



**T.R.
ONDOKUZ MAYIS UNIVERSITY
INSTITUTE OF GRADUATE STUDIES
DEPARTMENT OF STATISTICS**

FORECASTING TOURSIM INCOME OF TURKEY

Master's Thesis

Sura Faez Ali AL-HADHARIN

Supervisor
Prof. Dr. Vedide Rezan USLU

SAMSUN
2023

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ACCEPTANCE AND APPROVAL OF THE THESIS

The study entitled “**FORECASTING TOURSIM INCOME OF TURKEY**” prepared by **Sura Faez ALI AL-HADHARIN**, and supervised by **Prof. Dr Vedide Rezan Uslu**, was found successful and unanimously accepted by committee members as Master thesis, following the examination on the date.

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ÖZET

FORECASTING TOURISM INCOME OF TURKEY

Sura Faez Ali AL-HADHARIN

Ondokuz Mayıs Üniversitesi

Lisansüstü Eğitim Enstitüsü

İstatistik Anabilim Dalı

Yüksek Lisans / Ocak 2023

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Turizm, ekonomiyi iyileştirme ve istihdam gibi çeşitli fırsatlar yaratma, ekonomik büyümeyi geliştirme ve aynı zamanda hem yabancılar hem de vatandaşlar arasındaki kültürel alışverişi kolaylaştırma gibi önemli yararları nedeniyle küresel finansal sistem için önemli kabul edilmektedir. Turizm geliri, toplam gelir olarak tanımlanmaktadır. yabancıların ve yurt dışında yaşayan vatandaşların Türkiye'de bireysel ve paket turlarla geçirdikleri harcamalar (gayrimenkul harcamaları, konut bakım-onarım giderleri, dayanıklı tüketim malları, transferler vb. hariç). Turizm geliri, turistik gezilere hazırlanırken ve geziler sırasında tüketim malları ve hizmetleri ile kişisel eşyalara harcanan tutarı içerir; ziyaretçinin yaptığı her türlü masrafı karşılar. Bu, toplu taşımanın yanı sıra konaklama veya yemek gibi standart ürünleri içerebilir, ancak aynı zamanda değerli eşyaları (sanat eseri gibi) ve kişisel kullanım için küçük eşyalar, hediyelik eşyalar ve aile ve arkadaşlar için hediyeler gibi dayanıklı tüketim mallarını da içerebilir. kişisel bakım ürünleri vb., Turizm gelirleri Türk ekonomisinin gelirlerine önemli katkı sağlamaktadır. Bu nedenle, gelecekte turizm gelirini tahmin etmek kritik öneme sahiptir. Bu çalışmada Türkiye İstatistik Kurumu'ndan (TÜİK) turizm gelirini tahmin etmek için Otoregresif Entegre Hareketli Ortalama (ARIMA), Üstel Düzeltme ve Uyarlanabilir Nöro-Bulanık Çıkarım Sistemi gibi zaman serisi tahmin yöntemleri kullanılmış ve sonuçlar test kullanılarak karşılaştırılmıştır. performans, veriler için en iyi modeli belirlemek üzere Kök Ortalama Kare Hatasını (RMSE) ölçer. Diğer modellerle karşılaştırıldığında, sonuçlar ANFIS'in en düşük RMSE ile daha iyi performans gösterdiğini göstermektedir

Anahtar Kelimeler: Turizm geliri, Uyarlamalı ağ tabanlı bulanık çıkarım sistemi, Otoregresif entegre hareketli ortalama, Holt-Winter, Diferansiyel gelişim algoritması, HW-DEA, Hata Kareler Ortalamasının Karakökü.

ABSTRACT

FORECASTING TOURSIM INCOME OF TURKEY

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Institute of Graduate Studies

Department of Statistics

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Tourism is regarded as important to the global financial system because of its significant benefits for improving the economy and creating various opportunities such as jobs, developing economic growth, and also facilitating cultural exchange between both foreigners and citizens, Tourism income is defined as the total amount spent in Turkey on individual and package tours by foreigners and citizens living abroad (excluding real estate expenditures, repair-maintenance expenses for residences, durables, transfers, etc.). Tourism income includes the amount spent on consumer goods and services, as well as personal belongings, in preparation for and during tourist trips; it covers any costs incurred by the visitor. This can include standard products like lodging or meals, as well as public transportation, but it can also include valuables (like artwork) and consumer durables like buying small goods for personal use, souvenirs, and gifts for family and friends, as well as all personal care products, and so on., Tourism income contributes significantly to the Turkish economy's revenue. That is why forecasting tourism revenue in the future is critical. Time series forecasting methods such as Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing, hold winter-differential evolution algorithm (HW-DEA), and Adaptive Neuro-Fuzzy Inference System were used in this study to forecast tourism income from the Turkish Statistical Institute (TÜK), and the results were compared using the test performance measure Root Mean Square Error (RMSE) to determine the best model for the data. When compared to the other models, the results show that ANFIS outperforms with the lowest RMSE.

Keywords: Tourism income, Adaptive Neuro-Fuzzy Inference System, Autoregressive Integrated Moving Average, Holt-Winter, Differential Evolution Algorithm, HW-DEA, Root Mean Square Error.

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SYMBOLS AND ABBREVIATIONS

TÜİK:	Turkish Statistical Institute (Türkiye İstatistik Kurumu)
RMSE:	Root Mean Square Error
ARIMA:	Autoregressive Moving Integrated Average Model
SARIMA:	Seasonal Autoregression Integrated Moving Average
HW:	Holt-Winter Exponential Smoothing method
DEA:	Differential Evaluation Algorithm
HW-DEA:	Holt-Winter- Differential Evaluation Algorithm
ANN:	Artificial Neural Network
ANFIS:	Adaptive Fuzzy Inference System
MAPE:	Mean Absolute Percentage Error

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1. INTRODUCTION

People have always enjoyed traveling and meeting new people, but with more free time, longer lives, higher income levels, advancements in transportation, accommodation expansion, and promotion, effective advertising activities, travel packages as well as the advancement of new technology, resulted in the expansion of mass communication, and so on, this is becoming more common. As a result, the increased number of tourists and these objectives have resulted in an increase in the global tourism movement. 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. These people are called visitors (which may be either tourists or excursionists; residents or non-residents) and tourism has to do with their activities, some of which imply tourism expenditure (United Nations World Tourism Organization, 2008).

Tourism has grown to become one of the world's largest and fastest-growing industries in the second half of the twentieth century. Perhaps more than any other activity, tourism embodies aspects of "post-industrial society" and provides insight into the specialty's future developments. The tourism industry is typically thought of as a collection of customer activities spread across a variety of business and consumer categories. Tourism as an industry lacks a distinct foundation, instead encompassing a diverse range of businesses and organizations from various industries that serve clients with varying entrances, tastes, and objectives. It also deals with a diverse range of urban and rural cityscapes, as well as government organizations with differing intentions and preferences. The primary actors and elements that constitute the tourism sector seem to be customers, distributors, and government entities. Tourism has become a major source of job creation and income generation in some regions, countries, often replacing resource extraction, industrial, and farming industry, and a number of these countries are investing in facilitating hotels, stores, exhibitions, restaurants, as well as other tourist facilities. Aside from all of these effects, tourism helps to bring people from various backgrounds together. A civilization of harmony and understanding evolves in communities that interact with one another.

Tourism income is defined as the total individual and package tour expenditures made in Turkey by foreigner and citizen visitors resident in abroad (excluding real estate expenditures, repair-maintenance expenses for residences, durables, transfers etc.). Tourism income expenditures include a wide range of items like food and beverages, accommodation, health, transportation in Turkey, sports, education, culture, international transportation with Turkish firms, mobile phone roaming expenditures, marina service expenditures, also from the purchase of consumer goods and services inherent in travel and stay to the purchase of small durable goods for personal use, souvenirs, and gifts for family and friends.

Furthermore, Tourism income represents a significant portion of the Turkish economy's revenue according to the Turkish Statistical Institute (Turk Stat). Turkey's total tourism income increased by 122.4% year on year, reaching \$5.4 billion in the first quarter of 2022. That is why Tourism has many positive contributions to the country's economy. The developing and growing tourism sector has many effects, such as increasing foreign exports, opening new business areas, contributing to foreign debt payments, providing foreign currency inflow, and increasing growth (DuBarry, 2004) That is why it is critical to forecast tourism income, hence new income is injected into the economy when the tourism sector or the size of tourist operations grows. Forecasting is obviously a very important issue which aims to predict the dependent variable as soon as possible by using recently published data. In this thesis I have aimed to generate forecasts for the tourism income data for Turkey. To achieve this the conventional approaches such as Autoregressive Integrated Moving Average (ARIMA) , HW-DEA ,and Exponential Smoothing as well as Adaptive Neuro Fuzzy Inference System (ANFIS) which is the most recent one, were applied to the tourism income data. Any research about forecasting the tourism income data just as univariate case has not been encountered in the literature. It emphasizes this research should be done. Therefore, it has been aimed to show that the best result is obtained from ANFIS for the data of the tourism income for Turkey.

2. LITERATURE REVIEW

In this section some research related with the current method ANFIS, and the conventional methods like ARIMA, are introduced briefly.

The study conducted by Talpur H. N. and et al. (2017) is about how four popular shapes of membership functions affect ANFIS performance when solving different classification problems. Experiments revealed that the Gaussian membership function outperformed its counterparts in terms of accuracy while requiring less computational complexity. Therefore, the computational cost of ANFIS increases significantly with the number of data inputs and training samples. Future studies may concentrate on alterations to ANFIS's five-layered architecture. Reducing the number of steps among input and output, as well as using effective input space partitioning methods will result in less computation and higher accuracy.

Husein, et al (2018) proposed two distinct techniques. In the first step, they utilize medical data from 2015-2016 to forecast the need for medicines using the standard ANFIS structure, and they measure the Root Mean Square Error (RMSE) value for training and testing. In the second approach, they still use ANFIS algorithm but after the process of clustering from the K-Means algorithm. They discovered from the testing results that the proposed technique offered good forecasting rates based on the evaluation analysis of RMSE compared to existing processes. The application of the K-Means Algorithm against ANFIS has an impact on the timing of the training process and provides a classification accuracy significantly.

Sinan Q. Salih et al. (2019) proposed an approach, known as the co-active neuro-fuzzy inference system (CANFIS) which combines the advantages of fuzzy systems and neural networks to enhance the performance of the neural network system in the research of evaporation modelling from meteorological variables. For the relationship mapping between predictor and response variable, CANFIS uses centre-weighted sets instead of global weight sets, resulting in higher prediction accuracy. In this study, changes are made to CANFIS's back-propagation algorithm to allow for fully automated upgradation of membership rules and better forecasting accuracy. The CANFIS model's predictive ability is validated using three well-known artificial

intelligence (AI) models. The results show that the CANFIS model predicts evaporation more accurately than the other AI models.

Wang, and Deng, et al (2017) proposed a new method that is a combination of ARIMA and nonlinear autoregressive neural network (NAR). They applied this method to the incidence of tuberculosis (TB) from January 2007 to March 2016 and compared this method with ARIMA. This study demonstrates that developing and applying the ARIMA-NAR hybrid model is an effective technique for fitting the linear and nonlinear patterns of time-series data and that this model could be beneficial in the prevention and regulate of tuberculosis. The NAR network is a powerful class of models capable of representing random complex nonlinear mappings and has favourable characteristics for modelling dynamic systems and forecasting nonlinear time series as an architectural approach to recurrent neural networks with embedded memory.

There are numerous methods for forecasting time series data by combining or separating linear and non-linear models. Büyükşahin, and Ertekin (2019) proposed a hybrid method which is a combination of the ARIMA model and artificial neural network to improve the accuracy of forecasting time series. Finally, they concluded that the hybrid method shows that techniques for analysing data and the combined linear and nonlinear models throughout the hybridization process are crucial elements in forecasting performance of the methods.

Taher A. Shehab Eldeen et al (2019) offered a new method for predicting Friction Stir Welding (FSW) parameters and making a decision by integrating a modified version of the adaptive neuro-fuzzy inference system (ANFIS) with Harris Hawks optimizer (HHO). The proposed model, known as ANFIS-HHO, has two major stages: training and testing. During the training stage, the algorithm creates a set of solutions that reflect the parameter configuration. Then, based on the current solution, ANFIS is produced for each generated solution. To select the best solution, the value of the arrangement (solution) is calculated using a predetermined objective function. Once the best solution has been determined, all existing solutions are upgraded using the HHO operators, and the method is repeated till the stopping criterion is met. Meanwhile, the evaluation stage begins with the choice of the trained ANFIS model based on the ideal configuration, followed by the application of the test set to it. The

target output is then determined by calculating, and the model's performance is assessed using statistical measures. The ANFIS-HHO method was found to be an effective optimization tool for predicting FSW parameters to achieve high joint strength. Harris hawk's optimizer (HHO): HHO starts by determining the initial value for a collection of agents X that symbolizes the solution of the issue under consideration.

Alaba Timothy Owoseni et al (2020) proposed an improved ANFIS that employs an agglomerative-based clustering ensemble of fuzzy c-means to aid in the extraction of rules representing a method, event, or system from a given dataset. The ensemble employs probability trajectories of random walk methods on the dataset's base grouping partitions to optimize direct co-association relationships or links between many data objects of the base partitions, thus also enhancing these relationships, which afterward metamorphosed into fuzzy rules and, finally, a higher accuracy. When they compared the proposed method to the traditional ANFIS for lithology prediction using two standard petrophysical datasets, they discovered that the proposed method produces superior results in terms of forecasting stability and accuracy. Despite this, both maintain the same architecture regarding the number of rules, tuneable variables, and training phase.

A Case Study in Predicting Biochar Yield was made by Ahmed A. Ewees and Mohamed Abd Elaziz in 2020. They proposed a hybrid method combining the adaptive neuro-fuzzy inference system (ANFIS) and the Gray wolf optimization (GWO) algorithm method that mimics the hierarchical society of wolves. This method is split into two phases. GWO is used in the first phase to understand the parameters of ANFIS using the training dataset, and the test dataset is used in the second phase to evaluate the effectiveness of the proposed ANFIS-GWO method. They tested this method using three different data sets. After determining the result and comparing it to another method, they discovered that the proposed method (ANIFS-GWO) outperforms both.

In another study done by Babak Mohammadi et al in 2020, the main goal is to investigate the performance of integrating new novel hybrid models for river streamflow forecasting in the Vu Gia-Thu Bon River. Six various situations for the model input-output architecture were researched. The hybrid model combines the adaptive neuro-fuzzy inference system (ANFIS) with the shuffled frog-leaping

algorithm (SFLA). SFLA is a meta-heuristic optimization algorithm derived from nature. Eusuff and Lansey (Eusuff et al. 2006) created a new algorithm in recent years called (ANFIS-SFLA). The results indicate that the proposed ANFIS-SFLA model outperforms the classic ANFIS model; additionally, the proposed method is adaptable to any river data globally.

Muhammad Najamuddin, and Sareen Fatima conducted a study titled 'A Hybrid BRNN-ARIMA Model for Financial Time Series Forecasting' in 2022. They proposed a hybrid method combining the ARIMA model and Bayesian regularized neural network (BRNN) to forecast the exchange rate. It is difficult to predict the exchange rate since it changes over time, they took 6 countries' datasets from the first quarter of 1970 to the second quarter of 2021. The result obtained from hybrid method (ARIMA-BRNN), ARIMA, BRNN, and random walk were compared. They found hybrid method gave the best result from the regularizable neural network. The regularized neural network is one type of ANN that is used to solve the overcome fitting problem.

Samad Emamgholizadeh, et al (2023) they offered new method to method for predicting the Cation exchange capacity (CEC) by using artificial intelligence (AI) models with soil properties that are readily available may be the best solution. in this study the companied ANFIS with differential evolution (ANFIS-DE), coupled by particle swarm optimization (ANFIS-PSO to CEC prediction are used. They find out the coupled models (ANFIS-DE and ANFIS-PSO) outperformed the standard ANFIS model in terms of efficiency.

