Tourism and Energy Consumption: Impact Analysis, Forecasting and Policy Measurements.

DOCTORAL THESIS/TESIS DOCTORAL

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Abstract

The world faces unprecedented challenges to ensure energy security, sustainability and competitiveness, particularly, when the escalating demand of energy results in depletion of natural resources and a concomitant threat to the global climate from the emissions of greenhouse gases (GHG). Similarly, tourism and its sub-sectors, such as transport, accommodation, and attractions, constitute an increasingly important part of many economies, and their contribution to energy use requires more research. However, there is almost a total consensus among researchers that sectors such as energy and tourism should no longer be considered in isolation. A global approach is now necessary, especially that each sector evidently has its own specificities but each is an integral part of a whole system and can have an impact on the other. Accurate estimation of energy consumption on the one hand, can lead to an appropriate evaluation of the aggregated impact of tourism on energy use. On the other hand, contributes to considerable savings in energy generation along with reduction in GHG emissions when customer demand is met. The approach involves a time series analysis of historical energy and tourist arrivals data, and has been applied to the case study of the Balearic Islands (Spain). The results show that, in terms of electricity consumption, tourism cannot be considered a very energy-intensive sector, and the inclusion of daily arrivals and people stocks in model specification improves accuracy of forecast. This study also discusses the appropriateness of fuel tax when it is applied only in the high season. Finally, the analysis implemented to test periodicity and trends demonstrates that periodically or conventionally integrated process best captures the movements in the tourist arrivals and total electricity consumption series in Balearics Islands.

Resumen

El mundo afronta desafíos sin precedentes para garantizar la seguridad, sostenibilidad y competitividad energética, particularmente, cuando la creciente demanda energética causa el agotamiento de los recursos naturales y supone una amenaza para el cambio climático a través de las emisiones de gases de efecto invernadero (GHG). De la misma manera el turismo y sus subsectores, como transporte, alojamiento y atracciones, constituyen una parte cada vez más importante en muchas economías y su contribución al uso energético no está suficientemente investigada. No obstante, hay un consenso casi general entre los investigadores para dejar de considerar por separado sectores como el turismo y la energía. Ahora se necesita un enfoque global, en el sentido de que cada sector tiene sus propias particularidades pero a la vez es una parte integral de un sistema completo y puede tener un impacto sobre otro sector. Un cálculo exacto del consumo de energía puede conducir, por una parte, a una evaluación apropiada del impacto en el uso energético asociado al turismo. Por otra parte, contribuye a un ahorro considerable en la generación de energía y, a la vez, a una reducción en las emisiones GHG cuando la demanda del cliente se cumple. El cálculo incluye análisis de series temporales de datos históricos de llegada de turistas y consumo energético, y se ha aplicado al caso de estudio de las islas Baleares (España). Los resultados muestran, en términos de consumo eléctrico, que el turismo no puede ser considerado como un sector muy intenso energéticamente, y que la inclusión de llegadas diarias y stock de personas en la especificación del modelo mejora la exactitud del pronóstico. Este estudio también discute la conveniencia de un impuesto sobre el combustible cuando se aplica sólo en la temporada alta. Finalmente, el análisis llevado a cabo para probar la periodicidad y las tendencias demuestra que el proceso integrado periódicamente o convencionalmente es el que mejor captura los

movimientos de las series de llegadas de turistas y consumo eléctrico total en las islas Baleares.

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I. INTRODUCTION

1 General Introduction

The close relationship that historically has been shown between energy resources and human activities remains in force today more than ever, since most of the environmental impacts, visible and invisible, are related strongly with processes using fossil fuels. The fact is that during recent decades, the demand for fossil fuel energy resources has evolved significantly, mainly by increased production and consumption of goods and services resulting from population growth and the accelerated economic progress. While energy constraints pose a threat to the global economy, continued extraction and combustion of fossil fuels at current, or increased, rates is now accepted to be the main producer of greenhouse gas emissions (GHG) and the dominant driver of Global Warming (IPCC, 2007, p. 136).

Demand of energy resources and, therefore, pressure and resulting effects vary considerably between different areas. Different factors such as climatic conditions, resource availability and essentially economic level determine substantially the general pattern of resources consumption. Similarly, the intensity of energy use varies between different economic activities and especially the services sector which records, both directly and indirectly, the most share of global energy demand.

Tourism sector is considered as one of the productive segments highly dependent on the current energy model, especially if the importance of its related activities such as transports, accommodation, and mobility is taken into account. It is estimated that 85% of the world’s energy is based on the consumption of fossil fuels (Biesiot and Noorman, 1999), and as one of the largest industries in the world economy, the growth and benefits of tourism have been fuelled mainly by is use of fossil fuels (Gössling et al., 2005). Because of the extensive use of energy-intensive technologies that deliver tourist amenities, and the substantial energy required to construct new infrastructure, accommodations and other facilities, energy use in tourism destinations is typically much greater than that associated with other similar-sized communities (Kelly et al., 2007). Tourism destinations also rely on substantial amounts of energy for importing food and other material goods, transporting water and disposing waste (Gössling el al., 2002). Tourist attractions, including theme parks with use of mechanised activities, also may generate substantial demand in destinations. Energy is used in up- and down-stream business functions (e.g. tour office administration, marketing and good transportation) that support the delivery of these activities (Becken and Simmons, 2002). GHG emissions from international air and sea transport are a substantial and growing component of global emissions. Air travel accounts for a major share of tourism-related energy use, particularly for developing countries and island destinations where the vast majority of tourist arrive by air (Gössling, 2000).

In recognizing the confrontation between Tourism/ Hospitality and climate, many Internationals conferences on climate change and tourism was held as a global strategy, respectively in Djerba, Tunisia in April 2003, Davos, Switzerland 2007 etc... Those conferences were all convened to evaluate the relation between climate change and tourism. Since Djerba conference, or even before, several studies have examined the relationship between climate change and tourism (Gössling, 2002; Hall & Higham, 2004). Complementary to this interest, the literature on tourism-related energy issue is also growing, particularly as it relates tourism to its contribution to greenhouse gases, and to global climate change (Gössling et al., 2005; UNEP, 2003). It is estimated that 85% of the world's energy is based on the consumption of fossil fuels (Biesiot and Noorman, 1999), and as one of the largest industries in the world economy, tourism growth and benefits have been fuelled mainly by the extensive use of fossil fuels. The associated environmental costs of heavy reliance on fossil fuels may thus ultimately threaten the industry, particularly in developing countries and small islands (UNEP, 2003; WTO, 2003).

For this reasons several countries and even entire regions, are moving now towards implementing long-run comprehensive climate change mitigation policies. Mitigation policies related to technological, economic and socio-cultural changes that can reduce GHG emissions. However, such policies would add to the cost of tourism subsequent price rises, making tourism less attractive. The home tourism product becomes more expensive and hence, will have a negative impact on a country's competitive position in the international tourism. In the short run, during which time firms have little scope to adapt, some of the cost would fall on tourism firms. In the long run, most of the impacts are likely to be passed on the consumers/tourists. Therefore, higher price of tourism is likely to lead to a reduction in its demand and competitiveness, and possibly will impact the trip duration, with more distant visitors opting for fewer, longer trips.

Indeed, tourist destinations and travel patterns will be among the main areas affected, as the necessary reduction of GHG emissions will require the transformation of the generation and use of energy for transportation, increasing the cost of these items and modify the patterns of tourist mobility. The effects of climate change on tourism vary significantly by market segment and geographical locations. Climate affects a wide range of the environmental resources that are critical to tourism. It also influences various facets of tourism operations. The major types of climate change impacts projected by IPCC(2007) that have the greatest potential significance for tourism sector, can be summarized in four broad categories. First, direct impacts of changed climate include geographic and seasonal redistribution of climate resources for tourism and changes in operating costs. Second, indirect impacts of environmental change impacts include induced-environmental changes such as water shortages, damage to infrastructure, etc. Third, mitigation policy and tourism mobility include changes in tourist flow due to increased prices, alteration to aviation routes and changes in the proportions of short-haul and long-haul flight. Fourth, indirect societal change impacts include changes in economic growth, development patterns, social-political stability and personal safety in some regions.

Tourism official and industry leaders are now well aware of the extremely serious situation in many destinations. The UNEP report on a high-profile tourism seminar on climate change adaptation and mitigation, held at Oxford University in 2008, includes a comprehensive list of "tourism resort & product vulnerabilities" due to climate change, reaching from sea level and temperature rises; flooding and drought, landslides; storm surges and wildfires; biodiversity loss and ecosystem changes; water scarcity and impact on food security; negative impact on health and spread of diseases; damage to infrastructure and impaired tourist attractions; to security and insurability issues.

Energy is at the heart of global warming, being one of the main sources of GHG emissions. As it is hard to imagine tourism without travel, it is difficult to find tourism without energy. In tourism, energy is used for transport, accommodation and activities. Transport includes travel to and from the destination (Origin to Destination, or O/D transport), as well as travel at the destination. Tourist infrastructure (hotels, roads) is also energy intensive, as is its maintenance. Finally, tourists are involved in various activities that entail energy use.

The relationship between tourism, energy and climate change is complex. In fact, the production and use of energy is the primary cause of global warming through the emission of the green house gases, and tourism being one of energy-intensive sectors contributes in this process. In turn, climate change in addition to its direct and indirect impacts on tourism sector, will eventually affect (directly or indirectly) the production and use of energy. This thesis will focus on one direction of the "the reciprocal implications." between tourism and climate change through energy use. To be precise, the impact of tourism on energy demand will be covered and the impact of climate policy on tourism will be examined. The impact that climate change will have on tourism and in particular on the demand for destinations will not be covered here. In addition a special attention is attributed to analyze seasonality present in the couple tourism and energy data.

