# A Study on Tracing Reasons of Recent Influx of US tourists into Slovenia: A Forecasting Model

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***Abstract***

Ever since Melanie Trump has become a first "first lady" in the US with roots from Slovenia, the number of American tourists' inflow into Slovenia substantially increased presumably due to the curiosity of Americans around her. With an increasing inflow of American tourists, planning and forecasting the US tourists' inflow to Slovenia have gained attention amongst scholars and practitioners. This study, therefore, was conducted to forecast the American tourists' inflow to Slovenia using one of the predictive models based on the exponential smoothing approach, namely Holt-Winters damped additive (HWDA) exponential smoothing method. The model was modified by several improvements, while the results were generalized to other supply chain components. The results show that the forecasting system can predict well the observed inflow, while the methodology used to derive the model might have enriched the plethora of existing practical forecasting approaches in the tourism domain.

***Keywords***
*Tourism forecasting; Melanie Trump; US tourists; Slovenian Tourism; Damped Holt-Winters additive model; Time series analysis and prediction*.

## Introduction

The United States contribute in the inflow of both business and leisure tourists in large numbers in the worldwide tourism industry. Tourists are drawn to Slovenia for its natural, cultural and historical attractions. Since the date of launching a promotional Slovenian tourism destination identity campaign, so-called "I feel Slovenia" in April 2016(www.slovenia.info, 2016), the Slovenian tourism industry started to boost up. Recently, the Melanie Trump has become a first "first lady" in the US with roots from Slovenia and ever since then, this increasingly accelerated growth has been even multiplied, presumably due to the curiosity to know more about her. With increasing growth of US tourists, the significance of planning and forecasting has gained attention among scholars and practitioners. Therefore, the higher the number of the tourists' inflow, the more precise the planning and forecasting ought to be. As a consequence, a proper planning and forecasting of the tourists' inflow in a tourism supply chain are important research area. Indeed, an ineffective tourism supply chain today will negatively impact the tourism industry tomorrow.

Therefore, the future success of the tourism industry is directly dependent realistically forecasting the tourist population and planning the supply chain accordingly. The tourism industry is a complex industry. There are many factors and indicators pertinent to its supply chain components which can not be simply ignored. This study was conducted to forecast the American tourists' inflow to Slovenia using one of the predictive models based on the exponential smoothing. The model was modified by several improvements, while the results were generalized to other supply chain components. This uniquely deployed a composed modeling framework in regard to forecasting through modeling design heuristic procedure prior to testing and validating the model. It is argued that the findings of the study can be used by practitioners and scholars who are interested in the application of forecasting within the context of tourism industry in any country.

## The importance of the tourism industry for national economies

The tourism industry is one of the main contributors to the countries' national economy. Since introduction of the Tourism and Travel Competitiveness Index (TTCI) by World Economic Forum (WEF) back in 2015, two criteria have been set to be significant in measuring the TTCI (Aratuo & Etienne, 2019); (a) quality of tourism supply/value chain and (b) characteristics of the destination country in itself. It was in this context that the competition occurred, emphasizing on infrastructure, cultural and natural resources indicators of the TTCI, for example, transportation infrastructure, tourism service providing ecosystem, cultural and sports attractions, and world heritage properties (WEF, 2015). This revolutionary trend, namely Tourism-led Economic growth triggered a heated debate between the scholars whether the relationship between tourism and economic growth is bidirectional and interactive, if so, whether the previous research results are non-conflicting and consistent or not. An in-depth review of previous literature can be divided into two strands; re-looking to this concept from a holistic and detailed-oriented point of view. To elaborate some of the holistic-oriented studies, for example, an empirical study conducted in Spain revealed that there are a unidirectional cause and effect relationships between tourism and economic growth (Balaguer & Cantavella-Jorda, 2002). In addition, a study was conducted in 2003 in which 13 OECD countries were investigated (Lanza, Temple, & Urga, 2003); the results revealed that tourism and economic growth are positively interconnected. Moreover, another study conducted in Uruguay uncovered a relational attribution of tourism costs on GDP per capita (Brida, Lanzilotta, Lionetti, & Risso, 2010). Dritsakis in 2012 conducted a study covering seven Mediterranean countries. Results of the study provided a solid confirmation on positive effects of tourism on GDP (Dritsakis, 2012). It seems that there is a firm consensus among scholars regarding the positive impacts of tourism on nations' economy across 55 countries (Pablo-Romero & Molina, 2013). Studies conducted in Turkey (Gunduz & Hatemi-J, 2005), Tunisia (Belloumi, 2010), southern European countries (Proença & Soukiazis, 2008), Singapore (Katircioğlu, 2010) and South Africa (Brida, Risso, & Events, 2010) have also shown the same results. However, scholars who used the detailed-oriented perspectives put the emphasis on the role of sub-industries in tourism supply chain and tourism economic growth networks at the sub-industrial level such as travel agents, hotels and airlines (Chen, 2007; Dragan, Keshavarzsaleh, Jereb, & Topolšek, 2018; Mill & Morrison, 2002; Tang & Jang, 2009). Therefore, it can be concluded that planning the infrastructure and deploying the forecasting models in any destination countries will pay off;

however, there is a need to put more efforts on the models' efficiency, concomitantly to consider the inclusion of external exogenous effects as well.

**Planning the infrastructure and the significance of forecasting in tourism**

Competitiveness in tourism has its roots in numerous indicators such as destination country's economy, tourism sector infrastructure, tourists' income level, and other economic and political indicators such as buying power, currency rates, social openness, religious and culture etc. Tourism industry is a complex industry sector that needs to be considered as a monolithic block in which its all supply chain components matter, particularly the tourism infrastructure. It can be said that there is a robust relationship between tourism development and the infrastructure (Adebayo & Iweka, 2014). The infrastructure base of each country can be seen as a determinant of that country's tourism destination attractiveness. Therefore, planning the infrastructure and the significance of forecasting in tourism industry context cannot be ignored anymore. Since the performance of the tourism sector is highly tied to socio-political factors (Zheng & Zhang, 2013), infrastructure development (Khadaroo & Seetanah, 2007), immigration and visa policies (Cheng, 2012), and political events (Goodrich, 2002); thereby, there is a need for proper forecasting. The forecasting in tourism research has been highlighted in the previous literature extensively. For example, in regards to destinations' future tourism demand forecasting, many economic factors are considered including both macroeconomic factors and microeconomic ones (Chatziantoniou, Degiannakis, Eeckels, & Filis, 2016; Morley, 1992). Therefore, it can be asserted that in order to obtain an effective planning, the necessity of forecasting in tourism need to be intensified.

