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Advanced Computational Approaches for Predicting Tourist Arrivals: the Case of Charter Air-Travel

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1. Introduction

Tourism is one of the major industries profiting various sectors of the economy, such as the transportation, accommodation, entertainment and so on. According to the World Tourism Organization (2008), international tourism grew at around 5% during the first four months of the year 2008. Fastest growth was observed in the Middle East, North-East and South Asia, and Central and South America. Even though, uncertainty over the global economic situation is affecting consumer confidence and could hurt tourism demand, for 2008 as a whole, UNWTO maintains a cautiously positive forecast. Moreover, international trends show that tourists are becoming more discerning in their choice of destinations and, therefore, becoming less predictable and more spontaneous in terms of their consumption patterns (Burger et al. 2001).

Air transportation is probably the most important mode for international travel and leisure. A typical characteristic of air tourism in Europe is the extensive use of non-scheduled/charter flights and the existence of low-cost carriers in the leisure travel market, that account for 8% of passengers and 3% or revenues in the aviation industry (Dresner 2006). Non-scheduled demand is typical in Mediterranean countries where connections are essentially touristic and characterized by non-scheduled services.

In this type of air travel, the ability to accurately predict tourist arrivals is of importance in the successful management and operation of the airport facilities, as well as the adjacent transportation network. Yet, the literature has little to offer in modeling demand stemming from non-scheduled flights, as such series exhibit seasonality, intense variability and inherent unpredictability.

This paper develops and tests advanced computational approaches in order to predict non-scheduled/charter international tourist demand. The computational challenges that may arise in such a problem are twofold: first, to treat seasonal and stochastic characteristics of non-scheduled tourist demand, and, second, to develop models that consider past tourist demand characterists. This paper focuses on developing ARFIMA models that consider both non-stationarity and long-term memory effects in the auto-regressive process and temporal neural networks with advance genetically optimized characteristics that treat both nonlinearity and non-stationarity.

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2. Motivators and prediction of non-scheduled air-travel demand

A major motivator for the emergence and growth of non-scheduled air travel has been the low-cost carriers (LCC) and their prevalence in global aviation. From the period after 9/11 period that caused a decreasing trend in the airline travel demand, global aviation and travel demand, particularly in Europe and the Mediterranean Region LCCs offered an attractive alternative for price-sensitive clients during the tight economic times. Whereas traditional airlines have concentrated on large cities and major airports, low-cost airlines have turned to under-utilized airports at some distance from the main population centers embracing a business model much different in its customer base, air network, and provision of services by focusing on the more cost-sensitive leisure travel and working in a way that traditional airlines cannot (Barrett 2000).

LCC market providing point-to-point (rather than hub-based) service owes its growth not only to low-cost service, but also to the ability to focus on customer segments not emphasized by larger carriers; European low-cost leaders Ryanair and EasyJet, for instance, focus on providing air services for travelers seeking to visit friends and relatives. By focusing on these groups, LCC have demonstrated an ability to grow the overall passenger market, particularly on routes with strong tourist appeal (Dennis 2004).

Literature emphasizes the role of LCC in the development of multiple airport systems and the emergence of secondary airports (Bonnefoy & Hansman 2004). LCC appeal to secondary airport is in that they provide reduced congestion and lower cost, while still providing access to key population centers.

The shift to secondary airports, along with the reduced gap between charter flights and "no-frills" / budget flights have significant impact on the volatility of traffic for the entire airport system; literature indicates that periods of high volatility and uncertainty in demand exist during the developmental phases of secondary airports that can last up to 20 year after the opening of such facilities (de Neufville, 1995).

Regarding leisure airline traffic, the ability to provide custom-made services to tourists has been shown to be critical. Tourists increasingly expect to experience a personalized and close to their life-style service (Graham 2006). A characteristic example of charter airports is Greece where approximately 80% of the total tourist arrivals every year are accommodated by air transportation. The importance of non-scheduled international arrivals is depicted in Figure 1 that depicts annual evolution of total arrivals for 1989 and 2006 period, along with the evolution of non-scheduled and scheduled international arrivals. As can be observed, for the period after 2001, nearly 70% of air-travel arrivals concern international flights and 62% of the international arrivals are accommodated by non-scheduled flights.

From a methodological standpoint, although the prediction of tourist demand has been extensively treated (a review of approaches can be found in Law et al. 2007, Song & Li 2008) little has been done towards the prediction of non-scheduled arrivals. Summarizing the methodologies implemented to date for to tourist demand prediction, both econometrics and other computational methods have been applied and compared. Law et al. (2007) state that, comparing classical econometric prediction techniques that are highly exploited but with marginal improvement to modeling touristic demand, the incorporation of data mining techniques has led to some "ground breaking outcomes".

Moreover, several papers on tourism forecasting problems report neural networks as having better performance than classical statistical techniques, such as ARIMA models, exponential smoothing and so on (Law and Au 1997, Law 2000, Burger et al. 2001, Kim et al. 2003, Cho 2003). These studies compare advanced computational approaches that have enhanced capabilities in modeling nonlinear characteristics (for example neural networks) with simple linear and stationary approaches such as the ARIMA models. Quite recently, hybrid ARIMA and simple static neural networks, as well as mixtures of static neural network models have also been found to perform better that classical time-series approaches (Aslanargun et al. 2007).

