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HIBRIDNI INTELIGENTNI MODEL PROGNOZIRANJA TURISTIČKE POTRAŽNJE

A HYBRID INTELLIGENT MODEL FOR TOURISM DEMAND FORECASTING

SAŽETAK: Rast turističke potražnje diljem svijeta dovela je do porasta broja metoda za prognoziranje turističke potražnje. Nove su tehnike polučile pouzdane prognoze turističkih dolazaka s ciljem boljeg ekonomskog planiranja. Ovo istraživanje ima za cilj prognozirati i usporediti djelotvornost dvaju nelinearnih pristupa umjetne inteligencije u predviđanju broja turističkih dolazaka u Singapur. Mjesečni podaci o dolasku turista u Singapur korišteni su za prognoziranje mjesec, dva, četiri i šest mjeseci unaprijed pomoću nelinearnih autoregresivnih (NAR) neuronskih mreža i neuro-*fuzzy* (neizrazitih) sustava. Točnost predviđanja neuronskih mreža NAR uspoređivala se s onom neuro-*fuzzy* sustava pomoću različitih mjerenja učinkovitosti. Studija je pokazala da su neuro-*fuzzy* sustavi učinkovitiji od mreže NAR u svim razdobljima prognoze i kod svih zemalja. Predložena neuro-*fuzzy* metoda poboljšava učinkovitost prognoziranja tehnika temeljenih na umjetnoj inteligenciji. Ova studija predstavlja doprinos literaturi u području turizma i mogu je koristiti menadžeri za učinkovito planiranje i provođenje mjera u okviru turističke politike.

KLJUČNE RIJEČI: turistička potražnja; predviđanje; nelinearna autoregresivna neuronska mreža; prilagodljivi neuro-*fuzzy* (neizrazit) sustav zaključivanja

ABSTRACT: The ever increasing demand of the tourism sector worldwide has led to an increase in tourism demand forecasting methodologies. New techniques yield much reliable predictions of tourist arrivals for better economic planning. The study aims to forecast and compare the performance of two non-linear artificial intelligence approaches in predicting the number of tourist arrivals to Singapore. The Singapore inbound monthly tourism data were utilized to generate one, two, four and six month ahead forecasts with non-linear autoregressive (NAR) neural networks and neuro-fuzzy systems. The predictive accuracy of NAR neural networks and neuro-fuzzy systems were compared with various performance metrics. The study revealed that neuro-fuzzy systems outperformed NAR networks in all forecasting horizons and for all countries. The proposed neuro-fuzzy methodology helps in improving the forecasting performance of artificial intelligence based techniques. The study contributes to hospitality literature and could be utilized by managers to effectively plan and implement tourism related policy measures.

KEYWORDS: tourism demand; forecasting; non linear autoregressive neural network; adaptive neuro-fuzzy inference system

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1. UVOD

Pokazalo se da međunarodna putovanja i turizam predstavljaju značajan pokretač gospodarskog rasta; na njega otpada oko 10 posto globalnog bruto domaćeg proizvoda te jedno od 10 novih radnih mjesta na svijetu u posljednjih deset godina (WEF, 2017). Zemlje u razvoju mogu imati velike koristi od turizma. Singapur je važna turistička destinacija i nalazi se na 13. mjestu na svijetu po putovanjima i turizmu (WEF, 2017). Singapur je odabran jer se nalazi na drugome mjestu u svijetu po pridavanju važnosti putovanjima i turizmu te na prvome mjestu po svojoj otvorenosti (WEF, 2017). Oko 16,4 milijuna inozemnih posjetitelja zabilježeno je u Singapuru 2016. godine, što je 7,7% više u odnosu na prethodnu godinu. Istovremeno, prihod od turizma u 2016. iznosio je oko 24,8 milijardi dolara. Potrebno je točno prognozirati turističku potražnju kako bi se mogla alocirati ulaganja u javnom i privatnom sektoru (Reynolds *et al*., 2013) te kako bi se mogle donijeti dobre poslovne odluke vezane uz poslovanje i politike cijena. Za planiranje su važne i dugoročne i kratkoročne prognoze. Planiranje infrastrukture destinacija zahtijeva dugoročne prognoze za i po nekoliko godina unaprijed, dok bi kratkoročne prognoze turističke potražnje za naredni mjesec, dva ili tri, destinacije mogle koristiti za prilagođavanje svojeg poslovanja (Gunter i Onder, 2015).

Prognoziranjem turističke potražnje bavilo se niz studija u posljednjih nekoliko desetljeća. Song i Li (2008) napravili su iscrpan pregled 119 objavljenih studija metoda prognoziranja turističke potražnje između 2000. i 2007. Tehnike prognoziranja u grubo su podijelili na one temeljene na vremenskim nizovima, na umjetnoj inteligenciji, ekonometrijskim metodama te hibridnim modelima. Studije prognoziranja turističke potražnje najviše su koristile skupove podataka godišnjih vremenskih nizova. Skupovi podataka o turizmu za vremenski niz od jednog mjeseca koriste se u manje od

1. INTRODUCTION

International travel and tourism have manifested itself to be the notable drivers of economic growth, accounting approximately 10 percent of global gross domestic product and for 1 in 10 jobs on earth in the past decade (WEF, 2017). Developing countries can greatly benefit from the tourism sector in moving up the value chain. Singapore is a major tourist destination of the world, ranked 13th globally in travel and tourism (WEF, 2017). Singapore was selected as it has been ranked 2nd in prioritization of travel and tourism and 1st in international openness in the world (WEF, 2017). Around 16.4 million foreign visitors arrived in Singapore in 2016, a 7.7 % rise in comparison to the previous year. Meanwhile, tourism receipts accounted to approximately $24.8 billion for 2016. Accurate forecast of tourism demand is needed to allocate investments by public and private sectors (Reynolds *et al*., 2013) and make business based decisions such as operation and pricing policies. Long-term and short-term forecasting are both essential for planning purposes. Destination infrastructure planning requires long term forecasting while short term forecasting of tourism demand for one, two or three month ahead could be utilized by destination for operational adaptability (Gunter and Onder, 2015).

Tourism demand forecasting has been the focus of many studies in the past decades. An exhaustive review of 119 published studies on tourism demand forecasting methodologies between 2000 and 2007 was performed by Song and Li (2008). The forecasting techniques are broadly classified into time series, artificial intelligence based approaches, econometric methods and hybrid models. Tourism demand forecasting studies have mostly utilized annual time series datasets. Monthly tourism time series datasets have found less than 10% utility in

10% studija prognoziranja turističke potražnje (Song *et al*., 2009). Korištenje mjesečnih podataka povećava količinu podataka, a precizna predviđanja izuzetno su važna za upravljanje kako na kratki rok tako i za poslovanje općenito (Gunter i Onder, 2015).

Modeli koji se baziraju na vremenskim nizovima poput eksponencijalnog izglađivanja (Athanasopoulos i de Silva, 2012) i integriranog autoregresijskog modela pomičnih prosjeka (ARIMA) (Assaf *et al*., 2011; Claveria i Datzira, 2010; Gounopoulos *et al*., 2012) turističke dolaske prognoziraju upotrebom povijesnih podataka. Ekonometrijski modeli pomno istražuju odnos između turističke potražnje i čimbenika koji utječu na potražnju poput modela vektorske autoregresije (Song i Witt, 2006), korekcije pogreške i modela kointegracije (Veloce, 2004; Ouerfelli, 2008; Lee, 2011), statičkih modela gotovo idealne potražnje (Han *et al*., 2006) i modela promjenjivog parametra vremena (Song *et al*., 2011). Predlaže se da se za prognoziranje turističke potražnje koriste hibridni modeli poput onih koji kombiniraju ekonometriku i metodologije rudarenja podataka (Pai *et al*., 2014; Sun *et al*., 2016). Usto, za prognoziranje turističke potražnje koriste se i analiza singularnog spektra te metaanaliza (Hassani, *et al*., 2015; Peng *et al*., 2014).

Tehnike umjetne inteligencije (AI) mogu lako prepoznati nelinearne uzorke u skupovima podataka pa stoga predstavljaju ključnu metodologiju za prognoziranja u ekonomiji i turizmu. Pristupi bazirani na umjetnoj inteligenciji modeliraju nelinearne skupove podataka koristeći metodu potpornih vektora (SVM), metodu približnih skupova, umjetne neuronske mreže (ANN) i *fuzzy* vremenske nizove. Hadavandi *et al*. (2011) predlažu model baziran na genetskom *fuzzy* sustavu (GFS) za predviđanje turističke potražnje u Tajvanu. Pai *et al*. (2014) predlažu hibridnu metodologiju tako što kombiniraju fuzzy c-prosjeke (FCM) i logaritamsku vektorsku regresiju podrške najmanjih kvadrata (LLS-SVR) za predviđanje turističke potražnje u Hong Kongu i na Tajvanu. Pristup približnih

tourism demand forecasting studies (Song *et al*., 2009). The utilization of monthly data increase the number of data points and precise predictions are extremely crucial from short-term or operation management viewpoints (Gunter and Onder, 2015).

