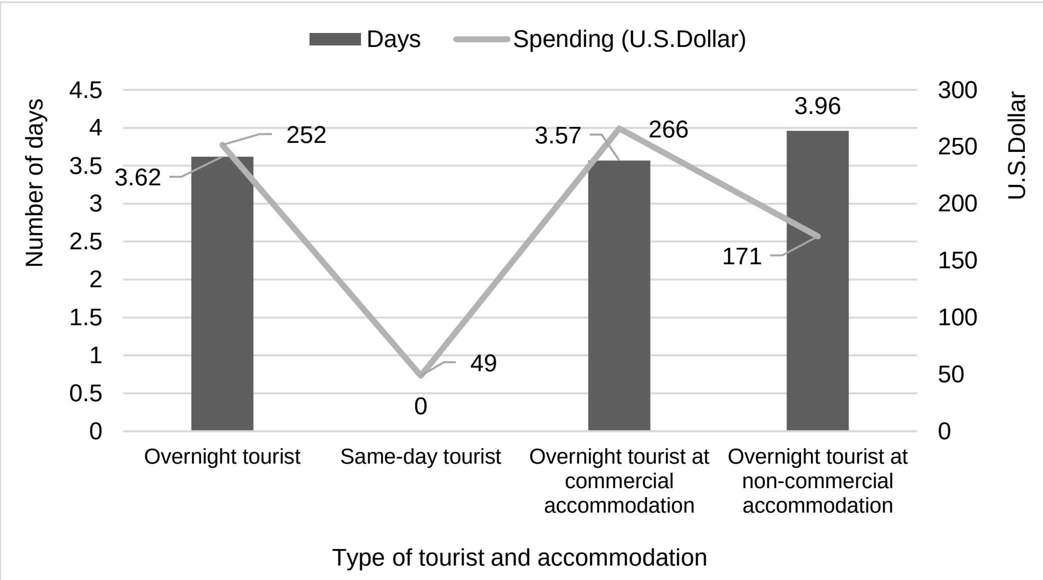


Figure 18. Average expenditure per domestic tourist in 2019.

Source: VNAT (2019).

2.2. Tourism supply

The Vietnamese tourism sector has seen continuously robust growth over the period 2010-2019 thanks to increasing tourism demand, strong investments, healthy government support and rising incomes in key developed and emerging source markets. The COVID-19 pandemic ruined tourism growth as the industry has been suffering exceptionally new lows due to border closure, investment constraints and a poor macroeconomic outlook. However, with rich history and culture together with natural beauty, Vietnam is expected to relive its success story in the next few years once the virus is under control and international flights are opened again. The expectation is based on strong government supports such as enormous infrastructure spending, investment incentivizing, and market potential. Most investors prudently keep a confident view for the tourism sector's recovery in the medium-term.

2.2.1. Major tourist attractions

The potential of Vietnam's tourism is rooted in its diversity of tourist attractions from intact natural reserves, mountains and beaches, historical legacies to bustling cities like Ho Chi Minh City and Hanoi. The country possesses a mixture of UNESCO World Heritage sites, including Ha Long Bay, Hội An Ancient Town, the Complex of Huế Monuments, Tràng An Scenic Landscape Complex, My Son Sanctuary, and so on (Vietnam National Administration of Tourism, 2019). Vietnam also offers tropical forests as well as white and sandy beaches and mountain retreats. Thanks to the strategic location in Southeast Asia, Vietnam has enjoyed proximity to several key regional economies including China, Korea, Japan, Singapore, Malaysia and so on. The diversity of tourist destinations together with the country's long geography could mitigate the effects of seasonality, providing year-round travel opportunities for tourists.

As the capital of Vietnam, Hanoi is home to cultural diversity and historical attractions, including the Hanoi Old Quarter, Ho Chi Minh Mausoleum Complex, Ngoc Son Temple and the Water Puppet Show at the Hoan Kiem Lake. The city is connected regionally and globally by Noi Bai International Airport with numerous airlines providers such as Vietnam Airlines, AirAsia, Cathay Pacific, Hong Kong Airlines, Thai Airways, Tiger Airways, and so on. Hanoi is highly accessible thanks to its connections to major travel hubs, such as Hong Kong, Thailand, Singapore, and Qatar. Hanoi is also connected via rail links along the eastern coast to the south of the country and north to China. Tourists can find a variety of accommodation options in this city from high-end international brand hotels, such as Hilton Opera, Movenpick, Intercontinental and Sofitel Legend Metropole which hosted the Trump-Kim summit in late February 2019 to many budget guesthouses and backpacker-style hostels (Fitch Solutions, 2020).

One of the most significant tourism destinations in Vietnam is Hạ Long Bay - the UNESCO World Heritage site - in the north of the country. Hạ Long Bay can be reached via the airport in Hanoi or via Cat Bi International Airport in Hai Phong Province. Tourists also can travel to the region by international cruises. Although Hạ Long City is small, it can offer various types of accommodations including international brands, such as Novotel and Wyndham.

Ho Chi Minh City located in the south of Vietnam is the most vibrant metropolitan city in Vietnam. It is one of the top tourism locations with numerous historical attractions including the Reunification Palace, the Notre Dame Cathedral, the War Remnants Museum, and the Cu Chi Tunnels. Ho Chi Minh City is connected to local and international regions by Tan Son Nhat International Airport, the largest and busiest airport in the country with an annual capacity of a maximum of 17 million passengers. Ho Chi Minh City is also connected to Hanoi Capital via the North-South Railway. Numerous accommodation options in this city could match tourists´ all budget levels. The well-known historical Hotel Majestic is also a tourist attraction.

Vietnam also enjoys strategic tourism locations along its lengthy coastline. These include other UNESCO World Heritage sites such as the Complex of Monuments in Hue, the Ancient Town of Hoi An and the My Son sanctuary. Hue, Da Nang cities are connected to Hanoi and Ho Chi Minh City via the North-South Railway while Hoi An is also just around an hour's drive from Da Nang. Hue, Da Nang and Nha Trang which offer pristine beaches and islands are easily accessible because they are linked with other cities by airports that provide domestic and international flight connections. Nha Trang which offers many direct flights is a major beach resort destination, especially for Russians. Da Nang – a coastline city in the central part of Vietnam – is the key hub for tourism thanks to the recent expansion of Da Nang International Airport with a serving capacity for over 6.5 million passengers annually. In addition to the locations, other tourist attractions include Mekong River Delta in the far south, Son Đoong cave - the world's largest natural cave in the center of the country, the town of Sa Pa in the northwest and the surrounding rice fields, and Phu Quoc Island in the furthest south. In most locations, accommodation options are extensive from low-cost hostels to upscale resorts (Vietnam National Administration of Tourism, 2019).

2.2.2. Transport infrastructure

The development of the tourism industry has accelerated investments in transport infrastructure, including airports, railways, and waterways. It is acknowledged that transportation by air has become the most popular way of travel for international tourists to Vietnam. According to VNAT, roughly 80% of total international tourists came to Vietnam by air in 2019, considerably higher than the world's average rate of 58%. According to the Report on Travel and Tourism Competitiveness in 2019 by the World economic forum (World Economic Forum, 2019), Vietnam's air transport infrastructure indicator ranked 50/140 countries, showing an increase of 11 places compared to 2017 thanks to the rapid development of air operators, domestic and international available seat kilometres, and aircraft departures. Conversely, the quality of air transport infrastructure decreased from 85 to 99 while airport density ranked low at 96th showing the expansion of air transport infrastructure has not matched the rapid growth of travel demand. At present, Vietnam has 22 commercial airports of which half for international flights and the other half for domestic ones (Vietnam National Administration of Tourism, 2019). According to the Civil Aviation Administration of Vietnam, Vietnam´s airports received 115.5 million passengers in 2019, up by 11.4% compared to 2018. In terms of international flights, 71 foreign airlines and 4 Vietnamese air carriers are running approximately 140 international air routes connecting Vietnam with 28 countries/ territories. Domestically, Vietnamese airlines which account for nearly a half of the air transportation market share in Vietnam are providing more than 50 routes with over 55 million passengers in 2019. According to a forecast of IATA during 2019-2035, Vietnam would be the 5th fastest-growing aviation market in the world in terms of additional passengers per year (IATA, 2018).

Vietnamese Government considers air travel one of the key tools to promote tourism. Therefore, a large amount of government investments has been put into building airports and expanding underdeveloped ones. The Air transport capacity of Vietnam is expected to serve 150 million passengers by 2035. The construction of a major airport project in Long Thanh Province started in the second quarter of 2020 and is expected to open to serve 100 million passengers by 2025. The largest airport in Vietnam – Tan Son Nhat International Airport - is also undergoing an expansion project (Centre for Aviation, 2021). An additional terminal is planned to serve extra 50 million passengers annually. Many other provinces are seeking investments for road construction to connect with other regions.