Regarding modeling of non-scheduled demand, previous work has applied regression models to predict charter international arrivals to major Greek airports and has highlighted that although there is uncertainty and variability in their evolution, historical data can be used to provide good predictions (Karlaftis and Papastavrou 1998). However, no previous work has been conducted in the direction of predicting non-scheduled international arrivals in secondary airports with intense seasonal characteristics.

3. Computational approaches

3.1 Fractionally integrated autoregressive moving average processes

Commonly applied AR(I)MA models are able to describe processes that are covariance stationary *I(0)* or non-stationary through differencing *I(1)*. It has been observed that the erroneous consideration of having a unit root leads to models with inflated estimates of the moving average component (Box-Steffensmeier and Smith, 1998). In order to account for long memory processes Fractional integration is introduced to autoregressive processes to account for the processes that are neither I(0) or I(1) in the form of the differentiation operator (Baillie 1999):

$$(1-L)^{d} = \left\{1 - dL - d(d-1)\frac{L^2}{2!} - d(d-1)\frac{L^3}{3!} - \dots\right\} \tag{1}$$

In the conditional mean, the fractionally integrated autoregressive moving average process of orders p and q – ARFIMA(p,d_m,q) introduced by Granger and Joyeux (1980) and Hosking (1981) is represented by the following equation:

$$(1-L)^{d_m}\Psi(L)(y_t-\mu) = \Theta(L)\varepsilon_t \tag{2}$$

$$\varepsilon_t = \sigma_t z_t \quad z_t \sim N(0,1) \tag{3}$$

where μ is the unconditional mean of y_t, $\Psi(L) = 1 - \psi_1 L - \psi_2 L^2 - \dots - \psi_p L^p$ and $\Theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \dots + \theta_q L^q$ are the AR and MA polynomials having all roots outside the unit cycle, while innovations ε_t are i.i.d distributed with σ_t^2 being the conditional variance and a positive, time-varying, and measurable function with respect to the information set, which is available at time t-1 (Baillie et al. 2002). The differentiation parameter (d_m) is associated with the following statistical properties of a (time) series (Hosking 1981, Odaki 1993):

- For every region where $d_m < 1/2$, then y_t is stationary,
- When $-1 < d_m < -1/2$, the series exhibits invertibility,

- When $-\frac{1}{2} \le d_m < 0$, the stationary process y_t is antipersistent,[1]
- When $d_m = 0$, the stationary process y_t has short memory and is mean reverting,
- When $0 < d_m \le \frac{1}{2}$, y_t is fractionally integrated and exhibits long memory,
- When $\frac{1}{2} < d_m < 1$, the process y_t is mean-reverting, but the stationarity property cannot be verified and,
- When $d_m = 1$, y_t is a unit root process.

Fractionally integrated processes are significant in dealing with two issues: first, data is being modeled more precisely, as the knife-edged restriction of an *I(0)* or *I(1)* process is avoided and both long term persistence and, second, short-term correlation structure of a series can be modeled (Hosking 1981).

3.2 Temporal genetically optimized neural networks

Temporal Neural Networks can be considered as an extension of the static Multi-layer Perceptrons (MLP) that has been extensively applied to touristic demand prediction. They differ from the commonly used MLPs in that they incorporate memory mechanisms in their structure that can be limited to the input layer or extend to the entire network. The memory acts as a time-series reconstruction module with the aim to embed the scalar series $S(t)$ to a vector $\mathbf{S}(t) = \{S(t-\tau), ..., S(t-(m-1)\tau)\}$ in an m-dimensional vector space known as Phase Space, where τ is the time delay of and m is the dimension.

We implement a neural network called time-lagged neural networks (TLNN) with a complex Gamma memory mechanism in the input layer and the hidden layer (de Vries and Principe 1992). Moreover, in order to develop a fully non-stationary model we set the network to predict under the iterative consideration: Given the time-series of a variable a single step ahead model is constructed to produce a prediction $\hat{S}(t)$ at time t that is then fed backwards to the network and is used as new input data in order to produce the next step $\hat{S}(t+1)$ prediction at t+1:

$$\hat{S}(t+1) = \left\{\hat{S}(t), S(t), S(t-1)...\right\} \tag{4}$$

The training of TLNN under iterative consideration feeds back the prediction at time t+1 and utilizes it as an input for the generation of next prediction step t+2. The training in the specific iterative neural network model is conducted via the temporal back-propagation algorithm known as Back-propagation to time (BPTT) (Webros 1990); all weights are duplicated spatially for an arbitrary number of time steps τ; as such, each node that sends activation to the next has τ number of copies as well. For a training cycle n, the weight update is given by the following equation (Haykin 1999):

$$\mathbf{w}_{ji}(n+1) = \mathbf{w}_{ji}(n) + \eta\delta_j(n)\mathbf{x}_i(n) \tag{5}$$

where, $\mathbf{w}_{ji}(n+1)$ and $\mathbf{w}_{ji}(n)$ are the weights of the i-th synapse of the neuron j at training cycle n+1 and n respectively, η is the learning rate, $\mathbf{x}i(n)$ (i=1,2,…n) is the input vector and $\delta_j(n)$ is given by:

[1] Anti-persistence is a property of an ACF that exhibits slow decay, but the original series are not characterized by the long memory property; rather, the autocorrelations (in the ACF) alternate in signs.