Time series models like exponential smoothening (Athanasopoulos and de Silva, 2012) and autoregressive integrated moving average (ARIMA) models (Assaf *et al*., 2011; Claveria and Datzira, 2010; Gounopoulos *et al*., 2012) forecast the tourist arrivals using historical data. Econometric models scrutinize the relationship between tourism demand and the factors affecting the demand such as vector autoregressive models (Song and Witt, 2006), error correction and co-integration models (Veloce, 2004; Ouerfelli, 2008; Lee, 2011), static almost ideal demand system models (Han *et al*., 2006) and time varying parameter models (Song *et al*., 2011). Hybrid models such as combination of econometric and data mining methodologies have been proposed in forecasting tourism demand (Pai *et al*., 2014; Sun *et al*., 2016). Moreover, singular spectrum analysis and meta-analysis have also been employed in tourism demand forecasting (Hassani, *et al*., 2015; Peng *et al*., 2014).

The Artificial intelligence (AI) techniques can easily capture non-linear patterns in the dataset, making them crucial methodology for economic and tourism forecasting. AI approaches model non-linear datasets utilizing, support vector machines (SVMs), rough set method, grey theory, artificial neural networks (ANNs) and fuzzy time series. Hadavandi *et al*. (2011) proposed a genetic fuzzy system (GFS) based model to forecast tourism demand to Taiwan. Pai *et al*. (2014) proposed a hybrid methodology by combining fuzzy c-means (FCM) and logarithm least-squares support vector regression (LLS-SVR) for predicting tourism demand to Hong Kong and Taiwan. Rough set approach was utilized in predicting UK and USA tourism demand for Hong Kong (Goh skupova koristio se za predviđanje turističke potražnje za Hong Kongom u Ujedinjenoj Kraljevini i SAD-u (Goh *et al.*, 2008). Siva teorija i *fuzzy* vremenski nizovi korišteni su za prognoziranje godišnjih turističkih dolazaka u SAD (Yu i Schwartz, 2006). Metoda potpornih vektora prvi puta se koristila za predviđanje turističke potražnje za Barbadosom (Pai *et al.*, 2006). Pokazalo se da metoda potpornih vektora nadmašuje integrirani autoregresijski model pomičnih prosjeka (ARIMA) kod prognoziranja kvartalnih dolazaka turista u Kinu (Chen i Wang, 2007).

Ne postoji suglasje oko toga koji je najbolji pristup za prognoziranje turističke potražnje (Kim i Schwartz, 2013), ali postoji konsenzus oko važnosti primjene novih pristupa u prognoziranju turističke potražnje (Song i Li, 2008). Pokazalo se i da su za modeliranje poslovanja nelinearni modeli djelotvorniji od linearnih (Cang, 2014).

Umjetne neuronske mreže (ANN) djelotvorni su modeli umjetne inteligencije za modeliranje i prognoziranje nelinearnog ponašanja bez teorijskog znanja o povezanosti ulaznih i izlaznih veličina. Pattie i Snyder (1996) prvi su puta koristili umjetne neuronske mreže za prognoziranje turističke potražnje. Pokazalo se da su za predviđanje turističke potražnje umjetne neuronske mreže djelotvornije od modela vremenskog niza (Law, 2000; Cho, 2003; Claveria i Torra, 2014). Umjetne neuronske mreže mogu se podijeliti u dvije skupine, ovisno o njihovoj arhitekturi: acikličke mreže i mreže s povratnom vezom. Kod acikličkih mreža informacije se kreću samo u jednome smjeru dok kod mreža s povratnom vezom teku u dva smjera. Višeslojni perceptron (MLP) najčešće je korištena aciklička umjetna neuronska mreža za prognoziranje turističke potražnje (Claveria *et al.*, 2015). Drugi tip acikličke arhitekture su neuronske mreže s radijalno zasnovanom funkcijom (RBF). Nedavno su se mreže s radijalnom funkcijom koristile za prognoziranje potražnje za turističkim krstarenjima u Izmiru u Turskoj (Cuhadar *et al.*, 2014). Elmanova neuronska mreža predstavlja oblik mreža s povratnom vezom. Nelinear-

et al., 2008). Grey theory and fuzzy time series have been utilized to forecast annual tourist arrivals to USA (Yu and Schwartz, 2006). SVMs were first employed to predict tourism demand to Barbados (Pai *et al.*, 2006). SVMs have also been shown to outperform ARIMA models in forecasting quarterly tourist arrivals to China (Chen and Wang, 2007).

The most appropriate approach for tourism demand forecasting cannot be determined unanimously (Kim and Schwartz, 2013) but there is consensus on the significance of implementation of new approaches to forecast tourism demand (Song and Li, 2008). It has also been shown that non-linear models perform better than linear models in modeling economic operations (Cang, 2014).

ANNs are efficient AI models for modeling and forecasting non-linear behavior without theoretical knowledge about the association between input and output variables. Pattie and Snyder (1996) first employed ANNs for tourism demand forecasting. It has been shown that ANNs outperform time series models in predicting tourism demand (Law, 2000; Cho, 2003; Claveria and Torra, 2014). ANNs can be categorized into two types depending upon its architecture: feed forward networks and recurrent networks. In feed forward networks the information moves only in one direction while in recurrent networks the information flow is bidirectional. Multi layer perceptron (MLP) is the most commonly utilized feed forward ANNs in tourism demand forecasting (Claveria *et al.*, 2015). Another type of feed forward architecture is the radial basis function (RBF) neural networks. Recently, RBF networks have been employed to forecast the demand of cruise tourist to Izmir, Turkey (Cuhadar *et al.*, (2014). Elman neural networks constitute a type of recurrent networks. Non-linear dynamic systems have been modeled extensively by recurrent networks (Haykin, 1998; Ljung, 1998). Elman networks have been ni dinamički sustavi uvelike su modelirani pomoću mreža s povratnom vezom (Haykin, 1998; Ljung, 1998). Elmanova mreža korištena je za predviđanje turističkih dolazaka u Hong Kong (Cho, 2003). Nedavno su Claveria *et al.* (2015) koristili višeslojni perceptron, mrežu s radijalno zasnovanom funkcijom i Elmanovu neuronsku mrežu za predviđanje broja turističkih dolazaka u Kataloniju u Španjolskoj. Modeli nelinearne autoregresivne neuronske mreže (NAR) koristili su se za modeliranje nelinearnih sustava, poput višesatnog prognoziranja blagog sunčevog zračenja (Benmouiza i Cheknane, 2016), u svrhu kontrole kvalitete rijeka (López-Lineros *et al.*, 2014) i potrošnje energije u javnim zgradama (Ruiz *et al.*, 2016). Nije bilo moguće pronaći literaturu o korištenju nelinearnih autoregresivnih (NAR) neuronskih mreža za prognoziranje turističke potražnje. Ovo je prvi rad koji koristi nelinearne autoregresivne mreže za prognoziranje turističke potražnje.

Hibridne tehnike umjetne inteligencije sve se više koriste za prognoziranje potražnje zbog sve veće složenosti i nejasnoće tržišta. Integriranje neuronskih mreža i *fuzz*y logike predstavlja jednu od tih hibridnih tehnika. Vrlo malo studija bavi se proučavanjem turističke potražnje koristeći pri tome neuro-*fuzzy* sustave. George i Ioana (2007) navode da su se neuro-*fuzzy* sustavi pokazali djelotvornijima od autoregresivnog modela pokretnih prosjeka (ARIMA) i autoregresivnih (AR) modela kod predviđanja godišnjeg broja dolazaka turista na Kretu u Grčkoj. Chen *et al.* (2010) navode da su se prilagodljivi neuro-*fuzzy* sustavi pokazali boljima od izmijenjenog Markovljevog rezidualnog modela, *fuzzy* vremenskih nizova i sivog prognostičkog modela za predviđanje mjesečnog broja dolazaka turista iz četiriju zemalja na Tajvan.

Ova se studija bavi primjenom i komparativnom analizom točnosti predviđanja dolazaka inozemnih turista u Singapur pri čemu se koriste dvije paradigme učenja, nelinearna autoregresivna (NAR) neuronska mreža i prilagodljivi neuro-*fuzzy* sustavi zaključivanja (ANFIS). U tu svrhu korišten

utilized to predict tourist arrivals to Hong Kong (Cho, 2003). Recently, Claveria *et al.* (2015) utilized MLP, RBF and elman neural networks to predict the number of tourist arrivals to Catalonia, Spain. NAR neural network models have been used to model non-linear systems such as multi-hour forecasting of small scale solar radiation (Benmouiza and Cheknane, 2016), quality control purposes of river stage (López-Lineros *et al.*, 2014) and energy consumption in public buildings (Ruiz *et al.*, 2016). No literature studies could be found adopting non-linear autoregressive (NAR) neural networks in tourism demand forecasting. This is the first study that utilizes NAR networks in tourism demand forecasting.