## The Tourism industry in Slovenia and the context of the study

Tourism is known to be an important economic activity globally due to its direct and indirect economic impacts. Slovenia due to its strategic geographical location has always been seen as a great destination for tourists, particularly in the areas such as transit tourism, winter sport and summer seaside vacations (Gosar, 1990; Konecnik & Go, 2008). Tourism in Slovenia is at the pivotal point of its history(www.slovenia.info, 2016). The tourism industry in Slovenia has undergone any changes over the years, more importantly, privatization. It is argued that this country although it is mature in tourism product development, it lacks a service culture. The privatization of the industry has positively contributed to the nations' economy because private ownership performed much better regarding sustainability, internationalization, marketing strategies and tourism product development (Assaf & Cvelbar, 2011; Mihalič, Žabkar, & Cvelbar, 2012; Žabkar, Brenčič, & Dmitrović, 2010). The final fruit of all above-said efforts has led to attracting many tourists from all around the world, especially from the United States, particularly for the reason that they are on average the best spending a lot of money. With an increasing number of American tourists' inflow to Slovenia over the past two decades, this study conducted to forecasting of the United States tourists' inflow to Slovenia an improved exponential smoothing model. During the last few years, presumably also due to the fact, that the US has for the first time got a Slovenian first lady, the increase in arrivals of US tourists is even much more significant. This fact has been most likely caused by the fact that Slovenia has become widely recognized in the eyes of many US citizens. Also, the tourists who have already been in Slovenia non-stop spread a good opinion about this country all over America. This increasing tourists' inflow has led to a continuous research effort regarding the tourism industry in Slovenia and its tourism supply chain specifications. Since the launch of "I feel Slovenia", the Slovenian tourism industry has gained a tremendous boost(www.slovenia.info, 2016). Although it is boosting up with time, intensified competitions have impeded the progress towards reaching to the tourism-led economic growth competitiveness. The competitiveness cannot be achieved overnight; thereby, planning and forecasting are key imperatives to future success of the Slovenian tourism industry. The US tourists' inflow historical cumulative time series data to Slovenia(SSD, 2016)have been analyzed and predicted by using the well-known Holt-Winters Damped Additive exponential smoothing model (HWDA)(R. Hyndman, Koehler, Ord, & Snyder, 2008; Taylor, 2003) that was carefully investigated and improved with a special heuristic. Here, some essential enhancements have been conducted with respect to its basic version. Some of the ideas for these improvements have been initiated due to inspiration from some of our previous studies (Dragan, Kramberger, Lisec, & Intihar, 2017; Intihar, Kramberger, & Dragan, 2015; Intihar, Kramberger, & Dragan, 2017). It must be emphasized that the HWDA model is generic, which means that at least in principle, it might have been used for any similar type of forecasting in any industry, as well as in any country or cluster of countries. It is argued that this study contributes to knowledge, along with the possible contribution from the applicative vantage point in the following ways:

(a) The model is proven to be more or less effective for the case of the observed country. However, it could also be generalized to cover other supply chain members within a certain industry or industries, in general, irrespective of their size, type, and location. The latter means that a presented model could be due to its generalization conducted for any similar types of forecasting (e.g. the demand forecasting, sales forecasting, road freight transport forecasting, etc.).

(b) There are practically no similar studies identified in the tourism management context, introducing a specially composed modeling framework for the forecasting considering the proposed modeling design heuristic procedure, and

(c) The latter possesses a broad spectrum of the different rigorous criteria for model testing and validation that can rarely be found in other comparable studies.

(d) There were no studies found that would systematically analyze the predictive models in any context regarding the tourism industry in Slovenia.

(e) The derived model was identified within the quarterly based time interval (2003-2016). Afterward, its forecasts were compared with the real data from different sources (the actual data obtained from different tourism facilities), as well as with the official forecasts for the year 2017 (such as from Slovenian Statistical Department (SSD) and Department for Macroeconomic Analyses and Development (DMAD)). The model has on average significantly outperformed official forecasts for 2017 (app. 85.000 US tourists) and have approached much closer to the real data (on average about 101.000 tourists).

The first objective of this study was conceptual and related to the improved methodology regarding the modeling design of the conducted predictive model. The second one was applicative since we wanted to check to what extent the Slovenian first lady in the USA really influences the rising of tourism inflow of American tourists. The model has more accurately recognized a possible impact that Melanie Trump has had on an increased inflow of US tourists than it was detected by Slovenian official institutions. Naturally, maybe there are also some other additional reasons for such unusually enormous rise of the US tourists' inflow in just one observed year (from the end of 2016 to the end of 2017). These reasons perhaps related to a good state of US economics' indicators including the increased Consumption Price Index, or the global rise of the tourists' visits worldwide. Yet, it is still unusual that even a 19.8% increase in tourists happens in just one year. If we denote a time-dependent inflow with symbol $y(t)$, we are dealing with situation:

$y(2016Q4) = 81000 \rightarrow y(2017Q4) = 101000 \rightarrow 19.8\%$ *increase* of US tourists in only one year. Before Trump was elected for the US president, Melanie's hometown called Sevnica was just an average boring small town. Conversely, after his election, in just a couple of years, it has transformed into an important modern touristic spot. Even more, according to the official records(e.g. SSD: https://www.stat.si/StatWeb/Field/Index/24), the huge tourists' inflow increase has happened in Sevnica, while the majority of new visitors have been Americans!