The current thesis is concerned about forecasting tourism income. There are also some researches related to this subject. It will be introduced here some of them. Zhang JK (2021) studied to investigate the nonlinear effects of tourism on urban-rural income inequality and rural income inequality based on data from China's provincial regions over the period 1995-2018, using the dynamic panel data approach. The results demonstrate that for the national sample, there exists a significant cubic curve relationship between domestic tourism and rural income inequality and inbound tourism's relationship with rural income inequality is not significant.

Most of papers are related to the relationship between tourism and economic growth. The article produced by Aydin (2016) analyzed tourism income to find a model for forecasting with panel data method. Sun et al (2012) took the disposable income of urban residents, the number of foreign tourists, and the number of travel agencies as the major influence factors of tourism income in Shandong. Feckless et al. (2012) examine the relationship between the cyclical components of Greek GDP and international tourism income for Greece for period 1976-2004. Their analysis showed that the cyclical component of tourism income is significantly influencing the cyclical component of GDP in Greece. Beneki et al (2012) used singular spectrum analysis (SSA) for signal extraction and forecasting of UK tourism income. They also applied SARIMA and showed that SSA slightly outperformed SARIMA.

3. MATERIALS AND METHODS

3.1. Time Series

The basic definition of time series is a series of data points of a variable y_t $t=0,1,2,\dots$ that has been recorded over a specific period (year, month, week, winter, summer, etc.) in time. According to this definition time series is a sequence of discrete time data. Such as the daily weather temperatures, stock prices, rainfall measurements and etc. can be examples of time series data. Time series analysis consists of a number of statistical methods and methodologies to understand how the data behaves and what the characteristics of the data are over time in order to make projections to future.

The time series data are changing over time with different structures. These are called the components of the time series: Trend, Seasonal Variations, Cyclic Variations and Irregular Fluctuations (Brockwell P.J. and Davis R. A., 2002)

Trend:

It's the general tendency of the data to increase or decrease during a long period of time, the direction or movement may change on the short-term period but the overall tendency will be remaining the same in trend.

Seasonal Variations:

Seasonal variations can be considered as the variations in a time series which occurs at specific time intervals such as weekly, monthly or quarterly. The variations recur regularly. The sales on the holiday seasons will increase and will repeat in the same period of each year.

Cyclic variations:

It depicts a cyclical pattern with up and down movement. It may last more than a year and recur after a period from time to time. But it is not necessary that the periods have the same length. It is very difficult to predict cycles because they do not occur at regular intervals.

Irregular Fluctuations:

This component is erratic. Every time series contains an element of unpredictability which makes the time series the random variable. The goal of prediction is to "model" all of the components until only the random component remains unexplained.

3.2. Box-Jenkins Methodology

Time series analysis methods are classified into two parts, one is “univariate time series analysis” and the other is “multivariate time series analysis”. In this thesis we are dealing with univariate time series analysis.

Box-Jenkins Methodology includes a class of models used in univariate time series analysis. This class is called Autoregressive Integrated Moving Average (ARIMA) models. George E.P. Box and Gwilym M. Jenkins introduced their approaches in 1970 about the analysis of univariate time series data. They provide the method to develop forecasts using the past values of the data points in time order. Since then, this analysis is referred as Box-Jenkins Analysis. This methodology assumes that the time series is stationary. Since it is an important feature of the time series for applying this methodology, it should be discussed first.

3.3. Stationarity

The first step in developing the methodology is to determine that the time series is stationary. Because this methodology requires the relevant time series should be stationary. Stationarity can be viewed as one of the types of statistical balance in the stochastic process. The characteristics of a statistical process, such as the mean, variance and autocorrelation structure, do not depend on the time. Being stationary for a time series is a very important feature in developing the time series model that is profitable for forecasting the future. It is obvious that the time series with trends and seasonality is not stationary time series since they affect the mean value of the time series at different periods.

There are two types of stationary time series which are strictly stationary and weakly stationary. If the joint probability distributions of the observations $(y_t, y_{t+1}, \dots, y_{t+n})$, is exactly the same as the joint probability distribution of the observation $(y_{t+k}, y_{t+k+1}, \dots, y_{t+k+n})$ then we say that the time series is weakly stationarity. When these joint probability distributions are the same then we will have a strictly stationary time series (Montgomery, Jennings and Kulahcı, 2015).

Many time series encountered in practice exhibits nonstationary behaviour. Since Box-Jenkins methodology is applied only the stationary time series we have to make the time series stationary before a model is developed. The most common way of making a non-stationary time series stationary is to compute the differences between consecutive observations. The differences, for example first order differencing, can be done by subtracting each value from the subsequent observation. The formula for the first order differencing is defined as

$$\nabla x_t = x_t - x_{t-1} \quad (3.1)$$

If the first order differencing cannot be enough for reaching stationarity, then the process can be repeated d times until a stationary data is obtained where d symbolises the order of differencing. In most cases a non-stationary data is converted to the stationary one by taking differences only once or twice. This process is called the integrated of order d or $I(d)$.

3.4. Autoregressive Model

Autoregressive models are shortened as AR models, and a p-order model is written as AR(p), where p is the number of previous observations taken into account by the model. The variable of interest is a linear combination of past values of the variable against itself. Then AR(p) model can be mathematically expressed as below:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t \quad (3.2)$$

y_t and ε_t are presented as the actual value and random error at the period t, ϕ represented the variable coefficients of the lagged observation and it is willing for them to be estimated, c is the constant, and the integer p is the model order.

3.5. Moving Average Model

Another common approach for modelling a univariate time series is to use Moving Average (MA) model. It describes a variable's value at time instant t as a weight function of the previous independent error terms. The model is written as MA(q), where q denotes the number of error terms (Box and Jenkins, 1994). It is expressed as below:

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \quad (3.3)$$

y_t is time series value being estimated and, ε_t is the random error at the period t, θ 's represent coefficients for the lagged random variables.

3.6. Autoregressive Moving Average Model

Autoregressive Moving Average Model (ARMA) is a combination of the autoregressive model (AR) and the moving average (MA). These models provide a better understand the data and to predict the future observations of the data. When we combined this two method we get ARMA (p,q) which be overall beneficial to the class of linear time series models. ARMA merges the concepts of the AR process and the MA process. In general, ARMA model can be presented as blow:

$$y = c + \varepsilon_t + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{i=1}^q \theta_i \varepsilon_{t-i} \quad (3.4)$$

the model of ARMA(p,q) refer to p autoregressive part and q moving average part of the model (Box and Jenkins, 1994).

3.7. Autoregressive Moving Integrated Average Model

Autoregressive Moving Integrated Average Model is symbolized as ARIMA where 'I' represents differencing and it is corresponding to the integrated part of the model. ARIMA is composed of (p, d, q) where p is the order of regression (AR), d is the degree of difference(I), and q is the order of moving average (MA). Then ARIMA(p,d,q) model can be presented as below:

$$Y_t = \mu + \varphi_1 Y_{t-1} + \dots + \varphi_p Y_{t-p} + \theta_p \varepsilon_{t-p} + \dots + \theta_1 \varepsilon_{t-1} + \varepsilon_t \quad (3.5)$$

ARIMA model considers being critical in the field of time series analysis and future value forecasting (Box and Jenkins, 1994).

3.8. Identification of ARIMA Model

When you start to analyse your data the first step of developing a model is to determine that your data is stationary or not. For doing this the time series plot and the autocorrelation function will help.

Autocorrelation Function (ACF):

The autocorrelation analysis is an important stage in time series forecasting. This will help to detect for randomness. Autocorrelation is the correlation coefficient between two values at different time points in a time series (Montgomery, Jennings and Kulahci, 2015). The basic concept of autocorrelation refers to how the observation at time t is related with the observation at previous times, by simply measuring the correlation between the current and previous observations. Under the assumption of stationarity correlations must be the same for all times t. The covariance between y_t and y_{t+k} , at the lag k defined as below:

$$\gamma_k = cov[y_t, y_{t+k}] = E[(y_t - \mu)(y_{t+k} - \mu)] \quad (3.6)$$

Similarly, the autocorrelation at lag k is define as below.

$$\rho_k = \frac{E[(y_t - \mu)(y_{t+k} - \mu)]}{\sqrt{E(y_t - \mu)^2 E(y_{t+k} - \mu)^2}} = \frac{E[(y_t - \mu)(y_{t+k} - \mu)]}{\sigma_Y^2} \quad (3.7)$$

In case the stationarity the variance σ_Y^2 is equal to γ_0 the same at time t as at time $t + k$

Autocorrelation coefficient at lag k is defined as

$$\rho_k = \frac{\gamma_k}{\gamma_0} \quad (3.8)$$

which holds that $\rho_0 = 1$. The sample correlation at lag k is converted to the following formula.

$$r_k = \frac{\sum_{t=2}^n (Y_t - \bar{Y}_t)(Y_{t-k} - \bar{Y}_{t-k})}{\sqrt{\sum_{i=1}^n (Y_t - \bar{Y}_t)^2} \sqrt{\sum_{i=2}^n (Y_{t-k} - \bar{Y}_{t-k})^2}} \quad (3.9)$$

$$r_k = \frac{\sum_{t=k+1}^n (Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{i=1}^n (Y_t - \bar{Y})^2}$$

Partial Autocorrelation function:

The partial autocorrelation function is a stationarity process of y_t at the lag k , the correlation between y_t and y_{t-k} after the intermediate variables $y_{t-1}, y_{t-2}, \dots, y_{t-k}$ have adjusted. Then the partial autocorrelation commonly represented by ϕ_{kk}

$$\phi_{kk} = \text{corr}(y_t, y_{t-k} / y_{t-1}, y_{t-2}, \dots, y_{t-k+1}) \quad (3.10)$$

ϕ_{kk} is considered the correlation coefficient between the variables y_t and y_{t-k} with $y_{t-1}, y_{t-2}, \dots, y_{t-k}$.

For the identification of ARIMA Table 3.1 is presented in the book by Yaffee (1999).

Table 3.1. The identification of ARIMA models

Model	ACF	PACF
ARIMA (0,0,0)	No significant spikes	No significant spikes
ARIMA(p,0,0)	Exponentially decay	First p spikes are significant
ARIMA (0,0, q)	First q spikes are significant	Exponentially decay
ARIMA (p,0, q)	First q spikes are significant	First p spikes are significant

3.9. Seasonal Autoregression Integrated Moving Average

Periodic (also known as seasonal in ARIMA context) behaviours is common in time series data and this periodic series is distinguished by a trend that recurs every s time period, where s is also known as the periodicity length. ARIMA takes into account the past values of the time series and predicts the future values. Seasonal ARIMA models is referred as SARIMA (the letter 'S' stands for seasonal). SARIMA similarly uses past values and at the same time it takes into account any seasonal spikes in the time series (Box, George E. P., 2015). A "season" can be a single day, a week, a year, or an entire century. SARIMA model just like ARIMA model approach using the same three-stage which they are: identification, estimation, and diagnostic; however, when working with seasonal data, the autocorrelation coefficients in the ACF and PACF plots at seasonal lags $s, 2s, 3s$, and so on must be taken into consideration. If the data has seasonal non-stationarity, as indicated by autocorrelation coefficients at the seasonal lags of the ACF plot, the correct order of seasonal differencing (defined by 'D') may be required to make the data seasonal stationary. In addition, the presence of seasonal autoregressive and moving average coefficients in the data must be determined using the autocorrelation coefficients of ACF and PACF plots at seasonal lags, just as non-seasonal ARIMA models were. Typically, components SARIMA $(p, d, q) \times (P, D, Q)_s$, a mixed seasonal-non-seasonal model are used to represent it, non-seasonal parts are indicated by lowercase letters in parentheses, while seasonal parts are indicated by uppercase letters. Generally, the mathematic formulation of SARIMA $(p, d, q) \times (P, D, Q)_s$ model is given as below

$$\phi(\beta^s)\phi(\beta)(1 - \beta^s)^D(1 - \beta)^d y_t = \theta(\beta^s)\theta(\beta)\varepsilon_t \quad (3.11)$$

3.10. Holt-Winters Exponential Smoothing

Holt-Winter (HW) is one of the classical exponential smoothing forecasting methods. It is considered as one of the simplest and most commonly used method for forecasting time series data with seasonal patterns. This method involves level, trend, and seasonal components, each of which contains three parameters α , β , γ to be estimated. Typically, there are two types of HW models: additive and multiplicative seasonality models. The additive method is preferred when the seasonal variations are nearly constant throughout the series, while the multiplicative method is preferred when seasonal variations change proportionally to the series level. Using the additive method, the seasonal component is expressed in absolute value in the scale of the observed series, and the series is seasonally adjusted in the level equation by subtracting the seasonal component (Chatfield, 1978). The seasonal component will close to zero each year. However, using the multiplication method where the seasonal component is expressed in relative terms (percentages), and the series is seasonally adjusted by dividing by the seasonal components, Holt-Winter models are described below:

The equations for additive model

$$S_t = \alpha(y_t - I_{t-L}) + (1 - \alpha)(S_{t-1} + b_{t-1}) \quad \text{overall smoothing} \quad (3.12)$$

$$b_t = \gamma(S_t - S_{t-1}) + (1 - \gamma)b_{t-1} \quad \text{trend smoothing} \quad (3.13)$$

$$I_t = \beta(y_t - S_{t-1} - b_{t-1}) + (1 - \beta)I_{t-L} \quad \text{seasonal smoothing} \quad (3.14)$$

Forecasts are determined

$$F_{t+m} = (S_t + mb_t) + I_{t-L+m} \quad (3.15)$$

The equations for multiplicative model

$$S_t = \alpha \frac{y_t}{I_{t-L}} + (1 - \alpha)(S_{t-1} + b_{t-1}) \quad \text{overall smoothing} \quad (3.16)$$

$$b_t = \gamma(S_t - S_{t-1}) + (1 - \gamma)b_{t-1} \quad \text{trend smoothing} \quad (3.17)$$

$$I_t = \beta \left(\frac{y_t}{S_{t-1} + b_{t-1}} \right) + (1 - \beta)I_{t-L} \quad \text{seasonal smoothing} \quad (3.18)$$

Forecasts are obtained from the following equations.

$$F_{t+m} = (S_t + mb_t)I_{t-L+m} \quad (3.19)$$

Here S_t is the estimate of current level, α is the smoothing constant for the level ($0 < \alpha < 1$), b_t is the trend estimate, γ is the smoothing constant for the trend estimate, I_t is the seasonal estimate, β is the smoothing constant for the seasonal estimate ($0 < \beta < 1$), F_{t+m} is the forecast at m period ahead, L is the number of seasonal behaviours consisted of in the whole data. The performance of the exponential smoothing techniques depends on the smoothing parameters α , β and γ . These parameters sometimes are set arbitrarily to values between 0.05 and 0.3. Alternatively, they can be chosen by minimizing the prediction error or another error criterion.

3.11. Differential Evolution Algorithm

Differential Evolution Algorithm (DEA) was introduced by Storn and Price in 1995. DEA is a stochastic optimization algorithm of the evolutionary type. This algorithm is based on finding a new solution by subjecting the chromosomes, each of which contains a solution in itself. Mutation and crossover operators are used in these processes. If the new individual's fitness, or proximity to the solution, is better than the old ones, the new individual is transformed into the following population. DE can direct the search toward the optimum solution thru the repetitive cycles of mutation, crossover, and selection. The basic algorithm parameters in DEA are the size of the population, the number of variables (D), the maximum iteration number, the crossover rate (CR), and the scaling factor (F). The algorithms' process steps can be defined as

variable task and population formation, individual fitness calculation, mutation, crossover, selection. The presentation that follows is based on the original/classic DEA method.

Initialization

It, like other evolutionary algorithms, begins with an initial population variable that is generated at random when no previous knowledge of the solution space is accessible. The DE algorithm seeks to evolve a population of NP D -dimensional parameter vectors, known as individuals, that encode candidate solutions. would be a D-dimensional vector which can be initialized as follows

$$PG = \{x_1, G, x_2, G, \dots, x_{NP}, G\}$$

$$x_{i,0}^j = x_{min}^j + rand(0,1)(x_{max}^j - x_{min}^j) \quad j = 1, 2 \dots D \quad (3.20)$$

where $x_i, G = \{x_1^i, G, \dots, x_G^i, G\}, i = \{0, 1 \dots, NP\}$ x_i, G symbolizes a population decision variable (or individual), The population size is represented by NP, and the aspect of decision vectors is symbolized by D. PG represents a population after G generations (0 is an initial generation), rand is symbolizing a random variable with a uniformly distributed in the range [0, 1]. And $(x_{max}^j - x_{min}^j)$ represent the lower and upper parameter bounds in the initialization.