Hybrid artificial intelligence techniques are finding ever increasing utilization in demand forecasting due to increasing complexity and vagueness of the markets. Integration of neural networks and fuzzy logic are one of those hybrid techniques. Very few studies have focused on tourism demand forecasting using neuro-fuzzy systems. George and Ioana (2007) depicted that neuro-fuzzy systems outperformed autoregressive–moving-average (ARMA) and autoregressive (AR) models in predicting annual tourist arrivals to Crete, Greece. Chen *et al.* (2010) showed that adaptive neuro-fuzzy systems performed better than Markov residual modified model, fuzzy time series and grey model in forecasting the monthly number of tourist arrivals to Taiwan from four countries.

This study focuses on adopting and comparative analysis of predictive accuracy of international tourist arrivals to Singapore using two learning paradigms namely, non-linear autoregressive (NAR) neural networks and adaptive neuro-fuzzy inference systems (ANFIS). The official statistical dataset of monthly tourist arrivals to Singapore from Jan 2006 to Feb, 2017 was employed for this purpose. The intelligent methods were evaluated for one, two, four and six months ahead forecast using differ-je službeni statistički skup podataka mjesečnih dolazaka turista u Singapur, od siječnja 2006. do veljače 2017. Evaluirane su inteligentne metode prognoziranja za jedan, dva, četiri i šest mjeseci, pri čemu su za evaluaciju korištene razne tehnike mjerenja, poput RMSE i MAE. Konačno, točnosti prognoziranja kod navedena dva modela uspoređene su pomoću Diebold–Mariano (DM) testa.

2. MATERIJALI I METODE

U svrhu prognoziranja turističkih dolazaka u Singapur korištena su dva modela učenja. Postupak se sastojao od tri faze: pred-obrada podataka, modeliranje i uspoređivanje točnosti predviđanja oba modela.

2.1 Nelinearne autoregresivne mreže

Teško je modelirati vremenske nizove korištenjem linearnog modela, i to zbog velikih varijacija i tranzijentnih karakteristika tih skupova podataka te je stoga korištena nelinearna metoda. Nelinearne autoregresivne (NAR) neuronske mreže tip su dinamičkih mreža s povratnom vezom. Sastoje se od vremenskog niza *y* u vremenu *t* i koriste prošle *d* vrijednosti vremenskog niza kao ulazni signal. Osnovni oblik nelinearne autoregresivne neuronske mreže, kad se primjenjuje na prognoziranje vremenskih nizova, može se označiti kao:

$$y(t) = h(y(t-1), y(t-2)\ldots, y(t-d)) + \O(t) \quad (1)$$

Glavni cilj *fuzzy* mreže jest optimiranje težina i pristranosti mreže kako bi se procijenila funkcija (*h*). U jednadžbi (1), Ø(t) označava odstupanje serije y u vremenu t. Karakteristike *d*, *y(t-1), y(t-2)…., y(t-d)* predstavljaju kašnjenja povratne veze. Nelinearne autoregresivne mreže nude fleksibilnost u pristupu s obzirom na odabir broja skrivenih slojeva i neurona. Povećanjem broja neurona u skrivenom sloju može se model učiniti složenijim, dok mali broj neurona može smanjiti sposobnost generalizacije mreže (Ruiz *et al*., 2016).

ent evaluation metrics such as RMSE and MAE. Finally, the forecasting accuracies of the two models are compared using the Diebold–Mariano (DM) test.

2. MATERIAL AND METHODS

Two learning models were employed for the purpose of forecasting tourist arrivals to Singapore. The methodology involved three stages, namely data pre-processing, modeling and comparison of prediction accuracy of both the models.

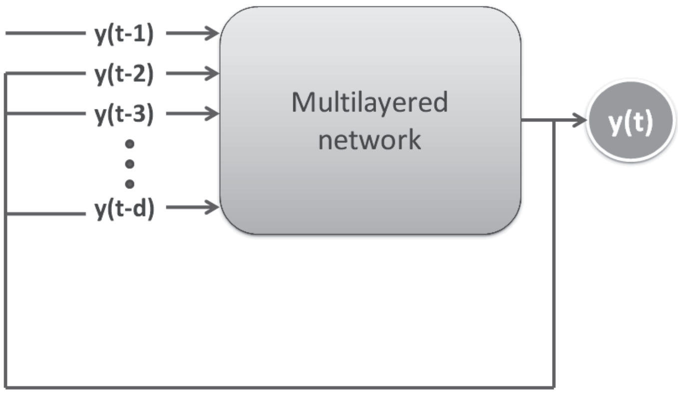
2.1 Non linear Autoregressive networks

Modeling time series using a linear model is difficult owing to high variation and transient characteristics of the datasets, hence a non-linear methodology was utilized. Non-linear autoregressive (NAR) neural networks are a type of dynamic recurrent networks. It consists of a time series *y* at time *t* and utilizes the past *d* values of time series as inputs. The basic form of non-linear autoregressive neural network when applied to time series forecasting can be depicted as:

$$y(t) = h(y(t-1), y(t-2)\ldots, y(t-d)) + \O(t) \quad (1)$$

The main objective of the network training is optimization of weights and bias of the network for estimation of the function *h()*. In equation (1), Ø(t) is the error term of the series *y* at time *t*. The *d* features *y(t-1), y(t-2)…., y(t-d)* are referred to as feedback delays. NAR offers a flexible approach in terms of selection of number of hidden layers and neurons. Increasing the number of neurons in hidden layer may make the model more complex, while small number of neurons may hinder the generalization capabilities of the network (Ruiz *et al*., 2016).

Slika 1. Nelinearna autoregresivna (NAR) mreža /
Figure 1. Non-linear autoregressive (NAR) network



*Višeslojna mreža=Multilayered network

U početku je korištena otvorena nelinearna autregresivna mreža koja izvodi predviđanje samo za jedna korak unaprijed pa je za potrebe predviđanja više koraka unaprijed korištena mreža sa zatvorenom petljom (Benmouiza i Cheknane, 2016). Levenberg-Marquardt povratni postupak (LMBP), kvazi-Newtonov algoritam, primijenjen je u ovoj studiji za *fuzzy* nelinearne autoregresivne mreže. Levenberg-Marquardt povratni postupak je obično najbrži povratni algoritam (Ruiz *et al*., 2016). Kod LMBP, derivacija drugog reda je procijenjena bez izračunavanja Hesseove matrice.

Initially in open state, the NAR network performs only one-step ahead prediction hence, for multi-step prediction the closed loop network was utilized (Benmouiza and Cheknane, 2016). Levenberg-Marquardt backpropagation procedure (LMBP), a quasi-Newton algorithm was implemented in our study for training the NAR network. LMBP is usually the fastest backpropagation algorithm (Ruiz *et al*., 2016). In LMBP, the second order derivative is estimated without the need to calculate Hessian matrix.

2.2 Neuro-*fuzzy* sustavi

Drugi model koji se koristio u ovoj studiji je model poznat kao i prilagodljivi neuro-*fuzzy* sustav zaključivanja (ANFIS) kojega je predložio Jang (Jang, 1993). On objedinjuje karakteristike *fuzzy* logike i neuronske mreže. *Fuzzy* logika ne može učiti iz podataka, a neuronske mreže lako mogu učiti iz podataka, ali je podatke poput onih o značaju pojedinog neurona i njegovoj težini teško razumjeti. Temelji *fuzzy* logike koriste se kako bi se mapirali ulazi i izlazi pomoću sustava zaključivanja koji se sastoji od (a) osnovnih pravila koja sadrže *fuzzy*

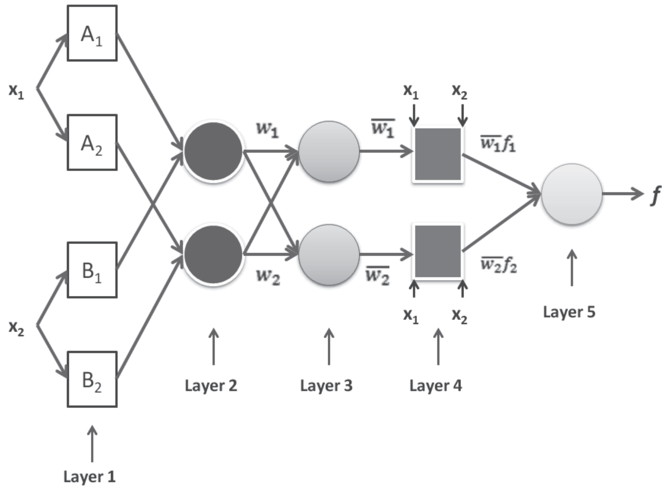
2.2 Neuro-fuzzy systems

The second model used in our study is the hybrid intelligent model known as adaptive neuro- fuzzy inference system (ANFIS) proposed by J.S.R. Jang (Jang, 1993). It inherits the characteristics of both fuzzy logic and neural network. Fuzzy logic cannot learn from the data by itself and neural networks can easily learn from the data but the information such as significance of each neuron and its corresponding weight is difficult to apprehend. Fuzzy logic fundamentals are used to map inputs to outputs with the help of a inference system, which is composed of (a) a rule base, comprising fuzzy IF-THEN

AKO-ONDA pravila, (b) baze podataka koja objašnjava funkcije članstva i (c) sustava zaključivanja za kombiniranje *fuzzy* pravila i rezultata. Dva tipa najčešće korištenih *fuzzy* sustava zaključivanja su (1) Takagi-Sugeno FIS i Mandami FIS. I Takagi-Sugeno i Mandami FIS razlikuju se po definiranju parametara zaključaka pravila u mreži. U ovoj studiji koristi se Takagi-Sugeno FIS u kojemu je pravilo AKO-TADA izvedeno na osnovi ulazno-izlaznih parova (Slika 2).

rules, (b) a database explaining the membership functions and (c) an inference system for combining fuzzy rules and producing results. Two types of commonly utilized FIS are (1) Takagi-Sugeno FIS and (2) Mandami FIS. Both Takagi-Sugeno and Mandami FIS differ in the definition of consequent parameters in the network. Takagi-Sugeno FIS is employed in our study, where IF-THEN rule base are generated from input-output pairs (Figure 2).