The expansion plan of Noi Bai International Airport in Hanoi is also under assessment. The project aims to receive 35 million passengers by 2030 and 50 million by 2050. Plans for the development of several other airports across the country have also been studied or implemented. These include the construction of Lao Cai International Airport in Sapa, Phu Cat Airport which opened its new terminal in Bình Định Province in May 2018, Van Don International Airport near Ha Long Bay started its operation in December 2018 with the capacity of up to 2.5 million passengers (Centre for Aviation, 2021).

2.2.3. Tourism enterprises and human resources

A favourable business environment and relaxed regulations on travel business have facilitated the rapid increase of newly established travel enterprises. In 2019, there were more than 1,000 applications submitted to the Vietnam National Administration of Tourism (VNAT) regarding licensing new establishments, business modification, renewal, and withdrawal of tour providers. Also in this year, the total number of inbound and outbound operators reached 2.667, doubling the number of 2015 and increasing by 22.5% compared to that of 2018 (Vietnam National Administration of Tourism, 2019) (Fig.19).

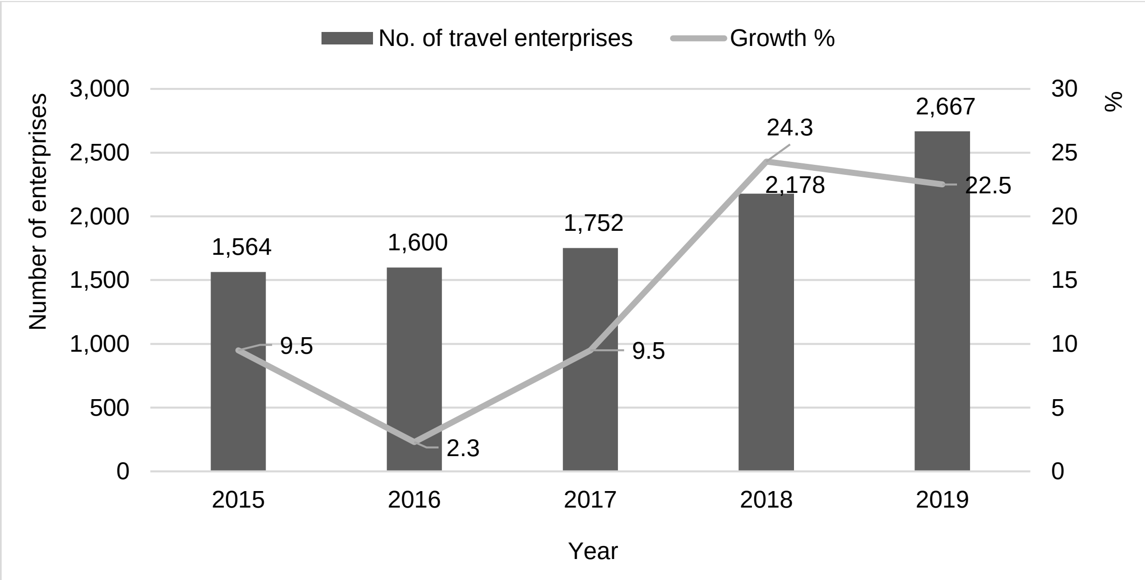


Figure 19. Growth of enterprises in the tourism sector.

Source: VNAT (2019).

Concerning the structure of tourism enterprises, limited companies accounted for 62.4%, joint-stock companies follow 36.3%. VNAT is the key governmental body responsible for providing official training, examinations, certification, and inspection of tourism services.

According to VNAT´s report in 2019, 27,683 licensed tour guides were joining the tourism market including 17,825 international tour guides, 9,134 domestic ones and 724 on-site. The number increased by 15% compared to that of 2018. 71.3% of tour guides have university and higher education degrees, 18% with a college degree and 10.7% with others. Corresponding to the key international source markets, most tour guides speak English (52.7%), Chinese (24.6%), and French (7.8%) (Fig.20). VNAT has organized various training courses for tour guides in different provinces across the countries. Less developed provinces have been supported further on tour operating and improving guiding skills.

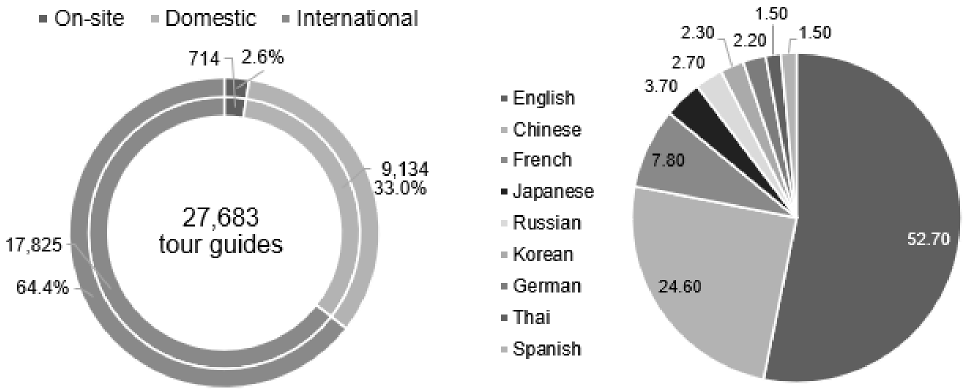


Figure 20. Licensed tour guides and Tour guides by languages in 2019.

Source: VNAT (2019).

2.2.4. Accommodations

Vietnam's inbound tourism market is largely led by Asian Pacific countries. Many of the larger hotels and resorts have developed tourism packages specifically tourism source markets in Asia. Hanoi Capital and Ho Chi Minh City have much of the accommodation development with the presence of the top international hotel groups. With a larger number of tourists from key markets such as China, South Korea and Japan, the development of regional hotel groups with well-known brands such as Japan-based Nikko Hotels is quite visible, which already has several properties in the country.

As Vietnam is increasingly developing its reputation as a luxury travel destination, there is a trend in the development of high-end and luxury resorts under internationally branded hotel chains. By the end of 2019, Vietnam had around 140 hotels (Vietnam National Administration of Tourism, 2021). The potential of a blossoming tourism market helps Vietnam to gain recognition from top global hotel chains. Accor, Hilton, Hyatt, Marriott International, Sheraton, InterContinental Hotels Group, The Reverie, Windsor and so on already have a presence in the country. Most of the chains have between two and five hotels in Vietnam and many have plans for new developments (Fitch Solutions, 2020).

Regarding the low-budget travel sector, Vietnam can offer a variety of choices from hostels, individually owned guesthouses, homestays, and domestic motel groups and so on. Vietnam also has a legacy of state-owned hotels, but to compete with international and private hotel groups the companies have increasingly been privatized. Therefore, there are opportunities in the midmarket sector and for destinations outside of established tourism locations in the long term.

According to the Vietnam National Administration of Tourism, accommodations for tourism especially for the high-end segment have experienced rapid growth. By 2019, the number of hotels and tourism establishments was approximately 30,000 with 650,000 rooms, increasing by 2,000 accommodations and 100,000 rooms compared to 2018. During, the number of tourism accommodations went up by 1.58 times within 4 years (2015-2019), equivalent to average annual growth of 12.0%; the number of rooms increased by 1,76 times, from 370,000 to 650,000 (Fig.21). There is a sharp decline in accommodations and rooms in 2013 but the reason is unclear.

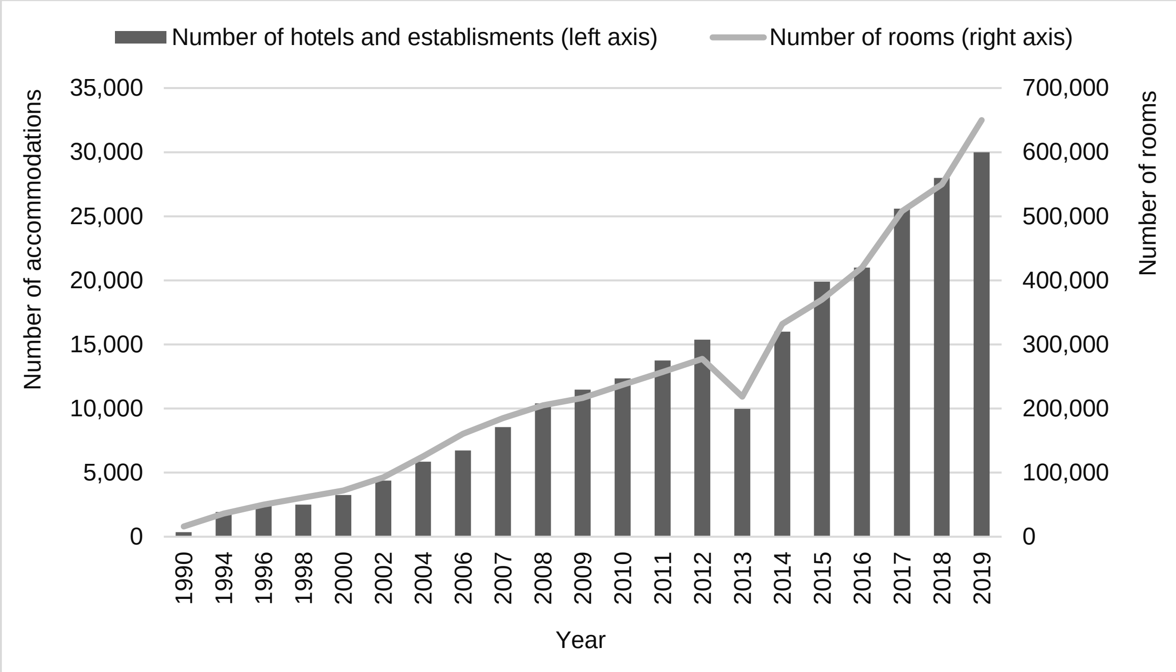


Figure 21. Accommodations and rooms.