GHG emissions from tourism have grown steadily over the past five decades. If the current amount of emissions is put in relation to tourism growth forecasts, a further substantial increase in the sector's total contribution to climate change can be expected. Results show that CO2 emissions in tourism are projected to rise by 152 % (UNWTO, 2007a, p. 18). This development is in stark contrast with EU targets to reduce GHG emissions by 30 % until the year 2020 (EU, 2007) and thus very likely to interfere with post-Kyoto agreements. In this context, UNWTO's Davos Declaration on Tourism and Climate Change recognizes the urgent need "[…] to mitigate its GHG emissions, derived especially from transport and accommodation activities" (UNWTO, 2007b, p. 2). One of the strategic areas for reducing carbon emissions in tourism sector is represented in reducing energy use. Reducing energy use aims at avoidance of energy consumption and is seen as the most essential mitigation strategy.

In this context, Chapter 2 sheds light on the relation between tourism and electricity use. The background information on tourism, electricity use in the Balearics islands was provided. Chapter 2 reviews the contemporary literature on the relationships between tourism and energy use, then assesses the electricity demand pattern and investigates the aggregated contribution of tourism to electricity consumption using the case study of the Balearic Islands (Spain).The perspective is then shifted to the future, by computing different simulations to evaluate the impact of the tourism as an aggregated sector, the implications of promoting (or discouraging) tourism during different seasons and to assess the marginal effect of tourism on total electricity consumption.

The tourism sector must rapidly respond to climate change, within the evolving UN framework and progressively reduce its Greenhouse Gas (GHG) contribution, if it is to grow in a sustainable manner, this will require action in another strategic area: energy-efficiency. In this scope, Chapter 3 focuses on the role of population stock (including tourists) in improving electricity forecasting in isolated territories. In this chapter, dynamic models such as ARMAX that includes meteorological variables and population stock are used for forecasting for lead times from 1 to 10 days ahead.

Transport, which is at the heart of travel and tourism is an evident challenge, not only the high profile air transport with its direct interrelationship to green house gases, but also road and rail transport which are major factors in intraregional and domestic tourism. Recently UNWTO takes some policies and initiatives to concern about this transport pollution. However, there is no unanimity at all on the most appropriate policies to reduce GHG emissions in the transport sector. Mostly car use and air traffic are targeted but the type of policy instrument to be used remains unclear. Proposals include higher fuel taxes, speed limits, gas guzzler taxes on vehicles but also subsidies for mass transit. The intention of this study is not to survey the whole field of transport and the environment, rather than assessing the possibility of implementing a seasonal fuel (diesel, gasoline) tax in a highly touristic destination.

In Chapter 4, formulation and estimation of petroleum products (diesel and gasoline) demand functions in Balearic Islands at both level and difference for the period 1986 to 2009 are investigated. The estimated price elasticities for both petroleum products diesel oil and Gasoline have been computed. Various tax scenarios have been implemented and their implications on growth of fuel demand were assessed. Given the pervasive character of energy consumption and its related impacts, assessing the relative effects of various energy conservation policies and strategies in tourism destinations represents a valuable step towards creating a more sustainable tourism industry. In many cases, these strategies involve the implementation of innovative planning, design, and management practices associated with transportation, building design and construction, and energy supply infrastructure to achieve reductions in energy consumption and GHG emissions associated with tourism destinations. However, before such initiatives are implemented, it is important to have tools for estimating the potential implications of various tourism-energy management approaches. In addition, the unique characteristics of energy consumption behavior in resort destinations make it difficult to assess the relative merits of various energy management options.

In Chapter 5, analysis of the different trend and periodicity aspects of tourism arrivals and electricity demand time series in Balearic Islands is implemented. It is well known that most tourism destinations experience seasonal patterns of tourist visitation. The impact of seasonal demand variation is one of the dominate policy and operational concerns of tourism interests in both the public and private sector. However, it is interesting that while seasonality is one of the most prominent characteristics of tourism, it is also one of the least examined. It has been generally recognized that seasonality may result in severe economic and social issues such as an unstable labor market caused by temporal employment in a destination (Goeldner and Ritchie, 2003). Conversely, a few studies found that seasonality does not always have negative effects on a destination or tourists. The wide array of issues related to seasonality has attracted economic research, which has investigated this phenomenon both in a qualitative and in a quantitative way.

There is a wide body of research that has tried to elicit the best statistical techniques to be used in describing seasonality. It is worth mentioning that the Gini coefficient, the Peak Season's Share and the Coefficient of Variation seem to be most widely used tools (Koenig & Bischoff, 2003). On the other hand, the econometric approach to seasonality has used the ARIMA models in order to have the possibility to forecast future developments of tourism demand (Lim & McAleer, 2000). Due to the non-trivial characteristic of seasonality, models that capture movements in seasonally unadjusted sub-annual time series are different from those required for annual time series and seasonally adjusted time series. Recently, seasonal integration and the periodic integration have been the main approaches applied to describe most of the macroeconomics time series. Special attention has been attributed to the latter approach, where number of studies show that periodic processes can arise naturally from the application of economic theory to modelling decisions in an economic context, and their role should not be dismissed. Osborn (1988) argues that a process of this type arises when modelling the seasonal decisions of consumers, while Hansen and Sargent (1993) suggest that it could also arise from seasonal technology.

Seasonal and periodic integration analysis is implemented using data of monthly tourist arrivals and sectoral energy consumption time series. Using the conventional tests analysis for seasonal and periodic integration, in this section the analysis is extended with the efficient HEGY-GLS test proposed by Rodrigues and Taylor (2007), in addition to nonparametric tests suggested by del Barrio Castro and Osborn (2011). In Chapter 5, the complete analysis is implemented using GAUSS system.

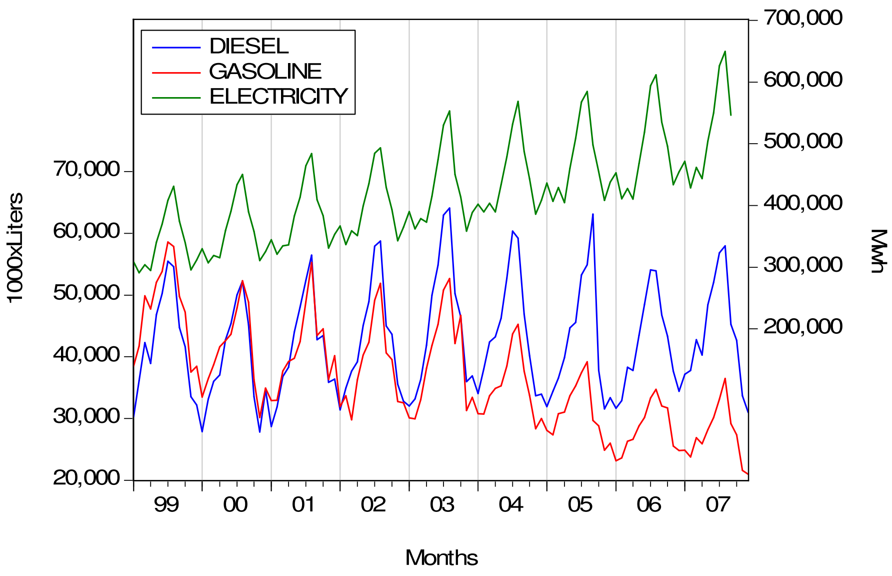
In the final Chapter, the results of the previous chapters are summarized, and their relevance to the research field of tourism and energy use, to the tourism industry and to policy is discussed. The general conclusions which evolved from this thesis are also presented in this Chapter.

2 Balearic Islands as a case study

In the interface between tourism, energy and climate change, it is no longer possible to consider each topic in isolation. Global and regional approaches are now necessary. Each of energy and tourism sectors evidently has its own specificities but each is an integral part of a whole system and can have an impact on the other. Balearic Islands are not an exception, being one of the most popular destinations in the Mediterranean, attracting 10 million tourists every year, i.e. a ratio of 14:1 to the local population. Being extremely dependent on tourism can be problematic because tourism revenues are seasonal, create uneven demands on infrastructure, cause concern about environmental issues and, overall, can fluctuate according to global and regional trends.

Balearic Islands, in this general context, holding much of the energy pressure on the demand made by the transport sector, which is explained in part by the predominance of tourism, but in any case, lies heavily influenced to the particular characteristics of the island, which reduces access to the archipelago by air-and to a lesser extent, by sea, and exclude other alternative means of transport. In parallel, ensuring mobility through public transport services is essential in a context in which the intensive use of private vehicles, both by residents and by tourists, stands as one of the most important energy demanding sector (see Figure 1.1).

Figure I 1 Demand for gasoline and diesel for transportation and electricity in Balearic Islands



In this sense, and according to the Balearics' tourism white paper (Aguiló and Riera, 2009), the behavior of the regional power bundle during the period 1987-2006, is explained as a result of consumption made in terms of:

- Electricity: Electricity demand has tripled under intense urbanization process arising from the expansion of population census and the increasing use of electrical appliances, although they have improved in terms of energy efficiency. Thus, the increase in annual turnover (5,359,261 MWh, 2006 vs. 1,806,216 MWh, 1987) highlights a remarkable increase in domestic consumption (228.1%) and especially the highvoltage (424.7%), although this segment continues explaining the lower part of the counter (24.6%, 2006 vs. 13.9 %, 1987). By sector, services have registered since the nineties the greatest growth rates in consumption (206.9%), together with the construction sector (144.5%), which has promoted the contribution of the tertiary sector on the energy demand to 52.9% (vs. 48.3%, 1991).