Slika 2. ANFIS arhitektura / Figure 2. ANFIS architecture



U ovoj ANFIS arhitekturi, izlaz *i*tog čvora u sloju *l* označavamo kao $O_{l,i}$. U ovoj studiji korišten je *fuzzy* model Sugeno prvoga reda na sljedeći način:

Pravilo 1:

Ako x_1 jest A_1, a x_2 jest B_1, onda je
$$f_1 = p_1x+q_1y+r1 \qquad (2)$$

Pravilo 2:

Ako x_1 jest A_2 , a x_2 jest B_2, onda je
$$f_2 = p_2x+q_2y+r_2 \qquad (3)$$
pri čemu su $\{p_i, q_i, r_i\}$ parametri premisa u prvome sloju.

Prvi sloj ANFIS-a poznat je kao sloj *fuzzy* pretvorbe. Svaki čvor u prvome sloju je prilagodljivi čvor pri čemu je funkcija čvora:

$$01,i = \mu Ai \text{ x } 1 \qquad za\ i = 1,2 \qquad (4)$$

In this ANFIS architecture, we denote the output of *i*th node in layer *l* as $O_{l,i}$. In this study, first order Sugeno type fuzzy model was used as following:

Rule 1:

If x_1 is A_1 and x_2 is B_1, then
$$f_1 = p_1x+q_1y+r1 \qquad (2)$$

Rule 2:

If x_1 is A_2 and x_2 is B_2, then
$$f_2 = p_2x+q_2y+r_2 \qquad (3)$$
where $\{p_i, q_i, r_i\}$ are referred to as premise parameters in the first layer.

First layer of ANFIS is known as fuzzification layer. Every node in the first layer is an adaptive node with node function given by:

$$01,i = \mu Ai \text{ x } 1 \qquad for\ i = 1.2 \qquad (4)$$

01,i = μBi – 2 x 2 *za i = 3,4* (5)

pri čemu su x_1 i x_2 ulazi u čvor i, a lingvistička oznaka vezana uz taj čvor označena je s A_i ili $B_{i\text{-}2.}$ Generalizirana funkcija zvona je:

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b}} \quad (6)$$

pri čemu je $\{a_i, b_i, c_i\}$ skup varijabli. Funkcija članstva mijenja se u skladu s vrijednosti parametara premise.

Drugi sloj zove se sloj članstva. Svaki čvor u drugome sloju je neprilagodljiv ili fiksni čvor. Snaga aktivacije svakog pravila određena je izlazom iz svakog čvora u ovom sloju. Umnožak svih ulaznih signala je izlaz iz svakoga čvora.

$$O_{2,i} = \omega_i = \mu_{Ai}(x).\mu_{Bi}(y) \quad \text{za } i = 1{,}2 \quad (7)$$

Sloj pravila je treći sloj u arhitekturi ANFIS. Svaki čvor u ovom sloju je i fiksni čvor. Omjer snage aktivacije svakog pravila i zbroja aktivacijske snage svih pravila računa se za svaki čvor u ovome sloju. Normalizirana snaga aktivacije označena je s $\bar{\omega}_i$.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad (8)$$

Defazifikacijski sloj tvori četvrti sloj ANIS-a. Čvorovi ovoga sloja povezani su s pojedinim čvorovima normalizacije u sloju pravila. Skup parametara ovoga čvora prikazan je s $\{p_i, q_i, r_i\}$. U njemu se parametri nazivaju i konsekventnim parametrima. Svaki čvor u ovome sloju je prilagodljiv, pri čemu je funkcija čvora:

$$O_{4,1} = \bar{w}_i f_i = \bar{w}_i\left(p_i x_1 + q_i x_2 + r_i\right) \quad (9)$$

Izlazni sloj predstavlja zadnji sloj ANFIS arhitekture. Sastoji se od samo jednoga čvora koji je po prirodi neprilagodljiv. On računa ukupan izlaz kao zbir izlaza iz defazifikacijskog sloja.

01,i = μBi – 2 x 2 *for i = 3.4* (5)

where x_1 and x_2 are the inputs to node i and the linguistic label associated with this node is denoted by A_i or $B_{i\text{-}2.}$ A generalized bell function is given by:

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b}} \quad (6)$$

where $\{a_i, b_i, c_i\}$ is the variable set. The membership function changes accordingly with the value of premise parameters.

The second layer is called as membership layer. Every node in the second layer is a non-adaptive or fixed node. The firing strength of each rule is depicted by output of each node of this layer. The product of entire incoming signals is the output of each node.

$$O_{2,i} = \omega_i = \mu_{Ai}(x).\mu_{Bi}(y) \; for \; i = 1.2 \quad (7)$$

Rule layer is the third layer of ANFIS architecture. Every node in this layer is also a fixed node. The ratio of firing strength of each rule to the sum of firing strength of all rules is calculated by each node of this layer. Normalized firing strength is represented by $\bar{\omega}_i$.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad (8)$$

Defuzzification layer forms the fourth layer of ANIS. Nodes of this layer are connected to the individual normalization node of the rule layer. The parameter set of this node is represented by $\{p_i, q_i, r_i\}$. In this later, the parameters are also known as consequent parameters. Every node in this layer is an adaptive node with node function as:

$$O_{4,1} = \bar{w}_i f_i = \bar{w}_i\left(p_i x_1 + q_i x_2 + r_i\right) \quad (9)$$

The output layer forms the last layer of ANFIS architecture. It consists of only one node which is non-adaptive in nature. It calculates the overall output as summation of outputs form the defuzzification layer.

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (10)$$

Za ustanovljavanje parametara ANFIS sustava korišten je hibridni algoritam učenja (Jang, 1991). Algoritam je kombinacija gradijentnog spuštanja i metode najmanjih kvadrata. Parametri zaključaka određuju se prilikom prolaska prema naprijed dok se parametri pretpostavke pravila postavljaju prilikom prolaska prema natrag. Ulazi u mrežu prenose se do četvrtog sloja gdje se metodom najmanjih kvadrata određuju parametri zaključaka pravila tijekom prolaska prema naprijed. U povratnom kretanju algoritmom gradijentnog spuštanja nadopunjuju se parametri pretpostavki pravila, a pogreška se prenosi širenjem signala unatrag.

Rezultati mreža NAR i ANFIS-a vrednovani su pomoću standardne devijacije (RMSE) i srednje apsolutne pogreške (MAE). MAE je moguće definirati kao prosjek apsolutnih pogrešaka. MAE pokazuje koliko su predviđene vrijednosti blizu ciljanih vrijednosti. RMSE predstavlja drugi korijen prosječne vrijednosti kvadrata odstupanja.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \left(t_i - f_i\right)^2}{n}} \quad (11)$$

$$\text{MAE} = \frac{\sum_{i=1}^{n} \left|t_i - f_i\right|}{n} \quad (12)$$

pri čemu je t_i ciljna vrijednost, a f_i prognozirana vrijednost.

Za komparativnu analizu prognoziranja turističke potražnje korištena je dvodjelna arhitektura. Za dizajniranje i učenje nelinearne autoregresivne neuronske mreže NAR korišten je MATLAB 2012a Neural Network Toolbox, a za dizajniranje i optimizaciju arhitekture ANFIS-a rabio se MATLAB's 2012a *Fuzzy Logic Toolbox*.

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (10)$$

Hybrid learning algorithm was employed for the identification of parameters in the ANFIS system (Jang, 1991). The algorithm is a combination of gradient descent and least squares method. The consequent parameters are tuned in the forward pass while premise parameters are adjusted in the backward pass. Network inputs are propagated up to layer 4 where consequent parameters are determined by least-squares method in the forward pass. In the backward pass, gradient descent updates the premise parameters and the error is propagated backwards.

The metrics used for valuating performance of the NAR network and ANFIS are root mean square error (RMSE) and mean absolute error (MAE). MAE can be defined as the average of absolute errors. MAE denotes how close the predicted values are to the target values. Meanwhile, RMSE involves square root of the average value of the square of the error.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \left(t_i - f_i\right)^2}{n}} \quad (11)$$

$$\text{MAE} = \frac{\sum_{i=1}^{n} \left|t_i - f_i\right|}{n} \quad (12)$$

where, t_i is the target value and f_i is the forecasted value.