Mutation

Mutation is defined in the nature-inspired meta - heuristic algorithm as a sudden switch or variation with the random element. The mutation step creates a new individual (also known as mutated vector) from each individual (also known as target vector), The most common definition of mutation is:

$$v_{i,G} = N_{r1,G} + F(N_{r2,g} - N_{r3,g}) \quad (3.21)$$

where r1, r2, and r3 are chosen at random from [1, NP], where r1 corresponds to the base vector. F is a real number between [0, 1] that represents the transformation function.

Crossover

The crossover is used to create the trial vector (off spring). $U_{i,g} = (U_{i,g}^1, U_{i,g}^2, \dots, U_{i,g}^j)$

To form the trial vectors, mutant vectors are blended with the initial individuals (target vector) of the existing population in this stage. In overall, binomial recombination occurs on each variable.

$$U_{i,g}^j = \begin{cases} U_{i,g}^j, & \text{if } rand(0,1) \leq CR \text{ or } j = j_{rand} \\ n_{i,g}^j, & \text{else} \end{cases} \quad (3.22)$$

CR is the crossover constant $\in [0, 1]$, j_{rand} where is chosen at random to ensure that the trial

The vector may obtain at least one element from the mutant ($j_{rand} \in [1, m]$) vector

Selection

The selection process is used to create the next generation population. Individuals with lower (or higher) principles are preserved, similar to the survival of the fittest in biology. Because parameter identification is clearly a minimum optimization problem, individuals with lower objective function values are maintained, and the selection operation is carried out.

$$N_{i,g+1} = \begin{cases} U_{i,g}, & \text{if } f(U_{i,g}) \leq f(N_{i,g}), \\ N_{i,g}, & \text{else} \end{cases} \quad (3.23)$$

where $f(.)$ indicates the objective function that is being optimized (minimized here).

3.12. HW-DEA approach

As previously stated, there are three smoothing components in the Holt-winter where exponential smoothing parameters are α , β , γ . Then the initial value of the level, trend and seasonal can be represented as follows

$$S_0, b_0, I_{-(s-1)}, I_{-(s-2)}, \dots, I_0$$

In this approach the different evaluation algorithm is used to determine the optimal of the initial value. In the initial set, the genes on each chromosome represent the values α , β , γ as in shown in the figure, Genes with α , γ , and β parameters are uniformly distributed in the range (0,1), and the genes with S_0 and b_0 initial values are obtained from the 95% confidence intervals formed by regression analysis estimates of the intercept and the slope coefficient, respectively.

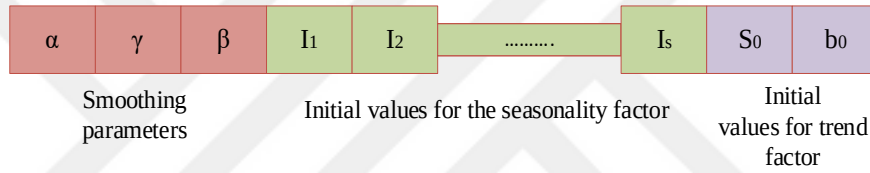


Figure 3.1. An example of a chromosome

Genes with seasonal smoothing initial values of $I_1, I_2, \dots, I_s$ are calculated as a result of the calculations expressed in equation (3.24) for each k. It is derived by selecting the smallest and largest range of values at random for the initial value. Following that, the DEA steps (mutation, crossover, and selection) are applied (Topal, Uslu and Demirci, 2016).

$$C_m = \frac{\sum_{t=(m-1)s+1}^{ms} y_t}{s}, \quad m = 1, 2, \dots, \frac{n}{s} \quad k = 1, 2, \dots, s$$

$$\min \left(\frac{y_{k+(1-1)s}}{C_1}, \frac{y_{k+(2-1)s}}{C_2}, \frac{y_{k+(3-1)s}}{C_2}, \dots, \frac{y_{k+(m-1)s}}{C_m} \right) < I_{-(s-k)} \quad (3.24)$$

$$I_{-(s-k)} < \max \left(\frac{y_{k+(1-1)s}}{C_1}, \frac{y_{k+(2-1)s}}{C_2}, \frac{y_{k+(3-1)s}}{C_2}, \dots, \frac{y_{k+(m-1)s}}{C_m} \right)$$

3.13. Artificial Neural Network

Artificial Neural Network (ANN) is regarded as one of the most well-known Artificial Intelligence (AI) methods. ANN is an information system that was developed and inspired by the structures of the human brain. Because of its ability to deal with complex, and nonlinear models, ANN is considered an information processing system that is very similar to the characteristics of a biological neural system and is thus used in a wide range of scientific fields, particularly weather and climate. ANN is made up of elements known as neurons, which are linked together by a plethora of synapses implemented by vectors and arrays of synaptic weights.

3.13.1. Artificial neural networks architecture

ANN architecture is made up of three layers. The first layer is the input layer, which is responsible for receiving input from the surrounding environment such as data, singles, features, or measurements. In this layer there is no rule requiring a certain number of neurons (input) in this layer; this layer can accept more than one input. The following layer consists of hidden layers. This layer is made up of neurons that to receive data more than the neurons in the previous layers of the input layer. The data in this layer is analysed by using various functions. The hidden layer could include more than one neuron based on the complexity and appropriateness of the current case. The computational outcomes of this layer are transferred to the output layer. The output layer is the final layer, and it is charged with determining the accuracy of data evaluated within the activation function's network sounds. The output can be utilized as a determinant of the current case's result.

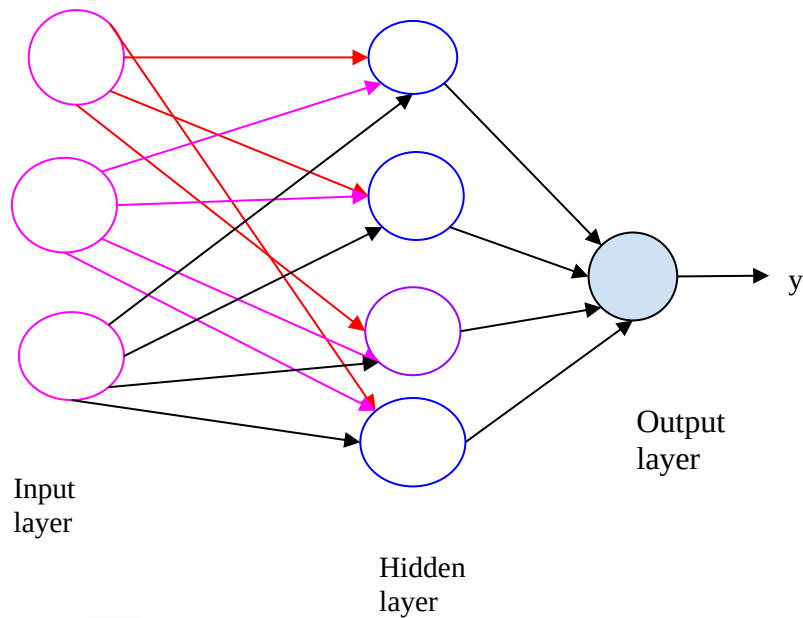


Figure 3.2. Artificial Neural Network

The primary design of artificial neural networks takes into consideration the placement of neurons as well as how they are connected, and the layer composed of them, therefore we can divide the artificial neural networks into feed-forward architecture and Feedback neural network (Yegnanarayana, B. 2009).

Feed-forward architecture

Feedforward is an architecture that does not require a feed link. Data in feedforward is only moved in one direction, which means that the output of each layer does not affect the previous layer. This architecture can be established into a single layer or multiple layers. The multiple layers typically are consisting of three layers: input layer, hidden layer, and output layer. The hidden layer component leads to enhanced computing power.

Feedback neural network

Feedback neural networks have similar architectures to feedforward neural networks, with the architecture designed to have supplemental feedback slow or feedback

previous layer, which that means the data or singles that have been enabled to propagate forward and feedback can be an input to the neurons before, and this network is utilized for dynamic applications such as time-variant systems.

Learning process

Typically, two types of learning processes have been commonly used in ANN; supervised and unsupervised learning.

Supervised learning; in general, supervised learning is information that has been given in the form of sample patterns that have been marketed or categorized, so that in the final layer of an ANN architecture. The output will be created and compared with the desired output pattern. If there is an error in the compared process, the network weights are amended and corrected so that the actual output matches up to the pattern output.

Unsupervised learning; In this type learning, there are no guidelines or target outputs in the learning process; instead, the networks receive many input samples and classify or characterize these samples in any way. When the stimulus is applied to the input layer, the response in the form of an output characterizes or classified will have characteristics that are similar to the input stimulus.

3.13.2. Fuzzy Inference System:

Fuzzy logic begins with the concept of a fuzzy set, and the purpose of developing a fuzzy set is to model a complicated system in an unclear and inaccurate environment. a fuzzy set is an addition of a classical set with elements that may or may not be members of that set. Assuming that X is input space and is elements defined by x , the fuzzy set A has described a set of order parts in X as express below:

$$A = \{x, \mu_A(x) \mid X \in x\} \quad (3.25)$$

$\mu_A(x)$ is considered a membership function (MF) which used to described how every element x in the input space is the degree of membership, membership usually is between range $[0,1]$.

A fuzzy inference system usually known as the fuzzy rule base is a non-linear model that uses IF-THEN rules to explain the relationship between input and output variables in a real system (Jang, J. S. 1993). A fuzzy inference system is composed of five functional blocks:

1. A rule base includes a set of fuzzy IF-THEN rules.
2. A database that identifies the fuzzy set membership functions utilized in the fuzzy rules.
3. A decision-making unit that performs rule inference operations.
4. A fuzzification inference that converts the degree of match with linguistic values from the crisp inputs.
5. A defuzzification interface that converts the inference's fuzzy results into a crisp output.

The rule base and the database are frequently described as the base of knowledge. Fuzzy inference consists of two parts which are the if and the then part which is referred to as the premise and consequent

Fuzzy inference systems perform fuzzy reasoning steps (inference processes based on fuzzy if-then rules). which are three blocks:

1. Fuzzification to achieve the membership values of every linguistic label, compare the input variables with the membership functions on the premise part.
2. Merge the membership values on the premise part (via a specific T-norm operator, usually multiplication or min.) to obtain the firing strength (weight) of each rule.
3. Determine the qualified consequence (fuzzy or crisp) of each rule based on the firing strength(weight)
4. Defuzzification Combine the qualified outcomes to produce a crisp output.

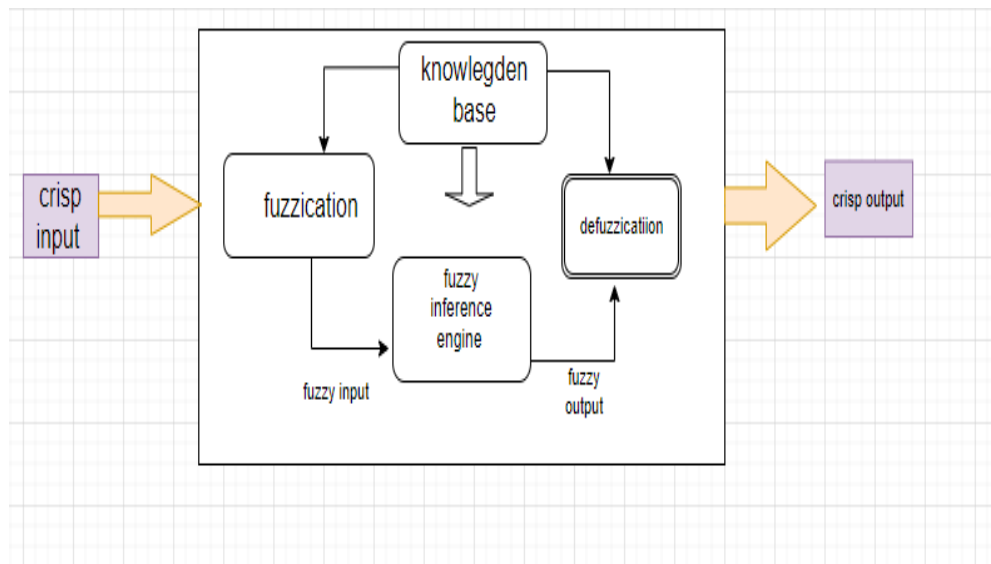


Figure 3.3. Fuzzy inference system

3.13.3. Type of Fuzzy Inference System

The fuzzy inference system is consistent in three methods Takagi Sugano Kang fuzzy inference system. This method was purposed by Takagi, Sugano, and Kang who developed a mathematical style that allowed to generate of fuzzy rules from the input and output variables in a Sugano fuzzy model, a usual fuzzy rule looks like this

$$\text{if } X \text{ is } A \text{ and } y \text{ is } B \text{ then } w = f(x, y)$$

Where A and B are recognized as fuzzy sets and $w(x, y)$ is the crisp function in the consequent, the fuzzy inference system is called the first-order Sugano fuzzy model if $f(x, y)$ is polynomial, and the zero-order Sugano fuzzy model if f is constant. The weighted average is used to calculate the output in this method.

Mamdani fuzzy inference system:

Originally, the Mamdani fuzzy inference system was designed to control the steam engine and boiler combination using a set of linguistic variables. The fuzzy rules in the Mamdani fuzzy inference system look like the following:

If x is small then y is small

If x is small then y is medium

The linguistic variables antecedent and consequent of the rules are both fuzzy in this case. Because the Mamdani fuzzy inference system produces output in fuzzy form, it is necessary to convert this fuzzy output to crisp form. Various defuzzification methods are utilized to define fuzzy output into crisp output.

Tsukamoto fuzzy model:

The result of fuzzy in the if-then rules is defined by a fuzzy set monotonical membership function in Tsukamoto. As a result, the output of each rule is defined as a crisp value. The total output is calculated as the weighted average of the output of each rule (Chaudhari and Bambhori 2014).

3.13.4. Adaptive fuzzy inference system

ANFIS is a Neuro-Fuzzy approach developed by Jang in 1993 that investigates fuzzy systems based on the Takagi and Sugano model (1985) and can be used to control application, prediction, or divination. ANFIS structure is very similar to a neural network, with radial functions and a few limitations. The process of learning neural networks is used to optimize the fuzzification parameter values (Jang, J. S. 1993). The process of the Neuro-Fuzzy consists of five layers.