- Petroleum products, the sale of fuels, mainly circumscribed to the transport area (especially the segments of private vehicles and commercial aviation), has doubled to reach a total of 2179.34 million litres.133. The largest increases have occurred in the demand for diesel oil A and C items which have increased by four and ten respectively. In term of sales diesel oil types have significantly increased their relative importance (47.7%; 2006 vs. 15.4%, 1987) compared to the gasoline (16% vs. 25.5% in 2006, 1987) and fuel (4.3% vs. 18.2% in 2006, 1987).

- Propane gas: Gas consumption, channeled only to Mallorca and practically to the entire town of Palma, has more than doubled as a result of the urban development process and creation of new homes over the last two decades. So, the annual turnover has reached a total of 427,681 kilotherm (176,441 vs. 1987), aimed mainly to domestic use (61, 6% 82.9% 2006 vs. 1987), although other uses, assigned mainly to the hospitality sector and some industries have increased significantly (38.4% vs 17.1% 2006, 1987) after moving, on average, at a quite dynamic annual rate (22.1% vs 4.1%, domestic use).

In this context, the close correlation that exists between energy demand and real demographic load is highly significant because it illustrates and justifies, beyond questions of efficiency, the increasing pressure on energy resources. In addition the persistence of a strong seasonal pattern constrains undertaken actions in various aspects, such as distribution, management and control of environmental impacts (such as carbon dioxide emissions to the atmosphere). Moreover, despite the fact that the growth rate of the energy products turnover has advanced the population growth rates, per capita ratios put into perspective the growth rates significantly, especially during the last decade. For instance, during the last decade, per capita ratios relativized considerably the rate of rise, in the case of electricity (42.5% vs 87.6%, total), for the petroleum products (6.2% vs 39.7%, total) and for gas (73.9% vs 142.4%, total). Thus, this fact must be considered because if one takes into account the real demographic load, the ratio of per capita consumption is reduced by about 20%.

Similarly, the seasonality of human pressure on the islands has almost an identical pattern of pressure on energy resources. Provided that more than ninety percent of primary energy consumed in the islands is imported and, therefore, is associated with a significant additional cost, the seasonality of human pressure plays a decisive factor of the energy availability in the islands. Thus, between June and September account for 46.2% of sales of petroleum products and 38.2% of sales of electricity, because during this period that coincides with the peak tourist season, the real demographic load exceeds about a quarter the resident population. The consumption of propane gas, for its part, is not so affected by the oscillation of population pressure, but also a clear seasonal pattern which accounts for 55.6% of consumption during the winter months which largely used in heating. Balearic Islands being one of the most popular touristic destination and due to their geographic isolation convert this destination to be an excellent case of study that will be covered in the next chapters of this thesis.

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II. EMPIRICAL CHAPTERS

CHAPTER 1

ESTIMATION OF TOURISM-INDUCED ELECTRICITY CONSUMPTION

Chapter 1 Estimation of tourism-induced electricity consumption

Abstract:

Tourism has started to be acknowledged as a significant contributor to the increase in environmental externalities, especially to climate change. Various studies have started to estimate and compute the role of different tourism sectors' contributions to greenhouse gas (GHG) emissions. These estimations have been made from a sectoral perspective, assessing the contribution of air transport, the accommodation sector, or other tourism-related economic sectors. However, in order to evaluate the impact of this sector on energy use the approaches used in the literature consider tourism in its disaggregated way. This chapter assesses the electricity demand pattern and investigates the aggregated contribution of tourism to electricity consumption using the case study of the Balearic Islands (Spain). Using a conventional daily electricity demand model, including data for daily stocks of tourists the impact of different population growth rate scenarios on electricity loads is also investigated. The results show that, in terms of electricity consumption, tourism cannot be considered a very energy-intensive sector.

Keywords: Daily data, electricity demand, tourism contribution.

1.1. Introduction

International tourism is considered nowadays to be one of the most important industries in the world, with an annual volume of 900 million arrivals (UNWTO, 2008) and a projection that this number will continue to grow, reaching a figure of 1.6 billion worldwide by 2020. In terms of its economic importance, the Tourism Satellite Accounts drawn up by the World Travel & Tourism Council estimate that travel and tourism accounted for 9.9% of the World Gross Domestic Product in 2008; a percentage that is expected to continue rising to 10.5% by 2018 (WTTC, 2008).

Although tourism sector is always associated to environmental degradation and natural resources depletion (Gössling and Hall,. 2005), only very recently literature has started to study energy consumption by tourist activities and the resulting greenhouse gas emissions that contribute to the anthropogenic component of global warming (Gössling and Hall,. 2005; Cárdenas and Rosselló, 2008). This research is being fueled by high recognition that the tourist industry is also one of the largest consumers of energy, mainly through the transportation of travelers and provision of amenities and supporting facilities at tourist destinations (Becken, 2002; Becken & Simmons, 2002, Tabatchnaia-Tamirisa et al., 1997).

Energy use and its contribution to greenhouse gas (GHG) emissions have received particular attention, especially that tourism is itself an important contributor to environment degradation, as result of the large amounts of fossil fuels needed for transport (Price & Probert, 1995, Penner et al. 1999, Gössling and Hall. 2005, Peeters and Schouten, 2006, Becken 2002, Macintosh and Wallace, 2009) , and accommodation sector

(Priyadarsini et al., 2009; Deng and Burnett, 2000; Simmons and Lewis, 2001, Priyadarsini et al., 2009, Karagiorgas et al 2007).

All the studies discussed in the literature review have taken sub-sectors of the tourist industry to estimate tourism's contribution to energy consumption. This disaggregation can be accounted for by the fact that tourism is not recognized to be an economic sector in the conventional economic sense, and its full consideration poses a problem, given the mixed nature of some of the sub-sectors that can be included in tourist products.[1] Nevertheless, additional information can be obtained by looking at the sector as a whole. Such information not only leads to an improved understanding of the development of the energy use and emissions, but also to ascribe an environmental responsibility to tourism activities in the sense that they can be regionally relevant in promoting or discouraging tourism development policies. To derive national and worldwide estimates of that contribution, methodologies must be developed that are accurate in assessing tourism's contribution to greenhouse gas emissions, as well as key areas within the field of tourism that should be the targets of mitigation strategies.

Consequently, the main objective of this chapter is to contribute toward assessing the energy consumption attributable to tourism by estimating an electricity demand model that explicitly takes into account the presence of tourists. The Balearic Islands are taken as a case study, first because of the relative importance of tourism in the region (which has a population of 1 million inhabitants and 13 million tourists per year); second, because of the islands' geographical circumstances, which make it possible to fully estimate the daily stock of tourists arriving at its ports and airports; and third because of the availability of the remaining variables that are required to conduct a study of this nature. The daily

[1] For instance, restaurants and some specific commercial activities can have both a local and a tourist component that are often difficult to isolate.

electricity demand is modeled as an explanation of the meteorological conditions of the archipelago such as outdoor temperature and humidity, a set of variables relating to the calendar for the working year that control for working and non-working days, and the stock of tourists present in the archipelago that day.

The chapter is structured as follows. Section 2 reviews literature on electricity demand modeling, providing the methodological cornerstones for the study. Section 3 provides key details of the data that was used, with special emphasis on the calculation of the daily stock of tourists. Section 4 presents the results and a discussion of them, and this chapter concludes with Section 5.

1.2. Methodology

Electricity cannot be stored. Consequently suppliers need to anticipate the future demand in a very accurate way. For short-term load modeling and electricity consumption forecasting, several variables are taken into consideration, such as time factors, weather data, and other determinants, like electricity prices, social events and possible classes of customers. Meanwhile different approaches have been adopted to combine these variables, giving birth to a variety of models.

1.2.1. Exogenous variables

Economic time series often contain multiple periodic cycles of different lengths. In particular, electricity demand time series often exhibit a persistent trend and significant seasonal variation. In the context of high frequency data (hourly or daily), the predominance of the working time effect is patent and often highlighted in applied exercises (Pardo et al., 2002; Valor et al., 2001).

One of the most common ways to capture the deterministic pattern exhibited in electricity load data is the use of dummy variables referring to the time of day, day of the week or month of the year. Although different models can be estimated referring to every single day of the week (Cancelo et al., 2008) or separating normal days from weekends (Ramanathan et al., 1997), leading studies have illustrated the effectiveness of modeling non-working days by using dummy variables, even reducing the number of dummies to six (Cottet and Smith, 2003) or three (Pardo et al. 2002), or else including a simple dummy variable for all special days (Soares and Souza, 2006).

Apart from time factors, weather conditions are among the most influential exogenous variables, especially for short-term load forecasting (Valor et al., 2001; Moral-Carcedo and Vicens-Otero, 2005). Various variables could be considered, but temperature and humidity are the most commonly used load predictors (Mirasgedis et al., 2006). Among the weather variables that are considered, two composite weather indicators - the THI (Temperature Heating Index) and WCI (Wind Chill Index) - are broadly used (Rahman and Hazim, 1993). Yan (1998) studied electricity consumption by the residential sector in Hong Kong using a weather stress index, and examined how it affects the use of electricity for cooling. Ranjain and Jain (1999) derived separate empirical models of electricity use in Delhi for each of the four seasons, based on population and weather conditions. The influence of a considerable number of meteorological parameters on the electricity demand in Spain was analyzed by Cancelo and Espasa (1996), affirming that the most significant of them are first temperature and second humidity.