A bipartite architecture was employed for the comparative analysis of tourism demand forecasting. For designing and training the NAR neural network, MATLAB's 2012a Neural Network Toolbox and for designing and optimization of ANFIS architecture, MATLAB's 2012a Fuzzy Logic Toolbox was employed.

2.3 Skup podataka

Mjesečni turistički podaci dobiveni su iz Statističkog odjela u Singapuru (www.singstat.gov.sg). Skup podataka obuhvaćao je broj dolazaka turista u Singapur od siječnja 2006. do veljače 2017. Za razdoblje od 12/2014 do 2/2017 izračunate su procjene deskriptivnih statistika turističkih dolazaka u Singapur. Od svih zemalja Kina pokazuje najveću varijaciju, a Malezija najveću asimetričnost i zaobljenost distribucije turističkih dolazaka (Tablica 1).

2.3 Dataset

The monthly tourism data was retrieved from Department of Statistics, Singapore (www.singstat.gov.sg). The dataset incorporated the number of tourist arrivals to Singapore from January 2006 to February 2017. Descriptive statistics of tourist arrivals to Singapore for the out-of-sample period (December 2014 to February 2017) were computed. China shows highest variation while Malaysia depicts highest level of skewness and kurtosis in tourist arrivals among all countries (Table 1).

Tablica 1: Deskriptivna statistika turističkih dolazaka (od prosinca 2014. do veljače 2017.) / Table 1. Descriptive statistics of tourist arrivals (December 2014 to February 2017)

Zemlje / *Countries*	Max	Min	Srednja Vrijednost / *Mean*	Standardna devijacija / *Std dev*	Asimetričnost / *Skewness*	Zaobljenost Distribucije / *Kurtosis*	Koeficijent varijacije (%) / *Var coeff (%)*
Indonezija / *Indonesia*	329994	184183	237192,3 / 237192.3	43308,77 / 43308.77	0,9962 / 0.9962	-0,0967 / -0.0967	18,2589 / 18.2589
Malezija / *Malaysia*	143276	81656	97607,3 / 97607.3	14968,25 / 14968.25	1,7848 / 1.7848	3,1196 / 3.1196	15,3352 / 15.3352
Filipini / *Philippines*	76646	41155	56551,19 / 56551.19	10152,38 / 10152.38	0,5007 / 0.5007	-0,7309 / -0.7309	17,9525 / 17.9525
Tajland / Thailand	63693	29889	43604,11 / 43604.11	8162,471 / 8162.471	1,0672 / 1.0672	0,9231 / 0.9231	18,7195 / 18.7195
Japan / *Japan*	93619	46687	65591,74 / 65591.74	11579,1 / 11579.1	0,7877 / 0.7877	0,7761 / 0.7761	17,6533 / 17.6533
Kina / *China*	316797	124615	210377,9 / 210377.9	60686,71 / 60686.71	0,2796 / 0.2796	-1,1850 / -1.1850	28,8465 / 28.8465
Južna Koreja / *South Korea*	74180	34346	48330,7 / 48330.7	10818,66 / 10818.66	0,9303 / 0.9303	0,0605 / 0.0605	22,3847 / 22.3847
Indija / *India*	141987	60016	87024,7 / 87024.7	18092,11 / 18092.11	1,5428 / 1.5428	3,0350 / 3.0350	20,7896 / 20.7896
SAD / *USA*	51555	32749	42964,96 / 42964.96	5121,77 / 5121.77	-0,2839 / -0.2839	-0,7105 / -0.7105	11,9208 / 11.9208
Australija / *Australia*	117073	61900	87262,07 / 87262.07	15941,03 / 15941.03	0,3095 / 0.3095	-0,7658 / -0.7658	18,2680 / 18.2680
Ostalo / *Other*	386153	250416	305774,5 / 305774.5	41422,87 / 41422.87	0,5442 / 0.5442	-0,6037 / -0.6037	13,5469 / 13.5469

Tablica 2. P-vrijednosti testova jediničnih korijena. Razdoblje procjene (siječanj 2006. – veljača 2017.). Granična p-vrijednost je 0.05. / Table 2. P-values of unit root tests. Estimation period (January 2006 – February 2017). Cut off p-value is 0.05.

Zemlje / *Countries*	I(0)			I(1)		
	ADF	**PP**	**KPSS**	**ADF**	**PP**	**KPSS**
SAD / *USA*	0,011 / 0.011	0,739 / 0.739	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	1,0000 / 1.0000
Australija / *Australia*	0,286 / 0.286	0,407 / 0.407	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	0,9480 / 0.9480
Kina / *China*	0,678 / 0.678	0,635 / 0.635	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	0,9990 / 0.9990
Južna Koreja / *South Korea*	0,761 / 0.761	0,564 / 0.564	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	0,9480 / 0.9480
Indija / *India*	< 0,0001 / < 0.0001	0,453 / 0.453	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	1,0000 / 1.0000
Japan / *Japan*	0,203 / 0.203	0,58 / 0.58	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	1,0000 / 1.0000
Tajland / *Thailand*	0,46 / 0.46	0,432 / 0.432	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	1,0000 / 1.0000
Malezija / *Malaysia*	0,875 / 0.875	0,573 / 0.573	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	0,7780 / 0.7780
Indonezija / *Indonesia*	0,769 / 0.769	0,529 / 0.529	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	0,9970 / 0.9970
Filipini / *Philippines*	0,163 / 0.163	0,588 / 0.588	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	0,9970 / 0.9970
Ostalo / *Other*	0,031 / 0.031	0,755 / 0.755	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	< 0,0001 / < 0.0001	1,0000 / 1.0000

Prije nego što smo nastavili procjenjivati modele, testirali smo elementarne procese koji su pridonijeli seriji – jesu li stacionarni ili nisu. Potrebno je diferenciranje da bi serije postale stacionarne ako se ustanovi da imaju jedinični korijen (Lim *et al*., 2009). Kao i Claveria *et al*. (2015), upotrijebili smo neke od uobičajenih metoda za testiranje hipoteze jediničnog korijena: Phillips-Perron (PP) test (Phillips i Perron, 1988), prošireni Dickey-Fullerov test (ADF) (Dickey i Fuller, 1979) i Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski *et al*., 1992). Nulta hipoteza jediničnog korijena za x_t testirana je pomoću ADF i PP, a nulta hipoteza stacionaranosti pomoću KPSS. Kao što je prikazano u Tablici 2, nulta hipoteza jediničnog korijena s 5% značajnosti nije odbačena za većinu zemalja kod ADF i PP testova. Među-

Before proceeding further to estimate the models, we tested the elemental processes which contributed to the series, if stationary or not. Differencing is required to make the series stationary, if found to possess a unit root (Lim *et al*., 2009). Following Claveria *et al*. (2015), we utilized some of the commonly used methods for unit root hypothesis testing: the Phillips-Perron (PP) test (Phillips and Perron, 1988), the augmented dickey-fuller (ADF) test (Dickey and Fuller, 1979), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski *et al*., 1992). Null hypothesis of a unit root in x_t is tested by ADF and PP while null hypothesis of stationarity is tested by KPSS. As seen in the Table 2, null hypothesis of a unit root at 5% significance level is not rejected in most of the countries in ADF and PP test.

tim, nulta hipoteza stacionaranosti odbačena je kod svih zemalja u KPSS testu. Ovi rezultati ukazuju na to da je za većinu slučajeva potrebno diferenciranje. Stoga je, kako bi se uklonio linearni trend, prvo provedena razlika prirodnog logaritma turističkih dolazaka u Singapur (Claveria *et al*., 2015).

3. REZULTATI

Za testiranje kompetencije umjetne neuronske mreže (ANN) korištena je metoda podijeljene validacije. Podaci su podijeljeni u tri skupa, u svrhu *fuzzya*, validacije i testiranja. Koristio se skup za *fuzzye* koji odgovara težinama modela NAR, skup za validaciju korišten je da bi se odabrao model koji ima najbolju sposobnost generalizacije, a skup za testiranje rabio se za testiranje odabranog modela na neviđenim podacima. Polazni skup podataka za *fuzzye* sastojao se od 68 mjesečnih opažanja (50%) od siječnja 2006. do kolovoza 2011., 39 mjeseci od rujna 2011. do studenog 2014. (30%) kao skup za validaciju, a posljednjih 20% kao testni skup.

Primijenjena je iterativna skica prognoziranja tako da je nakon svake prognoze veličina skupa povećana za jedno razdoblje, a validacija skupa proširena za dodatno razdoblje. Iterativni postupak ponavljan je sve dok skup za testiranje nije uključivao i razdoblje s procijenjenim podacima. Rezultati skupa za validaciju korišteni su za odabir optimalne topologije i parametara mreže. Nelinearna autoregresivna neuronska mreža s jednim ulaznim i jednim izlaznim neuronom trenirana je tijekom 1000 epoha. Kako bi se na najveću moguću mjeru smanjila greška između stvarnih i predviđenih vrijednosti, mreža je trenirana tako da se varirao broj neurona u skrivenom sloju. Mreže su simultano trenirane s različitim aktivacijskim funkcijama poput tangentno sigmoidalne, log sigmoidalne i linearne. Neuro-*fuzzy* model rabljen je s različitim tipovima i brojem funkcija članstva. Broj funkcija članstva varirao je između 2 i 6, a ulazne funkcije članstva bile

Meanwhile, null hypothesis of stationarity is rejected in all the countries in KPSS test. These results imply that differencing is required in most cases. Hence, first difference of natural log of tourist arrivals to Singapore is performed to remove linear trend (Claveria *et al*., 2015).