## Literature Review

### Forecasting approaches in the tourism industry

Forecasting has seen to be beneficial when it comes to the development and investment planning in tourism (Chan & Lim, 2011)as well as to demand fluctuation of tourism inflow (Gounopoulos, Petmezas, & Santamaria, 2012). There are many studies which deployed various types of forecasting models in tourism inflow forecasting and its other often-related areas. For example, a study conducted by Cho in 2003 aimed at forecasting tourists' arrivals in Hong Kong in which three predictive models were comparatively investigated (Cho, 2003). Findings of the study revealed that ANN (artificial neural networks) is the most accurate one comparing to Univariate ARIMA and the exponential smoothing method. Forecasting tourism arrival in Singapore was conducted by Chu in 2008 in which the fractionally integrated ARIMA models were investigated and ultimately comparatively compared with the traditional ARIMA models (Fong-Lin Chu, 2008). In another study which conducted by the same author in 2011 considering Macau as a destination, fractionally integrated ARIMA models, seasonal ARIMA and a piecewise linear model were investigated (Fong-Lin Chu, 2011). The findings of the study introduced a piecewise linear model as the most effective and accurate among others. The new forecasting model, namely TVP-STSM developed in a study conducted by Song & Collogues in order to both model and forecast quarterly Chinese, Korean, British and American tourist arrivals to Hong Kong (Song, Li, Witt, & Athanasopoulos, 2011). The empirical results, according to the authors, indicate that the proposed combination of TVP (time-varying parameter) and STSM (structural time series model) works appropriately compared to related traditional ones. Regarding U.S tourist arrivals, SSA (Singular Spectrum Analysis) using monthly data for tourists inflow to the U.S between the period 1996 and 2012 were investigated in a study conducted by (Hassani, Webster, Silva, & Heravi, 2015). The results of their study concluded as SSA can be an accurate approach for forecasting tourism demand and it worth to deploy in similar cases. It can be said that there have been too many forecasting techniques so far. To categorize, quantitative forecasting models which have been developed so far can be seen as Artificial Intelligence-based, time series models and the econometric methodical approaches. Time series models which are dependent to previous data in the series to forecast the future trends, can be divided to some sub-clusters including; SMA (Simple Moving Average), Navi, SES (Single Exponential Smoothing), DES (double exponential smoothing), ARIMA (autoregressive moving average) and BSM (basic structural time series). Although they are proven to be effective forecasting models when it comes to forecasting tourism inflow, they are substantially limited to non-economic factors (Peng, Song, & Crouch, 2014). This means the significance of tourists' behavioural attributions is not configured in these models. Some scholar, therefore, argued that the econometric models are performing better, assisting policymakers in assessing the effectiveness of the policies and strategies deployed (Witt, Song, & Li, 2008). An in-depth review of the literature indicates that there is a various way to forecast tourism demand/inflow or other often-related areas. Some models outweigh others in some cases, depending on various indicators either endogenous or exogenous. For example, the standard ARIMA aims at forecasting according to the past values of the forecast variable while its extended version, known as ARMA(X) includes another predictor (independent) variables in order to enhance the accuracy of a forecast in itself. The ARIMA(X) is deployed in many studies such as forecasting Turkey's tourism-led revenue(Akal, 2004) forecasting the international tourism demand in Japan(Lim, McAleer, & Min, 2009)and so on. Moreover, Holt-Winters damped additive exponential smoothing model could have positioned itself among other forecasting models due to its robustness and enhanced accuracy. This approach deployed in many studies which address long-lead times such as long-lead time forecasting of UK air passengers(Grubb & Mason, 2001)forecasting the international tourist arrivals to New Zealand and Australia from 11 destinations(Athanasopoulos & de Silva, 2012) monthly volume of tourism inflow into Bulgaria(Dimitrov, Kalinova, Gantchev, & Nikolov, 2015)etc. Somehow, to complement the literature, in this study we aim at introducing our forecasting technique as some counterpart competitive approach to other more common forecasting approaches and screen it against other models. Slovenia is considered as the targeted destination country in this study due to its emergent tourism industry with particular reference of tourists from the U.S. Regarding our modified HWDA forecasting model, number of criteria must be considered such as; (a) the model must be able to provide an accurate forecasting according to the direction on any possible changes occurred and (b) it must be able to consider short-run and long-run intervals.

## The historical data

### The historical data for US tourists' inflow to Slovenia

Slovenia has been the destination of many tourists. In addition to the Americans, the most important visitors are from the EU who they are considered the most significant contributors to the Slovenian tourism industry. America is categorized as the distant marketplace for Slovenians and vice versa(Gomezelj & Mihalič, 2008). Recently, Slovenia expanded and intensified its promotional tourism destination campaign in the USA. Maja Pak, the Director of the Slovenian Tourist Board, indicated that media's interest and the publicity have been a great advantage in order to intensify the Slovenian tourism destination promotional campaigns. At the second quarter of 2016, Slovenia was the destination of 78209 American guests. Compared to the second last quarter of 2015 when Slovenia was visited by 70488 American guests, there is an increase of 10.9 percent. According to the estimate of Director of the Slovenian Tourist Board, 2017 has witnessed 5 to 6 percent increase in American guests' arrivals; statistically, from the end of 2016 when the number of guests were about 81167 increased to about 85000 at the end of the year 2017. Similar estimates (about 85000) have been made from some other government institutions (SSD, DMAD). According to the government reports, the capital city of Ljubljana has been witnessing large number of visitors as well. The American tourists were ranked fourth regarding the overnight stay's statistics after UK, Germany, and Italy. The guests from USA have recorded highest number of overnight stays comparing to the tourists from the other distant markets. They also were spending the biggest amount of money for direct tourism-related expenses, as well as different indirect expenses (among all tourists in Slovenia as a whole). Figure 1 shows a rough estimate of US tourist arrivals and comparison to their overnight stays for years 2006-2015 ((WTTC), 2015; SURS, 2015).

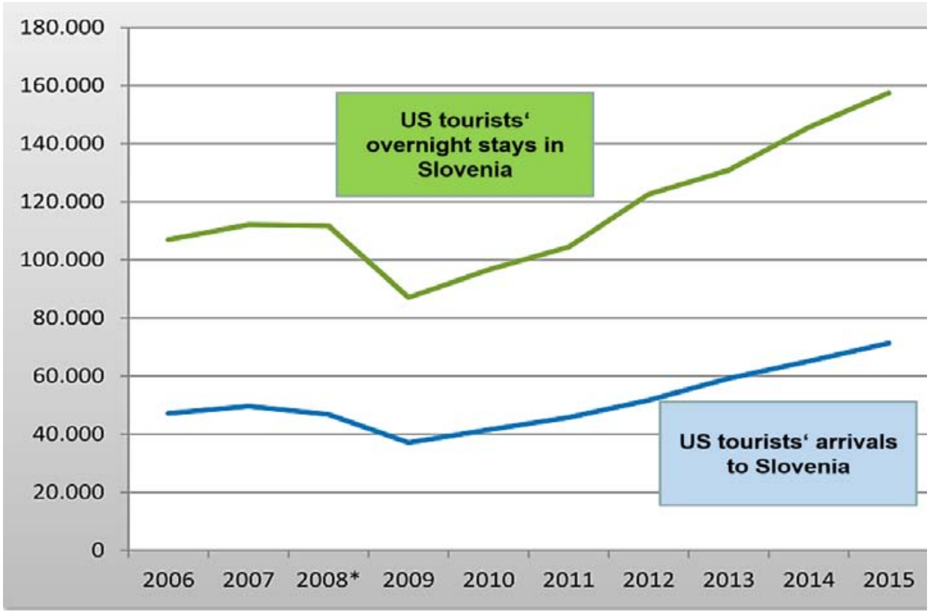


Figure 1: US tourist arrivals and comparison to their overnight stays for years 2006-2015

Figure 2 illustrates the quarterly cumulative inflow of US tourists between 2006 and 2016(SSD: https://www.stat.si/StatWeb/Field/Index/24). As can be seen, both volumes of arrivals and overnights stay in Slovenia has been growing gradually, except a sharp plunge in both volumes of arrivals and overnights stay in Slovenia 2009 due to the economic crisis in 2008. However, later it has captured a steady increasing trend again. For the years 2013 to 2016, the inflow has reached cumulative values (at the end of the fourth quarter): 60224, 66004, 74759, and 81167 tourists, respectively, thus percentage increases in values: 9.5%, 13.26%, and 8.5%, respectively. The time series shown in figure 2 is also the targeted output variable $y(t)$, for which we want to design our forecasting models.