ANFIS is made up of five layers:

1. fuzzification layer
2. produced layer
3. normalized layer
4. defuzzification layer
5. output layer

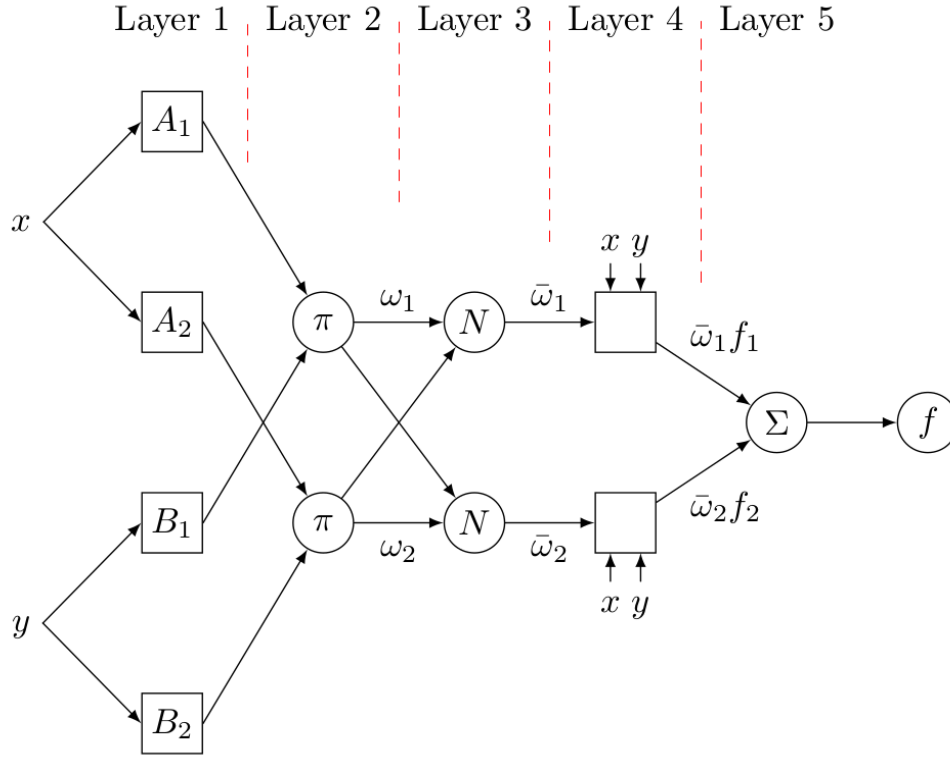


Figure 3.4. ANFIS architecture

ANFIS technology enhances learning capabilities by combining ANN and fuzzy logic. This hybrid ML(multi-layer) method is identical to a set of advanced fuzzy rules that can be used to model nonlinear flood functions. An ANFIS works by identifying and optimizing the parameters and structure of a FIS using neural learning rules. Using the dataset, the ANFIS attempts to discover missing fuzzy rules through the ANN training. ANFIS has increased in popularity, particularly in flood modelling, due to its quick and easy implementation, authentic learning, and powerful generalization abilities. By using online acknowledgment, an ANFIS model can be defined as a discrete control system and forecast a chaotic time series. The inputs and outputs are used to create the ANFIS membership function. The fuzzy inference system is implemented using a database and a rule-based system. ANFIS is made up of five layers

Layer 1: is referred to as the fuzzification layer the input value determines the membership function and belongs to them. During this, every node i layer is a square node with a node function

$$O_i^l = \mu_{A_i}(x) \quad i = 1, 2 \quad (3.26)$$

where x is the node i input and A_i , is the linguistic label (small, large, etc.) related to this node function, this layer's Parameters are regarded as premise parameters. the membership value of the input is the output of the Node.

In other words, O_i^l is A_i the membership function and it specifies the degree to which the given x satisfies the quantifier A_i . typically, we select $\mu_{A_i}(x)$ to be bell-shaped with a maximum of 1 and a minimum equal to 0, as the generalized bell function

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i} \right)^2 \right]^{b_i}} \quad (3.27)$$

or the Gaussian function

$$\mu_{A_i}(x) = \exp \left[- \left(\frac{x - c_i}{a_i} \right)^2 \right] \quad (3.28)$$

where (a_i, b_i, c_i) (or (a_i, c_i) in the latter case) denotes parameter set. t . Because the values of those parameters change, the bell-shaped functions change as well resulting in a variety of membership functions on the linguistic label A_i . Any continuous and piecewise differentiable functions, such as the frequently used trapezoidal or triangular-shaped membership functions, are also qualified candidates for node functions during this layer r . these layer Parameters are referred to as premise parameters.

The mathematical representation of trapezoidal as following:

$$\mu_{A_i}(x) = \max \left(\min \left(\frac{x - a}{b - a}, 1, \frac{d - x}{d - c} \right), 0 \right) \quad (3.29)$$

triangular-shaped membership functions

$$\mu_{Ai}(x) = \max \left(\min \left(\frac{x-a}{b-a}, 1, \frac{c-x}{c-b} \right), 0 \right) \quad (3.30)$$

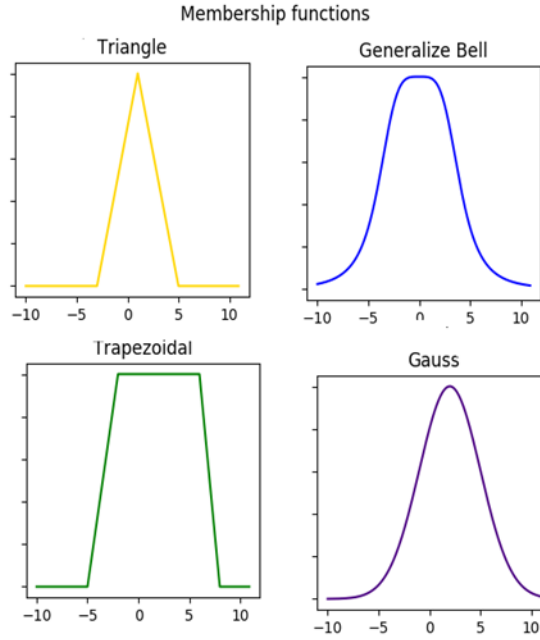


Figure (3.5): Basic shapes of membership functions

Layer 2: A fixed layer known as the rule layer. The second layer is in charge of determining the firing strengths for the rules. Every node in this layer is a labelled π circle node that multiplies the incoming signals and sends the product out. As an example,

$$O_i^2 = w_i = \mu_{Ai}(x) * \mu_{Bi}(y) \quad i=1,2 \quad (3.31)$$

Layer 3: This layer is known as the normalization layer because it divides each value by the total firing strength. This layer's nodes are all circle nodes labelled N. The node i th computes the ratio of the firing strength of the i th rule to the sum of the firing strengths of all rules.

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i=1,2 \quad (3.32)$$

Layer 4: This layer is known as the defuzzification layer because it takes the normalized values as inputs and the result parameter set $\{p_i, q_i, r_i\}$. In this layer, every node i is a square node with a node function.

$$O_i^4 = \bar{w}_i * f_i = \bar{w}_i(p_i x + q_i y + r_i) \quad i=1,2 \quad (3.33)$$

Where $\bar{w}_i$ is the output of layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set.

Layer 5: The output layer, which has only one node as part of the overall output. The output value is defined as

$$O_i^5 = \sum \bar{w}_i * f_i = \frac{\sum w_i f_i}{\sum w_i} \quad (3.34)$$

3.14. Model Selection Criteria

We use a variety of accuracy measurement parameters to evaluate the performance of each model. The following standard metrics are employed in this study:

Mean Square Error (MSE):

It calculated as the average squared difference between the observed and predicted values.

$$MSE = \frac{\sum (y_i - \hat{y}_i)^2}{n} = \frac{\sum_{i=1}^n e_i^2}{n} \quad (3.35)$$

Root Mean Square error (RMSE):

represents the square root of the differences between predicted values and observed values

$$RMSE = \sqrt{MSE} \quad (3.36)$$

Mean absolute percentage error (MAPE):

is a measure of prediction accuracy of a forecasting methods

$$MAPE = \frac{1}{n} \sum \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (3.37)$$

4. APPLICATION

In this study it has been aimed to obtain the forecasts of the tourism income data for Turkey. The tourism income datasets were obtained from Turkish Statistical Institute (TÜİK). This data consists of 126 observations represented monthly from January 2012 until June 2022. According to the literature research there has not been a study in which a univariate time series analysis was applied for Tourism Income especially by using some new generation methods just as methods from artificial intelligence class. Therefore, in this thesis ANFIS method was applied to the data with expectation that the best forecasts will be obtained comparing with the classical methods. The data set unfortunately has got three missing observations from April to June in 2020 due to pandemic. Since we cannot use the data as it is we have to estimate these values in somehow. In this study these missing observations were estimated as the average of the values of the relevant months in the past years. The final version of the data was represented in Figure 4.1. In order to measure performances of the methods the data was splatted into two parts as training and testing. For this purpose, the ratios of %90-%10, %80-%20 and %70-%30 were tried. All methods included in this study were applied for all ratios.

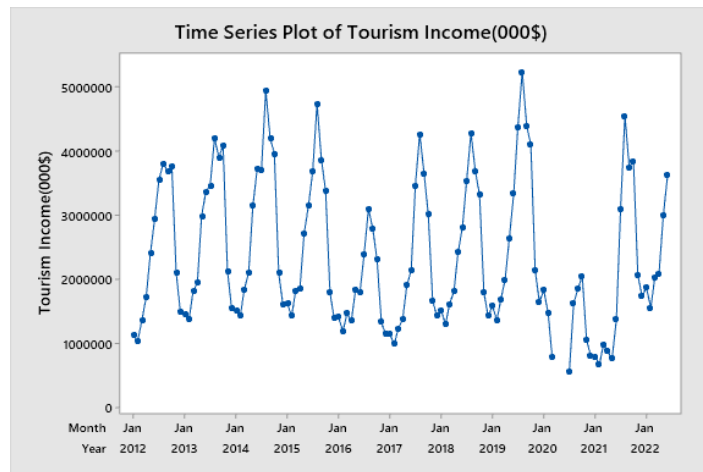


Figure 4.1. The time series plot of Tourism Income

Table 4.1. The tourism Income Data

	Year	Data (\$)
1	01/01/2012	1128718
2	01/02/2012	1038923
3	01/03/2012	1356781
4	01/04/2012	1718082
⋮		
⋮		
124	01/04/2022	2093478
125	01/05/2022	2993574
126	01/06/2022	3630051

4.1. SARIMA Application

First of all, the data has to be checked for stationarity because of the assumption of SARIMA. From the Figure 4.1 it is very clear that the data has got seasonality. The autocorrelation function presented in Figure 4.2 shows a pattern of positive and negative spikes that alternates. It also exhibits a recurring pattern every 12 lags, indicating a seasonality effect.

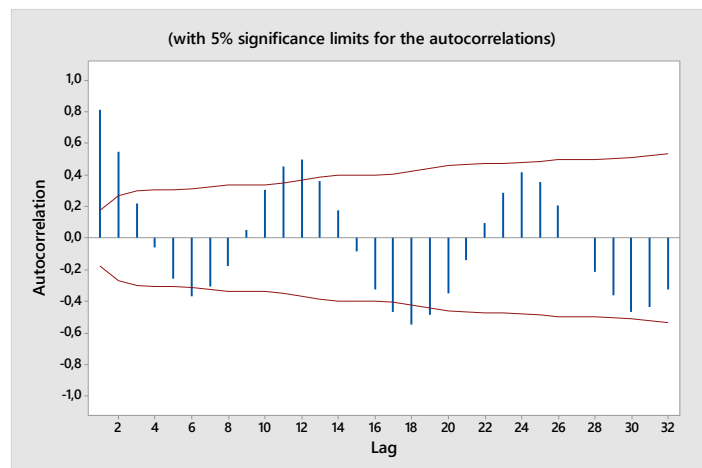


Figure 4.2. ACF for the transformed data

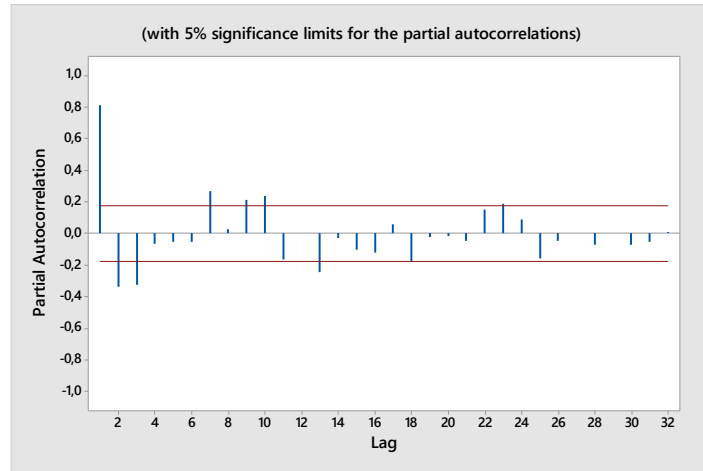


Figure 4.3. PACF for the transformed data

This indicates that the time series is not stationary. Since our data is seasonal, we will forecast the data using the SARIMA model, and since the Minitab program finds it difficult to estimate the initial data, we will justify the tourism income data by using the logarithmic transformation. After the logarithmic transformation whole data set is divided into two groups as training and testing data for three different percentages (80%-20%, 70%-30%, 90%-10%). PACF plot for the transformed time series data is in Figure 4.3. If it is referred that acf decays very quickly in the first recurring pattern and there are first 3 significant spikes in pacf then the orders for the models will possibly be as SARIMA (3,1,0), (3,1,0)₁₂. If it is referred that pacf decays very quickly in the first recurring pattern and there are first 2 significant spikes in the acf then the model orders will possibly be as SARIMA (2,1,0), (2,1,0)₁₂. To find a suitable model order for both seasonal and non-seasonal part we tried many values for them. Finally, the best SARIMA model is chosen according to the smallest Root Mean Square Error (RMSE) of testing data.

The results from SARIMA with the ratio 80%-20%

Since our data is seasonal and it considers part of ARIMA, The Seasonal ARIMA model combines non-seasonal and seasonal components, and can be specified as SARIMA(p, d, q)(P, D, Q) _{m} . When we divide the transformed data with respect to the

ratio (80%-20%) training data has got 101 and testing data has got 25 observations. Lots of SARIMA models has been tried and the most convenient ones are presented in Table 4.2. The choice of the best one was determined based on the smallest testing RMSE result.

Table 4.2. SARIMA results for the ratio 80%-20%

SARIMA (80%-20%)	RMSE		Ljung-box test	Model coefficients
SARIMA (0,1,1), (1,0,0) ₁₂	training	0.125055	The residuals are uncorrelated	All coefficients are significant
	testing	0.685009		
SARIMA (2,1,1), (1,0,0) ₁₂	training	0.125299	The residuals are uncorrelated	All coefficients are significant
	testing	0.696108		

When we compared the results in Table 5.2, we discovered that the best result was obtained from SARIMA (0,1,1), (1,0,0)₁₂ which is giving us the smallest testing RMSE with value 0.685009. When the residual plots obtained from the best model is checking by using 4-plots which is given in Figure 4.4 it can be seen that there is a problem. The normality seems to be not satisfied but, we may say that there is no heteroscedasticity and autocorrelation problem. These findings lead us to believe that our model does not provide a good fit.

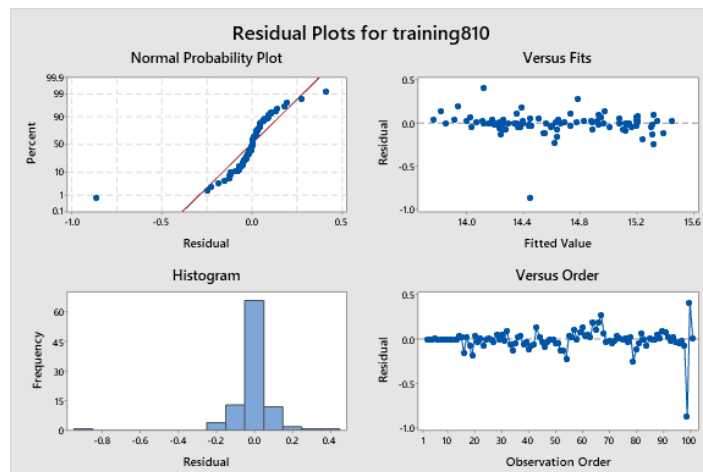


Figure 4.4. Diagnostic plots of Residuals from SARIMA (0,1,1), (1,0,0)₁₂

Forecasts from SARIMA (0,1,1), (1, 0, 0)₁₂

One of the most important objectives in the analysis of a time series is to forecast its future values. Forecasting is a planning tool that assists management in making decisions. It attempts to deal with the unknowns of the future by relying primarily on information gathered from previous and present trend analysis. Forecasting is also the process of making predictions about an unknown quantity. Table 4.3 shows the result of 25 forecasts from June 2020 until June 2022 against actual values. In order to assess the fitness between the actual observations and the forecasted values for the testing data the plot of actual observations against forecasted values with the regression will help. This plot is illustrated in Figure 4.5. In this graph R^2 , which is a measure of goodness of fit, was found 0.181 which is not very good.