$$\delta_j(n) = \begin{cases} e_j(n)\phi'(\upsilon_j(n)), \ j \text{ neuron in the output layer} \\ \phi'(\upsilon_j(n))\sum_{r\in A}\mathbf{\Delta}_r^{\mathrm{T}}(n)\mathbf{w}_{rj}, \ j \text{ neuron in the hidden layer} \end{cases} \tag{6}$$

where, $e_j(n)$ is the network's error, ϕ is the nonlinear activation function. Moreover, if A is a set of all neurons whose inputs are fed by the j neuron in the hidden layer is a forward manner, then $\upsilon_j(n) = \sum_{i=1}^{m} \mathbf{w}_{ji}\mathbf{x}_i(n) + b_j$ is the induced local field of neuron r that belongs to the A and $\mathbf{\Delta}_r^{\mathrm{T}}(n) = [\delta_r(n), \delta_r(n+1), ..., \delta_r(n+m)]^T$ is the local gradient vector.

The iterative neural network approach introduced provides a fully non-stationary and nonlinear environment for treating time series problems. However, regardless of being static or dynamic, neural networks suffer from the lack of an automatic manner to self-optimization mainly with respect to their structure (number of hidden units) and learning parameters. Recently, genetic algorithms have gained significant interest as they can be integrated to the neural network training to search for the optimal architecture without outside interference, thus eliminating the tedious trial and error work of manually finding an optimal network. Genetic algorithms are based on three distinct operations: selection, cross-over and mutation (Mitchell 1998); these operations run sequentially in order for a fitness criterion (in the specific case the minimization of the cross-validation error) to converge. Details for the specific optimization approach can be found in Vlahogianni et al. (2005).

4. Case study: greek island airports

We focus on the influence of Non-Scheduled International (NSI) arrivals to the secondary airports and a prediction of their temporal evolution. Three case studies from Greek island secondary airports are evaluated: Heraklion (Crete), Kefalonia and Rhodes. All three cases exhibit significant demand during the peak summer period; however, these case studies differ in the overall demand levels, as well as their seasonal arrival characteristics. As can be observed in Figure 2, where the evolution of arrivals (passengers per year) and flights per year and per airport for the period of 1999-2006 is depicted, Kerkyra is characterized by low volumes, whereas Heraklion and Rhodes exhibit high demand during the year. The difference is in the volume of the NSI arrivals; as can be seen in Figure 3, where monthly arrival variation is depicted for all airports tested, Kerkyra and Rhodes have significantly more acute monthly variation, reaching extremely low NSI demand during the off-peak periods.

The analysis to follow will, first, focus on revealing long-term memory features in the manner NSI arrivals evolve in time and, second, search for similarities or differences in the dynamics of NSI arrivals across the airports selected with different demand distributions. Third, advanced neural network predictors will be developed that will apply the iterative approach in order to learn to approximate the dynamics of NSI arrivals; models will be developed for all the three airports and compared to each other.

4.1 Fractional dynamics in NSI arrivals

Several ARFIMA models were fitted to the available time –series in order to test whether there exist fractional dynamics in the evolution of non-scheduled international arrivals. The models are fitted to both three study airport, as well as to the pooled data, as well as data from the peak (months from May to September). Moreover, in the same datasets *I(1)* ARIMA processes are also fitted in order to compare the estimated autoregressive and moving average parameters from ARFIMA and ARIMA models. The choice of the best fitting model is done via Akaike's ($-2\frac{LogL}{n}+2\frac{k}{n}$, where logL is the log likelihood value, n is the number of observations and k the number of estimated parameters) and Schwartz's ($-2\frac{LogL}{n}+2\frac{\log k}{n}$) criteria. Furthermore, the Jarque-Bera test (JB test) goodness-of-fit test measuring the of departure from normality, $Q^2(i)$ statistics that indicate the possible existence of serial correlation in the standardized residuals, as well as the LM ARCH statistics that test the null hypothesis of no ARCH effect in the series tested are also presented; the above test will provide information of the quality of the ARFIMA models developed.

Results for the best fitted ARFIMA models are shown in Tables 1 to 3(parameter estimates depicted in the tables are significantly different from zero at the 1% significance level). Interestingly, for all case studies the fractional dynamics are similar. NSI arrivals in all airports tested are found to be best described by a fractionally integrated ARMA process with p=1 (autoregressive term) and q=1 (moving average term). Parameter d is found to vary between 0.24 and 0.46 indicating that NSI arrivals regardless of study period (peak or off-peak), as well as of the airport tested, exhibit long-term memory (for more details on the memory properties see Washington et al. 2003). We observe that the ARFIMA modeling results exhibit an apparent "inability" to approximate the monthly variability of NSI arrivals, particularly at low demand levels (off-peak months) (Figure 4).

4.2 Iterative predictions of NSI arrivals using temporal neural networks

For iterative predictions, the specifications of the TLNN are shown in Table 4. As can be observed, the depth of the Gamma memory of the TLNN (parameters τ and m) are genetically optimized during the learning, along with the number of hidden units h in the hidden layer and the learning rate η and momentum μ of back-propagation. The available data is separated into three subsets in order to test the training (cross-validation) and then test the performance of the network (testing). Moreover, the genetic algorithm optimization specifications are also depicted on Table 4; a roulette selection method is applied in order to select the parents according to their fitness. Moreover, the probabilities of cross-over and mutation are to be equal to 0.9 and 0.09 respectively, following literature that indicates that crossover should usually be selected at high values and mutation should approximate the inverse of the number of chromosomes (population) and be much lower than the crossover probability to avoid permutation (Gen and Cheng, 2000).