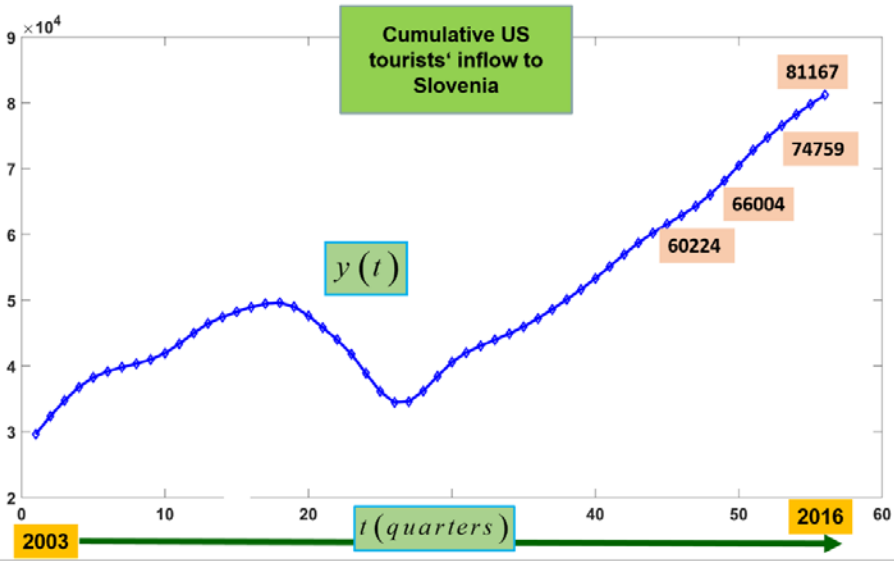


Figure 2: The time series data of quarterly cumulative inflow of US tourists in the time-period (2003-2016: $t = 1, 2, ..., N = 56$ quarters)).

## Methodology for a forecasting model

### The conceptual modeling framework

Figure 3 illustrates a conceptual modelling framework of our research. In block B, we can see the available collected data for the tourists' inflow time series $y(t)$ that represent a basis for the whole research. Block C refer to the basic version of a treated HWDA model, whose output $\hat{y}(t)$ is preferred to closely follow the time series $y(t)$ disturbed with the random noise $\varepsilon(t)$. In the modeling process, the basic model enters into the main advanced heuristic framework (block D, stage 1), which is optimized in such a way that can process thousands of model candidates in an acceptable amount of computation time. Further, for a HWDA structure that is always fixed, a wide set of possible parameter sets is settled, from where a different parameter set is assigned to each model candidate in each iteration *j* of the procedure (block E, stage 2). In the third stage (block F), the diagnostic checking is conducted, and goodness of fit (GOF) measures are calculated for each model candidate. Here, particularly important is a model candidate's error $e(t,j) = y(t) - \hat{y}(t,j)$ that is different in each iteration *j* depending on the specific calculated model's output $\hat{y}(t,j)$. A special sub-heuristic is developed during the model selection process which is employed in the fourth stage (block G) in order to obtain and find the best model comparing to many other model candidates. To do so, different pre-defined rules and statistical ones for each candidate have been also deployed. Such heuristic gives us the final most adequate HWDA model, which can be considered as the best one. Further, besides providing the well model's fit to the real data $y(t)$, the final obtained model satisfies all other rigorous mathematical and statistical conditions, particularly those related to the residual-based criteria. This way, when the modelling procedure is ended, we obtain the best model with a corresponding output:

$\hat{y}(t,j^*) = \hat{y}_{HWDA}(t,j^*) = \hat{y}^*,\ j^* - \textit{iteration with best criteria fulfilled}$, for which the optimal error $e^* = y - \hat{y}^*$ can be obtained (block H in figure 3)). Afterward, we can analyse the forecasting performance of the best model's output $\hat{y}^*(t)$ on the basis of different model-error based criteria (block I).

### Basic Holt-Winters damped additive exponential smoothing model (HWDA)

In general, exponential smoothing (ES) methods refer to a special class of forecasting methods.(R. Hyndman et al., 2008). There exists a whole plethora of methods that belong to the exponential smoothing class of methods. Their major property is that forecasts are weighted combinations of past observations, with more recent measurements being relatively more weighted than the older ones. The title "exponential smoothing" implies the fact that the weights decline exponentially as the measurements get older (R. J. Hyndman, Koehler, Snyder, & Grose, 2002). In general, we are dealing with three basic types of ES methods, i.e. the single ES (Brown's method), the double ES (Holt's method), and the triple ES (Holt-Winters method). The latter is suitable when we presume some evident trend and seasonality in the observed time series (R. J. Hyndman & Koehler, 2006). According to the empirical evidence,the basic Holt-Winters method has a tendency to make over-or-under forecasts, particularly for longer forecasting horizons(Gardner Jr & McKenzie, 1985, 1989; Tratar, Mojškerc, & Toman, 2016). For this reason, Gardner and McKenzie (1989) have applied a new parameter ϕ associated to the trend component that dampens the trend to a flat line, when the future becomes more distant. This way, we can obtain the Holt-Winters damped additive method (HWDA) in the following form with four parameters $\alpha, \beta, \gamma, \phi$ (R. J. Hyndman et al., 2002)