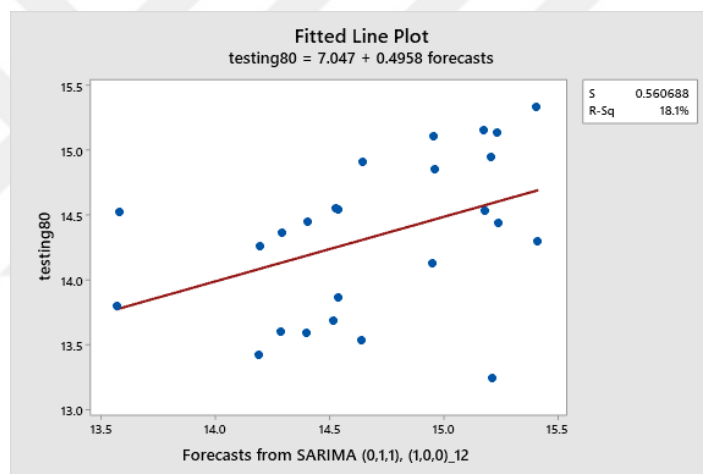


Figure 4.5 Regression between actual and forecasted values from SARIMA (0,1,1), (1,0,0)₁₂

Table 4.3. The actual and forecasted values from SARIMA (0,1,1), (1,0,0)₁₂ for the testing data.

Year	Actual Values	Forecasts
01/06/2020	14.8547	14.8752
01/07/2020	13.2382	15.1461
01/08/2020	14.2994	15.3235
01/09/2020	14.4364	15.1484
01/10/2020	14.5357	15.0772
01/11/2020	13.8662	14.4279
01/12/2020	13.6010	14.1666
01/01/2021	13.5860	14.2735
01/02/2021	13.4181	14.0588
01/03/2021	13.8006	13.4306
01/04/2021	13.6841	14.3800
01/05/2021	13.5378	14.4974
01/06/2021	14.1297	14.7208
01/07/2021	14.9473	14.9897
01/08/2021	15.3307	15.1655
01/09/2021	15.1355	14.9904
01/10/2021	15.1599	14.9187
01/11/2021	14.5379	14.2715
01/12/2021	14.3671	14.0105
01/01/2022	14.4458	14.1162
01/02/2022	14.2572	13.9017
01/03/2022	14.5190	13.2753
01/04/2022	14.5543	14.2199
01/05/2022	14.9120	14.3359
01/06/2022	15.1048	14.5576

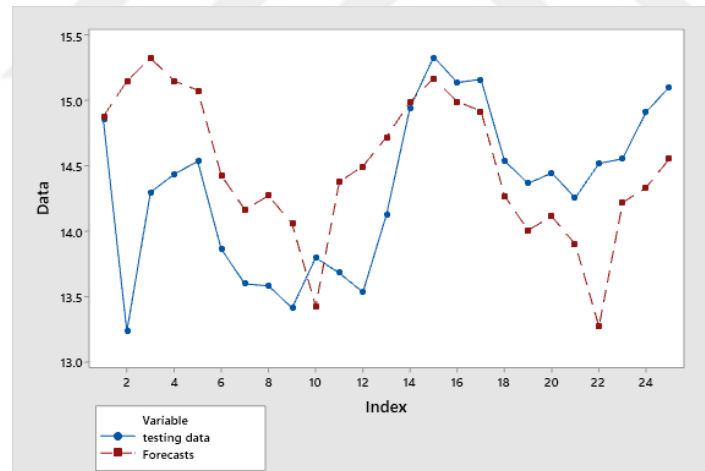


Figure 4.6: Time series plot for the comparison between actual and forecasts from SARIMA (0,1,1), (1,0,0)₁₂

Figure 4.6 is comparing the actual values and the forecasted values on time. In this graph two time series are not fit well in the beginning but the harmony between them is increasing as time goes by. Although we have used estimates instead of missing

observations, it can be thought that this result is caused by the fact that the data has these values.

The results from SARIMA with the ratio 70%-30%

When we divide the transformed data with the ratio (70%-30%) training data has got 88 observations and testing data has got 38. Many of SARIMA models has been tried and the most convenient ones are presented in Table 4.4. The choice of the best one was determined based on the smallest testing RMSE result.

Table 4.4. SARIMA result of the 70%-30% ratio

SARIMA (70%-30%)	RMSE		Ljung-box test	Model coefficients
SARIMA (1,1,2), (1,0,0) ₁₂	training	0.0808152	The residuals are uncorrelated	All coefficients are significant
	Testing	0.828126		
SARIMA (0,1,0), (1,0,0) ₁₂	training	0.0744708	The residuals are uncorrelated	All coefficients are significant
	Testing	0.631625		

When we compared the results in Table 4.4, we discovered that the best result was obtained from SARIMA (0,1,0), (1,0,0)₁₂ which is giving us the smallest testing RMSE with a value of 0.631625. When the residuals from that model were checking due to the residual plots all assumptions seem to be satisfied. It can be seen that there is no heteroscedasticity, autocorrelations and non-normality problems. These findings lead us to believe that our model provides a good fit that can help us better understand our time series data and forecast future values. In this trial the missing values are not included in the training data. May be that is why the model works well for the training data.

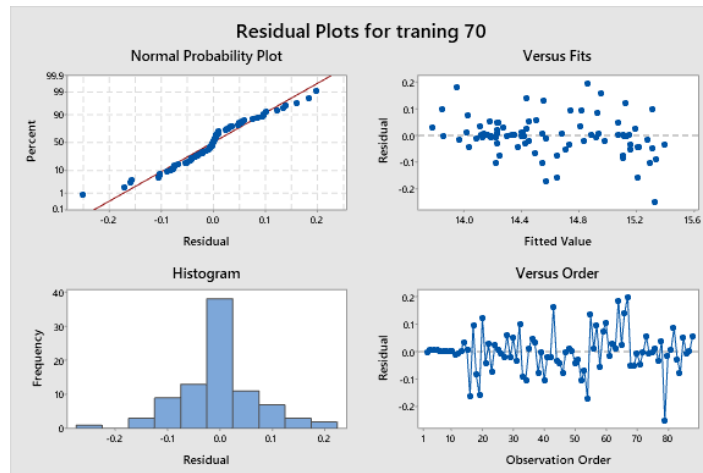


Figure 4.7. Diagnostic plots of Residuals from SARIMA (0,1,0), (1,0,0)₁₂

Forecasting SARIMA (0,1,0), (1, 0, 0)₁₂

Table 5.5 displays 38 forecasts from May 2019 to June 2022 for the testing data, along with the actual values. Figure 4.8 represents the testing data performance. R^2 was found 0.315 in this graph. This is very weak fitness because the missing values are included in the testing data.

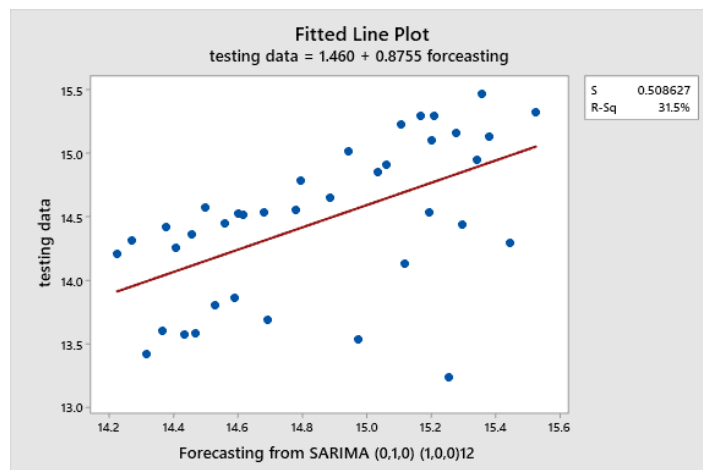


Figure 4.8 Regression between actual and forecasted values from SARIMA (0,1,0), (1,0,0)₁₂

Table 4.5. The actual and forecasted values from SARIMA (0,1,0), (1,0,0)₁₂ for the testing data.

Year	Actual Values	Forecasts	Year	Actual Values	Forecasts
01/05/2019	14.7862	14.7954	01/12/2020	13.6010	14.3640
01/06/2019	15.0208	14.9434	01/01/2021	13.5860	14.4667
01/07/2019	15.2937	15.1699	01/02/2021	13.4181	14.3148
01/08/2019	15.4726	15.3596	01/03/2021	13.8006	14.5256
01/09/2019	15.2976	15.2110	01/04/2021	13.6841	14.6919
01/10/2019	15.2269	15.1064	01/05/2021	13.5378	14.9752
01/11/2019	14.5755	14.4967	01/06/2021	14.1297	15.1202
01/12/2019	14.3138	14.2696	01/07/2021	14.9473	15.3425
01/01/2020	14.4220	14.3734	01/08/2021	15.3307	15.5286
01/02/2020	14.2072	14.2204	01/09/2021	15.1355	15.3820
01/03/2020	13.5769	14.4332	01/10/2021	15.1599	15.2787
01/04/2020	14.5314	14.6012	01/11/2021	14.5379	14.6786
01/05/2020	14.6500	14.8871	01/12/2021	14.3671	14.4549
01/06/2020	14.8547	15.0336	01/01/2022	14.4458	14.5565
01/07/2020	13.2382	15.2580	01/02/2022	14.2572	14.4056
01/08/2020	14.2994	15.4458	01/03/2022	14.5190	14.6144
01/09/2020	14.4364	15.2982	01/04/2022	14.5543	14.7791
01/10/2020	14.5357	15.1943	01/05/2022	14.9120	15.0597
01/11/2020	13.8662	14.5895	01/06/2022	15.1048	15.2033

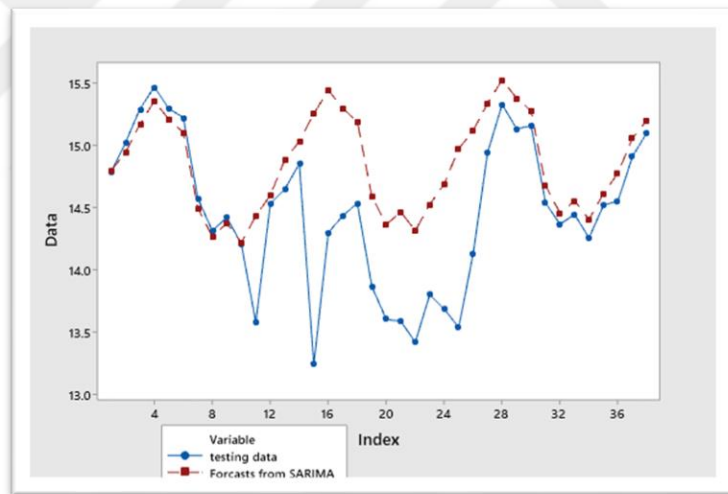


Figure 4.9: Time series plot for the comparison between actual and forecasts from SARIMA (0,1,0), (1,0,0)₁₂

Figure 4.9 is agreed with the result from Figure 4.8.

The results from SARIMA with the ratio 90%-10%:

When we divide the transformed data with the ratio (90%-10%) training data has got 113 observations and testing data has got 13. Many of SARIMA models has been tried

and the most convenient ones are presented in Table 4.6. The choice of the best one is generally determined based on the smallest testing RMSE result. But here L-Jung box test results from those models shows that the residuals are correlated.

Table 4.6. SARIMA results of 90%-10%ratio

SARIMA (90%-10%)	RMSE		Ljung-box test	model coefficients
SARIMA (0,1,1), (1,0,1) ₁₂	training	0.226762	The residuals are correlated $p(12)=0,005$ $p(24)=0.280$	All coefficients are significant
	testing	1.13312		
SARIMA (0,1,1), (0,1,1) ₁₂	training	0.235176	The residuals are correlated $p(12) = 0.019$, $p(24) = 0.476$	All coefficients are significant
	Testing	1.27448		

Even when we look at the 4-plots of residuals which is given Figure 4.10, they are looking strange. That means the residuals from those models are problematic and they support the result from Ljung-Box. Because of that, no models were found as the best for this ratio. All of the missing values are included in the training data. That may cause for us not to find a good model for the data. This analysis was excluded from the comparison.

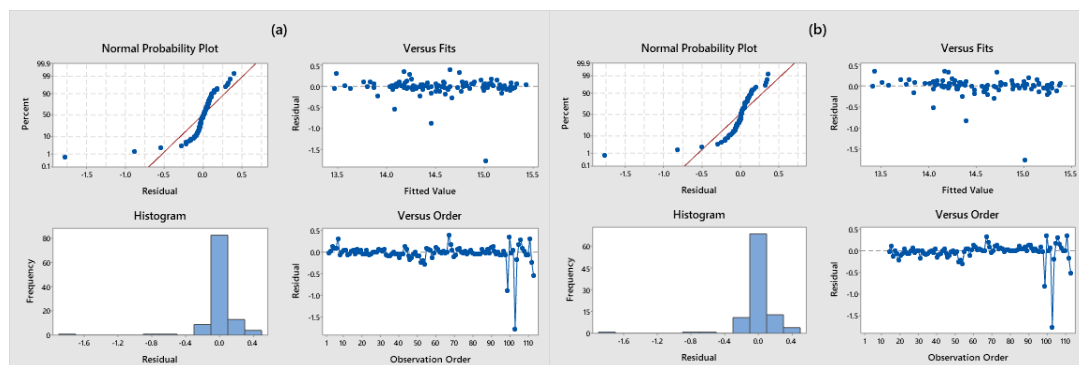


Figure 4.10 The residual plots (a) from SARIMA (0,1,1), (1,0,1)₁₂ (b) from SARIMA (0,1,1), (0,1,1)₁₂

4.2. Holt-Winters Methods

Unlike SARIMA models, Holt-Winters models examine a time series data of interest and divide it into three components: level, trend, and seasonal, and assign weights to each component on a scale of zero to one in order to fit the model and forecast future values. When the seasonal fluctuation length is getting bigger over time it is recommended to use multiplicative HW. In our data the length of fluctuation does not change over time. That is why we used additive Holt-Winters method with different ratio (80%-20%, 70%-30%, and 90%-10%). The best result was chosen based on the smallest testing RMSE. The results are as follows:

The Result from Holt-Winter with the ratio 80%-20%

We divided the tourism income data into 101 and 25 observations as training and testing sets, respectively. After trials we have found two competing models. For these models the level parameter (α), the trend parameter (β), and the seasonal parameter (γ) values are presented in Table 4.7. The best RMSE is obtained when $\alpha = 0.8, \gamma = 0.02, \delta = 0.2$ as 0.625838.

Table 4.7: Result of Holt-Winter of 80%-20% ratio

Holt-Winter	RMSE	
Holt-winters $\alpha = 0.8$ $\gamma = 0.9$ $\delta = 0.2$	training	0.183450
	Testing	1.61244
Holt-winters $\alpha = 0.8$ $\gamma = 0.02$ $\delta = 0.2$	training	0.139216
	Testing	0.625838

Forecasting Holt-Winter ($\alpha = 0.8, \gamma = 0.02, \delta = 0.2$)

Table 4.8 displays 25 forecasted values for the period from June 2020 until June 2022 which is the testing set. Figure 4.11 gives us the performance for testing data. In this graph it is seen that R^2 was found 0.360.