Results concerning the optimization of the look-back time window, or else the depth of the memory of the iterative temporal neural networks, are shown in Table 5. Interestingly, the required data to produce accurate predictions – as determined by the genetic optimization of the parameters τ and m during learning – differ between Heraklion airport and the rest of the cases examined. The recurrence of the dynamics in the Heraklion case is every 6 months, whereas NSI arrivals of Kerkyra and Rhodes are affected by data from up to 4 months in the past.

Results of the predictions (test set) using TLNN are seen in Table 6; predictions for the same period using ARFIMA (averaged for the three airports) are also illustrated. As can be observed, the TLNN has, overall, better accuracy that is evident both in the high and low demand periods in all three airport cases examined. The averaged behavior of the ARFIMA and TLNN models developed with respect to the actual and predicted NSI arrivals is graphically represented in Figure 5. Interestingly, the accuracy of predictions seems to decrease significantly in the case of low demand time periods, such as months between November and March, where touristic arrivals to Greek islands are, in general, significantly lower than the ones during summer months. The decreased accuracy in the case of Kerkyra indicates the existence of significant stochasticity in the manner in which arrivals evolve in low demand and off-peak period cases.

5. Discussion and conclusions

A large portion of tourist demand is conducted by air. Several air links can have intrinsic characteristics concerning the touristic demand evolution with strong non-stationary and seasonal characteristics. In this paper we implemented recent data mining techniques to model tourist demand and developed two advanced models of time-series prediction: a fractionally integrated autoregressive moving average model (ARFIMA) and a temporal genetically optimized iterative neural networks. These models originate from different methodological backgrounds and aim to evaluate different statistical properties of tourist demand (such as the existence of long-term memory, the parameters of memory depth for predictions and so on). To evaluate the proposed methodologies, three cases studies were examined that encompass three secondary airport located in the Greek Islands which exhibit different yearly and monthly demand distributions.

In terms of prediction accuracy, the advanced form of temporal neural networks implemented seems to outperform the ARFIMA model. This applies to both high and low tourist demand periods. In terms of the knowledge acquired by the modeling, both approaches revealed very interesting results; the fractional dynamics observed in both the pooled data and the peak demand period, show that the tourist arrivals are not always stationary or best described as most frequently - assumed - by ARIMA models. The fractionally integrated processes fitted to the available data showed that all case studies examined have similar fractional dynamics and exhibit long term memory. This finding has significant implications to the process of modeling NSI arrivals, as it suggests the persistence of the effect of several socio-economic issues to the evolution of NSI arrivals.

Moreover, the iterative approach to predicting NSI arrivals showed significant improvement to the prediction accuracy. The advanced genetic optimization implemented with regards to the look-back time window of the TLNN shows that the past could be utilized to predict the evolution of tourist demand. Nevertheless, the differences in the memory depth of the three TLNN models developed to approximate the dynamics of NSI arrivals in the three airports indicates the stochasticity of the temporal evolution of NSI arrivals during periods of low volume that significantly affect the accuracy of predictions.

Finally, lack of prediction accuracy during transitional conditions reveals that, as expected, the demand evolution can have multiple causal dimensions that need to be considered in an effective methodological framework that could integrate both the temporal and causal/relational characteristics of other possible influential variables in the prediction process. Our ongoing work focuses on extending the present methodological framework to iterative neural network prediction that incorporates other socio-economic data to develop influential relationships and evaluate whether they can improve predictability during periods of stochasticity in tourist demand.

6. References

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		Pooled	Peak Period
		p=1,*q*=1	*p*=1,*q*=1
Degree of differentiation	d_m	0.24	0.46
AR polynomial coefficients	ψ_1	0.66	0.02
	ψ_2	-	-
MA polynomial coefficients	θ_1	0.52	0.55
	θ_2	-	-
	θ_3		-
	θ_4		-
	θ_5		-
Log-likelihood		-2622.36	-1079.26
JB Test Null: normality		2.02	1.42
$Q^2(7)$ Null: serial independence		136.25**	66.18**
LM ARCH (1) Null: no ARCH effect		1.41	1.32

* rejection at 5% significance level

** rejection at 1% significance level

Table 1. Estimation Results for the ARFIMA(p,d_m,q) models for the Heraklion airport.

		Pooled	Peak Period
		p=1,*q*=1	*p*=1,*q*=1
Degree of differentiation	d_m	0.15	0.31
AR polynomial coefficients	ψ_1	0.66	0.05
	ψ_2	-	-
MA polynomial coefficients	θ_1	0.35	0.48
	θ_2	-	-
	θ_3		-
	θ_4		-
	θ_5		-
Log-likelihood		-2588.14	-1002.80
JB Test Null: normality		4.43	1.24
$Q^2(7)$ Null: serial independence		145.25**	64.54**
LM ARCH (1) Null: no ARCH effect		1.65	0.03

* rejection at 5% significance level

** rejection at 1% significance level

Table 2. Estimation Results for the ARFIMA(p,d_m,q) models for the Kerkyra airport.