3. RESULTS

The split validation method was implemented to test the competence of ANN. The data was split into three sets for training, validation and testing purposes. The training set is utilized to fit weights of the NAR model, the validation set is used to select the model which provides best generalization capability and the test set is employed for testing the selected model against unseen data. The initial training dataset consisted of first 68 monthly observations (50%) from January 2006 to August 2011, the next 39 months from September 2011 to November 2014 (30%) as validation set and the last 20% as test set.

An iterative forecasting scheme was implemented wherein after every forecast, the size of the set was increased by one period and the validation set was slided by another period. This iterative procedure was reiterated till the test set comprised of out-of-sample period. Validation set's performance was utilized for selecting the optimal topology and parameters of the network. The NAR network with one input and one output neuron was trained for 1000 epochs. To minimize the error between actual and predicted values, the network was trained by varying the number of neurons in the hidden layer. The networks were simultaneously trained with different transfer functions such as tangential sigmoid, log sigmoid and linear. The neuro-fuzzy model was run with different types and number of membership functions. The numbers of membership functions were varied between 2 to 6 and input membership functions were triangular (trimf),

Tablica 3. Vrijednosti drugog korijena srednje kvadratne pogreške (siječanj 2006.-veljača 2017.) / Table 3. Root mean square error values (January 2006 – February 2017)

Zemlje / *Countries*	Jedan mjesec unaprijed / *One month ahead*	Dva mjeseca unaprijed / *Two months ahead*	Četiri mjeseca unaprijed / *Four months ahead*	Šest mjeseci unaprijed / *Six months ahead*
SAD / *USA*				
NAR / *NAR*	0,2268 / 0.2268	0,1518 / 0.1518	0,1421 / 0.1421	0,1329 / 0.1329
ANFIS / *ANFIS*	0,1284 / 0.1284	0,1009 / 0.1009	0,0666 / 0.0666	0,0382 / 0.0382
Australija / *Australia*				
NAR / *NAR*	0,2805 / 0.2805	0,2272 / 0.2272	0,1991 / 0.1991	0,1176 / 0.1176
ANFIS / *ANFIS*	0,1871 / 0.1871	0,1021 / 0.1021	0,0849 / 0.0849	0,0448 / 0.0448
Kina / *China*				
NAR / *NAR*	0,3618 / 0.3618	0,3310 / 0.3310	0,3069 / 0.3069	0,2854 / 0.2854
ANFIS / *ANFIS*	0,2668 / 0.2668	0,2130 / 0.2130	0,1640 / 0.1640	0,0908 /0.0908
Južna Koreja / *South Korea*				
NAR / *NAR*	0,3348 / 0.3348	0,2759 / 0.2759	0,2523 / 0.2523	0,2466 /0.2466
ANFIS / *ANFIS*	0,2202 / 0.2202	0,1880 / 0.1880	0,1515 / 0.1515	0,1136 / 0.1136
Indija / *India*				
NAR / *NAR*	0,2469 / 0.2469	0,2143 / 0.2143	0,1948 / 0.1948	0,0957 / 0.0957
ANFIS / *ANFIS*	0,1884 / 0.1884	0,1203 / 0.1203	0,0713 / 0.0713	0,0294 / 0.0294
Japan / *Japan*				
NAR / *NAR*	0,3506 / 0.3506	0,3227 / 0.3227	0,2036 / 0.2036	0,1983 / 0.1983
ANFIS / *ANFIS*	0,1836 / 0.1836	0,1610 / 0.1610	0,0820 / 0.0820	0,0669 / 0.0669
Tajland / *Thailand*				
NAR / *NAR*	0,3231 / 0.3231	0,2860 / 0.2860	0,2625 / 0.2625	0,2412 / 0.2412
ANFIS / *ANFIS*	0,2101 / 0.2101	0,1968 / 0.1968	0,1803 / 0.1803	0,1002 / 0.1002
Malezija /*Malaysia*				
NAR / *NAR*	0,2329 / 0.2329	0,2041 / 0.2041	0,1912 / 0.1912	0,1859 / 0.1859
ANFIS / *ANFIS*	0,1504 / 0.1504	0,1348 / 0.1348	0,1229 / 0.1229	0,0787 / 0.0787
Indonezija / *Indonesia*				
NAR / *NAR*	0,3014 / 0.3014	0,2530 / 0.2530	0,2384 / 0.2384	0,2269 / 0.2269
ANFIS / *ANFIS*	0,1668 / 0.1668	0,1302 / 0.1302	0,0915 / 0.0915	0,0760 / 0.0760
Filipini / *Philippines*				
NAR / *NAR*	0,2168 / 0.2168	0,1907 / 0.1907	0,1854 / 0.1854	0,1644 / 0.1644
ANFIS / *ANFIS*	0,1712 / 0.2168	0,1444 / 0.1444	0,1243 / 0.1243	0,0357 / 0.0357
Ostalo / *Other*				
NAR / *NAR*	0,2027 / 0.2027	0,1830 / 0.1830	0,1673 / 0.1673	0,0581 / 0.0581
ANFIS / *ANFIS*	0,1426 / 0.1426	0,1112 / 0.1112	0,0426 / 0.0426	0,0289 / 0.0289

su trokutastog (trimf), trapeznog (trapmf), Gaussovog (gaussmf), zvonolikog (gbellmf) i sigmoidalnog (sigmf) tipa, ovisno o broju ulaza u model ANFIS za određivanje optimalne topologije. Funkcije članstva izlaza odabrane su između konstantnih i linearnih. Broj razdoblja iznosio je 100. Neuro-*fuzzy* sustavi nakon učenja također zahtijevaju postupak validacije kako bi se validirali podaci i potvrdila njihova sposobnost generalizacije (Efendigil *et al*., 2009). Kao i kod Chen *et al*. (2010), kao skup za validaciju korišteni su neviđeni podaci kako bi se potvrdila sposobnost generalizacije modela neuro-*fuzzy* sustava (rujan 2011. – veljača 2017.).

Pretpostavlja se da model ANFIS s minimalnom standardnom devijacijom nakon jedne epohe *fuzzya* može konvergirati u niži model standardne devijacije nakon više epoha *fuzzya* (Mohammed *et al*., 1995). Optimalna učinkovitost modela AI može se postići kombinacijom parametara. Stoga je primijenjena eksperimentalna metoda pokušaja i pogreške ili 'promijeni jedan po jedan faktor' (Efendigil *et al*., 2009). Korištena je tehnika višestrukih pokretanja pri čemu je faza *fuzzya* ponavljana tri puta kako bi se postigle niske vrijednosti odstupanja i izbjegao problem lokalnih minimuma (Claveria *et al*., 2015). Rezultati predstavljeni u studiji odgovaraju najboljoj topologiji i najnižim vrijednostima odstupanja.

Provedeno je iscrpno istraživanje kako bi se ustanovila optimalna topologija mreža koja daje najmanje grešaka. Korištena je metoda mrežne podjele za generiranje optimiziranih *fuzzy* pravila za ANFIS sustav. Odabrana je poopćena zvonolika funkcija kao eksperimentalna funkcija članstva pošto ona daje najniže vrijednosti RMSE. Pokazalo se da nelinearni parametri mogu najbolje poopćiti pomoću zvonolikih funkcija članstva (Mladenovic *et al*., 2016). Usto, u našoj studiji za funkciju članstva izlaza odabran je linearni tip. Najbolji rezultati za NAR mreže postignuti su s topologijom s jednim skrivenim slojem i 10 do 30 skrivenih neurona.

trapezoidal (trapmf), gaussian (gaussmf), bell-shaped (gbellmf) and sigmoidal (sigmf) types, depending upon the number of inputs in ANFIS model for identification of optimal topology. The output membership functions were chosen between constant or linear. The numbers of epochs were set to 100. Neuro-fuzzy systems also require a validation procedure after training to validate the data and confirm its generalization capabilities (Efendigil *et al*., 2009). Following Chen *et al*. (2010) an unseen data was used as validation set to confirm the generalization potential of neuro-fuzzy model (September 2011 to February 2017).

It is assumed that the ANFIS model with the minimum RMSE after one epoch of training can converge to a lower RMSE model after more epochs of training (Mohammed *et al*., 1995). Optimal performance of AI models can be achieved through a combination of parameters. Hence, trial and error or 'change one factor at a time' experimentation methodology was implemented (Efendigil *et al*., 2009). A multi-start technique was employed, in which the training phase was repeated three times to obtain low error values and avoid the problem of local minima (Claveria *et al*., 2015). The results presented in the study correspond to the best topology and lowest error values.