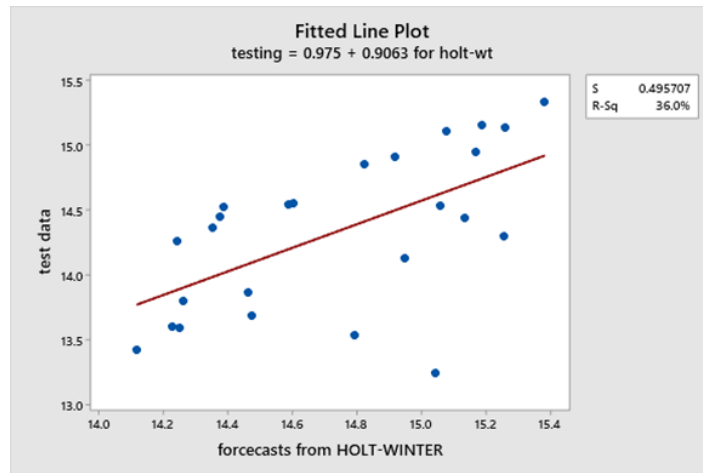


Figure 4.11 Regression between actual and forecasted from Holt-Winter 80%-20% ratio

Table 4.8: The actual values and forecasted values from Holt-Winter 80%-20%ratio

Year	Actual Values	Forecasts
01/06/2020	14.8547	14.8243
01/07/2020	13.2382	15.0433
01/08/2020	14.2994	15.2567
01/09/2020	14.4364	15.1350
01/10/2020	14.5357	15.0615
01/11/2020	13.8662	14.4613
01/12/2020	13.6010	14.2248
01/01/2021	13.5860	14.2476
01/02/2021	13.4181	14.1164
01/03/2021	13.8006	14.2590
01/04/2021	13.6841	14.4747
01/05/2021	13.5378	14.7930
01/06/2021	14.1297	14.9508
01/07/2021	14.9473	15.1699
01/08/2021	15.3307	15.3833
01/09/2021	15.1355	15.2616
01/10/2021	15.1599	15.1880
01/11/2021	14.5379	14.5879
01/12/2021	14.3671	14.3514
01/01/2022	14.4458	14.3742
01/02/2022	14.2572	14.2429
01/03/2022	14.5190	14.3856
01/04/2022	14.5543	14.6012
01/05/2022	14.9120	14.9196
01/06/2022	15.1048	15.0774

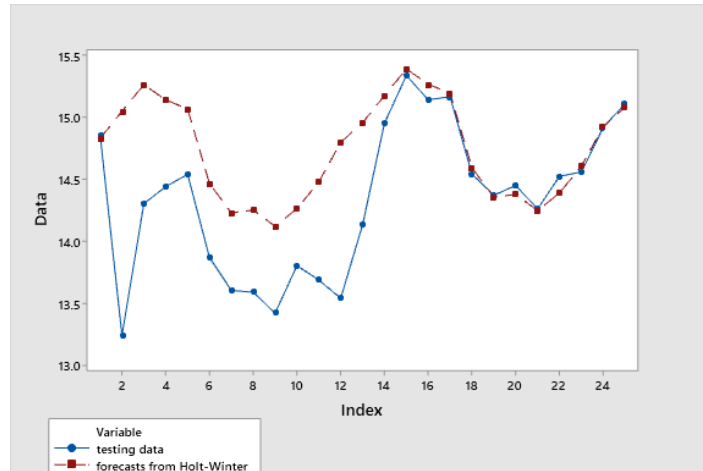


Figure 4.12: Time series plot for the comparison between actual and forecasts from Holt-winter 80%-20%

The Result from Holt-Winter with the ratio 70%-30%:

When we divide the data with respect the ratio 70%-30% the training set has 88 and the test set has 38 observations. In this class two models have been chosen competing each other then they are presented Table 4.9. From that table it is seen that the best result for RMSE of the testing data is obtained from the model where the smoothing parameters are as $\alpha = 0.8, \gamma = 0.02, \delta = 0.2$. For this model RMSE is found as 0.815667.

Table 4.9: Result of Holt-Winter of 70%-30% ratio

Holt-Winter	RMSE	
Holt-winters $\alpha = 0.8$ $\gamma = 0.9$ $\delta = 0.2$	training	0.100787
	Testing	1.15435
Holt-winters $\alpha = 0.8$ $\gamma = 0.02$ $\delta = 0.2$	training	0.0693253
	Testing	0.815667

Forecasting Holt-Winter ($\alpha = 0.8, \gamma = 0.02, \delta = 0.2$)

The resulted forecasted values for the testing data from May 2019 to June 2022 was obtained. Figure 4.11 gives us the performance for testing data. In this graph R^2 was found as 0.264.

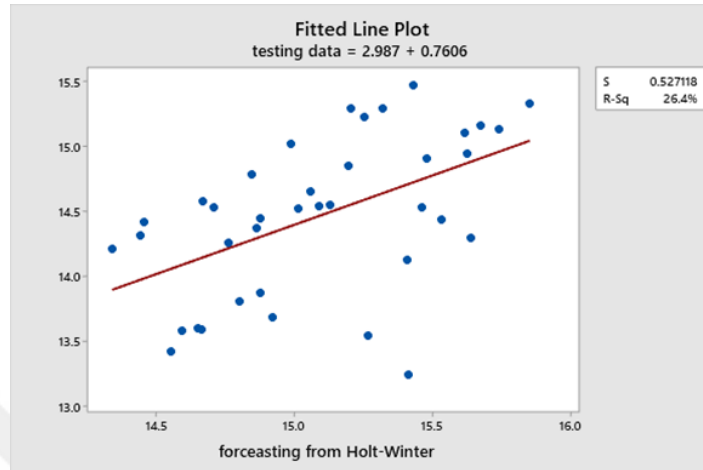


Figure 4.13 Regression between actual and forecasted from Holt-Winter 70%-30% ratio

Table 4.10: The actual values and forecasted values from Holt-Winter 70%-30%ratio

Year	Actual Values	Forecasts	Year	Actual Values	Forecasts
01/05/2019	14.7862	14.8481	01/12/2020	13.6010	14.6521
01/06/2019	15.0208	14.9882	01/01/2021	13.5860	14.6652
01/07/2019	15.2937	15.2046	01/02/2021	13.4181	14.5529
01/08/2019	15.4726	15.4299	01/03/2021	13.8006	14.8040
01/09/2019	15.2976	15.3223	01/04/2021	13.6841	14.9198
01/10/2019	15.2269	15.2542	01/05/2021	13.5378	15.2690
01/11/2019	14.5755	14.6683	01/06/2021	14.1297	15.4092
01/12/2019	14.3138	14.4416	01/07/2021	14.9473	15.6255
01/01/2020	14.4220	14.4548	01/08/2021	15.3307	15.8508
01/02/2020	14.2072	14.3425	01/09/2021	15.1355	15.7432
01/03/2020	13.5769	14.5935	01/10/2021	15.1599	15.6752
01/04/2020	14.5314	14.7094	01/11/2021	14.5379	15.0892
01/05/2020	14.6500	15.0585	01/12/2021	14.3671	14.8625
01/06/2020	14.8547	15.1987	01/01/2022	14.4458	14.8757
01/07/2020	13.2382	15.4150	01/02/2022	14.2572	14.7634
01/08/2020	14.2994	15.6403	01/03/2022	14.5190	15.0144
01/09/2020	14.4364	15.5327	01/04/2022	14.5543	15.1303
01/10/2020	14.5357	15.4647	01/05/2022	14.9120	15.4795
01/11/2020	13.8662	14.8788	01/06/2022	15.1048	15.6196

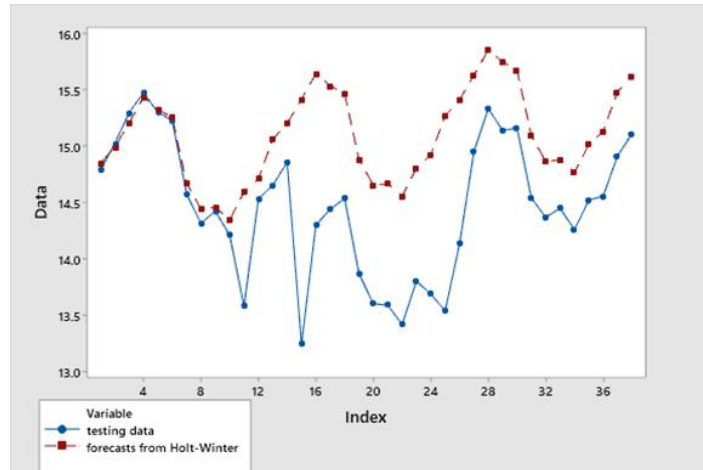


Figure 4.14: Time series plot for the comparison between actual and forecasts from Holt-winter 70%-30%

The Result from Holt-Winter with ratio90%-10%:

First step is for us to divide the data into 113 training and 13 testing. After trials it has been chosen two models with different smoothing parameters values. The obtained results are show in the following Table 4.11.

Table 4.11: The results from Holt-Winter of 90%-10% ratio

Holt-Winter	RMSE
Holt-winters $\alpha = 0.8$ $\gamma = 0.9$ $\delta = 0.2$	training= 0.312090
	testing= 4.27715
Holt-winters $\alpha = 0.8$ $\gamma = 0.02$ $\delta = 0.2$	training= 0.229325
	testing= 1.23277

From the table 4.11 it is seen that the best value of RMSE of testing data is obtained as 1.23277 when the parameters are $\alpha = 0.8, \gamma = 0.02, \delta = 0.2$ for Holt-Winter method.

Forecasting Holt-Winter ($\alpha = 0.8, \gamma = 0.02, \delta = 0.2$)

We used HW method to forecasting 13 values from June 2021 to June alongside actual value, Figure 4.15 gives us the performance for testing data. In this graph R^2 was found 0.552 the results show as below.

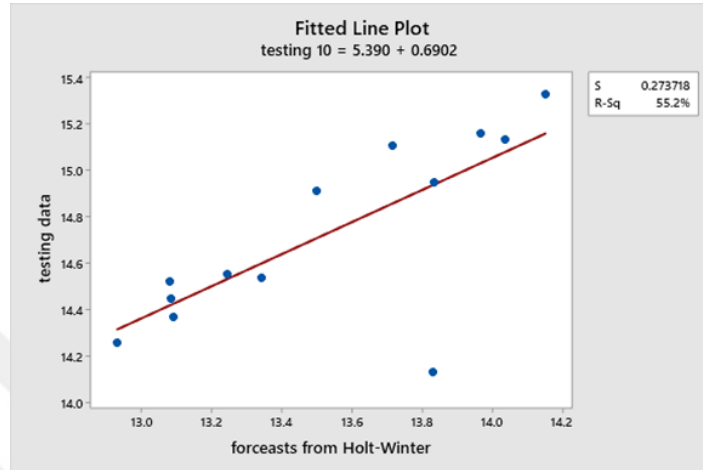


Figure 4.15 Regression between actual and forecasted from Holt-Winter 90%-10% ratio

Table 4.12: The actual values and forecasted values from Holt-Winter 90%-10%ratio

Year	Actual values	Forecasts	Year	Actual values	Forecasts
01/06/2021	14.1297	13.8296	01/12/2021	14.3671	13.0882
01/07/2021	14.9473	13.8339	01/01/2022	14.4458	13.0826
01/08/2021	15.3307	14.1530	01/02/2022	14.2572	12.9287
01/09/2021	15.1355	14.0377	01/03/2022	14.5190	13.0800
01/10/2021	15.1599	13.9662	01/04/2022	14.5543	13.2425
01/11/2021	14.5379	13.3419	01/05/2022	14.9120	13.4989
			01/06/2022	15.1048	13.7151

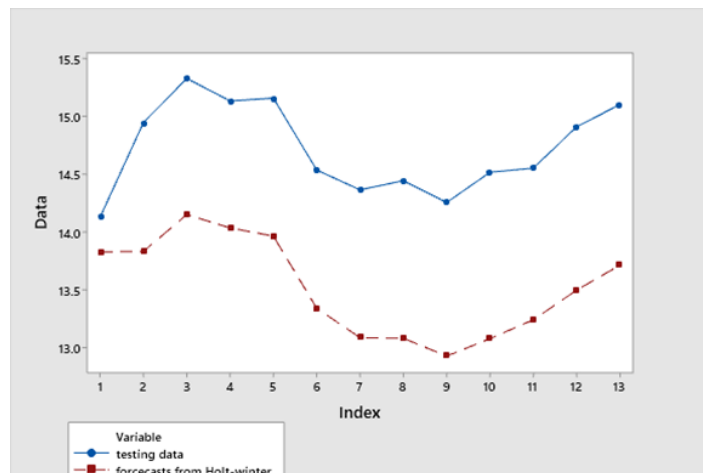


Figure 4.16: Time series plot for the comparison between actual and forecasts from Holt-winter 90%-10%

4.3. HW-DEA Application

The HW-DEA approach the Holt-Winters parameters α, γ, δ and the initial values $S_0, b_0, I_{-(s-1)}, I_{-(s-2)}, \dots, I_0$ are obtained by using the Differential Evaluation Algorithm, the initial values of S_0 , and b_0 , are obtained by drawing at random from the intersection and slope parameter confidence intervals is being completed

The Result from HW-DEA with ratio 80%-20%:

Divided the data into 101 training and 25 testing, the parameters are obtained from this approach as follows $\alpha = 0.4391, \gamma = 0,0022, \beta = 0,9997$, the result shown in Table 4.13.

Table 4.13: the result from HW-DEA $\alpha = 0.4391, \gamma = 0,0022, \beta = 0,9997$

HW-DEA Method	RMSE
HW-DEA $\alpha = 0.4391$ $\gamma = 0,0022$ $\delta = 0.9997$	RMSE (training)= 0.1199 RMSE (testing)= 0.6150

Forecasting from $\alpha = 0.4391, \gamma = 0,0022, \beta = 0,9997$:

Table 4.14 shows the result of 25 forecasts from June 2020 until June 2022 with actual values. Figure 5.17 gives us the performance for testing data. In this graph R^2 was found 0.197:

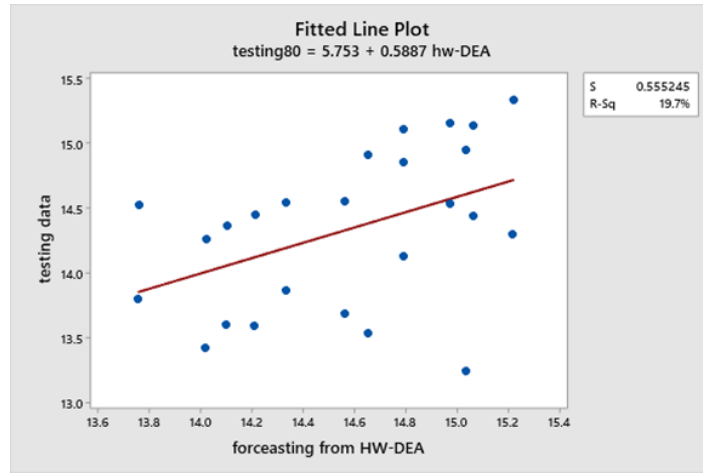


Figure 4.17 Regression between actual and forecasted from HW-DEA $\alpha = 0.4391, \gamma = 0,0022, \beta = 0,9997$

Table 4.14: The actual values and forecasted values from the HW-DEA $\alpha = 0.4391, \gamma = 0,0022, \beta = 0,9997$

Year	Actual value	Forecasts
01/06/2020	14.8547	14.7898
01/07/2020	13.2382	15.0368
01/08/2020	14.2994	15.2198
01/09/2020	14.4364	15.0640
01/10/2020	14.5357	14.9728
01/11/2020	13.8662	14.3317
01/12/2020	13.6010	14.0995
01/01/2021	13.5860	14.2102
01/02/2021	13.4181	14.0176
01/03/2021	13.8006	13.7543
01/04/2021	13.6841	14.5607
01/05/2021	13.5378	14.6517
01/06/2021	14.1297	14.7915
01/07/2021	14.9473	15.0386
01/08/2021	15.3307	15.2216
01/09/2021	15.1355	15.0658
01/10/2021	15.1599	14.9745
01/11/2021	14.5379	14.3334
01/12/2021	14.3671	14.1011
01/01/2022	14.4458	14.2118
01/02/2022	14.2572	14.0192
01/03/2022	14.5190	13.7559
01/04/2022	14.5543	14.5624
01/05/2022	14.9120	14.6534
01/06/2022	15.1048	14.7933

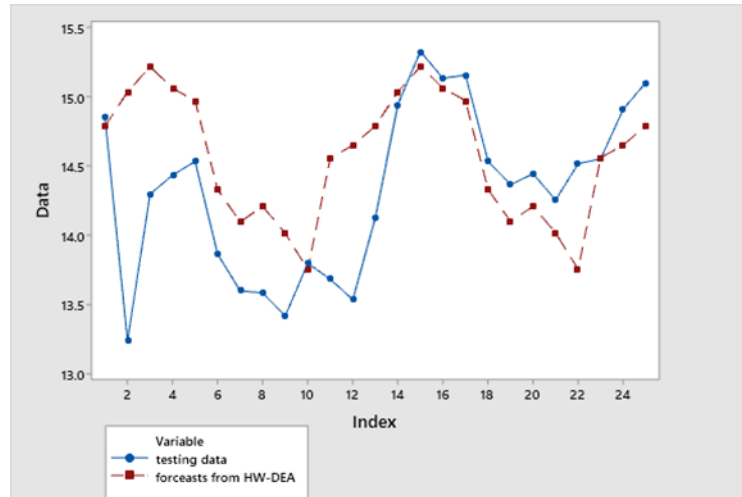


Figure 4.18: Time series plot for the comparison between actual and forecasts from HW-DEA $\alpha = 0.4391, \gamma = 0.0022, \beta = 0.9997$

The Result from HW-DEA with ratio 70%-30%:

Divided the data into 88 training and 38 testing, the parameters are obtained from this approach as follows $\alpha = 0.99937, \gamma = 0.00408, \beta = 0.771213$, the result shown in Table 4.15.