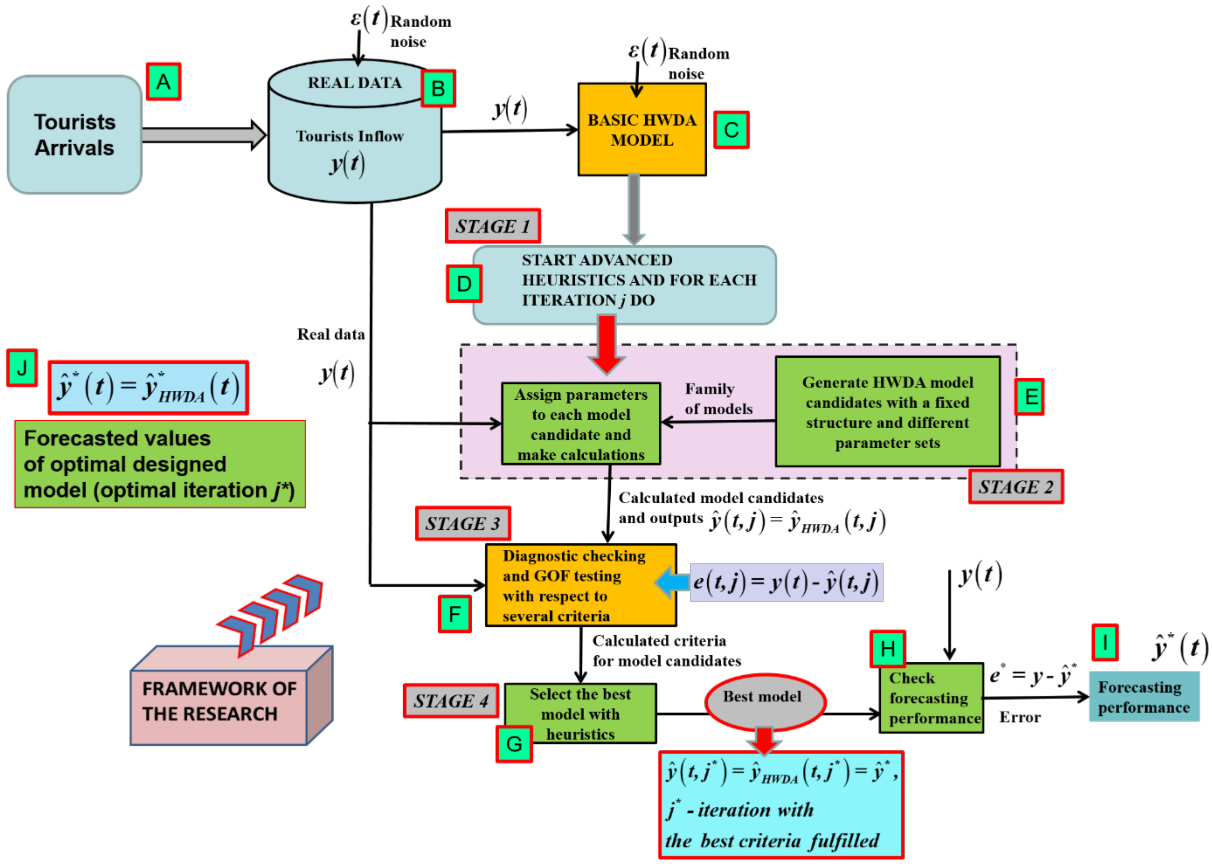


Figure 3: A conceptual modelling framework of the research and a conducted HWDA-based decision support system forecaster (DSSF)

$$
\begin{aligned}
&Level: && \ell(t)=\alpha\cdot\left(y(t)-s(t-m)\right)+(1-\alpha)\cdot\left[\ell(t-1)+\phi\cdot b(t-1)\right]\\
&Growth: && b(t)=\beta\cdot\left[\ell(t)-\ell(t-1)\right]+(1-\beta)\cdot\phi\cdot b(t-1)\\
:&Seasonality: && s(t)=\gamma\cdot\left(y(t)-l(t-1)-\phi\cdot b(t-1)\right)+(1-\gamma)\cdot s(t-m)\\
&Forecast: && \hat{y}\left(t+h|t\right)=\ell(t)+\phi_h\cdot b(t)+s\left(t-m+h_m^+\right),\\
&where: && \phi_h=\phi+\phi^2+...+\phi^h,\ h_m^+=\left[(h-1)\bmod m\right]+1,\ m-number\ of\ seasons|year\\
&h-time\ points\ of\ the\ future\ horizon
\end{aligned}
\tag{1}
$$

Conversely to the other exponential smoothing methods that can be linked with a linear Box-Jenkins methodology and state space approach, the HWDA is nonlinear in its nature(R. Hyndman et al., 2008).

**Brief discussion of the advanced heuristics conducted in the modeling mechanism**

Modeling mechanisms related to the HWDA model was extensively explained in some of the previously conducted studies(Dragan et al., 2017; Intihar et al., 2015; Intihar et al., 2017). However, the corresponding heuristics were in previously conducted researches implemented inside the wider structure of the so-called DFM-ARIMAX model (ARIMAX model, whose inputs were the dynamic factors from the dynamic factor analysis). Moreover, since then, many additional novelties have been engaged in this research. If we carefully observe figure 3 and the description of an HDWA model in the previous section, we can see that the HWDA model has a fixed structure with four parameters $\alpha,\beta,\gamma,\phi$ (see (1)). If we are generating a family of HWDA models by changing the sets of parameters $\alpha,\beta,\gamma,\phi \in \left[0+\varepsilon, \Delta j, 2\Delta j ..., 1-\varepsilon\right], \Delta j \to 0, \varepsilon \to 0$, we can obtain a huge group of model candidates.

The more in detail illustrated working mechanism of an applied heuristic for stages 3 and 4 from figure 3 is shown in figure 4. As can be seen from figure 4, three types of tests were first calculated at each iteration of the procedure for each model candidate. Stage 3 has covered the computation of different statistical tests, the residual-based tests (for model's error $e \to e_j\left(t\right) = y\left(t\right) - \hat{y}_j\left(t\right), j-th\ iteration$), and the future dynamics' tests (checking of the future out-of-sample (FOS) forecasts: $\left|\hat{y}_j\left(t+h\right)\right| \leq thresholds?, h-FOS\ horizon$). Also, the model's error of each candidate was carefully investigated to check whether it holds approximate properties of the normal white noise or no. Immediate exclusion of candidates with inadequate future responses, i.e.,$\left|\hat{y}_j\left(t+h\right)\right| >> thresholds$ was needed to avoid unusual or impossible future situations compared to the past trend's dynamics of $y\left(t\right)$. We have also applied so-called Dynamic Time Warping (DTW) giving a DTW value(Mitchell, 2012; Sueur, 2018) that have measured the "distance" between two signals $y\left(t\right), \hat{y}_j\left(t\right)$ by using the Kullback-Kleibler distance: $d\left[y, \hat{y}_j\right] = \sum_{t=1}^{N}\left[y\left(t\right) - \hat{y}_j\left(t\right)\right]\cdot\left[\log y\left(t\right) - \log \hat{y}_j\left(t\right)\right]$. The testing of DTW values for different candidates was essentially important since it has in a refined way determined how truly "far" among each other are the signals $y\left(t\right), \hat{y}_j\left(t\right)$ (citation). Let us emphasize that the calculations in stage 3, as well as a reducing procedure for excluding of inappropriate candidates in stage 4, were carried out by very sophisticated heuristics based on the sequence of carefully designed consecutive steps. This way, despite the significantly enormous amount of model candidates, the whole model selection procedure to find the best model candidate was executed in a reasonable computational time. A demand for simultaneously fulfilled all relevant tests in stage 4 was so strict that only a few candidates remained in the reduced set. In the final step, the best candidate was chosen according to the best %FIT, i.e. the bestfit: $\hat{y}_j\left(t\right)_{best} = \hat{y}\left(t, j^*\right) = \hat{y}_{HWDA}\left(t, j^*\right) = \hat{y}^*\ (j^*\text{ - }iteration\ with\ \ the\ best\ criteria\ \ fulfilled)$ of the model's output to the measured time series $y\left(t\right)$.