		Pooled	Peak Period
		p=1,q=1	p=1,q=1
Degree of differentiation	d_m	0.34	0.37
AR polynomial coefficients	ψ_1	0.67	0.05
	ψ_2	-	-
MA polynomial coefficients	θ_1	0.43	0.58
	θ_2	-	-
	θ_3		-
	θ_4		-
	θ_5		-
Log-likelihood		-2689.31	-1017.48
JB Test Null: normality		3.48	2.48
$Q^2(7)$ Null: serial independence		122.52**	75.67**
LM ARCH (2) Null: no ARCH effect		0.82	0.10

* rejection at 5% significance level
** rejection at 1% significance level

Table 3. Estimation Results for the ARFIMA(p,d_m,q) models for Rhodes airport.

		Specifications
DATA		TR–CV–TE *: 60%-20%-20%
Structure		Input layer: Gamma memory (genetically optimized memory depth) 1 hidden layer (genetically optimized number of hidden units h)
Learning		Back-propagation
Genetic algorithm optimization	Chromosome	$h \in [5,15]$, $\gamma \in [0.01 - 0.1]$, $\mu \in [0.5 - 0.9]$, $\tau \in [1,5]$, $m \in [1,12]$ **
	Fitness function	Mean square error (cross-validation set)
	Selection	Roulette
	Cross-over	Two point (p=0.9)
	Mutation	Probability p=0.09

* *Training - Cross-validation - Testing*
** *h: neurons in hidden layer, γ: learning rate, μ: momentum, τ: time delay, m:dimension*

Table 4. Data and neural network specifications for iterative short-term prediction.

	Pooled NSI Arrivals	
	τ	m
Heraklion	1	6
Kerkyra	1	4
Rhodes	1	4

Table 5. Estimates of the depth of the Gamma memory (parameters τ and m) of the genetically-optimized TLNNs for the three cases.

	Pooled Data	Peak Demand Period
GA-TLNN*		
Heraklion	17%	2.8
Kerkyra	26%	3.4
Rhodes	18%	3.2
ARFIMA *(average over cases tested)*	37%	8.2

**genetically optimized TLNN*

Table 6. Mean Absolute Percent Error of predictions using ARFIMA and genetically optimized TLNN.

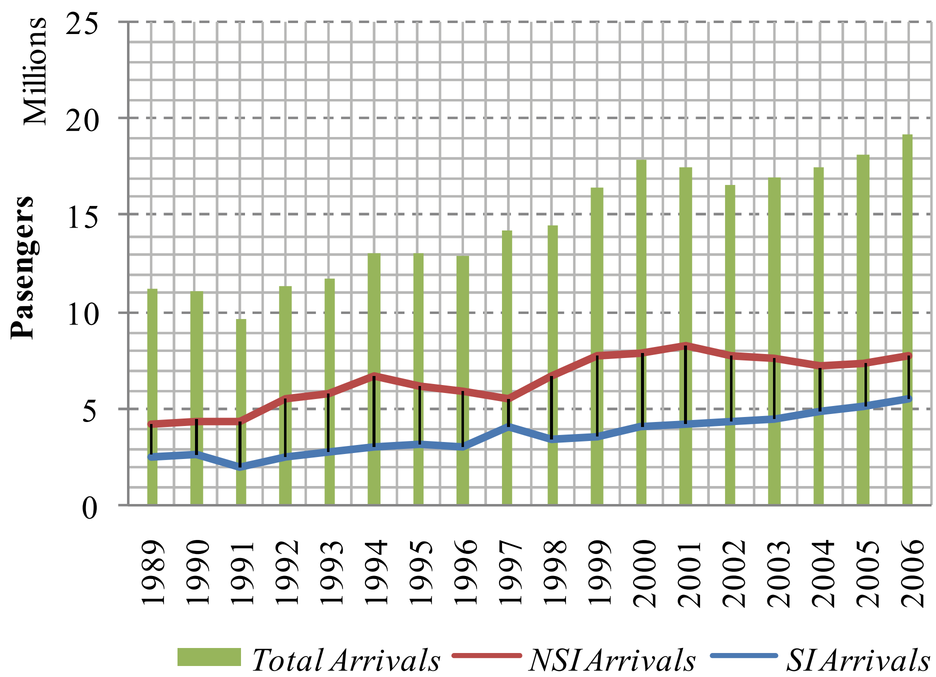
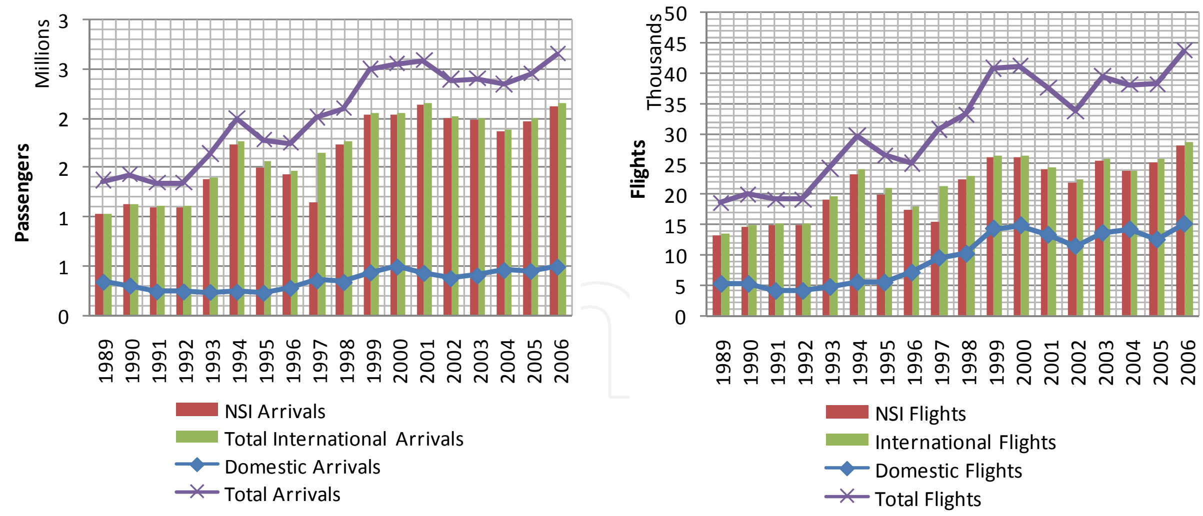
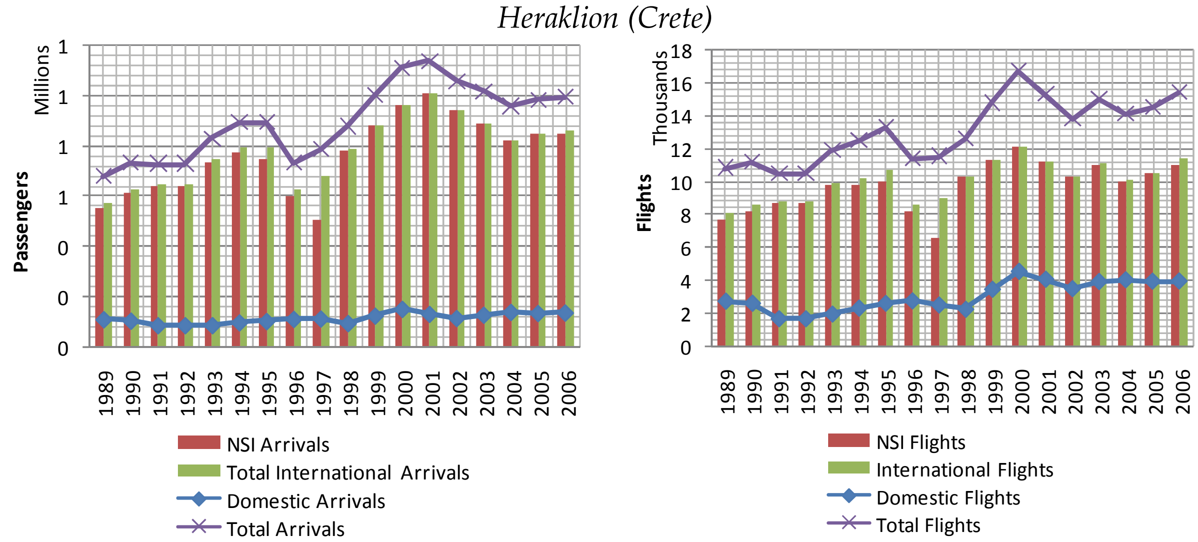