Table 4.15 the result from HW-DEA $\alpha = 0.99937, \gamma = 0.00408, \beta = 0.771213$

HW-DEA Method	RMSE
HW-DEA $\alpha = 0.99937$ $\gamma = 0.00408$ $\delta = 0.771213$	RMSE (training)= 0.0760 RMSE (testing)= 0.5645

Forecasting from $\alpha = 0.99937, \gamma = 0.00408, \beta = 0.771213$:

The result of forecasting 38 data from May 2019 to June 2022, Figure 4.19 gives us the performance for testing data. In this graph R^2 was found 0.337 as you can see.

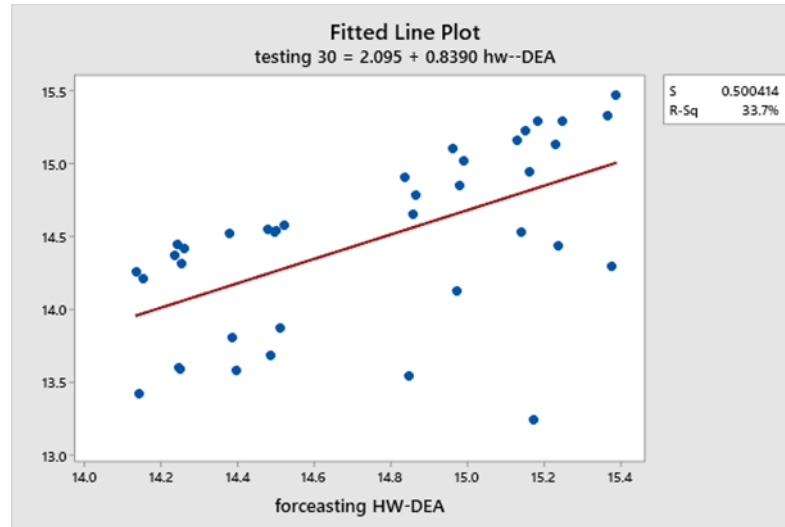


Figure 4.19 Regression between actual and forecasted from HW-DEA $\alpha = 0.99937, \gamma = 0.00408, \beta = 0.771213$

Table 4.16: The actual values and forecasted values from the HW-DEA $\alpha = 0.99937, \gamma = 0.00408, \beta = 0.771213$

Year	Actual values	Forecasts	Year	Actual values	Forecasts
01/05/2019	14.7862	14.8667	01/12/2020	13.6010	14.2459
01/06/2019	15.0208	14.9912	01/01/2021	13.5860	14.2519
01/07/2019	15.2937	15.1820	01/02/2021	13.4181	14.1438
01/08/2019	15.4726	15.3870	01/03/2021	13.8006	14.3870
01/09/2019	15.2976	15.2487	01/04/2021	13.6841	14.4875
01/10/2019	15.2269	15.1495	01/05/2021	13.5378	14.8469
01/11/2019	14.5755	14.5215	01/06/2021	14.1297	14.9713
01/12/2019	14.3138	14.2554	01/07/2021	14.9473	15.1618
01/01/2020	14.4220	14.2614	01/08/2021	15.3307	15.3665
01/02/2020	14.2072	14.1533	01/09/2021	15.1355	15.2283
01/03/2020	13.5769	14.3966	01/10/2021	15.1599	15.1293
01/04/2020	14.5314	14.4972	01/11/2021	14.5379	14.5021
01/05/2020	14.6500	14.8568	01/12/2021	14.3671	14.2364
01/06/2020	14.8547	14.9812	01/01/2022	14.4458	14.2423
01/07/2020	13.2382	15.1719	01/02/2022	14.2572	14.1344
01/08/2020	14.2994	15.3767	01/03/2022	14.5190	14.3774
01/09/2020	14.4364	15.2385	01/04/2022	14.5543	14.4779
01/10/2020	14.5357	15.1394	01/05/2022	14.9120	14.8370
01/11/2020	13.8662	14.5118	01/06/2022	15.1048	14.9613

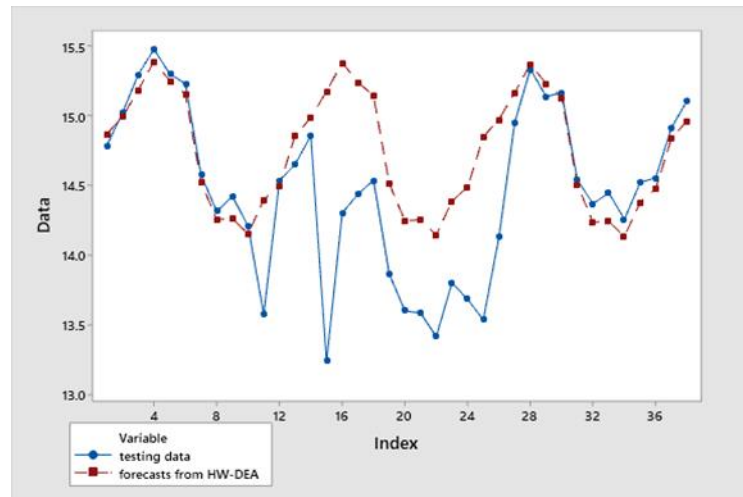


Figure 4.20: Time series plot for the comparison between actual and forecasts from HW-DEA $\alpha = 0.99937, \gamma = 0.00408, \beta = 0.771213$

The Result from HW-DEA with ratio 90%-10%:

Divided the data into 113 training and 13 testing, the parameters are obtained from this approach as follows $\alpha = 0.46986, \gamma = 0.00142, \beta = 0.034861$, the result shown in table 4.17 the following:

Table 4.17: the result from HW-DEA $\alpha = 0.46986, \gamma = 0.00142, \beta = 0.034861$

HW-DEA Method	RMSE
HW-DEA $\alpha = 0.46986$ $\gamma = 0.00142$ $\delta = 0.034861$	RMSE (training)= 0.2110 RMSE (testing)= 1.0446

Forecasting from $\alpha = 0.46986, \gamma = 0.00142, \beta = 0.034861$

we used HW method to forecasting 13 values from June 2021 to June alongside actual value, Figure 4.21 gives us the performance for testing data. In this graph R^2 was found 0.578 the results show as below:

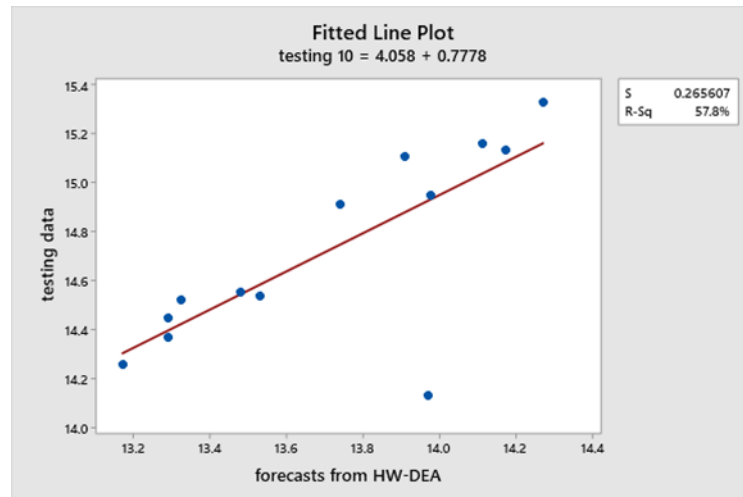


Figure 4.21 Regression between actual and forecasted from HW-DEA $\alpha = 0.46986, \gamma = 0.00142, \beta = 0.034861$

Table 4.18: The actual values and forecasted values from the HW-DEA $\alpha = 0.46986, \gamma = 0.00142, \beta = 0.034861$

Year	Actual value	Forecasts
01/06/2021	14.1297	13.9710
01/07/2021	14.9473	13.9780
01/08/2021	15.3307	14.2724
01/09/2021	15.1355	14.1744
01/10/2021	15.1599	14.1117
01/11/2021	14.5379	13.5314
01/12/2021	14.3671	13.2888
01/01/2022	14.4458	13.2880
01/02/2022	14.2572	13.1686
01/03/2022	14.5190	13.3245
01/04/2022	14.5543	13.4801
01/05/2022	14.9120	13.7419
01/06/2022	15.1048	13.9108

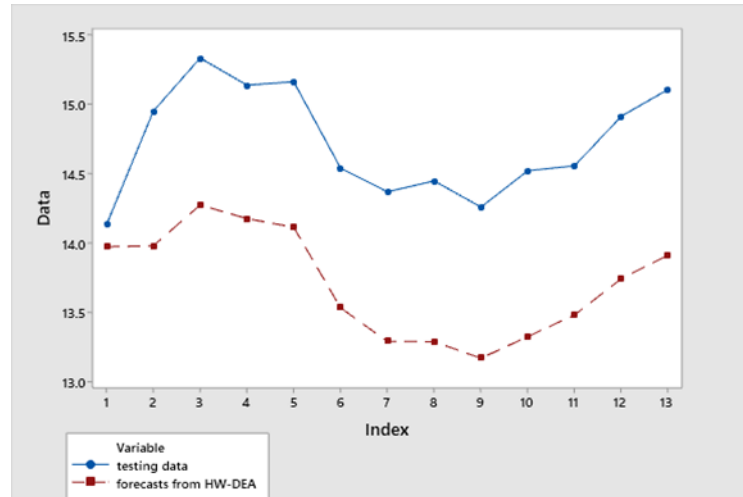


Figure 4.22: Time series plot for the comparison between actual and forecasts from HW-DEA $\alpha = 0.46986, \gamma = 0.00142, \beta = 0.034861$

4.4. ANFIS Application

A fuzzy inference system based on neural networks (ANFIS) is a hybrid system that combines neural networks and fuzzy logic. It is a content method for solving function approximation problems in a neural network platform. Since their inception, ANFIS networks have been successfully applied to classification tasks, rule-based process control, pattern recognition, and other similar problems based on the fuzzy rules obtained from the input-output data set. Takagi and Surgeons, fuzzy model, which they establish a systematic approach to generating fuzzy rules from an input-output data set, is the foundation of a fuzzy inference system.

As previously stated, our data is seasonal, so we must justify the dataset by applying the logarithmic transformation, generating lag variables into (2,3, and 4) inputs, and then dividing our dataset into training and testing data with three different percentages (80%-20%, 70%-30%, and 90%-10%), we will use Sugano's type fuzzy inference system with three types of membership functions, which they are triangle (tri), trapezoidal (trap), and Gaussian (Gauss). Because these types are commonly used in the literature. ANFIS structure membership function number (mf) by selecting inputs and feeding them into the network, for example (m333) which is selecting the first three inputs. The implementation was done by using MATLAB program. The inputs were chosen based on their influence on the output format. Based on the smallest

training RMSE, we chose the best result performance. The model structures that we implement are presents in Table 4.19.

Table 4.19. Model structures for estimation of tourism income

Model	Input variables	Output
2	Y_{t-1}, Y_{t-12}	1
3	$Y_{t-1}, Y_{t-2}, Y_{t-12}$	1
4	$Y_{t-1}, Y_{t-2}, Y_{t-3}, Y_{t-12}$	1

The application for the ratio with 80% and 20%

Table 4.20: The results of ANFIS 80%-20%:

Input	2 inputs Y_{t-1}, Y_{t-12}		3 inputs $Y_{t-1}, Y_{t-2}, Y_{t-12}$		4 inputs $Y_{t-1}, Y_{t-2}, Y_{t-3}, Y_{t-12}$	
Mfs Type of mf	Lin.-Hyb.	Cons. – Hyb.	Lin.-Hyb.	Cons. – Hyb.	Lin.-Hyb.	Cons. – Hyb.
Tri	0.88884(m23)	0.51634(m22)	1.7426(m222)	0.60298(m242)	5.137(m2423)	0.82251(m2222)
Trap	0.61898(m42)	0.5479(m22)	4.819(m232)	0.68625(m332)	5.8449(m4323)	0.60293(m2322)
Gauss	0.60404(m22)	0.54849(m22)	3.5712(m232)	0.41586(m242)	3.3077(m3432)	0.62371(m24222)

Based on the testing RMSE, the best result from the table is constant hybrids gaussian membership function, which equals 0.41586. This model is symbolised with m242

Forecasting from gaussian membership function with the choice of m242

Table 4.21 shows the result of 25 forecasts from June 2020 until June 2022 with actual values. Figure 4.23 gives us the performance for testing data. In this graph R^2 was found as 0.580.

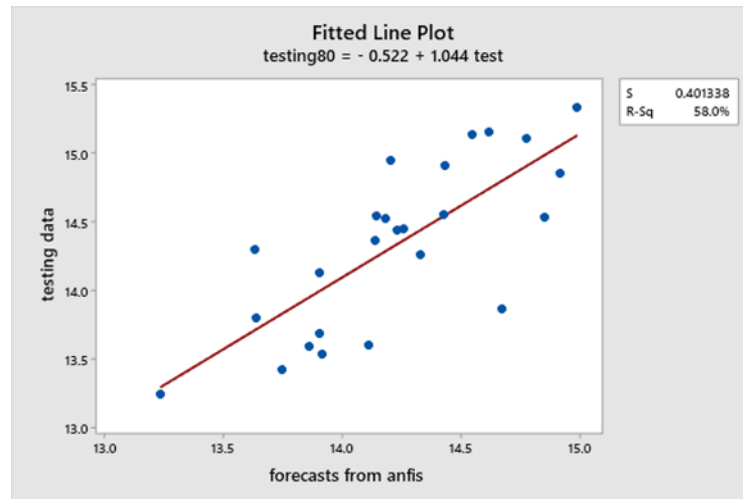


Figure 4.23: Regression between actual and forecasted from ANFIS with 80%-20% ratio

Table 4.21: The actual values and forecasted values from ANFIS with 80%-20% ratio

Year	Actual values	Forecasts
01/06/2020	14.8547	14.9192
01/07/2020	13.2382	13.2336
01/08/2020	14.2994	13.6306
01/09/2020	14.4364	14.2336
01/10/2020	14.5357	14.8548
01/11/2020	13.8662	14.6757
01/12/2020	13.6010	14.1102
01/01/2021	13.5860	13.8582
01/02/2021	13.4181	13.7468
01/03/2021	13.8006	13.6365
01/04/2021	13.6841	13.9063
01/05/2021	13.5378	13.9123
01/06/2021	14.1297	13.9045
01/07/2021	14.9473	14.2053
01/08/2021	15.3307	14.9886
01/09/2021	15.1355	14.5463
01/10/2021	15.1599	14.6169
01/11/2021	14.5379	14.1422
01/12/2021	14.3671	14.1404
01/01/2022	14.4458	14.2575
01/02/2022	14.2572	14.3281
01/03/2022	14.5190	14.1821
01/04/2022	14.5543	14.4302
01/05/2022	14.9120	14.4345
01/06/2022	15.1048	14.7758

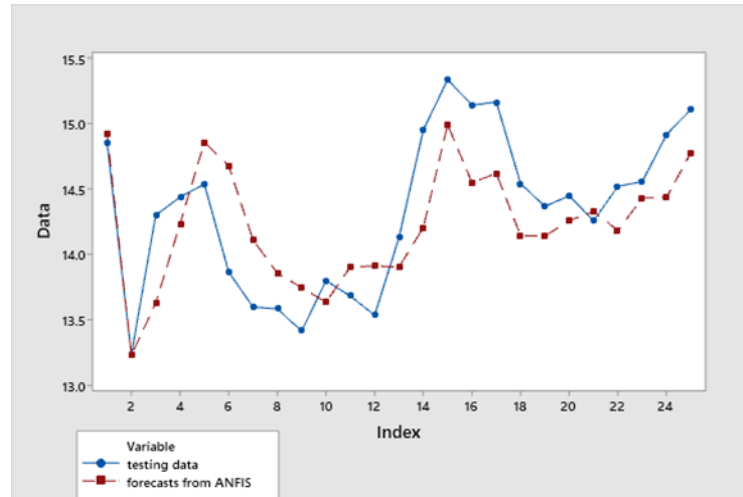


Figure 4.24: Time series plot for the comparison between actual and forecasts from ANFIS with 80%-20% ratio

The application for the ratio with 70% and 30%

For this ratio many structures were tried and the results are presented in Table 4.22.