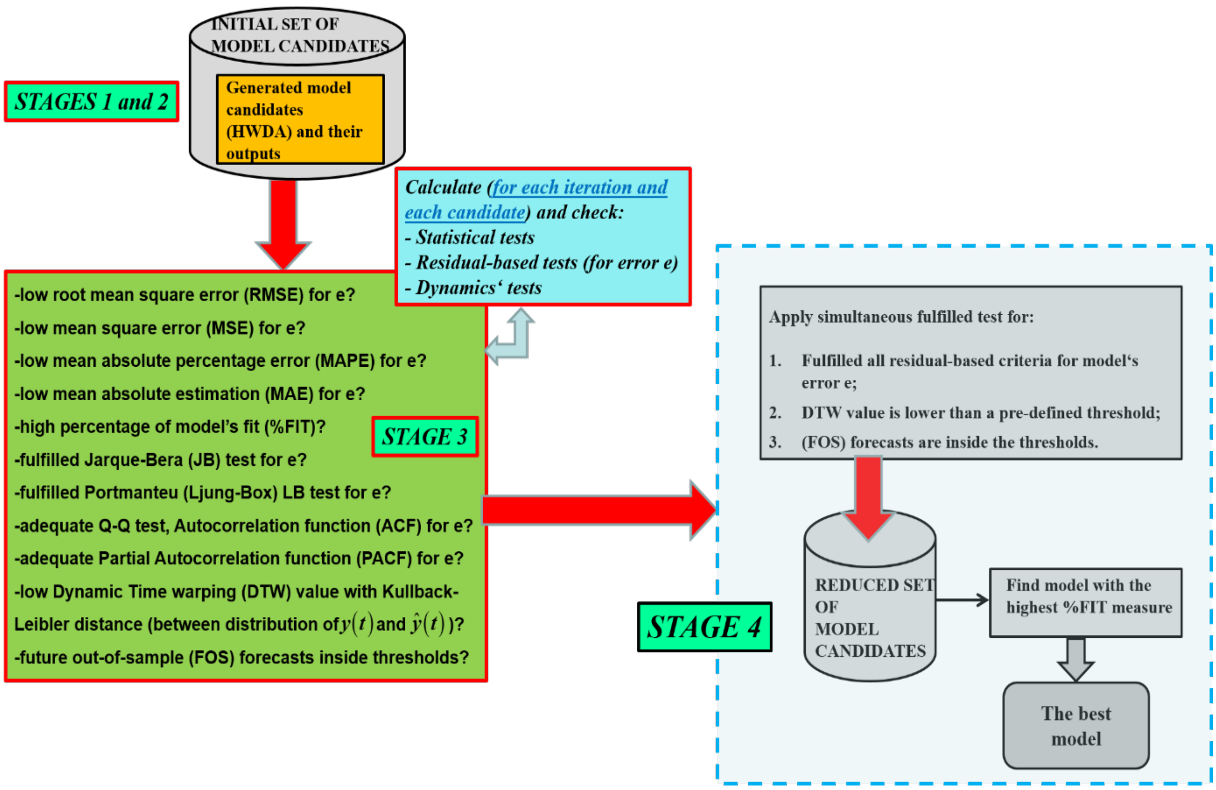


Figure 4: The more in detail illustrated working mechanism of an applied heuristic for stages 3 and 4 from figure 3.

Regarding all observed error-based and other criteria, of which some are not depicted in figure 4, the following set of expressions can be given for each iteration *j*(Bruce L. Bowerman, Richard O'Connell, & Koehler, 2005; Dragan, Kramberger, & Intihar, 2014; John E. Hanke & Wichern, 2013; Sueur, 2018):

$$MSE(j)=\frac{1}{n}\cdot\sum_{t=1}^{n}e^{2}(t,j),\qquad RMSE(j)=\sqrt{MSE(j)},\qquad MAE(j)=\frac{1}{n}\cdot\sum_{t=1}^{n}\left|e(t,j)\right|$$

$$MAPE(j)=\frac{1}{n}\cdot\sum_{t=1}^{n}\left|\frac{e(t,j)}{y(t)}\right|\cdot 100\qquad \max\_err(j)=\max\left|e(t,j)\right|$$

$$RMSE_{relative}(j)=\frac{RMSE(j)}{\max\left(y(t)\right)-\min\left(y(t)\right)}\qquad MAE_{relative}(j)=\frac{MAE(j)}{\max\left(y(t)\right)-\min\left(y(t)\right)}$$

$$\%FIT(j)=100\cdot\left[1-\frac{\left\|y(t)-\hat{y}(t,j)\right\|}{\left\|y(t)-mean\left(y(t)\right)\right\|}\right]$$

$$DTW\left[d(j)\right]=DTW\left\{d\left[y,\hat{y}_{j}\right]\right\}=DTW\left\{\sum_{t=1}^{N}\left[y(t)-\hat{y}_{j}(t)\right]\cdot\left[\log y(t)-\log\hat{y}_{j}(t)\right]\right\}$$

(2)

Here, *max_err* refers to the maximum absolute value of the $e(t,j)$, while $\Delta y = \max(y(t)) - \min(y(t)) = 81167 - 29647 = 51520$ (see figure 2) reflects the dynamic range of the $y(t)$. The interested reader can find the exact form of expressions for all other criteria (e.g. JB test, LB test, etc.) from figure 4 in the appropriate statistics based, time-series based, and econometrics literature.

## Practical numerical results

MATLAB, a technical computing environment, was deployed in order to calculate all the results. In order to extract the best model, The MATLAB environment was carried out in order to both generate and then identify the HWDA model candidates. Moreover, the Econometrics Toolbox, along with Machine Learning & Statistics Toolbox were considered to carry out the statistical testing and diagnostics of the model candidates. In order to merge all parts of the modelling process, MATLAB basic environment was considered.

### In-Sample Results for the best HWDA model

In this section, we discuss in-sample results for the best HWDA model, which means the results referring to the estimation and test interval. Figure 5 depicts the prediction results for the best HWDA model on those two intervals, as well as forecasts on the future out-of-sample (prediction) interval. In figure 5, the comparison between the observed time series $y(t)$ and the estimated forecasts $\hat{y}_j(t)_{best} = \hat{y}(t,j^*) = \hat{y}_{HWDA}(t,j^*)$ for the best model is provided. The separation between the "estimation interval" and the "test interval" is done in order to distinguish between the first 40 observations used to estimate the smoothing parameters $\alpha,\beta,\gamma,\phi$, and 16 observations used for testing the predictive power of the best HWDA model. As it turns out, the estimated values for the smoothing parameters of the best HWDA model (see 1) are:

$$\begin{aligned} \alpha^* &= \alpha(j^*) = 0.701 \\ \beta^* &= \beta(j^*) = 0.922 \\ \gamma^* &= \gamma(j^*) = 0.308 \\ \phi^* &= \phi(j^*) = 0.971 \end{aligned} \tag{3}$$

These parameter values were calculated at the “best” iteration $j^*$, where the following “best” criteria were simultaneously achieved (see figure 5):

$$
\begin{aligned}
&MSE\left(j^*\right)=\frac{1}{N}\cdot\sum_{t=1}^{N}e^2\left(t,j^*\right)=2.34\cdot10^6, \qquad RMSE\left(j^*\right)=\sqrt{MSE\left(j^*\right)}=1531.3,\\
&MAE\left(j^*\right)=\frac{1}{N}\cdot\sum_{t=1}^{N}\left|e\left(t,j^*\right)\right|=1324.7, \quad MAPE\left(j^*\right)=\frac{1}{N}\cdot\sum_{t=1}^{N}\left|\frac{e\left(t,j^*\right)}{y\left(t\right)}\right|\cdot100=2.8516\%\\
&\max\_err\left(j^*\right)=\max\left|e\left(t,j^*\right)\right|=2671.9\\
&RMSE_{relative}\left(j^*\right)=\frac{RMSE\left(j^*\right)}{51520}=0.029722\\
&MAE_{relative}\left(j^*\right)=\frac{MAE\left(j^*\right)}{51520}=0.025711\\
&\%FIT\left(j^*\right)=100\cdot\left[1-\frac{\left\|y\left(t\right)-\hat{y}\left(t,j^*\right)\right\|}{\left\|y\left(t\right)-mean\left(y\left(t\right)\right)\right\|}\right]=78.66\%\\
&DTW\left[d\left(j^*\right)\right]=DTW\left\{d\left[y,\hat{y}_{j^*}\right]\right\}=DTW\left\{\sum_{t=1}^{N}\left[y\left(t\right)-\hat{y}_{j^*}\left(t\right)\right]\cdot\left[\log y\left(t\right)-\log\hat{y}_{j^*}\left(t\right)\right]\right\}=
\end{aligned}
\qquad 4)
$$