The relationship between temperature and load is complex for two different reasons. First, it is suggested to be non-linear. There is an interval where the electricity load hardly changes with temperature variations but outside this interval, the electricity demand jumps with both increasing and decreasing temperatures because people will increase or decrease the use of electric heating appliances or air conditioners. Second, the response is asymmetric, in the sense that the impact of a one-degree increase in the case of a high temperature is not necessarily equal to the effect of a one-degree decrease for a low temperature (Valor et al., 2001; Ruth and Lin, 2006).

Finally, the effect of temperature on load is influenced by other factors. For example, Smith (2000) found that temperature has a different effect on the load in the case of working and non-working days, in the same way that the effect is different in workplaces as opposed to private residences.

In models using low frequency data (monthly, quarterly or annual data), factors related to electricity prices can also be included in load forecasting models (Chen et al., 2001). For non-residential, cost-sensitive industrial or institutional consumers, the financial incentives to adjust loads can be significant when it comes to durable goods, and so it can be useful to include price as a variable in medium and long-term electricity demand projections for these sectors. However, price as an explanatory variable for the short-run energy load has been revealed to be insignificant (Zachariadis et al, 2007). On the whole, electricity prices are therefore not expected to have a significant effect on the short-term demand, although they may be relevant in the case of some longer-term impacts associated with cost-saving efficiency measures and fuel switching, where feasible.

1.2.2. The model

Considerable attention has been given to modeling electricity consumption over the past fifty years, and a large variety of loading or forecasting methods have been tested with varying degree of success. Weron (2006) classified these methods into two broad categories: artificial-intelligence-based techniques and statistical approaches. Artificial-intelligence-based (or non-parametric) techniques mainly include artificial neural networks (ANN), have been compared with conventional approaches (Khotanzad et al. 1998; Hippert et al., 2005; Taylor et al., 2006; Darbellay and Salma, 2000), however no clear conclusion is reached in literature about the superiority of one model over the other. The limitation to Artificial-intelligence-based methods is the difficulty involved in estimating a quantification of the relationship between the variables used in the forecasting exercise (Smith, 1995).

Statistical approaches represent the electricity load as a function of different factors. A basic conventional structure decomposes the observed load into four components: the normal load, the weather sensitive part, special events, and a random component. Assuming a conventional aggregated energy demand relationship (Cancelo et al., 2008, Considine, T, J., 2000), an expansion of a log-linear model can be analytically expressed as:

$$Ln(C_t) = c + \alpha \cdot T + \sum_{p=1}^{i} w_p MET_{pt} + \sum_{n=1}^{6} d_n D_{nt} + \sum_{l=1}^{11} m_l M_{lt} + \sum_{k=1}^{j} s_k SD_{kt} + \beta \cdot PPI_t \qquad [1]$$

Where C_t denotes the electricity consumption on day t taken in natural logarithm; T is the trend; MET_p are i initially considered meteorological variables; D_t and M_t are dummy variables that control the day of the week (n) and month of the year (l); SD_k are j dummy variables that control other non-working days and holidays; and PPI is the variable that represent the pressure of the population and stand for population pressure index[2]; c, α, w_p, d_n, m_l, s_k, β_1 and β_2 are parameters to be determined, and u_t is the error term distributed

[2] This indicator is explained thoroughly in the section 3.3

normally and independently. It should be highlighted that a correct diagnosis of the u_t term not only improves the performance of the prediction, but also increases the efficiency of the estimations.

Many approaches have been applied to modeling the stochastic nature of the demand. Autoregressive methods are usually used as benchmarks for other methodologies, whereas autoregressive moving average models have been widely used in load modeling and forecasting. A standard autoregressive moving average analysis with explanatory variables (ARMAX) rests on the simplifying assumption that the mean and unconditional variances of time series are independent of time, i.e. the series are stationary. A plot of the autocorrelation function and partial autocorrelation function and some conventional tests, like the Augmented Dickey Fuller test (see Appendix 1), are used to decide whether a data series is stationary or not. Thus an ARMAX (p, q, b) model for the electricity load can be represented as:

$$\phi(p)\ln C_t = \eta(b)X_t + \theta(q)u_t + \varepsilon_t \qquad [2]$$

Where $\phi(p)$, $\eta(b)X_t$ and $\theta(q)$ are the lag polynomials for the natural logarithm of the electricity demand (C_t), the exogenous variables matrix (X_t, where the variables *p, s, CSD,* and *CWEA* are included) and the moving average term (u_t), respectively, and ε_t is white noise.

The relative success of ARMAX processes in modeling and forecasting the short-term electricity load is due to their capacity to generalize the time dependence and perform better than autocorrelation adjustment models, in addition to their flexibility in capturing a variety of dynamic effects (Ramanathan et al., 1997; Pardo et al., 2002; Taylor and Buizza, 2003). ARMA and ARMAX models are usually used for prediction purposes

(Chen et al., 1995; Huang and Shih, 2003; Soares and Medeiros, 2005; Juberias et al., 1999; Cancelo et al. 2008). However, it should be added that the good forecasting performance of ARMAX models is intrinsically associated with a well-specified model that can handle different exogenous effects on the electricity load (Pardo et al 2002).

At this point, it is important to highlight that ARMAX models assume that disturbances constitute a white noise sequence of identically and independently random variables. This assumption is violated in some economic data where small and large disturbance variations are observed in clusters. This suggests a form of heteroscedasticity in which the variance of the disturbance depends on the size of the preceding disturbance and hence the conditional variance is not constant over the sample period. More precisely, Engle (1982) showed that it was possible to model the mean and conditional variance of a series simultaneously; a study that was extended by Bollerslev (1986), who proposed the GARCH (p, q) process:

$$\sigma_t^2 = \omega + \vartheta(q)\sigma_{t-1}^2 + \psi(p)\varepsilon_t^2 \qquad [3]$$

Where, σ_t^2 is the one-period-ahead forecast variance based on past information from equation [1], called the conditional variance; ω is a constant term; ε_t^2 is the ARCH term, which collects news about volatility from previous periods, measured as the lag of the squared residual from the mean equation; σ_{t-1}^2 is the GARCH term, which includes the last period's forecast variance; and $\vartheta(q)$ and $\psi(p)$ are lag polynomials to be determined.

More particularly, some works have started to show that GARCH models can improve on previous models. Chen et al. (2006) therefore used a GARCH class approach to model and forecast the electricity load, finding that it performs better than classical

ARMAX models. Hor et al., (2006) used GARCH to model the residuals in the student-t distribution and to estimate the maximum load demand that would be likely to occur in the short-term.

Bearing in mind the importance of the correct specification of an electricity demand model that includes the role of tourism, this chapter considers a statistical formulation where the level of the electricity load is explained as a function of a set of conventional explanatory variables (including meteorological ones, holiday effects, a trend and seasonal components), a measure of tourism pressure is incorporated, and the disturbance is modeled using the ARMAX and GARCH alternatives.

1.3. Data analysis

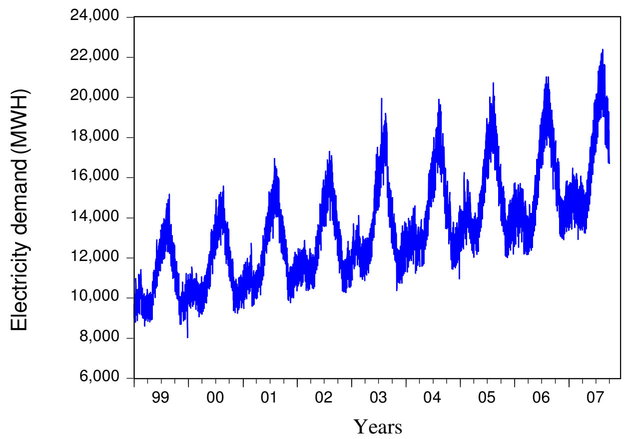
The proposed electricity models developed in this chapter take the case study of daily consumption data for the isolated electricity network of the Balearic Islands (Spain). According to official statistics, the power network in the Balearic Islands is responsible for supplying electricity to 1 million residents and 13 million tourists annually. In the case of the tourist population, it is important to highlight that tourist arrivals are concentrated during the summer months, with 60% of all arrivals between the months of June and September. This period coincides with peak electricity consumption in the islands. Thus for policy reasons it is crucial to separate consumption associated with tourism from the part that corresponds to extreme temperatures.

1.3.1. Electricity data

Data for electricity consumption in the Balearic Islands was provided by Red Electrica de España, the Spanish system operator, and it spans January 1995 to September

2007. The data set that was used comprises the daily electricity demand (C_t) in MW h for the entire period under consideration. The daily demand data aggregates all sectors of economic activity (industrial, commercial, residential, and agriculture), since disaggregated sectoral data was not available for this time frequency.

Figure 1 1 Daily electricity consumption in Balearics



In Figure 1.1, a strong trend can be clearly observed in the daily electricity demand. In applied exercises this drift is often captured by a linear trend and attributed to social, economic and demographic factors (Cancelo and Espasa, 1996). Previous works have discussed also significant seasonal daily and monthly components of electricity load series (Valor et al., 2001). In order to capture them, different dummy variables are often incorporated. Anomalous events related to holidays or special days have also been considered in order to capture different electricity patterns traditionally shown by the population on these special days. For example, electricity consumption decreases considerably during holidays and at weekends.

1.3.2. Weather data

The historical weather data that was required for the proposed models for the period in question was supplied by the *Centre de Recerca Econòmica* and taken from the Balearics Meteorological Center. The available data are collected from the three airport weather stations; Palma de Mallorca airport; Menorca airport and Ibiza airport.