Source: VNAT (2019).

The growth of rooms was higher than that of tourism accommodations, showing that there were more large-scale and high-end tourist accommodations with a higher capacity of serving larger groups and high-spending tourists (Fig.22).

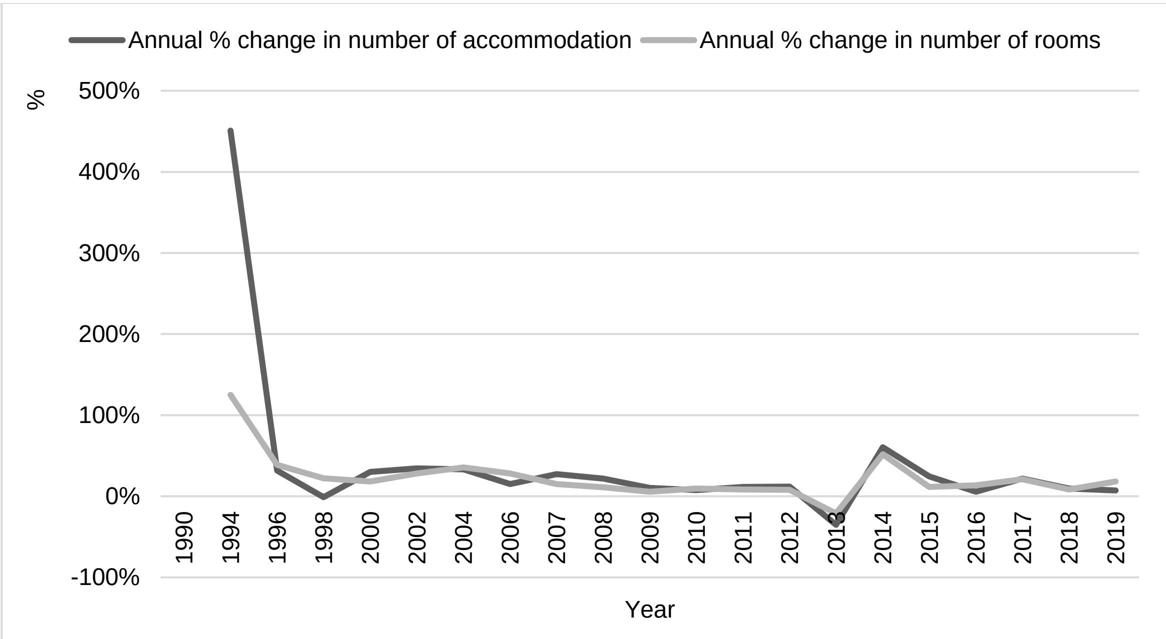


Figure 22. Annual % change in the number of accommodation and rooms.

Source: VNAT and GSO (2020).

The rapid growth of domestic and international tourism demand triggered local investment waves into the accommodations at tourism attractions. Various leading local corporations such as Sun

Group, Vingroup, FLC group and BIM group... have joined the market. In Khanh Hoa Province, a tourism attraction located in the South-Central Coast of Vietnam with a coastline of 385 km featuring numerous creek mouths, lagoons, river mouths, and hundreds of islands and so on), more than 6,000 new rooms were launched in 2019. Da Nang City, one of the most important port cities in Vietnam, offered 4,500 new rooms. In the Gulf of Thailand, Phu Quoc Island which is known for white-sand beaches, mountains, dense tropical jungle, hiking trails and wildlife launched 3,000 new rooms in the same year (Vietnam National Administration of Tourism, 2019).

There are 970 highly rated accommodations (from and above 3 stars) in 2019, representing an increase of 10% compared to 2018. 3-star tourism establishments increase strongly in terms of absolute number while luxury accommodation group has the highest percentage of change. Also in the same year, there were more than 5,400 1–3-star tourist accommodations, with over 162,024 rooms. However, the number of qualified tourist accommodations was much higher approximately 16,300 tourist establishments and 237,000 rooms as registration for ranking is not mandatory.

According to a report by the Vietnam National Administration of Tourism in 2019, the average room occupancy in 2019 was 52%, slightly lower than the previous year (54%) due to the larger increase of supply compared to that of demand and the decrease of length of stay. Regions recording strong growth of tourist accommodations like Da Nang, Khanh Hoa, Phu Quoc witnessed a decrease in room occupancy, sometimes below 50%. Hanoi and Ho Chi Minh City recorded moderate growth of room number and relatively high occupancy of over 60%. Provinces in the Central region had an average room occupancy of over 50%. Northern provinces including Ha Nam, Hai Duong, Bac Ninh, Nam Dinh, Phu Tho, Tuyen Quang recorded the rate of around 50%.

2.2.5. Other activities

The tourism sector has mobilized different sources from different stakeholders to promote tourism activities. Target markets are short-haul destinations in Asia, especially Northeast Asia, Southeast Asia, and India. Tourism promotion also focused on attracting high spending tourists from long-haul destinations such as Europe, North America, Russia, Australia and so on.

The tourism sector has also taken advantage of the development of digital technology in its business. Information and Communication Technology (ICT) applied is expected to add more value to tourism products and services as well as to improve state management and enhance the tourist experience. Vietnam has a plan to build a digital tourism database containing information regarding tour guides, travel businesses, accommodations, and so on. The database will connect information from businesses, local authorities to central management bodies to serve as a digital data platform for tourism management and promotion activities. The country also has the plan to build and launch the application “Vietnam Tour Guiding” to support tour guides, travel agencies and tourism management authorities (Vietnam National Administration of Tourism, 2019). The application aims at connecting tourists with tour guides and travel agencies during the travel itineraries; allowing evaluation and rating of tour guides and travel agencies; providing useful information about tourism products and services and facilitating e-payment. Designing a Dashboard of Vietnam tourism, upgrading Vietnam’s tourism promotional website and pushing tourism promotional campaigns via VNAT's social networks are also among the key tasks to be done soon.

Furthermore, VNAT has the plan to collaborate with Vietnam E-Commerce and Digital economy Agency - IDEA (Ministry of Industry and Trade) to integrate tourism into the "One National Card" Program which allows tourists to use tourist services in Vietnam and make payments conveniently, based on a shared database with different sectors. Also, to support smart tourism start-ups, VNAT hosted the contest "Vietnam Smart Tourism Start-ups". The competition lasted from March to June 2019, attracting various young innovative start-ups with creative ideas and advanced technologies. Also in late 2019, a contest "Mekong Innovative Start-ups in Tourism" (MIST) was officially announced (Vietnam National Administration of Tourism, 2019). Further VNAT has been organizing communication activities and training programs on information technology for tourism state management officials and tourism enterprises.

2.3. SWOT analysis of the tourism sector

Vietnam's tourism has experienced stellar expansion over the past decade. Strong investments, higher connectivity capacity between regions, improvement of air transport and accommodations infrastructure are among the main reasons behind the robust growth. However, the outlook for the next coming years has changed drastically due to the spread of the COVID-19 pandemic. Followings are strengths and weaknesses as well as opportunities and challenges the sector has to face:

Strengths

- Vietnam has a favourable geographical location including a long coastline with many beautiful landscapes, beaches, islands, wildlife parks and so on. A tropical climate is also an advantage for tourism.
- Vietnam has a long history of over 4000 years with diverse cultural traditions, culinary elite, oriental religious life and 54 ethnic communities. Each ethnic community has a unique culture and cuisine, highlighting the unique identity of the ethnic group and region.
- Vietnam is a safe and stable country. The country has been highly appreciated for the success of controlling the COVID-19 pandemic by implementing decisive, consistent, and effective prevention solutions by the World Health Organization and the international community.
- Vietnam´s tourism has received greater attention and support from the Government and close collaborations with other stakeholders such as local management, enterprises etc.
- Air connections between Vietnam and source markets have increasingly expanded. More international and domestic airlines expressed interest in joining the country´s emerging air transport market.
- The technical infrastructure for tourism has been upgraded. Many high-class hotels, resorts and entertainment and recreation complexes have been put into operation by such big Vietnamese business groups as Sun Group, Vingroup, FLC, BIM, BRG.

- In 2019, Vietnam´s tourism was honoured by reputable international organizations with global and regional awards. Vietnam is emerging as an attractive and safe destination, while there are still uncertainties in some other areas in the region and the world.