The results shown in (4) implicate that a percent of fit 78.66% to the real data was fairly good (c.f. figure 5). Also, the output of the best model never shown some more serious deviations from the real data, since $MAPE\left(j^*\right)=2.8516\%$ was quite small, and so were $RMSE_{relative}\left(j^*\right)=0.029722$, and $MAE_{relative}\left(j^*\right)=0.025711$. Even more importantly, from the engineering practical point of view, a maximum error has stayed within the 5% of the maximum dynamic range of the $y\left(t\right)$ (i.e., $\max\_err\left(j^*\right)\big/\Delta y=2671.9\big/51520=0.051$). Furthermore, as it turned out, all fulfilled diagnostic error-based tests (e.g., JB test, LB test, Q-Q test, ACF and PACF test) has shown that the best HWDA model's error $e\left(t,j^*\right)$approximately follows the required properties of the normal white noise. To conclude, our final HWDA model provides a relatively good fit to the real US tourists' inflow data, although it does not have such sophisticated working mechanism as some more advanced time-series models (e.g. Box-Jenkins family of models(Box, Jenkins, Reinsel, & Ljung, 2015). Furthermore, our model does not suffer from any significant overfitting and inadmissible oscillatory behavior at some specific time points as for example the other classical exponential smoothing models, including the basic version of an HWDA model. It is true that there are some more sophisticated details of the real data dynamics detected that are not covered by ourmodel. We believe that two major reasons are responsible for this fact:

- Firstly, the observed time series seems to contain a quite complex nature of its dynamics, which could not be captured with our model possessing a relatively simple structure. The stochastic mechanism that generates the time series most likely contains certain significant nonlinearities, while there might also be some other important external effects that have not been modeled. Although such phenomena remain un-modeled, our model still offers a useful tool for forecasting of the major variations in the time series dynamics.
- Secondly, the compendium of all required criteria for the selection of our final model was extremely rigorous, particularly concerning the requirements about model's error to be a white noise, so the best fit to the data was not the only criterion. Nevertheless, despite

this, the final model provides a satisfactorily well fit, particularly concerning the main trend's movements.

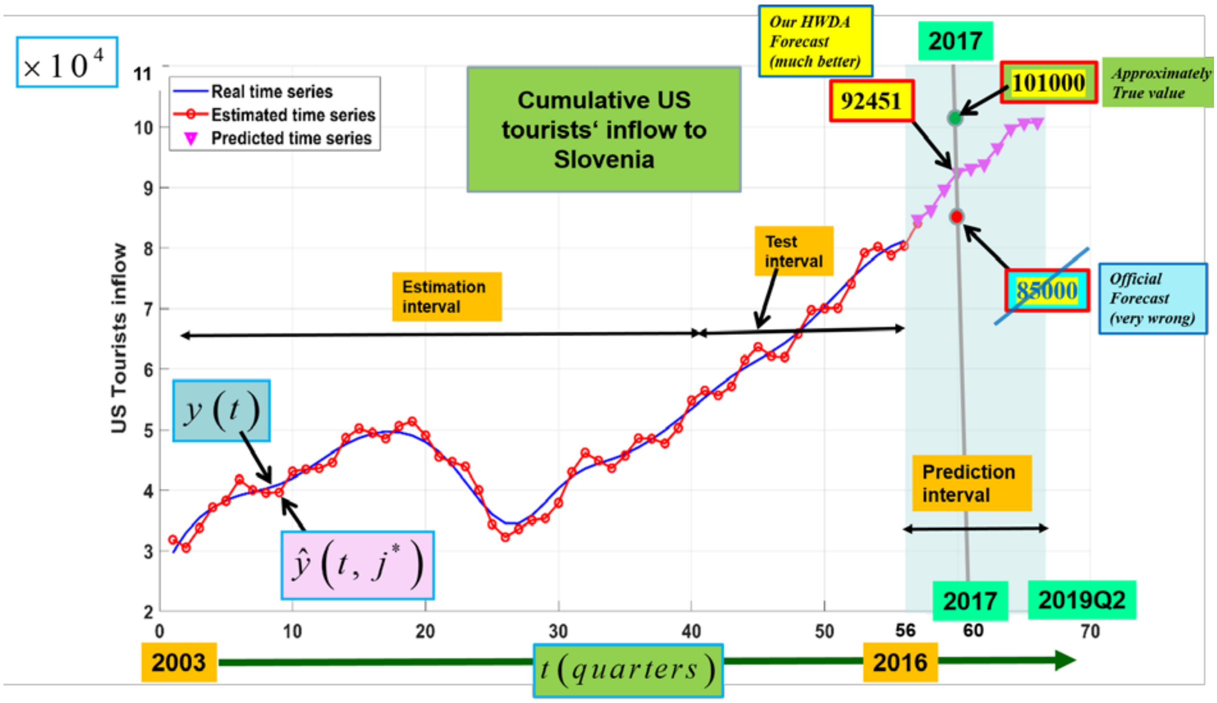


Figure 5 - The prediction results for the best HWDA model (estimation, test, and prediction interval).

## Out-of-Sample Results for the best HWDA model

Figure 5 also shows a predictive performance of our model on the future prediction interval from the first quarter of 2017 to the end of second quarter of 2019, i.e. forecasts $\hat{y}_{j^*}(N+h), N=56, h=1,2,...,10\ quarters$ for ten quarters ahead (from the end of 2016). The more precise details of this predictive behavior are shown in figure 6, where the prediction results for the best HWDA model are enlarged focusing exclusively on a prediction interval. As we can see from figures 5 and 6, our model gives quarterly forecasts {84735, 86277, 89642, 92451} tourists for the year 2017, quarterly forecasts {93133, 93810, 96544, 99629} tourists for the year 2018, and two forecasts $\{1.0062 \cdot 10^5, 1.0076 \cdot 10^5\}$ tourists for the first two quarters of the year 2019. If we are now focusing on the (end of the) year 2017 at first (c.f. figure 5), we can clearly see that our model has predicted the value 92451, while the official institutions have predicted the value around 85.000. Since the estimated true (real) value was on average about 101.000 tourists, obviously our model has significantly outperformed the official forecasts. Thus, our model has much more precisely identified the probable positive influence of the reputation of Melanie Trump that she has had on an enlarged inflow of US tourists than it was predicted by Slovenian official institutions.However, it has in rough terms predicted the true value with a time delay of about one year (c.f. the last two forecasts $\{1.0062 \cdot 10^5, 1.0076 \cdot 10^5\}$).Furthermore, the role of the possible future new crisis cannot be ignored and there might be a declining trend as well. Namely,surprisingly, the scope of the predicted trend seems to decline if looking at the last three forecasts $\{99629, 1.0062 \cdot 10^5, 1.0076 \cdot 10^5\}$. Thus, the implications of the forecasts for the forthcoming years till the end of the year 2019 or later can seriously worry us. Maybe we can even conclude that there exists certain possibility that some substantial (global?) negative macroeconomic behavior will happen again in the near future, perhaps in the US and/or the EU, or worse, worldwide. These fears can also be detectedfrom several other works (such as(Hsieh, 2017; Powell, 2017; Rahman, Muridan, & Najib, 2015), where scholars emphasize scares about new approaching dangerous economic events. Namely, in a couple of studies, a new economic stagnation or recession is forecasted somewhere in the period 2019-2020(Buiter et al., 2015; Rahman et al., 2015), while some academics even warn about an outbreak of the new global economic crisis(Hsieh, 2017). Their expectations are based on various analyses such as for example “what if” scenario playing analysis(Buiter et al., 2015; Powell, 2017), where China’s declining economic performance represents the biggest concern. The latter is even amplified after the eruption of serious economic war that was initiated by the USA recently against some other countries, where China seems to be a primary target(Rahman et al., 2015).