Because of the particularly high degree of humidity that characterizes the Balearic Islands, a Heat Index (HI) was incorporated as an alternative to the use of the simple mean temperature variable. Measurements have been taken in other studies, based on subjective descriptions of how hot subjects feel for a given temperature and humidity, allowing for the development of an index where a combination of a certain temperature and humidity corresponds to a higher temperature in dry, non-humid conditions. Whatever the case, the most commonly used formulation of an HI was proposed by Steadman (1979) and it is also adopted in this study.[3] For the measurement of the Balearic index, a population-weighted temperature index was constructed from the mean daily temperatures measured separately on the different islands (Valor et al, 2001).

$$TI_t = \sum_{i=1}^{3} \bar{T}_{ti} w_{ti} \qquad [4]$$

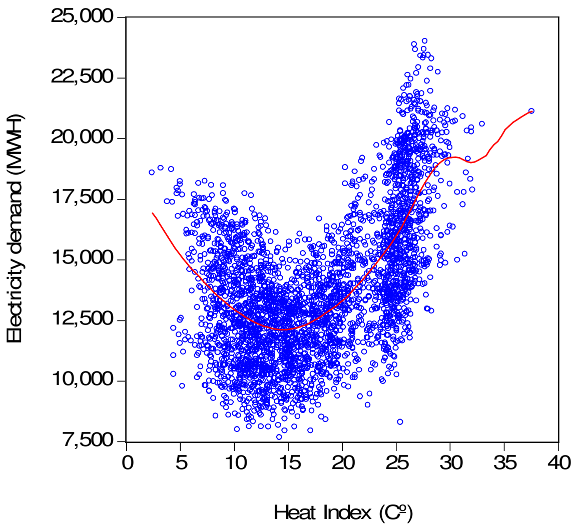
$$w_{ti} = \frac{p_{ti}}{\sum_1^3 p_{ti}} \qquad [5]$$

[3] Thus HI = -42.379 + 2.04901523T + 10.14333127R - 0.22475541TR - $6.83783\cdot10^{-3}T^2$- $5.48171710^{-2}R^2$ + $1.22874\cdot10^{-3}T^{2}R$ + $8.5282\cdot10^{-4}TR^2$ - $1.99\cdot10^{-6}T^2R^2$, with T = ambient dry bulb temperature degrees in Fahrenheit and R = relative humidity.

$\bar{T}_{ti}$ is the mean daily temperature on day t at weather station i and w_{ti} is a population weight of the area assigned to each station and p_{ti} being the total population (Tourists and Residents) on day t assigned to weather station i.

The population was selected as a weighting factor because climate influences electricity consumption through people's response to the weather; the larger the population, the greater the influence of weather conditions on the electricity demand. Figure 1.2 depicts the nonlinear influence of heat index on the electricity demand with a minimum around 15 ºC, a shape similar to that already found in Valor et al. (2001) and Pardo et al. (2002).

Figure 1 2 Daily Load and Heat Index in Balearics



When dealing with the non-linearity of the heat index effect, the most frequent approach in literature is to segment temperature into HDD and CDD, which we use to defined HDD* and CDD* as shown below:

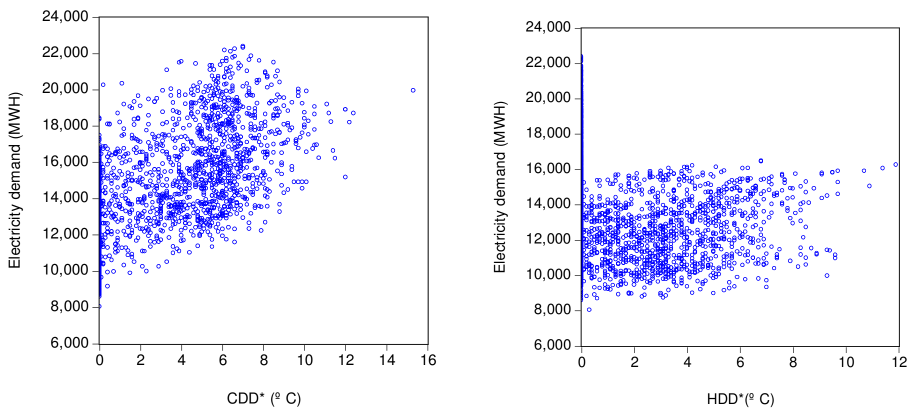
$$\mathrm{HDD}_t^* = \mathrm{Max}\ (\mathrm{HI}_{\mathrm{ref}} - \mathrm{HI}_{t},\ 0) \qquad [6]$$

$$\mathrm{CDD}_t^* = \mathrm{Max}\ (\mathrm{HI}_t - \mathrm{HI}_{\mathrm{ref}},\ 0) \qquad [7]$$

HI_t is the heat index for day t and HI_{ref} is a reference heat index that must be adequately selected to separate the hot and cold branches of the demand-heat index relationship. In combination, these functions reflect the number of days on which the heat index falls below or rises above the heating and cooling thresholds and by how many degrees. Since there is no strict quantification of the values of the "threshold", there can be many different versions of the HDD* and CDD* functions. In the context of this study, the selected reference heat index is equal to 20°C and 15°C for HDD* and CDD* respectively.

Thus Figure 1.3 presents the daily electricity consumption in the Balearics versus the HDD* and CDD*, built on the basis of the HI. It is clear that the two seasonal branches are separated into two functions, the first one for high temperatures and the second for low temperatures.

Figure 1 3 Daily electricity consumption en function of HDD* and CDD* in Balearics



1.3.3. The daily population stock

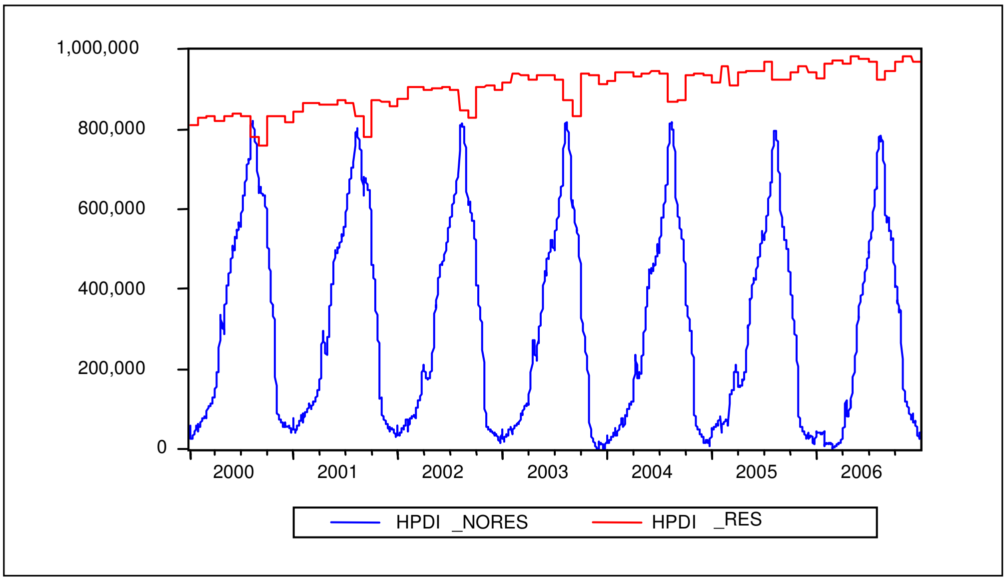
The number of people present in an area or region at a given moment can be very different from the data collected by the census office. Such divergences are due to the movement of people to destinations outside the places where they normally live, including movements for all purposes: for family, study, work or leisure-related reasons etc. The Balearic Islands, with their high specialization in tourism, are considered one of the regions that match this special pattern. In fact, tourist population on the islands is very important and can equal the number of residents on some days of the year.

Riera and Mateu (2007) developed a population pressure index called Human Pressure Daily Indicator (HPDI) for the Balearic Islands that captured the stock of people, at a daily level, on each one of the Balearic Islands, based on resident population data and arrivals and departures from the airports and ports. The HPDI is derived from the following expression:

$$HPDI = PR_0 + \sum_{d=1}^{D}(A_d - D_d) + \sum_{d=1}^{D}(V_d) \qquad [8]$$

Where PR_0 is the resident population on the first day of each year, based on official statistics; A_d-D_d is the difference between arrivals and departures during day d, taken from airport and port statistics; and V_d stands for the natural growth of the population as a consequence of births and deaths. Additionally, given the special purposes of this study, the HPDI is divided into the daily stock of the resident population (HPDI_RES) and the daily stock of the tourist population (HPDI_NORES) in order to isolate the effect of tourism from the residential population. This separation is based on *Familitur* data, the Spanish domestic tourism survey, from which it is possible to estimate how many residents in the Balearics are away on holiday. For the time period of the analysis, the plot for HPDI_RES and HPDI_NORES is shown in Figure 1.4.

Figure 1 4 HPDI for the residents and for the tourists in the Balearics



One of the most important results that can be derived from this analysis is the fact that tourists count for an average of 25.08% of the total population. It is relevant to mention though, that HPDI variability does not differ significantly from that of the airport arrival. However, using HPDI index will prevent the bias that can be produced by tourists' length of stay.