Weaknesses

- Adherence to tourism master plans in tourism destinations has often undermined tourism development objectives and sustainability. In many cases, the requirements according to the master plan have either not been properly followed or implemented. Some investments of this kind caused threats to the business and environmental sustainability.
- Most of Vietnam's tourism enterprises which are small and medium with limited resources have been severely impacted by the COVID-19 pandemic, resulting in business suspension or closure. This situation in return would negatively affect the competitiveness of the sector.
- According to the WEF competitiveness index, Vietnam´s tourism lagged other countries in Southeast Asia in terms of tourist service infrastructure, health and hygiene, ground and port infrastructure, environmental sustainability.
- The rapid increase in the number of tourists and the associated expansion in accommodations have stimulated the risk of overwhelming transport and service infrastructure. Some airports, especially Tan Son Nhat in Ho Chi Minh City, are facing overcapacity, resulting in a bottleneck for air travel. Besides, Vietnam still lacks seaports for receiving tourist cruise ships.
- The workforce supply in tourism has not been able to keep up with the strongly growing demand of the sector. There has been a shortage of tourism staff, especially high-quality human resources. The scarcity could prevent the sector from improving service quality. It also costs tourism enterprises more in terms of time and financial resources for re-training the staff to meet the market requirements.
- Labour productivity of tourism is rather low compared to other sectors in the country and tourism in competing countries, reflecting a visibly significant skill gap.

Opportunities

- Facing the COVID-19 pandemic, the Vietnamese tourism sector must re-structure towards higher flexibility and sustainability through reinforcing management, enhancing the quality of human resources, re-targeting source markets and promoting cooperation with various stakeholders.
- The highly opened economy could help Vietnam to attract more international resources. By participating in economic exchange activities and investment relationships, the tourism sector has the chance to attract foreign capital to improve the tourism infrastructure.
- The country has advantages thanks to its location in a fast-growing area of the Asia-Pacific region. Southeast Asia is an attractive destination for global tourists. Rising interests on Southeast Asian countries offers opportunities for Vietnam to exploit existing tourism resources.

- Vietnam is well-known for its social and political stability which makes the country a safer travel destination compared to other unstable territories and tourism markets worldwide.
- The development of information technology on the Internet platform has created great opportunities for developing countries including Vietnam to promote tourism activities with lower costs.

Threats

- Due to COVID-19 outbreak, Vietnam has been enforcing border closure, travel restrictions, cancelation of cultural festivals and entertainment activities, and shutdown of tourist attractions from March 2020. The pandemic has seriously affected all the socio-economic activities of which tourism and aviation are most heavily hit.
- The competition in tourism worldwide becomes fiercer. According to the World Economic Forum's (WEF), Tourism Competitiveness Index are the scores and ranks of countries according to a variety of physical and institutional factors relevant to tourism. In terms of its overall score on this index in 2019, Vietnam was ranked 63^{rd} globally, to the same degree as the average group of regional competitors. But compared to the top regional performers such as Thailand, Singapore, Malaysia, and Indonesia, the country is still behind.
- Climate change and unexpected weather variations like floods, tropical hurricanes, sea-water levels rising etc. have posed big problems to Vietnam. These events have severely deteriorated tourism infrastructure, especially in the Mekong River Delta.
- Rapid tourism growth threatens to intensify existing prominent environmental tensions and poor sustainability practices. Natural and historical assets at the main tourist attractions are especially at risk. For example, in Ha Long Bay (Quang Ninh province), tourist boats and floating fishing villages in the Bay are the main reason for pollution and damage to marine wildlife (The World Bank, 2019). Extreme tourism growth also jeopardizes the sustainability of major culture-based tourist areas.
- The global economic uncertainties such as financial and economic crises come in a cycle. With the higher level of globalization, Vietnam's tourism is vulnerable to such distressing events. Besides, the dependence on specific regions is also a threat to the sector when international tourists to Vietnam are mostly from China, South Korea, and Japan.

3. Research Methodology

3.1. Objectives of the study

The objectives of the study are as follows.

- Experiment with a set of MLP ANN models to forecast tourism demand based on the reference dataset of monthly international tourists to Vietnam from January 2008 to December 2020.
- Perform and forecast accuracy of the tested models to find out the best performers.
- Provide suggestions on applying ANN-based models to forecast tourism demand in Vietnam.

Although it can already foresee the difficulty given the pandemic situation of COVID-19, the study is expected to find a model that can make accurate forecasts for tourism demand once the pandemic shocks subside.

3.2. Data collection

Datasets for the study were mainly collected from two government organizations, i.e., the Vietnam National Administration of Tourism (VNAT) and the General Statistics Office of Vietnam (GSO). The collected data includes:

(1) Monthly number of international tourists to Vietnam from January 2008 to December 2020.

(2) Annual number of international tourists from January1995-December 2020.

(3) International tourists by mode of transport from 1995 to 2020.

(4) International tourists by region from 2008 to 2020.

(5) Average length of stay and expenditure of international tourists in Vietnam from 2005 to 2020.

(6) Accommodation’s growth and breakdown by rating from 2008-2018.

The time series most used in the research is the monthly number of international tourists to Vietnam because the income generated from this group of customers accounts for a larger part of total tourism revenues.

3.3. Research methods and data analysis

Multilayer Perceptron (MLP) is a supervised neural network based on the original simple perceptron model. The MLP is a system containing simple interconnecting nodes. In forecasting and modelling using MLP ANN models, it is important to carefully consider data preparation, input variable selection, network type and architecture selection, activation functions, training algorithm, training, validation and test sets. It is noted that network architectures with a single hidden layer are sufficient in estimating time series.

According to Teixeira and Fernandes (2015) the learning process requires the following stages:

1. Assign random numbers to the weights.
2. For every element in the training set, calculate output using the summation functions embedded in the nodes.
3. Compare the computed output with observed values.
4. Adjust the weights and repeat steps (2) and (3) if the result from step (3) is not below a threshold value; alternatively, this cycle can be stopped early by reaching a predefined number of iterations, or the performance in a validation set does not improve.

In this study, the prediction equation for computing a forecasted Y_i using selected past observations can be written as:

$$Y_i = f_2[(\sum_{j=1}^{N} W_{j,i}\, f(\sum_{k=1}^{M} W_{k,j}\, X_k + b_j) + b_i)] \quad [1]$$

where:

Y_i*:* is the output vector of the MLP at the time *i.*

M: the number of inputs nodes.

N: the number of hidden nodes.

i: the i^{th} output node.

j: the j^{th} hidden node.

k: the k^{th} input node.

X_k value of the k^{th} input node.

f: the hidden layer activation function.

f_2: the output layer activation function.

$W_{j,i}$ with *j* = 1, 2,…. N are weights from the hidden nodes to output nodes.

$W_{k,j}$ with *k* = 1, 2,… M are weights from the input nodes to hidden nodes.

b_j and b_i are the bias associated with the nodes in output and hidden layers, respectively.

Several ANN models with different architectures are compared. The models are different in the combination of the inputs, hidden activation functions, training algorithm, output activation function and the number of hidden nodes. Table 2 presents all parameters used in the study. Details are discussed further in the next sections.

Table 2. Summary of Parameters.

Titles	**Description**
Data	(1) Random test set (2) Fixed test set
Inputs	Number of international tourists in previous months, from 4 to 18 months plus 2 dummy variables
Outputs	The forecasted number of international tourists
Dummy variables	(1) COVID-19 pandemic (2) South China Sea conflict
Training Algorithm	(1) Levenberg-Marquardt algorithm (trainlm) (2) Resilient Backpropagation algorithm (trainrp) (3) Conjugate gradient backpropagation with Fletcher-Reeves updates (traincgf) (4) Bayesian Regularization backpropagation algorithm (trainbr)
Hidden Activation Function	(1) Tangent-hyperbolic transfer function (tansig) (2) Logarithmic sigmoid transfer function (logsig) (3) Elliot symmetric sigmoid transfer function (elliotsig) (4) Linear transfer function (purelin)
Output Activation Function	(1) Tangent-hyperbolic transfer function (tansig) (2) Logarithmic sigmoid transfer function (logsig) (3) Elliot symmetric sigmoid transfer function (elliotsig) (4) Linear transfer function (purelin)
Hidden layer Nodes	From 2 to 20
Measures of accuracy	(1) Mean Absolute Error (MAE) (2) Mean Absolute Percentage Error (MAPE) (3) Pearson's Correlation Coefficient (*r*)

Source: Author's own elaboration.

The descriptive analysis provides a deep look into Vietnamese tourism characteristics. MatLab program is employed to experiment with the forecasting capability of ANN models in this research.

3.3.1. Datasets

The datasets are divided into the training and validation set plus the test set. The training and validation sets are used during the training phase. The training set is used to iteratively adjust the weights of the ANN to minimize the error between the output and the target (real observed volume of international tourists for next month), for all the months used in the training set. The validation set is utilized also during the training stage to evaluate after each iteration if the error in this set still improving, otherwise the training is early stopped to avoid overfitting. The test set is never used during the training stage, it serves only after the training stage to test the system with completely new data that has never been seen during the training stage.