An exhaustive search was performed to identify the optimal topology of the networks which gives minimum error. Grid partition methodology was employed for generating the optimized fuzzy rules for the ANFIS system. A generalized bell shaped function was chosen as the experimental membership function as it gave lowest RMSE values. It has been shown that non-liner parameters can be best generalized by bell-shaped membership functions (Mladenovic *et al*., 2016). Meanwhile the output membership function was set to linear type in our study. The best results for NAR networks were obtained with the topology of one hidden layer and 10 to 30 hidden neurons. Upon analyzing

Tablica 4. Vrijednosti srednje apsolutne pogreške (siječanj 2006. – veljača 2017.) / Table 4. Mean absolute error values (January 2006 – February 2017)

Zemlje / *Countries*	Jedan mjesec unaprijed / *One month ahead*	Dva mjeseca unaprijed / *Two months ahead*	Četiri mjeseca unaprijed / *Four months ahead*	Šest mjeseci unaprijed / *Six months ahead*
SAD / *USA*				
NAR / *NAR*	0,1888 / 0.1888	0,1245 / 0.1245	0,1214 / 0.1214	0,1101 / 0.1101
ANFIS / *ANFIS*	0,1108 / 0.1108	0,0732 / 0.0732	0,0427 / 0.0427	0,0110 / 0.0110
Australija / *Australia*				
NAR / *NAR*	0,2296 / 0.2296	0,1849 / 0.1849	0,1621 / 0.1621	0,0961 / 0.0961
ANFIS / *ANFIS*	0,1433 / 0.1433	0,0760 / 0.0760	0,0292 / 0.0292	0,0142 / 0.0142
Kina / *China*				
NAR / *NAR*	0,3064 / 0.3064	0,2621 / 0.2621	0,2436 / 0.2436	0,2187 / 0.2187
ANFIS / *ANFIS*	0,2078 / 0.2078	0,1542 / 0.1542	0,0946 / 0.0946	0,0285 / 0.0285
Južna Koreja / *South Korea*				
NAR / *NAR*	0,2810 / 0.2810	0,2128 / 0.2128	0,1962 / 0.1962	0,1932 / 0.1932
ANFIS / *ANFIS*	0,1670 / 0.1670	0,1435 / 0.1435	0,0784 / 0.0784	0,0355 / 0.0355
Indija / *India*				
NAR / *NAR*	0,2079 / 0.2079	0,1810 / 0.1810	0,1580 / 0.1580	0,0771 / 0.0771
ANFIS / *ANFIS*	0,1480 / 0.1480	0,0861 / 0.0861	0,0466 / 0.0466	0,0101 / 0.0101
Japan / *Japan*				
NAR / *NAR*	0,2628 / 0.2628	0,2250 / 0.2250	0,1550 / 0.1550	0,1477 / 0.1477
ANFIS / *ANFIS*	0,1348 / 0.1348	0,0912 / 0.0912	0,0278 / 0.0278	0,0180 / 0.0180
Tajland / *Thailand*				
NAR / *NAR*	0,2642 / 0.2642	0,2273 / 0.2273	0,2157 / 0.2157	0,1992 / 0.1992
ANFIS / *ANFIS*	0,1770 / 0.1770	0,1180 / 0.1180	0,0878 / 0.0878	0,0291 / 0.0291
Malezija / *Malaysia*				
NAR / *NAR*	0,1763 / 0.1763	0,1478 / 0.1478	0,1472 / 0.1472	0,1412 / 0.1412
ANFIS / *ANFIS*	0,1130 / 0.1130	0,0941 / 0.0941	0,0784 / 0.0784	0,0239 / 0.0239
Indonezija / *Indonesia*				
NAR / *NAR*	0,2433 / 0.2433	0,2062 / 0.2062	0,1935 / 0.1935	0,1845 / 0.1845
ANFIS / *ANFIS*	0,1324 / 0.1324	0,0926 / 0.0926	0,0603 / 0.0603	0,0230 / 0.0230
Filipini / *Philippines*				
NAR / *NAR*	0,1620 / 0.1620	0,1570 / 0.1570	0,1517 / 0.1517	0,1229 / 0.1229
ANFIS / *ANFIS*	0,1323 / 0.1323	0,1151 / 0.1151	0,0365 / 0.0365	0,0127 / 0.0127
Ostalo / *Other*				
NAR / *NAR*	0,1584 / 0.1584	0,1417 / 0.1417	0,1332 / 0.1332	0,0443 / 0.0443
ANFIS / *ANFIS*	0,0990 / 0.0990	0,0602 / 0.0602	0,0148 / 0.0148	0,0105 / 0.0105

Nakon analize točnosti prognoziranja turističkih dolazaka, modeli ANFIS pokazali su niže vrijednosti RMSE i MAE od NAR mreža.

Kad se pomoću NAR mreže provelo predviđanje jedan mjesec unaprijed, ustanovljen je najniži RMSE od 0,2027 za ostale zemlje. Neuro-*fuzzy* model zabilježio je najniži RMSE od 0,1284 za SAD (Tablica 3). Najniži MAE od 0,1584 ustanovljen je za ostale zemlje kod modela NAR, dok je model ANFIS pokazao najniži MAE od 0,0990 za ostale zemlje (Tablica 4). Kod svih zemalja pri predviđanjima za jedan mjesec unaprijed model ANFIS pokazao se učinkovitijim od modela NAR i kod tehnika mjerenja RMSE i MAE.

Najniži RMSE od 0,1009 uočen je za SAD kod predviđanja ANFIS-om dva mjeseca unaprijed. Istovremeno model NAR postigao je RMSE od 0,1518 za USA (Tablica 3). Vrijednost MAE od 0,1245 za USA bila je najniža od svih zemalja kod NAR-a, dok je model ANFIS dao najniži MAE od 0,0602 za ostale zemlje (Tablica 4). I ovdje se neuro-*fuzzy* model pokazao boljim od modela NAR za predviđanja dva mjeseca unaprijed. Treba imati na umu da je MAE linearan rezultat kod kojega svaka greška doprinosi s istom težinom prosjeku, dok RMSE slijedi pravilo kvadratne pogreške. Kod RMSE, greške se računaju kvadriranjem nakon čega se izračunava prosjek pa stoga velike greške imaju veću težinu. Ta karakteristika može biti oportuna kad su velike greške neprihvatljive u statističkom modelu. Tehnika mjerenja grešaka treba biti dovoljno pogodna za razlikovanje rezultata prognoziranja dva modela. RMSE je tipično bolji kod sugeriranja razlika između učinkovitosti modela (Armstrong i Collopy, 1992).

Točnost predviđanja oba modela povećava se nakon dodavanja dodatnih informacija o dolascima turista u prethodnim mjesecima. Najniža vrijednost RMSE od 0,0289 uočena je kod ostalih zemalja (šest mjeseci unaprijed) dok su najniže MAE vrijednosti od

the forecasting accuracy of tourist arrivals, the ANFIS models display lower RMSE and MAE values than NAR networks.

When one month ahead prediction was performed with NAR network, the lowest RMSE of 0.2027 was observed for rest of the countries. Meanwhile the neuro-fuzzy model recorded the lowest RMSE of 0.1284 for USA (Table 3). The lowest MAE of 0.1584 was observed for rest of the countries for NAR model, while the ANFIS model recorded the lowest MAE of 0.0990 for the rest of the countries (Table 4). Among all the countries for one month ahead prediction, the ANFIS model outperformed the NAR model in both RMSE and MAE metrics.

The lowest RMSE of 0.1009 was observed for USA in two month ahead prediction of ANFIS. Meanwhile, the NAR model obtained the RMSE of 0.1518 for USA (Table 3). The MAE value of 0.1245 for USA was recorded the lowest among all countries in NAR while the ANFIS model gave the lowest MAE of 0.0602 for the rest of the countries (Table 4). Here also, neuro-fuzzy model outperformed the NAR model for two months ahead prediction. It should be kept in mind that MAE is a linear score where every error has equal weight in the average while RMSE has quadratic error rule. In RMSE, errors are squared and then average is taken, hence large errors possess higher weight. This trait can be convenient when large errors are unacceptable in a statistical model. The error metrics should be sufficiently competent to differentiate between the results of the forecast of two models. RMSE is typically better in suggesting the difference between models performance (Armstrong and Collopy, 1992)

The prediction accuracy of both models increases upon incorporating additional information of previous months of tourist arrivals. The lowest RMSE value of 0.0289 was seen in rest of the countries (six month ahead), while the lowest MAE value of 0.0101 was depicted for India (six month ahead) in all forecasting horizons. A considerable

Tablica 5. Test gubitka točnosti Diebold-Mariano, statistika za točnost predviđanja* / Table 5. Diebold-Mariano loss differential test statistics for predictive accuracy*