1.4. Results and discussions

1.4.1. Results

The results of the models are reported in Table 1.1. The adjusted R^2, Akaike Info Criterion (AIC) and Schwarz Criterion (SC) were used to select the best model to fit our data, and where the GARCH model revealed a high consistency in comparison with the ARMAX model. In addition, the F-test was used for the overall significance of the model and a t-test for testing the strength of each of its individual coefficients. The main results that were obtained with the introduction of a dynamic structure are presented in Table 1.1, where the different autoregressive terms AR(p) are shown (AR for simple autoregressive terms and SAR for seasonal autoregressive terms, and p is the order of the autoregressive part). For the moving average terms MA(q), being statistically insignificant, they are not reported in the Table 1.1.

The adjusted R-squared of the estimated models can be qualified as good, being higher than 0.96 for both models. In addition, a subset of variables in the model was tested for statistical significance to examine whether they could be omitted. Each of the insignificant variables was sequentially deleted, using the general-to-specific-model strategy, while significant parameters at a 1%, 5% and 10% level were retained.

The results of the estimated coefficients for the day-of-the-week dummy variables reveal that electricity consumption compared to the reference day (Sunday) is more pronounced during the working days and falls on Friday and Saturday. Friday and Tuesday are consequently the working day with lowest and highest electricity consumption, respectively. The coefficients for dummy variables related to the monthly seasonality are negative and significant, except the coefficients for February; June; July and August that are not significant (Not reported in the Table due to lack of space). These results imply that January, February, June, July and August are the months when more electricity is used.

Table 1 1 Estimated models for electricity consumption in the Balearics

	ARMAX		GARCH	
@TREND	(8.68E-06)	0.000121***	(9.68E-06)	0.000116***
D1	(0.0056)	0.029470***	(0.0021)	0.014245***
D2	(0.0055)	0.033425***	(0.0025)	0.019053***
D3	(0.0055)	0.031681***	(0.0024)	0.018513***
D4	(0.0056)	0.028902***	(0.0024)	0.016060***
D5	(0.0051)	- 0.028211***	(0.0024)	- 0.050358***
D6	(0.0051)	- 0.105724***	(0.0017)	- 0.131331***
SD05_1	(0.0119)	- 0.084873***	(0.0200)	- 0.103428***
SD06_1	(0.0111)	- 0.016502	(0.0119)	0.000852
SD16_1	(0.0114)	- 0.034970***	(0.0102)	- 0.040611***
SD20_1	(0.0094)	- 0.017176*	(0.0100)	0.006522
SD28_2	(0.0112)	- 0.080794***	(0.0079)	- 0.089668***
SD01_3	(0.0103)	0.012277	(0.0104)	0.017754*
SD30_4	(0.0121)	- 0.074209***	(0.0079)	- 0.097090***
SD14_8	(0.0114)	- 0.090787***	(0.0113)	- 0.094607***
SD11_10	(0.0110)	- 0.093382***	(0.0057)	- 0.103354***
SD12_10	(0.0110)	- 0.034739***	(0.0129)	- 0.018066
SD31_10	(0.0124)	- 0.161923***	(0.0051)	- 0.164223***
SD01_11	(0.0110)	- 0.030237***	(0.0124)	- 0.007263
SD05_12	(0.0118)	- 0.108315***	(0.0075)	- 0.105519***
SD06_12	(0.0114)	- 0.045012***	(0.0105)	- 0.022928**
SD07_12	(0.0120)	- 0.089030***	(0.0102)	- 0.095638***
SD09_12	(0.0125)	0.028125**	(0.0089)	0.011331
SD24_12	(0.0137)	- 0.112713***	(0.0060)	- 0.125040***
SD25_12	(0.0110)	- 0.093491***	(0.0104)	- 0.101865***
SD31_12	(0.0139)	- 0.078890***	(0.0155)	- 0.095588***
SDJVS_ST	(0.0099)	- 0.069747***	(0.0052)	- 0.049308***
CDD^*	(0.0012)	0.010488***	(0.0012)	0.005321***
(CDD^*)^2	(0.0001)	0.000278**	(0.0001)	0.000351***
HDD^*	(0.0012)	0.007386***	(0.0012)	0.005248***
(HDD^*)^2	(0.0002)	0.000537***	(0.0002)	0.000392**
C	(0.0795)	8.480177***	(0.0819)	8.325717***
HPDI_RES	(1.11E-07)	4.34E-07***	(1.11E-07)	5.86E-07***
HPDI_NORES	(2.01E-08)	3.71E-07***	(2.36E-08)	3.93E-07***
AR(1)	(0.0187)	0.458179***	(0.0216)	0.704687***
AR(2)	(0.0193)	0.128453***	(0.0288)	0.061863**
AR(3)	(0.0193)	0.125815***	(0.0299)	0.115401***
AR(4)	(0.0182)	0.095278***	(0.0244)	-
AR(7)	(0.0171)	- 0.256688***	(0.0168)	-
Equation				
Adjusted R-		0.971475		0.965592
Log likelihood		6154.008		6331.140
Durbin-Watson		1.893018		2.316683
AIC		-3.840886		-3.950403
SC		-3.751251		-3.855047
F-statistic		2354.644		1821.676
Proba(FStatistic)		0.000000		0.000000

Standard errors are given in parentheses. The individual coefficient is statistically significant at *** 1%, ** 5% or * 10%.SDdd_mm refers to a special day where dd is the day and mm is the month, SDJVS_ST is the Maundy Thursday. For example, SD06_01 is the 6th of January which is the Epiphany day.

With regard to weather-related parameters, the ARMAX model shows that the high temperature heating index and low temperature heating index are both significant at a 1% level. The squared term for these variables was added to the Balearic Island model in order to capture non–linear relationships, revealing a 5% significance level for high temperatures and 1% significance level for low temperatures for the ARMAX model, whereas in the GARCH model the said parameters were significant at a 1% level, except for the low temperature heating index, which was significant at a 5% level. Because of the non-linear relationship between electricity consumption and temperature, the obtained relationship between these two variables was investigated using the concept of elasticity, a standard measure for evaluating the sensitivity of the electricity load to temperature changes (Valor et al, 2001). Thus:

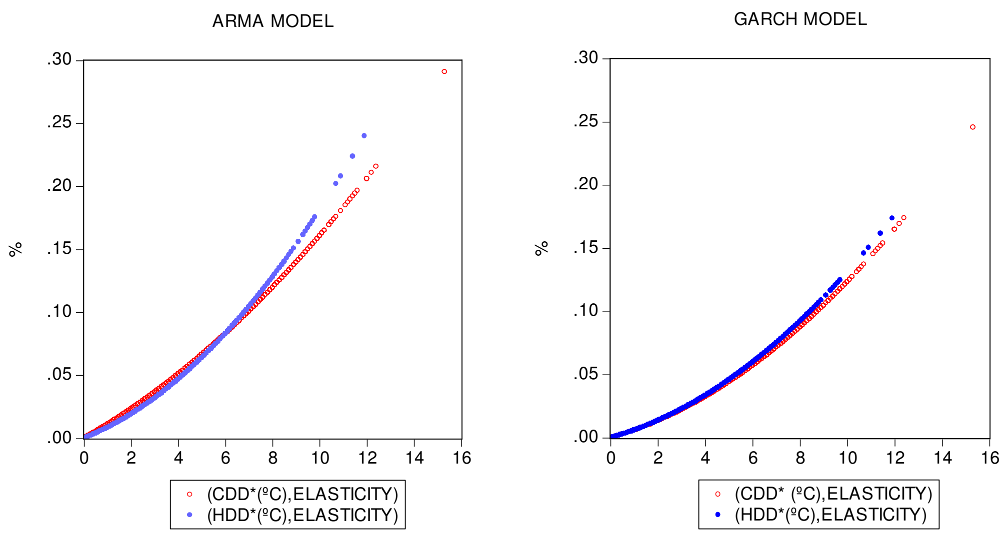
$$\varepsilon_{HT} = \frac{HT_{HI}}{C}\frac{\partial f(C)}{\partial HT_{HI}} \qquad [9]$$

$$\varepsilon_{LT} = \frac{LT_{HI}}{C}\frac{\partial f(C)}{\partial LT_{HI}} \qquad [10]$$

Where ε_{HT} and ε_{LT} are the elasticities for high and low temperatures, respectively, expressed as a function of the heat index. Figure 1.5 plots the estimated elasticities of the electricity demand for high and low temperatures, using the ARMAX and GARCH models. For extreme temperatures, the elasticity for low temperatures can be seen to be higher than the elasticity for high temperatures. In other words, the population has a higher sensitivity to temperature in winter than in summer. Moreover, the elasticity curves in the GARCH model are less steep and almost equal for high and low temperatures, while in the ARMAX model this sensitivity is almost equal until the high and low temperatures reach

7CDD and 7 HDD respectively, at which point a gap is visible between the two temperature ranges for values higher than 8 CDD and 8 HDD respectively.

Figure.5 Daily elasticity estimations from the electricity demand function



As for population stock variables, both the ARMAX and GARCH models show a high significance level for both residents and non-residents. As expected, positive signs are obtained, confirming that an increase in the population (residents or non-residents) will be associated with an increase in electricity consumption.

1.4.2. Simulations

Different approaches were taken in the sensitivity analysis of the impact of tourism on energy consumption. To this end, various simulations were developed for use with the obtained model, based on different population stock conditions. More specifically, the simulations can be summarized into three main effects: a marginal change in population stocks, a marginal seasonality effect and total tourism effect.

The first simulation aimed to assess the contribution of population growth to electricity consumption, by running a constant increase in the daily amount of the non-residents' population stock. Simulations were performed for two different years - 1999 and 2006 - and 5%, 8% and 10% percentage rates were selected to simulate the mean yearly population growth using ARMAX and GARCH approaches.