Since the final performance of the model depends on the initial values of the weights (randomly initialized), several training sessions for each architecture were performed. The error in the validation set is used to select the best model of each experimented architecture. Finally, the models are tested with the test set to produce the results presented in the next section.

Two approaches are used to divide the datasets. The first strategy is to divide all the datasets in a random way between each set with a proportion of 70%, 10% and 20 % for training, validation, and test set. This strategy is denominated as a 'random test set' (Fig.23). This is a very commonly used strategy when the data is balanced.

Figure 23. Random test set strategy.

Source: Author's own elaboration.

The second strategy is to use the last months (one year) to the test set, and the months of the last-but-one year for validation set (Fernandes, Teixeira, Ferreira, & Azevedo, 2008; Fernandes, Teixeira, Ferreira, & Azevedo, 2013; Teixeira & Fernandes, 2015). Anyhow, in the case of the number of international tourists along the time, the COVID-19 pandemic triggered a period with strong restrictions to the tourism sector as well as the number of international tourists. This situation caused a non-balanced period with the remaining period of the dataset. All data consist of 151 months but only 4 months during this lockdown period plus 2 in the transition period. For the ANN to learn the behaviour of the tourism demand in Vietnam during this period also some months need to be added to the training set.

Then, the second strategy is modified to guaranty that at least 2 months of this period belong to the test set. This allows the test of the model for this very different period for the tourism demand. Therefore, the second strategy denominated 'fixed test set', includes the data from the beginning of 2008 until December 2017, plus January to May 2020 (transitions and COVID-19 period) in the training set, the months from January to December of 2018 in the validation set, and January to December 2019, plus June to July 2020 in the test set (see Fig. 24).

Finally, a remark to notice that the length of the training dataset is variable according to the number of previous months used in the ANN input. The forecast can be made only for the months after the previous N months used in the input.

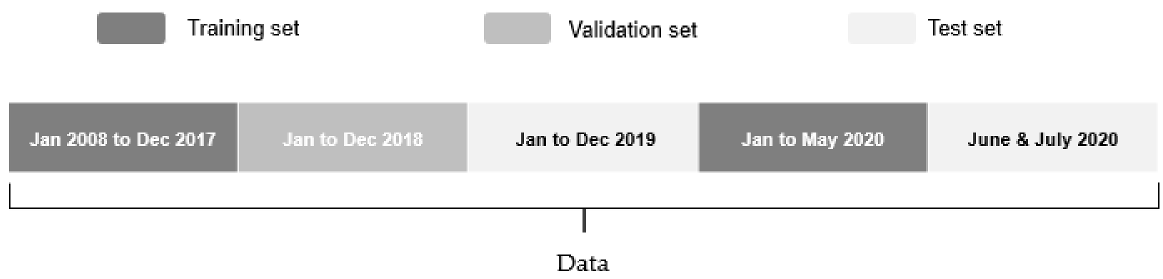


Figure 24. Fixed test set strategy.

Source: Author's own elaboration.

For Multilayer Perceptron networks to be used for forecasting, the structure of the network must be determined. The process of determining the network structure briefly includes the processes of determining how many layers the network will consist of, how many processing elements will be in each layer, and which transfer function these process elements will have. The learning process of the MLP network was realized by presenting the training data to the network. The implementation of the method was carried out with a MATLAB computer program.

3.3.2. ANN Inputs

Nodes in the input layer represent independent parameters of the system. The hidden layer is used to add an internal representation handling non-linear data. The output of the neural network is the solution for the problem The input of the ANN consists of the number of international tourists in previous months. The number of months can be variable and according to previous studies, it typically varies around 12 previous months (Fernandes, Teixeira, Ferreira, & Azevedo, 2008; Fernandes, Teixeira, Ferreira, & Azevedo, 2013; Teixeira & Fernandes, 2015). In the work, a variation between 4 and 18 months has been experimented with. The value of each month corresponds to one input of the ANN.

Additionally, because the abrupt lockdown caused by the COVID-19 pandemic led to a sudden plunge in the number of international tourists (Fig.6) after February 2020, a dummy variable is used to code the pandemic period. This variable is 0 before the pandemic period and 1 during the pandemic period. This variable requires one input in the ANN.

In order to model also the South China Sea conflict that caused a significant decrease in the international number of tourists to Vietnam between May 2014 and December 2015 (Fig. 7), another dummy variable is used. This variable is 0 outside the period and 1 in the period. Another input is required for this variable. Considering the input variables, the number of input nodes in the ANN is the number of previous months plus 2, for the dummy variables.

3.3.3. ANN architectures, training, and accuracy measures

The objective of the ANNs is to forecast the number of international tourists for next month as a way to forecast the tourism demand in Vietnam. Several architectures of MLP ANN models are experimented with using two different dataset organizations concerning the test set. The experimented architectures vary in their input length, the number of nodes in the hidden layer, activation functions in hidden and output layers, and training functions. The test set is organized in two different ways: random test set and pre-defined test set.

The ANN architectures are based on a Multi-Layer Perceptron (MLP) with one hidden layer, similar to the one presented in Fig. 2. The number of input nodes is variable to accommodate information about previous months, the COVID-19 period and South China Sea conflict information.

The output has only one node with the value of the forecasted number of international tourists. The number of nodes in the hidden layer varies between 2 and 20 in several experimental simulations.

The activation function in the hidden and output layer are also experimented between the Symmetric sigmoid transfer function also known as the tangent-hyperbolic transfer function (tansig), logarithmic sigmoid transfer function (logsig), Elliot symmetric sigmoid transfer function (elliotsig), and linear transfer function (purelin). The first three functions squeeze the input into an interval between -1 and 1 or between 0 and 1 with an "S-shaped" functions. Fig. 25 presents the activation transfer functions.

The current interest in the neural network technique as a forecasting tool has its reason for the development of the backpropagation learning algorithm. This algorithm gives the network the ability to form and modify its interconnections in a way that often rapidly approaches a goodness-of-fit optimum. The technique was first developed by Rumelhart and McClelland (1986). In this study, some back-propagation algorithms are also experimented with within the training stage of the ANN in combination with the varied architectures referred above thanks to their fast convergence, stability, and generally good results. The Levenberg-Marquardt algorithm (trainlm) (Marquardt, 1963; Hagan & Menhaj, 1994), the Resilient Backpropagation algorithm (trainrp) (Riedmiller & Braun, 1993), the Conjugate gradient backpropagation with Fletcher-Reeves updates (traincgf) (Demuth & Beale, 2000) and the Bayesian Regularization backpropagation algorithm (trainbr) (Demuth & Beale, 2000) are experimented.

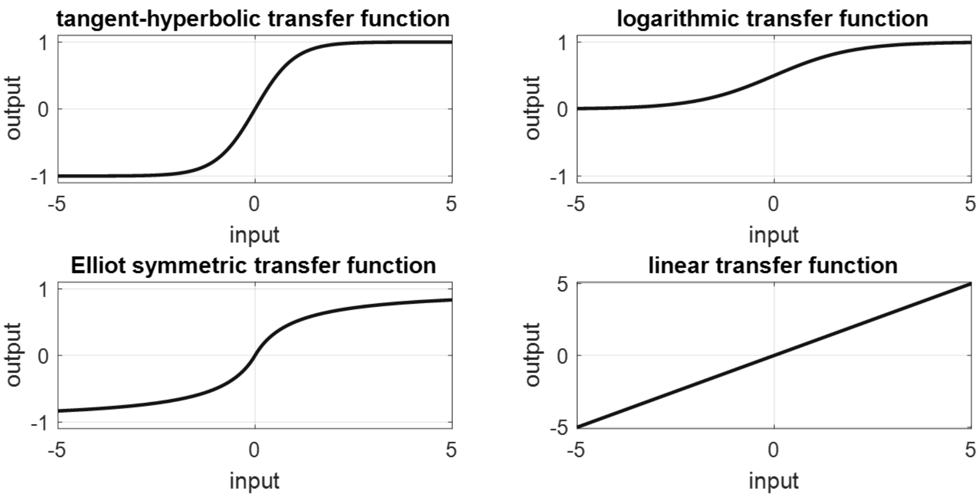


Figure 25. Activations transfer functions.

Source: Author's own elaboration.

In this work, Mean Absolute Error (MAE) (Eq. 2), Mean Absolute Percentage Error – MAPE (Eq. 3) and Pearson's Correlation Coefficient (*r*) (Eq. 4) are used to measure the accuracy of the experimented models (Teixeira & Fernandes, 2015). The MAE gives the magnitude of the average distance of the predicted values to the real values of the monthly number of international tourists to Vietnam. The MAPE gives this error in relation to the real values, therefore it allows a comparison with other models for other regions/countries. The Pearson correlation coefficient (*r*) measures the degree of linear association between two numerical variables (Constantino, Fernandes & Teixeira, 2016). In this case, the *r* mainly evaluates the similarity between the real and predicted curves of the international tourists to Vietnam time series.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |Real_i - Predicted_i| \qquad [2]$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \left| \frac{Real_i - Predicted_i}{Real_i} \right| \qquad [3]$$

$$r = \frac{n\sum Real_i Predicted_i - \sum Real_i \sum Predicted_i}{\sqrt{n\sum Real_i^2 - (\sum Real_i)^2}\ \sqrt{n\sum Predicted_i^2 - (\sum Predicted_i)^2}} \qquad [4]$$

Where:

MAE: Mean Absolute Error.