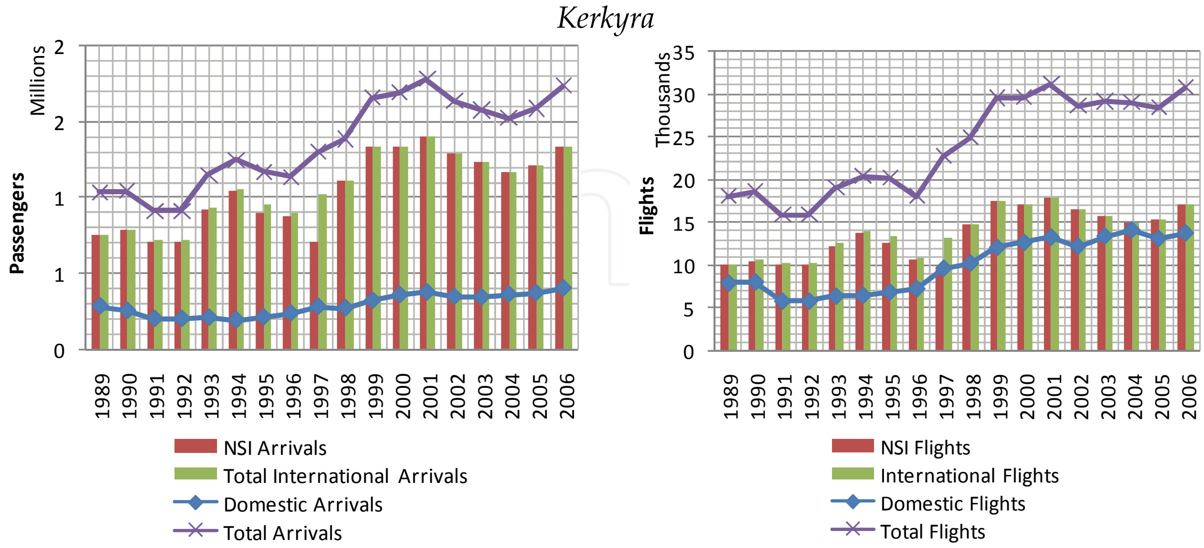
Fig. 1. Yearly evolution of the total arrivals, non-scheduled international arrivals (NSI Arrivals) and scheduled international arrivals (SI Arrivals) for the Greek airports.