Table 1.2 shows that an increase in the population stock for non-residents is associated with an increase in electricity consumption, with annual rates ranging between 0.5% and 1.3% for the three simulations. As for a comparison of the results of the ARMAX and GARCH approaches, a small difference can be observed in the growth rates of electricity consumption in the case of the non-resident population. To illustrate this difference, in the simulation with a 10% increase, the mean growth rate recorded in 1999 and 2006 respectively passed from 1.2% and 1% in the ARMAX model to 1.3% and 1% in the GARCH model.

Table 1 2 A simulation for tourist electricity consumption growth of Balearics

		5% increase	8% increase	10% increase
ARMAX	1999	0.6%	1.0%	1.2%
	2006	0.5%	0.8%	1.0%
GARCH	1999	0.6%	1.0%	1.3%
	2006	0.5%	0.8%	1.0%

The second simulation tries to evaluate the implications of promoting (or discouraging) tourism during different seasons on electricity consumption. Taking the number of tourist arrivals to the Balearics, three seasons were considered: the high season, which comprises June, July, August and September; the low season, which covers January, February, November and December; and the mid season, consisting of March, April, May and October. A seasonal analysis of electricity consumption was conducted by increasing the daily population stock by 3%, 5% and 10% and then computing the results for each season. Table 1.3 shows that, as expected, high electricity growth rates are recorded for non-residents during the high season, whereas minimums are reported in the low season. In addition, for the ARMAX and GARCH models, the seasonal growth rates associated with non residents remain fairly constant, with a lower level of variation between seasons.

Table 1 3 A simulation for tourist monthly electricity consumption growth of Balearics

		3% increase	5% increase	10% increase
ARMAX	High	0.68%	1.14%	2.28%
	Medium	0.27%	0.45%	0.90%
	Low	0.06%	0.10%	0.19%
GARCH	High	0.72%	1.20%	2.42%
	Medium	0.29%	0.48%	0.96%
	Low	0.06%	0.10%	0.20%

Finally, to estimate the marginal effect of tourism on total electricity consumption in the Balearic Islands, and considering the time period that ranges from January 1995 to September 2007, it is relevant to mention that using either ARMAX model or GARCH model, the marginal effect of an additional tourist in the Balearics islands is less than the marginal effect of an additional residents. For instance, in the case of ARMAX model the marginal effects for an additional tourist and additional resident are 0.371Wh and 0.434Wh respectively.

1.5. Conclusions

Assessing environmental impacts is essential if the sustainability of tourism is to be improved. Thus it is important to ascertain the magnitude of environmental impacts and their associated costs as a means of determining appropriate development strategies and solutions. Literature reveals that the costs associated with tourism have been evaluated from a sectoral perspective, given the non-recognition of the tourist sector in conventional public economic accounting. However a need to assess the environmental costs of tourism activities arises when different development policies are considered from a regional point of view.

A consistent methodology is required to assess the impact of tourism on electricity consumption in order to determine how the current pattern of the population stock will affect the demand for energy. Using the case study of the Balearic Islands, bearing in mind the advantages of the fact that it is an isolated tourism-intensive region, a stock variable for tourism pressure was developed to be included in a traditional electricity demand model. The feasibility of applying ARMAX and GARCH models to the daily electricity demand was examined and a high level of significance was obtained for both resident and non-resident population stocks. Strong evidence was found to show that the daily electricity load can be characterized by GARCH models. The sum of the GARCH coefficients is close to one, which means a persistence of the conditional variance. It was also demonstrated that the GARCH model performs better than the ARMAX model in terms of deviation measurement criteria, although results in terms of elasticity remain very close.

The findings suggest an electricity demand with an increasing sensitivity depending on the population stock. This increasing sensitivity is probably one result of an increasing number of tourists during the peak season. However, the analysis showed that the sensitivity of the electricity load to the population stock variable increased across the time period for residents and non-residents, with a higher sensitivity in the case of the resident population. This result coincides with the idea that residents' financial status has grown at a higher level than that of tourists, implying a higher growth level in electricity consumption.

Furthermore, three different approaches were taken in the sensitivity analysis. First the population effect was evaluated through a hypothetical increase in absolute values in the non-resident populations, results in an increase of electricity consumption, with annual rates ranging between 1.4% and 3% for the three simulations. Second, an assessment of the seasonality effect showed a growth in electricity consumption by non-residents of between 2.3% and 2.4% during the high season in the case of a 10 % increase in the population stock, contrasting with a growth rate of 0.2% during the low season. Finally, the marginal effect of an additional tourist is found to be 6.5% lower than a marginal effect of an additional resident.

These results are of considerable importance for tourism planners in helping to mitigate the effect of high energy consumption on the environment. The role of policymakers is to avoid hampering and, if possible, to facilitate the adjustment in the Balearic electricity market. The diversification into alternative sources of energy, such as solar, wind, geothermal, biomass and ethanol ect, can help to ensure a sufficient supply of energy in the future. Furthermore, to encourage energy conservation, the state government should implement educational programs that promote energy conservation by both the tourism and residential sector. Tax credits can be introduced for the installation of energy saving devices and equipment. Efficiency in energy use can be promoted by providing incentives for the design and the construction of energy-efficient housing and public infrastructure, as well as the use of more energy-efficient production equipment and power transmission by utility companies. Future research will have to explore evaluations of tourism’s share of the electricity load in other regions, by considering the intra-annual variability of monthly arrivals, assuming that this variable can be used for other regions. Results for other areas should be compared with those obtained in this study in order to validate them.

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CHAPTER 2

IMPROVING DAILY ELECTRICITY LOADS FORECASTING IN TOURIST ISOLATED AREAS

Chapter 2 Improving daily electricity loads forecasting in tourist isolated areas

Abstract

Electricity demand forecasting is becoming an essential tool for energy management, maintenance scheduling and investment planning. In small and isolated electric systems like in many islands, the power system is usually not extensively interconnected with enough number of electric generators and loads, hence it provokes an electric load shedding or forces the electric utility to take control actions such as temporary power outage. Despite this trouble, isolated territories are fortunate to have the possibility of estimating the population pressure in a very accurate manner, even at a daily level. This is possible thanks to the fact that entries to these territories are limited to ports and airports which in turn facilitate keeping the record of in/out flows to/from the territory. Investigating this problem, using the most classical and standard prediction techniques applied to the case of Balearic Islands (Spain) authors demonstrate how daily arrivals and people stocks improve accuracy of forecast.

Keywords: electricity load forecasting, isolated electric systems, daily models, population pressure, tourism

2.1. Introduction

The need of having an accurate electricity load forecast is of crucial importance to electricity planning in both short-term and long-term. The former is relevant because the national grid requires a balance between the electricity produced and consumed at any instant of the day, in other words it is essential to balance the generation capacity with the system demand. The latter is important for staffing, maintenance, and capital investment planning. As the operation and control processes for an electric utility are quite sensitive to forecasting errors, their costs can be easily increased due to the presence of large forecasting errors. For example Hobbs et al (1999) found that a reduction of 1% in the average prediction error can annually save millions of dollars for a typical utility whose annual fuel costs amount to several hundred million dollars.

Therefore, forecasting accuracy is a basic tool for determining the optimal utilization of generators and power stations, especially that electricity is not a storable item and some facilities are more efficient than others. In fact, overestimating the future load results in unused spinning reserve which is being burnt for nothing, in the other side underestimating future load is equally detrimental because high starting costs are incurred if the cold reserve has to be used. Furthermore, in situations when the option to buy at last minute from other suppliers remains obviously expensive; and when demand is exceeding power supply, electric companies may intentionally cut power partially or totally in order to avoid a total blackout of the power system. Technically speaking, a failure of a component or part of the general network causes a fixed load increase for other components, then the electric system becomes more loaded and a cascading failure of further components becomes more likely to occur (Dobson, Carreras, & Newman., 2003).

For small and isolated electric systems, their inability to be tapped into a continental transmission grid for emergency power, results in reliability and other economies of scale impacts. Thus, the power systems operate on the premise that the load is uncontrollable and that system voltage, frequency and stability are primarily maintained through the real-time control of the generation. Frequency is a necessary parameter for load control in interconnected systems, as it is considered as a measure of mismatch between demand and generation. Therefore, the Control systems in power plants detect changes in the network-wide frequency and adjust mechanical power input to generators back to their target frequency. However, in the great majority of islands and isolated areas power systems that are not extensively interconnected with many generators and loads, will not maintain frequency with the same degree of accuracy and therefore cause an automatic load shedding or other control actions such as temporary power outages. This scenario is more probable during heavy loads periods, when the accuracy of the system is hard to maintain (Qiu, Liu, Chan, & Lawrence, 2001; Trudknowski, Donelly, & Lightner, 2006).

Whatever the case, effective planning requires a thorough understanding of the prevailing electricity demand patterns. Thus, for modeling and forecasting purposes the existing literature has extensively analyzed the main features of demand. Actually, electricity consumption is subject to great cyclical and seasonal effects (daily and weekly cycles, holidays), special events, nonlinearity of meteorological variables and possible nonlinear time dependence, etc (Cancelo, 1996; Moral-Carcedo and Vicns-Otero, 2005; Pardo, Meneu, & Valor, 2002; Taylor and Buizza, 2003; Valor, Meneu, & Caselles, 2001).