MAPE: Mean Absolute Percentage Error

r: the Pearson correlation coefficient.

n: the number of observations used in the study (*i* = 1, 2, …, n).

$Real_i$: the actual number of international tourists.

$Predicted_i$: the number of international tourists. to Vietnam planned for the same period.

$Real_i$ - $Predicted_i$ specifies forecast error.

4. Results and discussions

This section presents the results of the most promising ANN models experimented in the study and discusses in detail the findings in comparison with other research using the similar methodology in this field.

4.1. Results

Table 3 presents the 10 most promising model architectures and results. For each model, the training algorithm, activation functions in hidden and output layers, the number of nodes in the hidden layer and the previous months' delays used in the input are presented.

Table 3. Comparison of the prediction model performance.

Architecture Model	Training Algorithm	Hidden Activation Function	Output Activation Function	Hidden layer Nodes	Input delays	Random Test Set (Strategy 1)			Fixed Test Set (Strategy 2)		
						MAPE (%)	MAE	*r*	MAPE (%)	MAE	*r*
M1	trainlm	logsig	purelin	10	01:06	11.3	88515	0.941	18.2	88965	0.985
M2	trainlm	elliotsig	purelin	3	01:12	11.9	66519	0.981	11.3	100884	0.980
M3	trainlm	elliotsig	purelin	12	01:12	17.3	88529	0.961	110.9	58009	0.975
M4	trainlm	tansig	purelin	2	01:12	34.5	53964	0.989	12.4	85304	0.972
M5	**trainlm**	**logsig**	**purelin**	**5**	**01:12**	**7.9**	**58040**	**0.976**	95.4	47389	0.995
M6	traincgf	tansig	purelin	15	01:09	10.1	61283	0.966	119.0	104735	0.977
M7	trainlm	logsig	purelin	12	01:12	32.1	40705	0.992	15.6	32900	0.993
M8	trainrp	tansig	purelin	6	01:12	27.4	79863	0.973	92.6	102855	0.971
M9	trainbr	logsig	tansig	3	01:12	9.8	72164	0.954	28.4	45328	0.997
M10	**trainlm**	**tansig**	**purelin**	**12**	**01:12**	**9.2**	**53967**	**0.979**	**8.5**	**55841**	**0.983**

Source: Author's own elaboration.

From the analysis of the results presented in Table 3, three models which have the lowest MAPE are M5 (7.9%), M10 (9.2%) and M9 (9.8%). M5 model has the lowest MAPE for the random test set (7.9 %), but a very high MAPE for the fixed test set (95.4%). M9 has a low MAPE for strategy 1 (9.8%) but a high MAPE for strategy 2 (28.4%). Only the M10 model presents the lower MAPE for both the fixed test set (8.5%) and the random test set (9.2 %).

Figure 26 presents the real and predicted values of the monthly number of international tourists for all datasets. Figure 27 presents the real and predicted values of the monthly number of international tourists only for the months according to the Random test set. Both use the M5 trained with the dataset of strategy 1 (Random sets).

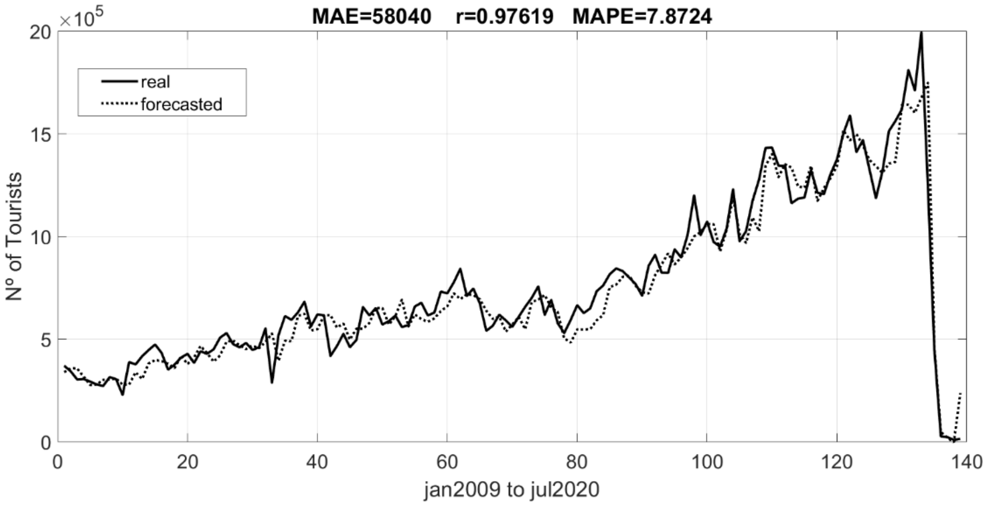


Figure 26. M5 with all datasets (learning with strategy 1).

Source: Author's own elaboration.

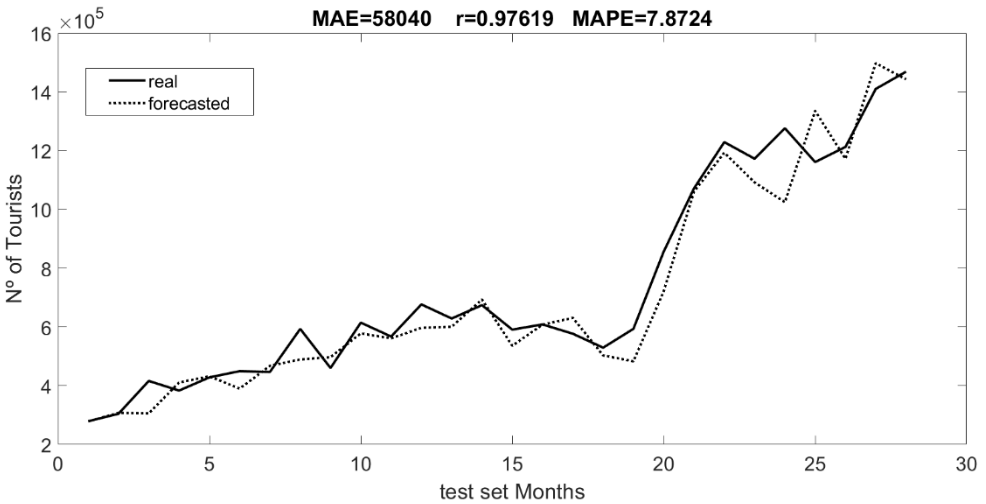


Figure 27. M5 for the Random test set (learning with strategy 1).

Source: Author's own elaboration.

Figures 28 and 29 present the real and predicted values of the monthly number of international tourists for all datasets and only the test set, respectively. Both using the M10 model trained with the dataset of strategy 1 (Random sets).

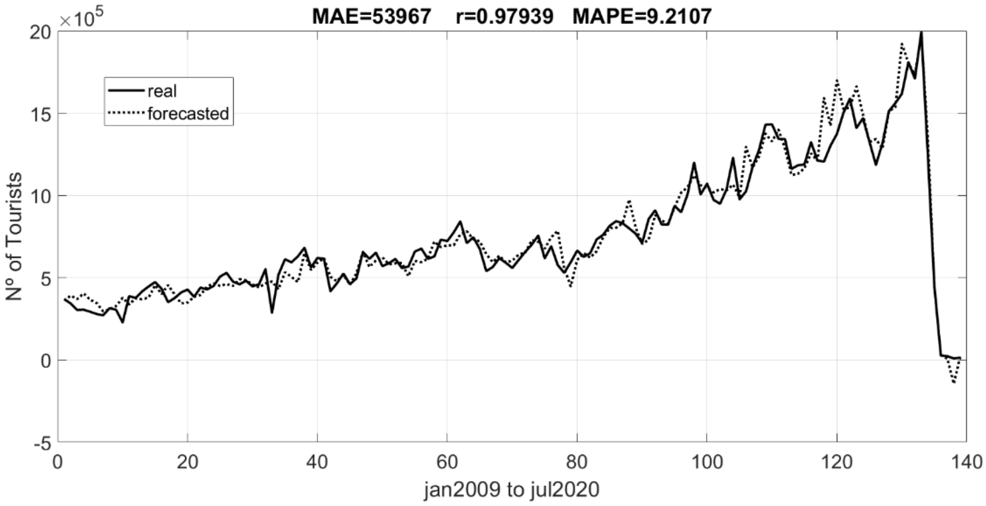


Figure 28. M10 with all datasets (learning with strategy 1)

Source: Author's own elaboration.