Heraklion (Crete)



Kerkyra



Rhodes

Fig. 2. Evolution of arrivals (passengers per year) and flights per year for the period of 1999-2006.

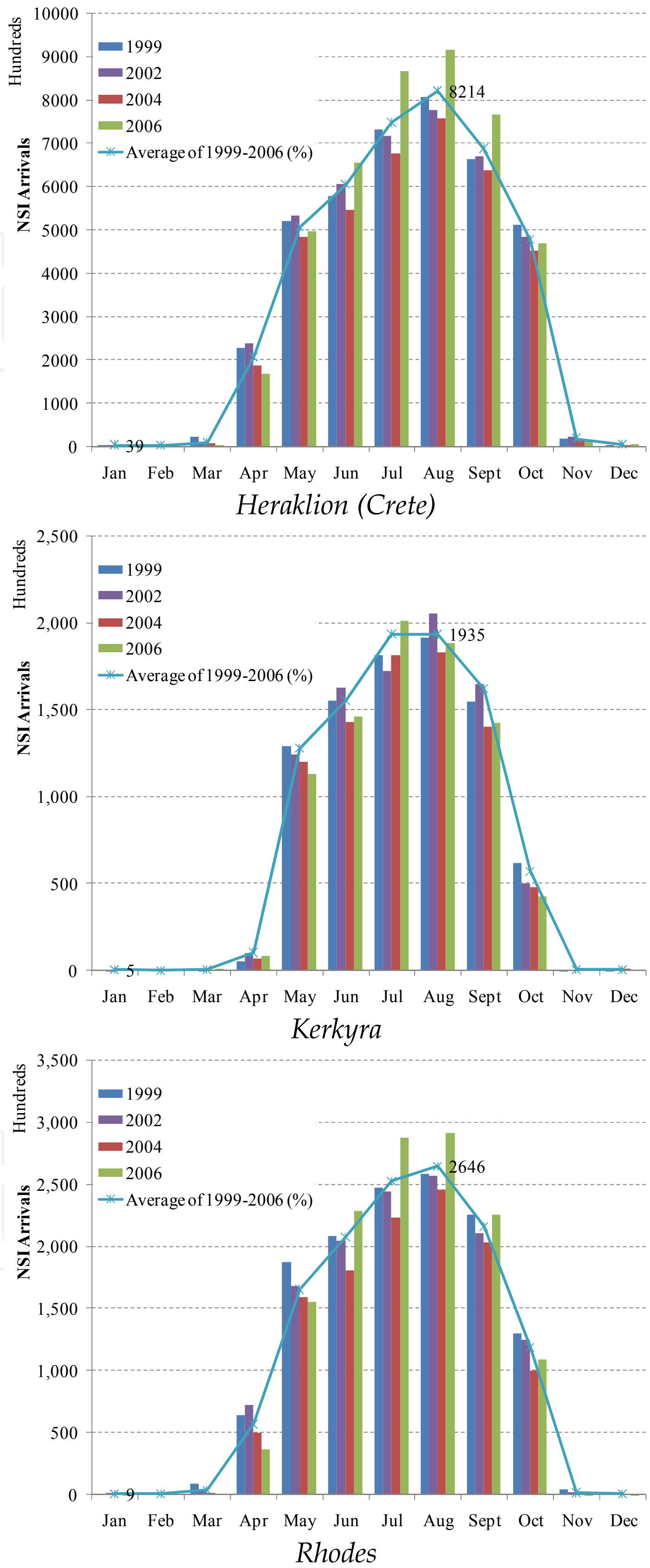


Fig. 3. Monthly variation of non-scheduled international arrivals in Rhodes for the period between 1999 and 2006.