Table 4.22. RMSE results for testing data from ANFIS 70%-30%:

Input	2 inputs Y_{t-1}, Y_{t-12}		3 inputs $Y_{t-1}, Y_{t-2}, Y_{t-12}$		4 inputs $Y_{t-1}, Y_{t-2}, Y_{t-3}, Y_{t-12}$	
Mfs Type of mf	Lin.-Hyb.	Cons. – Hyb.	Lin.-Hyb.	Cons. – Hyb.	Lin.-Hyb.	Cons. – Hyb.
Tri	0.87868(m22)	0.56207(m22)	1.4905(m322)	0.94855(m224)	0.98112+ (m2423)	0.58117(m3222)
Trap	0.60751(m22)	0.54638(m33)	1.3065(m323)	0.53489(m223)	1.3889(m3323)	0.55729(m2322)
Gauss	0.64086(m22)	0.59042(m22)	4.1423(m432)	0.50338(m223)	2.0707(m4222)	0.7680(m2242)

The best model has been chosen with respect to the smallest RMSE for the testing data. From this table it is seen that the best fit is obtained from the model m223. This model is working with Gaussian membership function and RMSE was found as.

Forecasting from gaussian membership function with the choice of m223.

For this choice the resulting forecast values which are corresponding to the period from May 2019 to June 2022, are presented in Table 4.23. As a goodness of fit statistics R^2 was found as 0.392. The regression analysis between actual and forecasted values are presented in Figure 4.25.

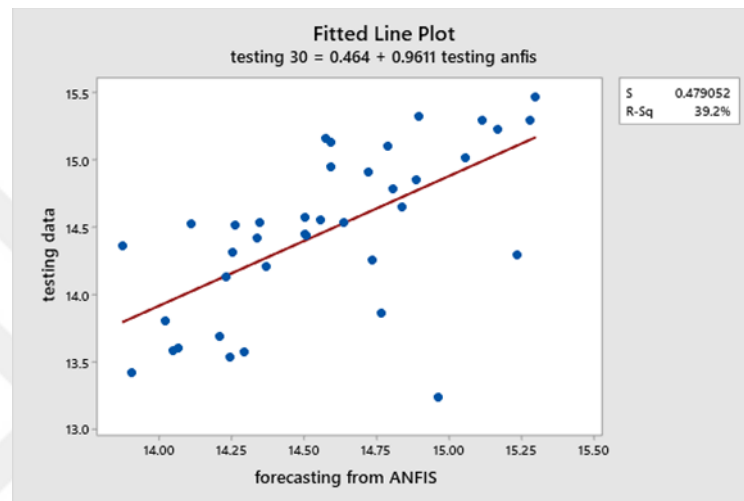


Figure 4.25: Regression between actual and forecasted from ANFIS with 70%-30% ratio

Table 4.23: The actual values and forecasted values from ANFIS with 70%-30% ratio

Year	Actual values	Forecasts	Year	Actual values	Forecasts
01/05/2019	14.7862	14.8055	01/12/2020	13.6010	14.0644
01/06/2019	15.0208	15.0573	01/01/2021	13.5860	14.0446
01/07/2019	15.2937	15.1148	01/02/2021	13.4181	13.9036
01/08/2019	15.4726	15.2991	01/03/2021	13.8006	14.0189
01/09/2019	15.2976	15.2825	01/04/2021	13.6841	14.2067
01/10/2019	15.2269	15.1691	01/05/2021	13.5378	14.2406
01/11/2019	14.5755	14.5042	01/06/2021	14.1297	14.2310
01/12/2019	14.3138	14.2512	01/07/2021	14.9473	14.5918
01/01/2020	14.4220	14.3370	01/08/2021	15.3307	14.8951
01/02/2020	14.2072	14.3666	01/09/2021	15.1355	14.5902
01/03/2020	13.5769	14.2914	01/10/2021	15.1599	14.5737
01/04/2020	14.5314	14.1085	01/11/2021	14.5379	14.3471
01/05/2020	14.6500	14.8388	01/12/2021	14.3671	13.8711
01/06/2020	14.8547	14.8886	01/01/2022	14.4458	14.5033
01/07/2020	13.2382	14.9638	01/02/2022	14.2572	14.7354
01/08/2020	14.2994	15.2358	01/03/2022	14.5190	14.2605
01/09/2020	14.4364	14.5085	01/04/2022	14.5543	14.5578
01/10/2020	14.5357	14.6372	01/05/2022	14.9120	14.7202
01/11/2020	13.8662	14.7686	01/06/2022	15.1048	14.7903

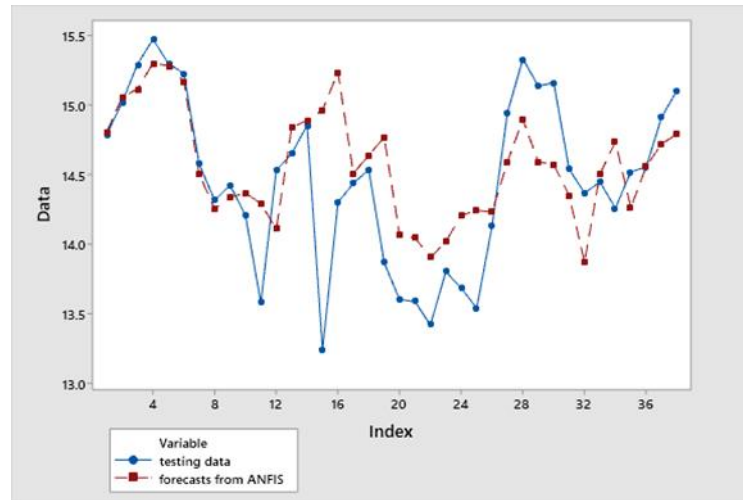


Figure 4.26: Time series plot for the comparison between actual and forecasts from ANFIS with 70%-30% ratio

Figure 4.26 will help for us to assess how the forecast fits the actual data. It is obvious that this fitness is not better than the first application with the ratio 80% - 20%.

The application for the ratio with 90% and 10%

The analyse was repeated for this ratio. Again, all of trail's results are presented Table 4.24.

Table 4.24: the result of ANFIS 90%-10%.

Input	2 inputs Y_{t-1}, Y_{t-12}		3 inputs $Y_{t-1}, Y_{t-2}, Y_{t-12}$		4 inputs $Y_{t-1}, Y_{t-2}, Y_{t-3}, Y_{t-12}$	
Mfs Type of mf	Lin.-Hyb.	Cons. – Hyb.	Lin.-Hyb.	Cons. – Hyb.	Lin.-Hyb.	Cons. – Hyb.
Tri	0.55841(m23)	0.39698(m22)	0.64604(m222)	0.33082(m232)	1.3314 (m2322)	0.41476 (m2422)
Trap	0.60001(m22)	0.46778(m22)	0.82735(m222)	0.4708(m222)	2.5072 (m3323)	0.40694 (m2322)
Gauss	0.52264(m32)	0.43162(m22)	0.6111(m232)	0.41147(m232)	2.6047 (m4332)	0.73843 (m2422)

From this table the smallest RMSE is corresponding to the model with constant hybrids triangle membership function, which is equal to 0.33082. The 13 forecasted values for the period from June 2021 to June 2022 are presented in Table 4.25. When we do the assessment for the criteria of goodness of fit, we can look at the regression between the actual and the forecasted values. This regression analysis result is presented in Figure 4.27. From this graph we can say that R^2 is getting better. This is the best ever performance measure with the value of 0.813.

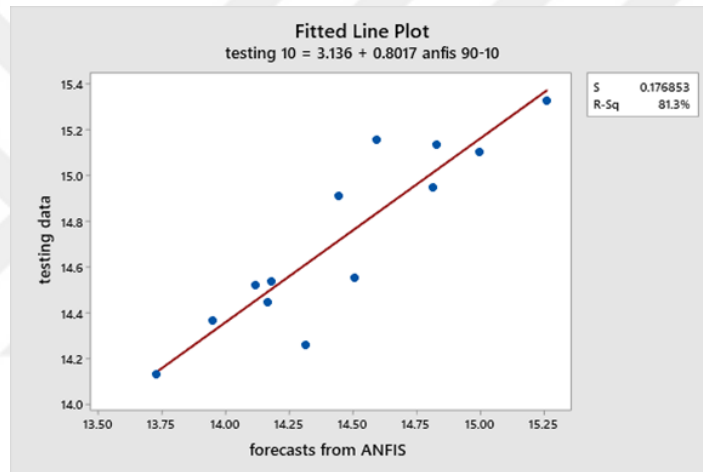


Figure 4.27: Regression between actual and forecasted from ANFIS with 90%-10% ratio

Table 4.25: The actual values and forecasted values from ANFIS with 90%-10% ratio

Year	Actual values	Forecasts
01/06/2021	14.1297	13.7259
01/07/2021	14.9473	14.8128
01/08/2021	15.3307	15.2630
01/09/2021	15.1355	14.8275
01/10/2021	15.1599	14.5941
01/11/2021	14.5379	14.1793
01/12/2021	14.3671	13.9461
01/01/2022	14.4458	14.1618
01/02/2022	14.2572	14.3114
01/03/2022	14.5190	14.1172
01/04/2022	14.5543	14.5061
01/05/2022	14.9120	14.4429
01/06/2022	15.1048	14.9998

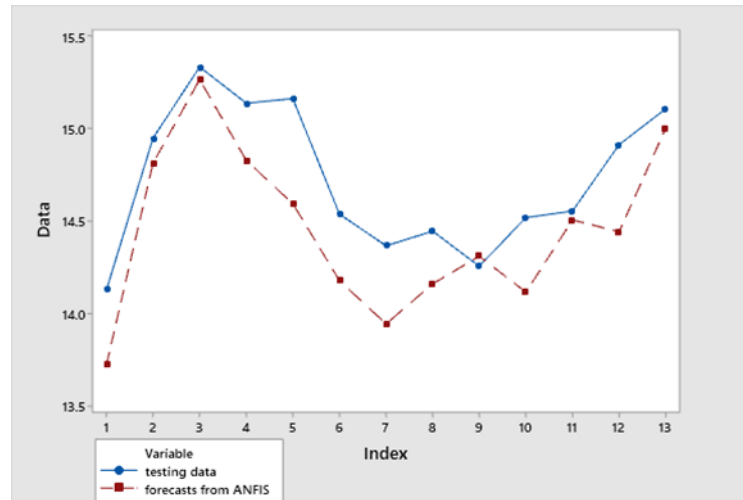


Figure 4.28: Time series plot for the comparison between actual and forecasts from ANFIS with 90%-10% ratio

4.5. Final Comparison

In this section I am planning to present the best models from four different type of methods for whole comparison. In that comparisons we add Mean Absolute Prediction Error (MAPE) since this criterion is also an important performance measure. Finally, we compare the four models according to the performance of the test data. When we do this comparison, we will do it separately for each ratio. Firstly, for the ratio 80%-20% the results were presented in Table 4.26. From this table it is obvious that the best result is obtained ANFIS method.

Table 4.26: the result of methods comparison with 80%-20%

Method	RMSE	MAPE	R^2
SARIMA(0,1,1), (1, 0, 0) ₁₂	0,685009	0.0395216	0.181
Holt-Winter $\alpha = 0.8, \gamma = 0.02, \delta = 0.2$	0,625838	0.0309999	0.360
HW-DEA	0.6150	0.0328853	0.197
ANFIS	0.41586	0.0237128	0.580

Table 4.27 displays the performance criteria of the models for the ratio of 70%-30%. From this table it is also seen that the best performance is obtained from ANFIS method.

Table 4.27: the result of methods comparison with 70%-30%

Method	RMSE	MAPE	R^2
SARIMA (0,1,0), (1, 0, 0) ₁₂	0.631625	0.0687534	0.315
Holt-winter $\alpha = 0.8, \gamma = 0.02, \delta = 0.2$	0.815667	0.0451141	0.264
HW-DEA	0.5645	0.0262707	0.337
ANFIS	0.50338	0.0239067	0.392

Table 4.28 displays the performance criteria of the models for the ratio of 90%-10%. From this table it is also seen that the best performance is obtained from ANFIS method. If we do a comparison according to the different ratios the best result is obtained for the ratio 90%-10%. It explains that the near future is always better predicted in time series.

Table 4.28: the result of methods comparison with 90%-10%:

Method	RMSE	MAPE	R^2
Holt-winter $\alpha = 0.8, \gamma = 0.02, \delta = 0.2$	1.23277	0.0814366	0.552
HW-DEA	1.0446	0.0686264	0.578
ANFIS	0.33082	0.0189615	0.813

Just to give graphical support I will introduce the comparative time series plot of the actual values with four forecasted values from best models of the all methods. This presentation will only be for the ratio 90%-10% since it is the best. Figure 4.29 is illustrated the case. As you can see in this figure the most fitted line is the line from ANFIS.

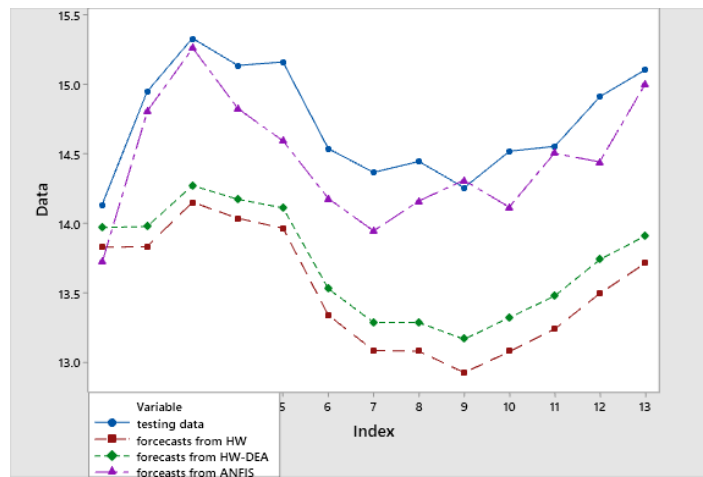


Figure 4.29: Time series plot for the whole comparison with 90%-10% ratio

5.CONCULSION

In this study the data of tourism income of Turkey was modelled by using classical method such as Seasonal Autoregression Integrated Moving Average (SARIMA) of Box- Jenkins method as well as Holt-Winter exponential smoothing method, and the new approaches like HW-DEA and Adaptive fuzzy inference system method (ANFIS). The methods included in this study were compared with respect to the performances for the testing data. As a performance criteria RMSE, MAPE and the goodness of fit measure as R^2 were used in this analysis. If we compare the ANFIS results with respect to the different ratios we have already seen that the best performance is obtained from the ratio of 90%-10%. Of course, this is an acceptable result since the near future is better predicted. Finally, we conclude that ANFIS method provides us a better picture of the future of the data of tourism income of Turkey consisting of 126 observations from June 2012 until June 2022. Findings from ANFIS should be useful for researchers who are interested to predict any concept on tourism sector.

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