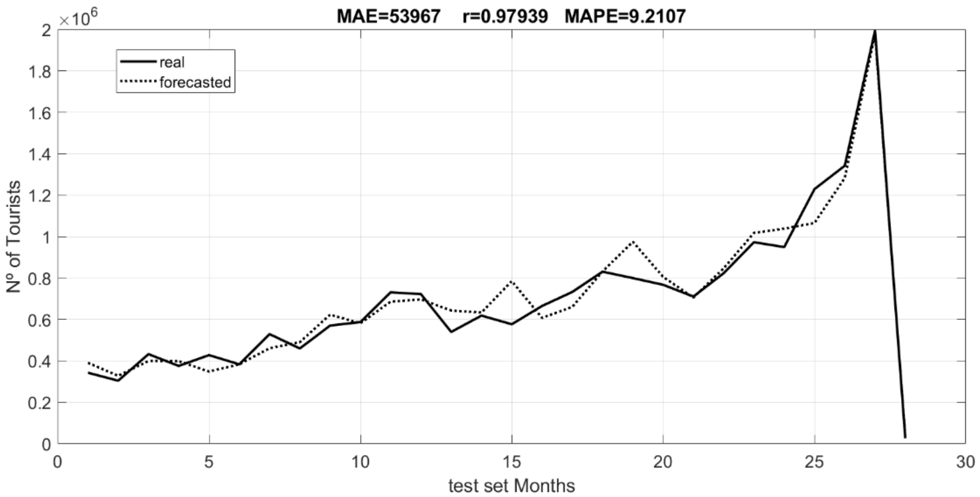


Figure 29. M10 with test set (learning with strategy 1).

Source: Author's own elaboration.

Figures 30 and 31 present the real and predicted values of the monthly number of international tourists for all datasets and only the test set, respectively. Both using the M10 model trained with the dataset of strategy 2 (Fixed sets).

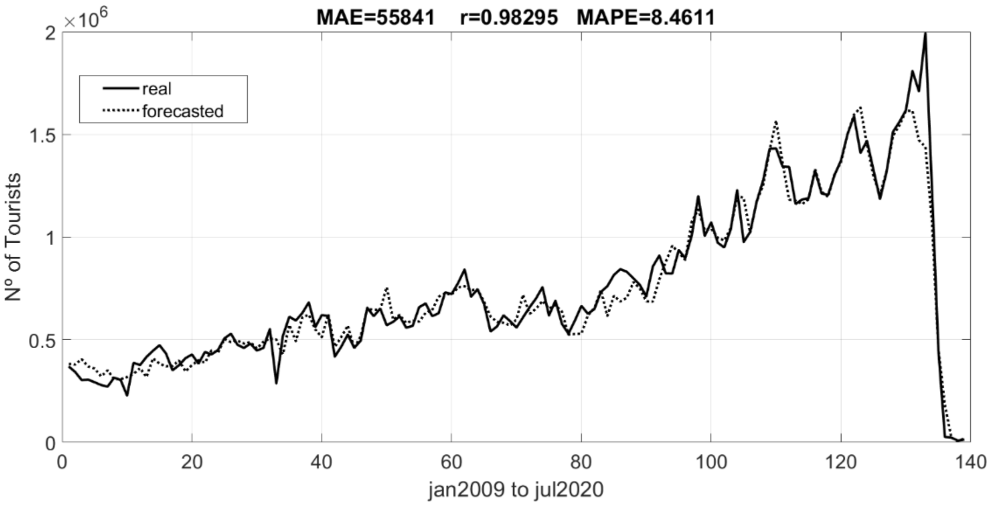


Figure 30. M10 with all datasets (learning with strategy 2).

Source: Author's own elaboration.

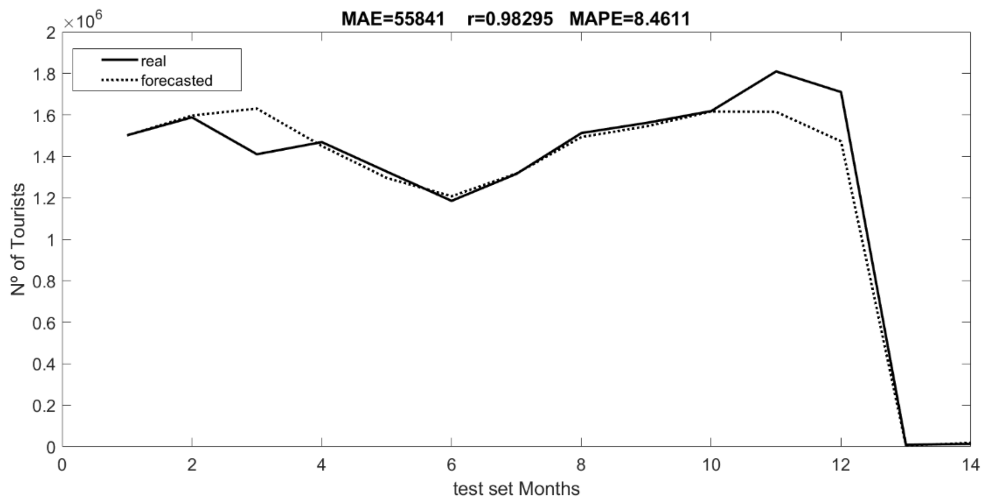


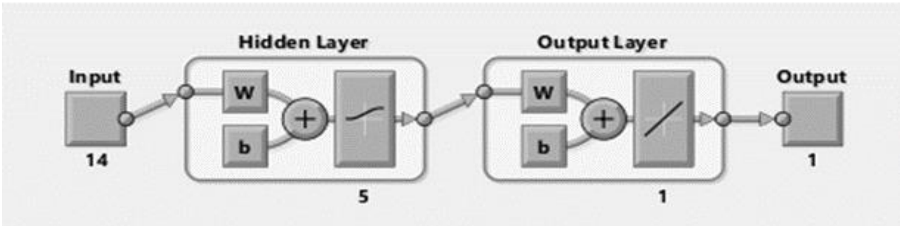
Figure 31. M10 with test set (learning with strategy 2).

Source: Author's own elaboration.

4.2. Discussions

The Mean Absolute Error (MAE) (Eq. 2), Mean Absolute Percentage Error (MAPE) (Eq. 3) and Pearson's Correlation Coefficient (*r*) (Eq. 4) present the results of each model applied to the test sets. The MAPE, MAE and *r* determined with the forecasted values over the test set are presented for the two strategies (random test set and fixed test set) in the study (Table 3). It is important to note that the best MAPE, MAE and *r* do not always match for the same model, therefore the model selections are based on the best MAPE because it is comparable with other models and independent of the magnitude of the values of the time series. In this study, the magnitude of the output is very different before and after the COVID-19 period. During the pandemic, the lower value of the real value produces a higher percentage error (MAPE) for the same absolute error (MAE).

According to the results presented in table 3, the models M5 and M10 are selected according to the MAPE value for each strategy used for the learning process of the models. M5 and M10 are similar in their architecture because both have in the input the previous 12 months plus the 2 dummy variables for COVID-19 and South China Sea conflict modulation. Both have a linear function in the output layer, and both use the Levenberg-Marquardt algorithm for the training procedure. They just diverge in the number of nodes and activation function in the hidden layer. M5 has 5 nodes and has the logarithmic transfer function while M10 has 12 nodes and the tangent-hyperbolic transfer function. Figure 32 shows the architectures of the best models M5 and M10.



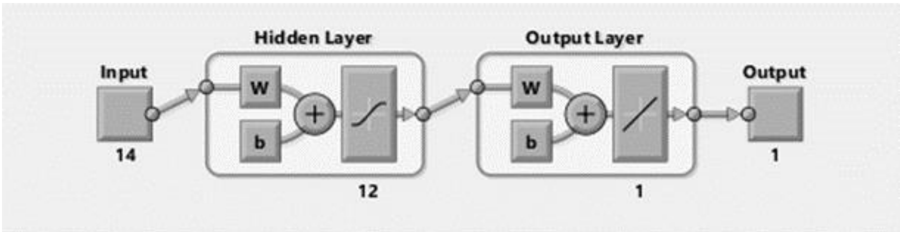


Figure 32. Architectures of model M5 (above) and M10 (below).

Source: Author's own elaboration.

While M5 presents the lower MAPE (7.9%) for the test set using strategy 1 but a poor MAPE for strategy 2 (95.4%), M10 model behaves more eclectic in both strategies. M10 gets the lower MAPE with strategy 1 (9.2%) and very low MAPE with strategy 2 (8.5%). M10 has MAEs between 53 and 56 thousand international tourists per month and the correlation coefficients are about 0.98 in both cases. Note that MAPE indicates the gap between the predicted and the real number of international tourists while the Pearson correlation coefficient (r) between the real and predicted values of the time series shows the similarity between patterns of the two data sets (Teixeira & Fernandes, 2014). In the case of the model M10, the MAPE is below 10% and the r value is close to 1, proving good forecasting accuracy. Regarding the curves of real and predicted values produced by the model M10, it shows a nice fitting curve between forecasted and actual values in both strategies considering only the test set or all datasets.