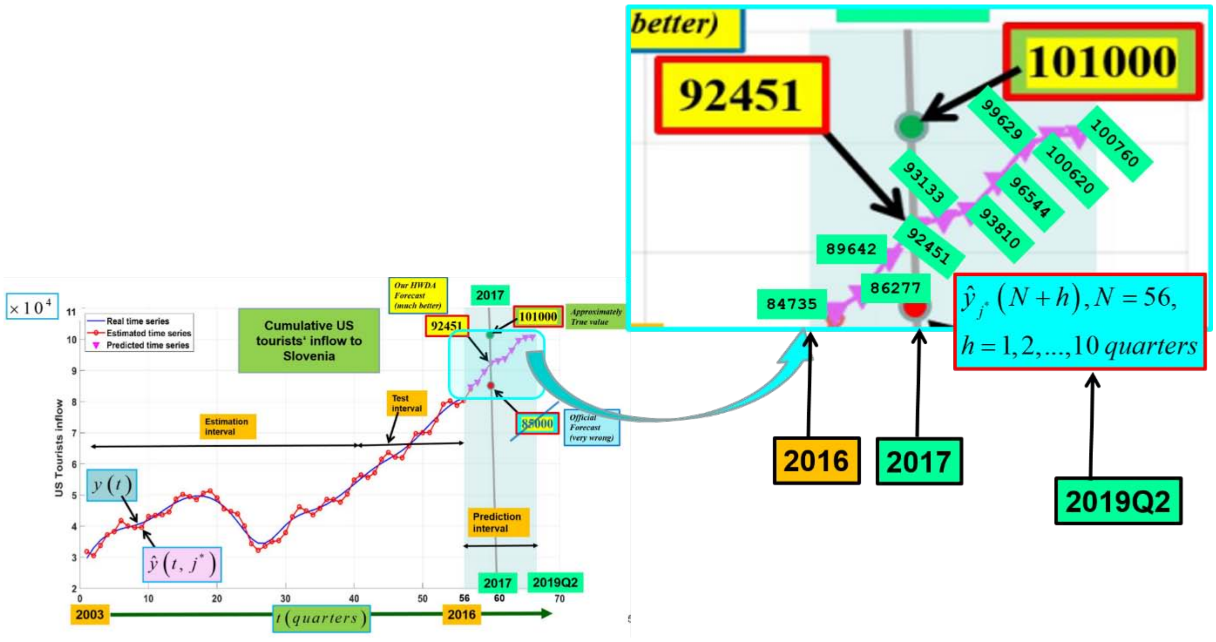


Figure 6 - The prediction results for the best HWDA model (enlarged details of the prediction interval).

## Main findings and implications of the study

Based on the results of this study, we can express some main findings and implications. The fact is that we have designed a modified working HWDA model driven by additional specially designed heuristics that helped to overcome the deficiencies of relatively simple exponential smoothing structure. Our model has significantly outperformed official forecasts for the year 2017, although they are usually based on much more complex models. We might have expected that this cannot be possible. Namely, at times of the last economic crisis, the global nature of the time series has become much more complex with an amplified volatility(Xie, Wang, Zhao, & Lai, 2013),. Consequently, since then, more sophisticated forecasting models are needed to incorporate a bigger complexity of the time series, as models with a simpler structure are not good enough anymore. Thus, we cannot imagine the reason why the official models have completely failed. Maybe there was some kind of misinterpretation of results or misuse of the models? Nevertheless, our model has managed to capture a 19.8% increase in the tourists' inflow in 2017 more precisely. We are aware that we have suggested only indirect assumptions that such large increase has happened primarily due to an important influence of Melanie Trump on US citizens. But whatever may be the reason , the contributions in this paper related to the methodological novelties of the designed model with a fairly good forecasting capability cannot be neglected. Particularly for the reason that we have observed only the targeted inflow time series without screening other time series, e.g. those reflecting the US economy (macroeconomic indicators), as the Box-Jenkins ARIMAX and other similar models are capable of(Box et al., 2015; Dragan et al., 2017; Intihar et al., 2015; Intihar et al., 2017).  In the future work, we intend to somehow incorporate more concrete quantification of Melanie's influence on the US tourists' behavior, maybe by integrating of additional time series reflecting the time-dependent percentage level of her influence.Also, we are planning to engage the US macroeconomic indicators time series by means of ARIMAX and other more sophisticated models that can involve the exogenous inputs. By simultaneously using additional variables in the model and adopting of similar heuristics as were presented in this paper, we expect to achieve even more adequate predictive behavior.

## Conclusion

In the paper, we have developed a forecasting module to predict the cumulative inflow of the US tourists to Slovenia. The modeling framework was designed in such a way that the classical Holt-Winters Damped model was upgraded with special heuristics to improve the forecasts of its basic exponential smoothing model's counterpart. In the modeling procedure, a sequence of carefully selected and categorized rigor criteria was adopted to find the best model among the large group of model candidates. The derived best model has achieved fairly accurate prediction results, particularly regarding the main trend's movements. As it turned out for In-Sample interval, it achieved even a 78.66% fit to the real-time series data, while the largest model's error did not exceed the 5% of the dynamic range of the observed time series. Regarding the Out-of-Sample Interval, our model has predicted 92451tourists for the end of 2017, while the official forecasts have achieved much worse results, i.e. 85000 tourists. Thus, our model has significantly outperformed the official forecasts and have got much closer to the real value of about 101000 tourists.

Besides the methodological issues, the particular emphasis was dedicated to the discussion about the American tourists, and presumably the important role Melanie Trump has had regarding an inflow's increase of even 19.8% of the tourists in just one year. The study has also debated about a growing role that the US tourists have within the scope of the Slovenian tourism. The model can used to predict the inflow and necessary preparation alongside supply chain which can impact the Slovenian economy positively.

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