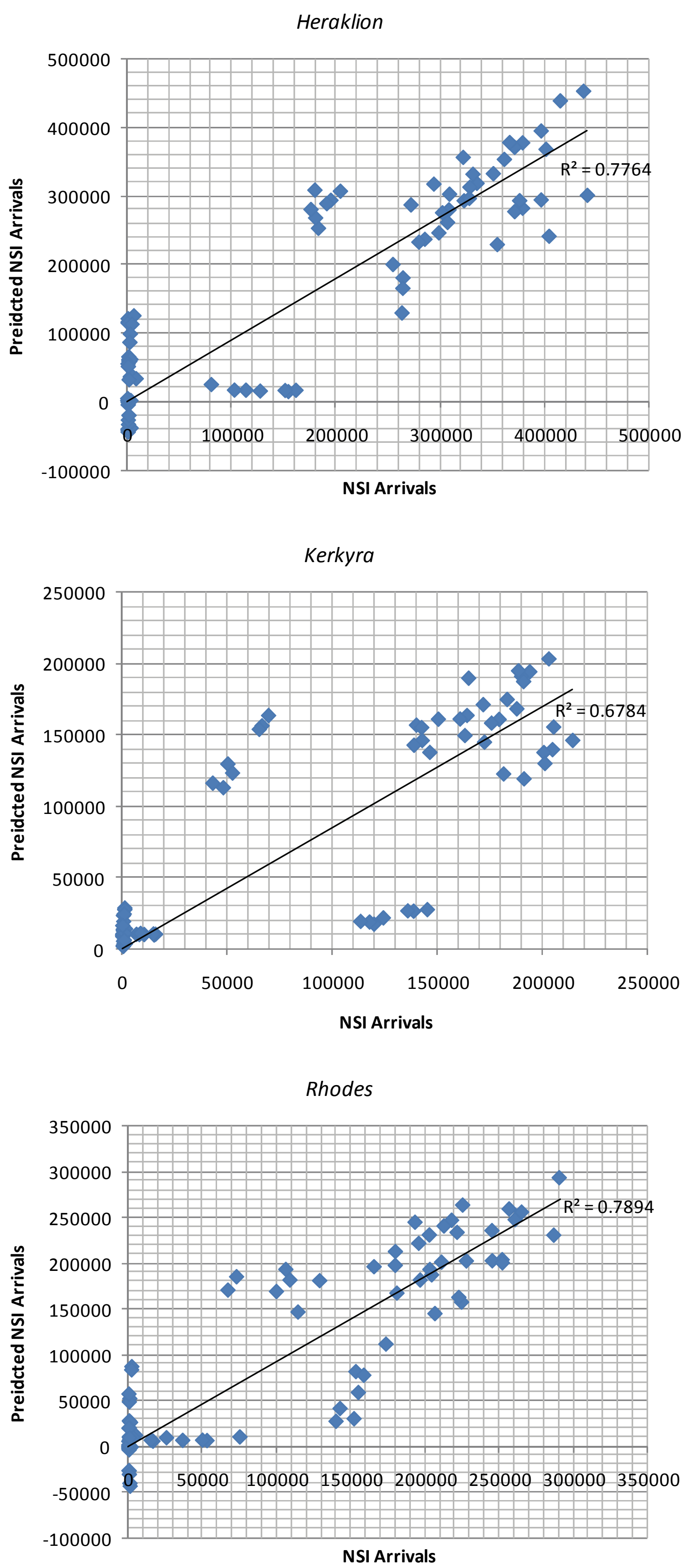
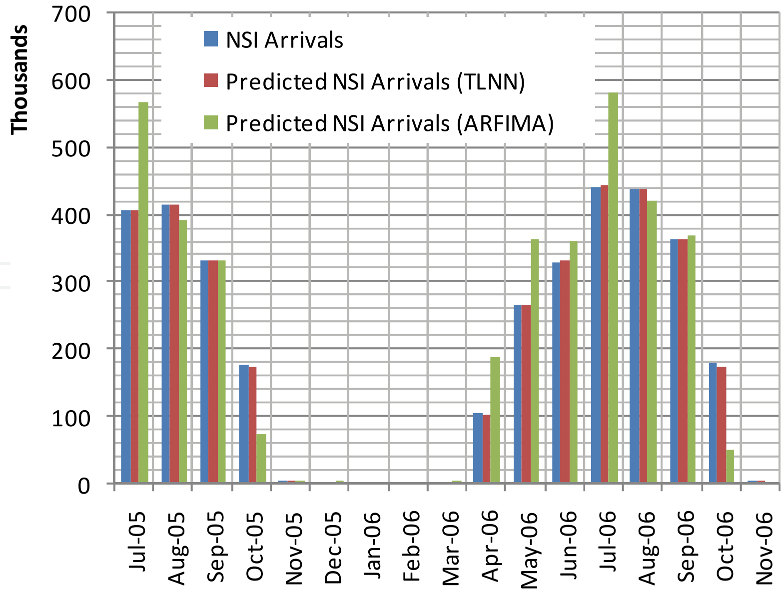


Fig. 4. Scatter plots of actual versus predicted values of NSI arrivals for the three airports.



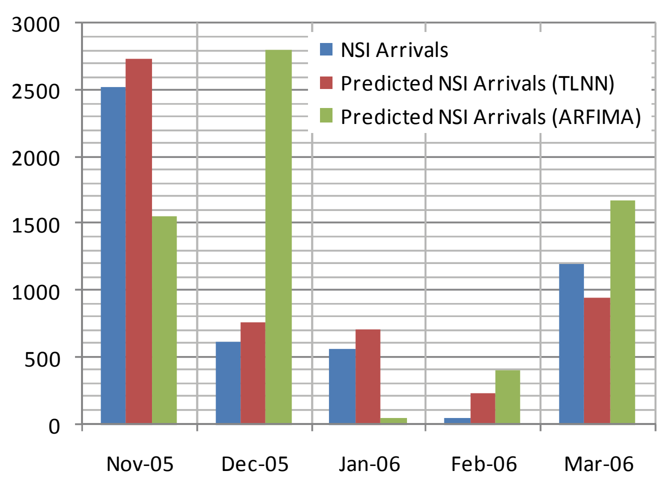


Fig. 5. Predictions using the ARFIMA and genetically optimized TLNN. Results from the three case study airports are aggregated both for ARFIMA and TLNN.

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This volume covers a diverse collection of topics dealing with some of the fundamental concepts and applications embodied in the study of nonlinear dynamics. Each of the 15 chapters contained in this compendium generally fit into one of five topical areas: physics applications, nonlinear oscillators, electrical and mechanical systems, biological and behavioral applications or random processes. The authors of these chapters have contributed a stimulating cross section of new results, which provide a fertile spectrum of ideas that will inspire both seasoned researches and students.