The plots of the output presented from Figures 28 to 31 confirm the forecasting competence of the MLP ANN model for the tourism time series in Vietnam. The result is consistent with the conclusions of other studies using ANN to forecast tourism demand (Fernandes, Teixeira, Ferreira & Azevedo, 2008; Teixeira & Fernandes, 2012; Claveria, Monte & Torra, 2013; Teixeira & Fernandes, 2014; Cuhadar, Cogurcu, & Kukrer 2014; Teixeira & Fernandes, 2015; Srisaeng & Baxter, 2017; Alamsyah & Friscintia, 2019; Çuhadar, 2020; Höpken, Eberle, Fuchs, & Lexhagen, 2021).

It is interesting to see that the MAPE of the model M10 in this work is higher than that of other studies using the same methodology. For example, Teixeira and Fernandes (2014) experimented several ANN models to forecast tourism demand time series in Portugal including Tourism Revenue, Total Overnights, Domestic Overnights and Foreign Overnights. The results showed that the MAPE values achieved were rather low, i.e., MAPE of 4.7% for Revenue time series, 6.0% for Total Overnights, 4.7% for Domestic Overnights and only the MAPE for Foreign Overnights was above 10%. In a study by Constantino, Fernandes and Teixeira (2015), the best model to predict the number of Overnight Stays in Mozambique achieved the MAPE of 6.5%. Çuhadar (2020) applied MLP ANN to forecast a monthly number of foreign tourist arrivals to Croatia. The experimented MLP ANN model showed the best performance with the MAPE of 6.5%. According to Srisaeng and Baxter (2017), the best ANN model used to predict Australia´s outbound airline passengers achieved the MAPE of 2.8%. This result (higher MAPE) in the case of Vietnam can be explained by the fact that the test set includes the COVID-19 data which is much more different than the remaining one and the target values for this COVID-19 period are very low, resulting in a higher MAPE.

For both test set strategies in this work, the best model M10 achieves *r* of about 0.98 which is similar to or even higher compared to that of other research. For example, *r* values of the best models in the study of Teixeira and Fernandes (2014) varied from 0.91 to 0.98. Constantino, Fernandes, and Teixeira (2015) found that the best model in their experiment achieved $r = 0.696$. It is worth noting that *r* measures the similarity between the sequence of values in the test set. In the thesis, the sequence includes the COVID-19 period with an extremely strong decrease that the model has been able to follow. This sharp variation in the sequence of values that is followed by the predicted values explains the higher *r*.

Conclusions, limitations, and implications for future works

Vietnam has been successful at promoting tourism in recent years and reaping the economic benefits from this booming activity. Tourism plays an essential role in economic development as it provides more job opportunities especially for women and young people as well as creates linkages with various sectors. The growth of tourism accelerates the expansion of many other industries such as transportation, food and beverage, real estate and so on.

Given the significant impact of the tourism sector on the economy, a precise forecasting model for tourism demand would help to predict economic growth in Vietnam. Hence, it is important to find a model with a highly predictive capability to forecast the tourism demand. In this study, several forecasting ANN models are examined with a special focus on international tourists. The datasets of monthly international tourists to Vietnam are collected from January 2008 to December 2020. The period also includes time series data of pre-and post-COVID-19 pandemic into its analysis. The ANN architectures are based on a Multi-Layer Perceptron (MLP) with one hidden layer.

The forecasted number of international tourists is the single output, while inputs contain the number of international tourists in previous months varying between 4 to 18 months plus 2 for the dummy variables, namely COVID-19 pandemic, and the South China Sea conflict. These two distress events caused some sharp declines in the number of international tourists to Vietnam.

The datasets are divided according to two strategies: random test set and fixed test set. Concerning the random test set, training, validation, and test set have a proportion of 70%, 10% and 20 % of all datasets. It is important to note that as the experiment considers the effect of the COVID-19 pandemic. The second strategy is the fixed test set approach in which the test set contains data of last months (one year) including at least 2 months of the lockdown period and the validation set covers the months of the last-but-one year.

The number of nodes in the hidden layer varies between 2 and 20 in several experimental simulations. The activation functions in the hidden and output layer include tangent-hyperbolic transfer function, logarithmic sigmoid transfer function, Elliot symmetric sigmoid transfer function, and linear transfer function. In the training stage, experimented back-propagation algorithms are the Levenberg-Marquardt algorithm, the Resilient Backpropagation algorithm, the Conjugate gradient backpropagation with Fletcher-Reeves updates and the Bayesian Regularization backpropagation algorithm.

There are two selected models out of the 10 most promising ones, i.e., M5 and M10. M5 model produces the lowest MAPE for the random test set (7.9 %) but very high MAPE for the fixed test set (95.4%) while the M10 model shows very low MAPE in both learning strategies with MAPE=8.5%, r=0.983 for the fixed test set and 9.2 % and 0.979 respectively for the random test set. Therefore, the model M10 is the best performer in the study. The best architecture for the reference datasets is achieved by using inputs of the previous 12 months plus 2 dummy variables, a linear function in the output layer, the Levenberg-Marquardt algorithm for training procedure, 12 nodes and the tangent-hyperbolic transfer function in the hidden layer.

The output plots presented from Figures 28 to 31 confirm the forecasting competence of the MLP ANN model for the tourism time series in Vietnam. This result is consistent with various research findings in different countries mentioned in the methodology section. Given the limited number of studies on forecasting tourism demand in Vietnam using the ANN approach, the contribution of the research is to fill this gap. In addition, the research provides policymakers and business managers in Vietnam with a useful instrument for planning tourism activities. Having suffered extreme losses due to the border closure for almost two years, the Vietnamese government and tourism businesses need accurate prediction of future demand to make vital decisions regarding pricing strategies, promotions, operations, and management, in order to gain full benefits out of their limited resources while keeping the sector sustainable. The recovery of tourism is more likely to create favourable effects on relevant sectors, which is expected to contribute significantly to the revival of the whole economy.

It is important to note that the size of the training set is one of three key factors influencing the generalization of the network (Haykin, 2008, p166). The intuition behind the learning process (training) is that the more data is assigned to a training set, the better forecasting performance a network can achieve until the learning rate slows down (Ahmad Alwosheel, 2018). Within this research, however, the number of international tourists after the country opens its border is not covered as Vietnam suspended the entry for international tourists from March 2020 until further notice due to continuous waves of COVID-19 (Dung, 2021). Also, the data related to the COVID-19 pandemic lockdown used for the training set and test set is limited to only two months. Therefore, the model can merely capture the past behaviour of tourists under normal circumstances and few months of COVID-19 lockdown while it is more likely that the behaviour would change considerably after the extreme period of COVID-19. New factors could have strong impacts on travel decisions, namely the restrictions and precautions that tourists must take while travelling. The rules on quarantining for 14 days; the limited choices of transports and accommodations; and the restricted access to tourist attractions, restaurants, and entertainment activities probably discourage tourists to visit the country.

According to the latest report from Worldometers, until 26 November 2021, the total number of COVID-19 infected cases per 1 million people and total deaths per 1 million people in Vietnam are rather low as the country ranks 149 and 133 respectively out of 221 reported countries and territories, (Worldometer, 2021). In early October 2021, the government of Vietnam announced a plan to reopen major tourist destinations to vaccinated tourists from countries with a low risk of COVID-19 from December 2021. On 20 November 2021, Vietnam received the first international tourists to the country’s largest Phu Quoc resort island after nearly two years of border closure (Reuters, 2021). A full resumption is intended to take effect from July next year (KC, 2021). Besides, domestic tourism demand has been accelerated to make up for the lost income from international tourists. It is expected that tourism demand in Vietnam will increase again and reach the pre-pandemic level in the next few years. Considering the post-pandemic outlook of tourism in Vietnam and the requirement for newly updated observations for ANN models to achieve adequately accurate predictions, an improvement in the ANN models in future research by using larger datasets on inbound tourism is recommended, including new data to be collected during the COVID-19 lockdown and recovery period. The improved model would facilitate all stakeholders in the sector to provide forward realistic action plans in order to efficiently utilise their depleted budgets while fully capturing the opportunity once Vietnam is entirely open for travel and tourism. Also, it is recommended to extend the forecasting research by including both inbound and outbound tourism demand in Vietnam given the increasing contributions of domestic tourists.

In addition, several studies confirmed the contributing impacts of other factors on forecasting tourism demand such as gross domestic product, exchange rate, airfares, flights, tourism attractiveness and so on in different contexts (Constantino, Fernandes, & Teixeira, 2015; Srisaeng & Baxter, 2017), but they are not experimented in the case of Vietnam. Hence, explanatory variables such as the gross domestic product of top source markets, the exchange rate between Vietnamese Dong and the United States Dollar/Euro/Chinese Renminbi, direct flights from key tourist markets to Vietnam etc would be added into the modelling stage to increase predicting accuracy of ANN models.

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