Zemlje / *Countries*	Jedan mjesec unaprijed / *One month ahead*	Dva mjeseca unaprijed / *Two months ahead*	Četiri mjeseca unaprijed / *Four months ahead*	Šest mjeseci unaprijed / *Six months ahead*
SAD / *USA*				
ANFIS *vs* NAR	-6,9172 / -6.9172	-5,8141 / -5.8141	-7,0039 / -7.0039	-6,8416 / -6.8416
Australija / *Australia*				
ANFIS *vs* NAR	-6,2904 / -6.2904	-6,7255 / -6.7255	-6,5016 / -6.5016	-5,0014 / -5.0014
Kina / China				
ANFIS *vs* NAR	-7,1250 / -7.1250	-4,1108 / -4.1108	-4,4908 / -4.4908	-4,8936 / -4.8936
Južna Koreja / *South Korea*				
ANFIS *vs* NAR	-6,3140 / -6.3140	-5,0426 / -5.0426	-3,2381 / -3.2381	-5,4646 / -5.4646
Indija / *India*				
ANFIS *vs* NAR	-4,9690 / -4.9690	-5,9996 / -5.9996	-6,6852 / -6.6852	-7,7359 / -7.7359
Japan / *Japan*				
ANFIS *vs* NAR	-5,4123 / -5.4123	-2,6288 / -2.6288	-5,6935 / -5.6935	-6,6364 / -6.6364
Tajland / *Thailand*				
ANFIS *vs* NAR	-5,4349 / -5.4349	-2,7065 / -2.7065	-2,0134 / -2.0134	-4,2253 / -4.2253
Malezija / *Malaysia*				
ANFIS *vs* NAR	-4,8715 / -4.8715	-3,0260 / -3.0260	-2,6256 / -2.6256	-4,7856 / -4.7856
Indonezija / *Indonesia*				
ANFIS *vs* NAR	-5,1715 / -5.1715	-5,1592 / -5.1592	-6,3364 / -6.3364	-6,3292 / -6.3292
Filipini / *Philippines*				
ANFIS *vs* NAR	-2,9069 / -2.9069	-4,7034 / -4.7034	-2,0578 / -2.0578	-5,8075 / -5.8075
Ostalo / *Other*				
ANFIS *vs* NAR	-5,6127 / -5.6127	-3,9495 / -3.9495	-6,3307 / -6.3307	-8,5895 / -8.5895

*Negativan znak ukazuje na to da serije koje se uspoređuju imaju više grešaka u prognoziranju. / Negative sign indicates that the competing series has more forecasting errors.

0,0101 ustanovljene kod Indije (šest mjeseci unaprijed) kod svih razdoblja prognoze. Uočena je značajna razlika vrijednosti RMSE i MAE kod mreža NAR i ANFIS za predviđanja četiri i šest mjeseci unaprijed. Te su vrijednosti pokazale trend pada nakon što je povećan broj vremenskih razdoblja. To znači da modeli ANN i ANFIS uz manje znanja nisu sasvim u stanju modelirati podatke i daju više vrijednosti RMSE i MAE.

Nadalje, kako bi se usporedila točnost predviđanja dviju prognoza, proveden je test DM (Diebold i Mariano, 1995) koji ocjenju-

difference was observed in the RMSE and MAE values of NAR and ANFIS networks during four and six month ahead predictions. The RMSE and MAE values of ANN and ANFIS displayed a decreasing trend upon increasing the number of time steps. This signifies that both ANN and ANFIS models with less knowledge are not capable enough to model the data and give higher RMSE and MAE values.

Furthermore, to compare the predictive accuracy of the two forecasts, Diebold-Mariano (DM) test was performed (Diebold and je koji model ima bolju točnost predviđanja ili kod kojega je smanjenje greške statistički značajno. Taj test za uspoređivanje točnosti testira nultu hipotezu prema kojoj dvije prognoze imaju istu prediktivnu točnost. Za procjenjivanje matrice kovarijanci gubitka točnosti korišten je procjenitelj Newey-West tipa. Pozitivan znak ukazuje na to da je pogreška u prognoziranju iz prve serije viša u usporedbi sa serijom s kojom se uspoređuje dok negativan znak označava suprotno. Prilikom evaluacije značajne razlike između dviju uključenih serija (Tablica 5), ustanovljeno je da je ANFIS model učinkovitiji od modela NAR za sva razdoblja prognoze i za sve zemlje.

Planiranje i kontroliranje priljeva turista od ključne je važnosti u turizmu. Točne prognoze turističke potražnje ključne su za ovu gospodarsku aktivnost jer ona u sebi objedinjuje neuskladištive proizvode poput hotelskih soba i sjedala u avionima. Precizne informacije o turističkoj potražnji i prilivu turista iz različitih regija mogu pomoći planerima politika u održavanju i povećavanju snage turizma određene zemlje. Opisana neuro-*fuzzy* metoda pruža bolje i točnije prognoze turističkih dolazaka nego neuronske mreže. Ova tehnika također prevladava nedostatke kako neuronskih mreža, tako i *fuzzy* logike. Neuro-*fuzzy* dizajn mogu koristiti menadžeri prilikom kreiranja marketinškog plana u turizmu. Točne prognoze mogle bi vladama i privatnom sektoru omogućiti kreiranje djelotvorne strategije i pružanje bolje usluge posjetiteljima, poput infrastrukture.

4. ZAKLJUČAK

U ovoj studiji predložili smo novu arhitekturu prognoziranja za predviđanje broja dolazaka turista u Singapur. Predviđanje turističke potražnje zahtijeva nelinearnu metodu zbog volatilnosti skupova podataka. Skup podataka sadrži obrasce koji mogu smanjiti djelotvornost neuronske mreže prilikom izvođenja za-

Mariano, 1995). The DM test assesses which model has better predictive accuracy or the statistically significant reduction in error. The DM loss-differential test for comparing accuracy tests the null hypothesis that the two forecasts have equal predictive accuracy. A Newey-West type estimator was utilized to estimate the covariance matrix for the loss differential. A positive sign implies that the forecasting error from the first series is higher in comparison to the competing series, while a negative sign denotes the opposite. While evaluating the considerable difference between the two participating series (Table 5), it was found that ANFIS model outperformed NAR model for all forecasting horizons and for all countries.

Planning and control of tourist inflow is essential for the tourism industry. The accurate forecasting of tourism demand is essential for this sector as it incorporates perishable products such as hotel rooms and airline seats. Precise information on tourism demand and tourist inflows from various regions may help the policy planners to maintain and augment the tourism sector of the country. The above proposed neuro-fuzzy methodology provides better and accurate forecasts of tourist arrivals than neural networks. This technique also overcomes the shortcomings of both neural networks and fuzzy logic. The neuro-fuzzy design could be utilized by managers in formulating a marketing plan for tourism sector of the country. Accurate forecasts could enable governments and private sector to formulate an efficient strategy and provide better facilities such as infrastructure to the visitors.

4. CONCLUSION

In this study we propose a new forecasting architecture for predicting the number of tourist arrivals to Singapore. Tourism demand forecasting requires a non-linear methodology due to volatility of the datasets. The dataset contains patterns that can hinder the effectiveness of neural network to de-

ključaka o složenim fenomenima iz vremenskog niza. *Fuzzy* logika i neuronske mreže su i međusobno komplementarne te se koristio kombinirani pristup kako bi se poboljšala uspješnost prognoziranja potražnje. Korištena su dva nelinearna inteligentna modela, neuro-*fuzzy* sustavi i nelinearne autoregresivne neuronske mreže kako bi se proizvele prognoze turističke potražnje za jedan, dva, četiri i šest mjeseci unaprijed. Ti modeli predstavljaju nekonvencionalan način obrade podataka o turističkoj potražnji. Glavni cilj ove studije bio je poboljšati učinkovitost prognoziranja turističke potražnje upotrebom hibridnih inteligentnih modela. Neuro-*fuzzy* model pokazao se boljim od NAR modela u svim razdobljima prognoze. Ustanovljeno je i da se točnost predviđanja kod oba modela znatno povećala s povećanjem količine podataka o turizmu iz prošlosti. Precizne prognoze turističke potražnje ključne su za upravljanje turizmom i temelj su poslovanja u privatnom i javnom sektoru. Studija ima određena ograničenja te je potrebno provesti dodatna istraživanja kako bi se dobivene podatke moglo generalizirati. Detaljnija testiranja sa skupovima podataka o drugim turističkim destinacijama mogla bi pružiti dodatna saznanja djelatnicima u turizmu.

duce complex phenomenon from time series. Fuzzy logic and neural networks are both complementary to each other, and hence a combinatorial approach is used to improve the demand forecasting performance. Two non-linear intelligent models, neuro-fuzzy systems and non-linear autoregressive neural networks were utilized to generate one, two, three and six month ahead forecast of tourism demand. The models represent unconventional ways of treating the tourist demand information. The main objective of this study was to improve the forecasting performance of tourism demand by using hybrid intelligent models. The neuro-fuzzy model outperformed the NAR model in all forecasting horizons. It was also found that on increasing the historical tourism information, the predictive accuracy of both the models improved significantly. Precise demand forecasts are crucial for tourism management and groundwork in business and public sectors. The study has some limitations as further work is required to generalize the findings. Exhaustive testing with different tourism destination datasets can provide additional insights to tourism professionals.

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