However, the specificity of an open space, where the mobility of people outside and within a country is usually unrestrained, impedes the inclusion of an accurate variable that captures the daily population pressure effect. Contrastingly, this indicator can be accurately measured in islands and isolated territories that control their population transit. For instance, in the case of islands, where the only means of access and exit are ports and airports, it is expected that for security reasons there is a thorough control on the daily flow of incoming and outgoing passengers. Majority of islands have the possibility to assess the daily population's weight present in their territory, which is generally characterized by its high fluctuations and seasonal aspects.

A natural a priori hypothesis is that the daily electricity demand depends on the population stock, and most likely this dependence is very relevant in isolated territories where high seasonal fluctuations could easily affect the efficiency of the electrical system and provoke serious and costly problems. A high level of seasonality is a distinctive feature of coastal tourist regions, a problem that often characterizes islands too. Therefore, the possibility of having a daily population indicator will definitely fulfils the need of an accurate forecasting model that can predict future electricity demand, and provide the utility company with a model that reduces the gap between supply and demand and its concomitant cost.

This article reports on the design and implementation of a medium-run forecasting model for daily system loads and an evaluation of the forecast performance of the Balearic Islands (Spain). An archipelago located in the western Mediterranean Sea that includes four inhabited islands Majorca, Minorca, Ibiza, and Formentera. The last two conform what is known as the Pitiüses, a special unity in terms of electricity system. The Balearic Islands system supplies electricity annually to 1 million residents and 13 million tourists concentrated during summer months. The Balearic Islands are taken as a case study because of their geographical characteristics and relative importance of tourism in the region.

2.2. Methodology

Literature does not show any consensus on the best approach to electricity demand forecasting. The range of different approaches used recently includes classical time series models (Cancelo, Espasa, & Grafe, 2008; Dordonnat, Koopman, Ooms, Dessertaine, & Collet, 2008; Gabreyohannes, 2010; Goia, May, & Fusai, 2010; Taylor, 2008 and 2010; Taylor, Menezes, & McSharry, 2006), and machine intelligence framework (da Silva, Ferreira, & Velasquez, 2008; Hippert, Bunn, & Souza, 2005). Although within each one of these categories the sophistication of the applied techniques can be qualified as high, in this chapter, I exclusively consider the most basic time series models i.e. naive and exponential smoothing as benchmarks and ARMAX for the inclusion of explanatory variables.

2.2.1. Benchmarks methods

The simplest benchmark method in forecasting exercises is often known as naïve method, assuming that the forecasted observation is the last real observation available, and is also the simplest benchmark method used in this work.

Additionally, the so called Exponential smoothing method is based on the idea of separating the time-series trend from its random disturbance, that is, it ‘‘smoothes” series behavior. It is important to remark that in this method the models are usually constructed based on empirical reasoning. The Winter’s method is one of several exponential smoothing methods that can analyze seasonal time series directly. A very interesting survey for this method can be found in Gardner (2006). Examples of this method's application to electric load forecasting problem can be found in Song, Ha, Park, Kweon, & Kim (2006), Taylor, Menezes, & McSharry (2006) and in Gould Koehler, Keith Ord, Snyder, Hyndman, & Vahid-Araghi (2008).

2.2.2. Multiple regression & time series models

A basic conventional structure decomposes the observed load into four components: the normal load, the weather sensitive part, special events, and a random component. Assuming a conventional aggregated energy demand relationship and following Cancelo, Espasa, & Grafe (2008) or Considine (2000), a log-linear model can be analytically expressed as:

$$\ln C_t = p_t + s_t + CSD_t + CWEA_t + u_t \qquad [1]$$

Where C_t denotes the electricity consumption on day t; p_t is the trend and s_t (part of) the deterministic pattern; CSD_t represents special days; $CWEA_t$ refers to the meteorological variables, and u_t is the disturbance term. The diagnostic of the transitory dynamics displayed by u_t term is performed using the ARMA structure. A plot of the autocorrelation function and partial autocorrelation function and some conventional tests, like the Augmented Dickey Fuller test, are used to decide whether a data series is stationary or not. Thus an ARMAX (p, q, b) model for the electricity load can be also represented as:

$$\phi(p)\ln C_t = \eta(b)X_t + \theta(q)u_t + \varepsilon_t \qquad [2]$$

Where $\phi(p)$, $\eta(b)X_t$ and $\theta(q)$ are the lag polynomials for the natural logarithm of the electricity demand (*C*), the exogenous variables matrix (*X)* (which is formed by the variables *p*, s, *CSD*, and *CWEA*) , the moving average term (*u*) and ε is white noise.

An extension of the equations [2] is proposed in this study by analyzing the inclusion of the population pressure (for residents and tourist) as an additional exogenous determinant. This variable can be easily obtained in isolated territories where a higher level of forecasting accuracy is specially appreciated. Thus, analytically, equation 1 can be extended, to:

$$lnC_t = p_t + s_t + CSD_t + CWEA_t + P_t + u_t \qquad [3]$$

where P_t denotes the population pressure. In a similar way equation 2 can be rewritten as

$$\phi(p)\ln C_t = \eta(b)X'_t + \theta(q)u_t + \varepsilon_t \qquad [4]$$

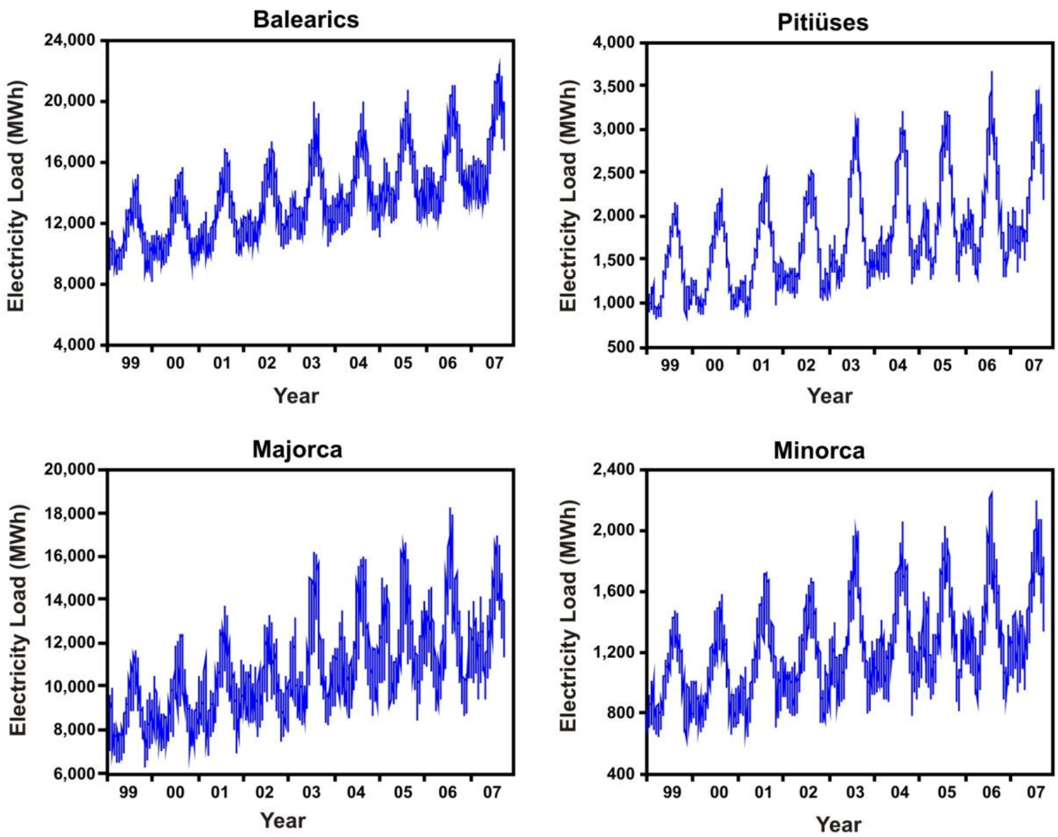
where *X*' includes the variables *p*, s, *CSD*, *CWEA* and P_t.

2.3. Data and forecasting evaluation strategy

2.3.1. Data

The dataset used in this study concerns daily time series for electricity consumption for Majorca, Minorca and Pitiüses (Ibiza and Formentera). The Balearics are considered jointly from January 1995 until September 2007. This is 4655 daily observations for each one of the four utility systems considered. The dataset was compiled by the Spanish System Operator Red Electrica de España and no missing observations were present. Charts of the time series. in Figure 2.1. show a clear trend along the whole sample, and depict different seasonal cycles. In this case, it should be highlighted that for many coastal areas in the Mediterranean Sea, high season is characterized with high temperatures and an important presence of tourists. Therefore, it is important to be aware that the seasonal movement of electricity load is not originated exclusively by weather pattern but also from differences in the population that is on the islands during the year.

Figure 2 1 Daily electricity consumption in the Balearic Islands



Meteorological variables were provided by the *Instituto Nacional de Meteorologia*, the Spanish official meteorological bureau, and are referred to the airport stations. From the experience of previous literature, the weather-related factors that can influence the electricity demand are temperature, humidity, wind and precipitation in decreasing order of importance (Engle, Mustafa, & Rice, 1992). However, the non-linear influence of temperature on the electricity demand (Valor, Meneu, & Caselles, 2001) suggests the use of two temperature derived functions: heating degree-days (HDD) and cooling degree-days (CDD). When dealing with the non-linearity of the temperature effect, the most frequent approach is to segment temperature into HDD and CDD, defined as shown below:

$$\mathrm{HDD}_t = \mathrm{Max}\ (T_{\mathrm{ref}} - T_t, 0) \qquad [5]$$

$$\mathrm{CDD}_t = \mathrm{Max}\ (T_t - T_{\mathrm{ref}}, 0) \qquad [6]$$

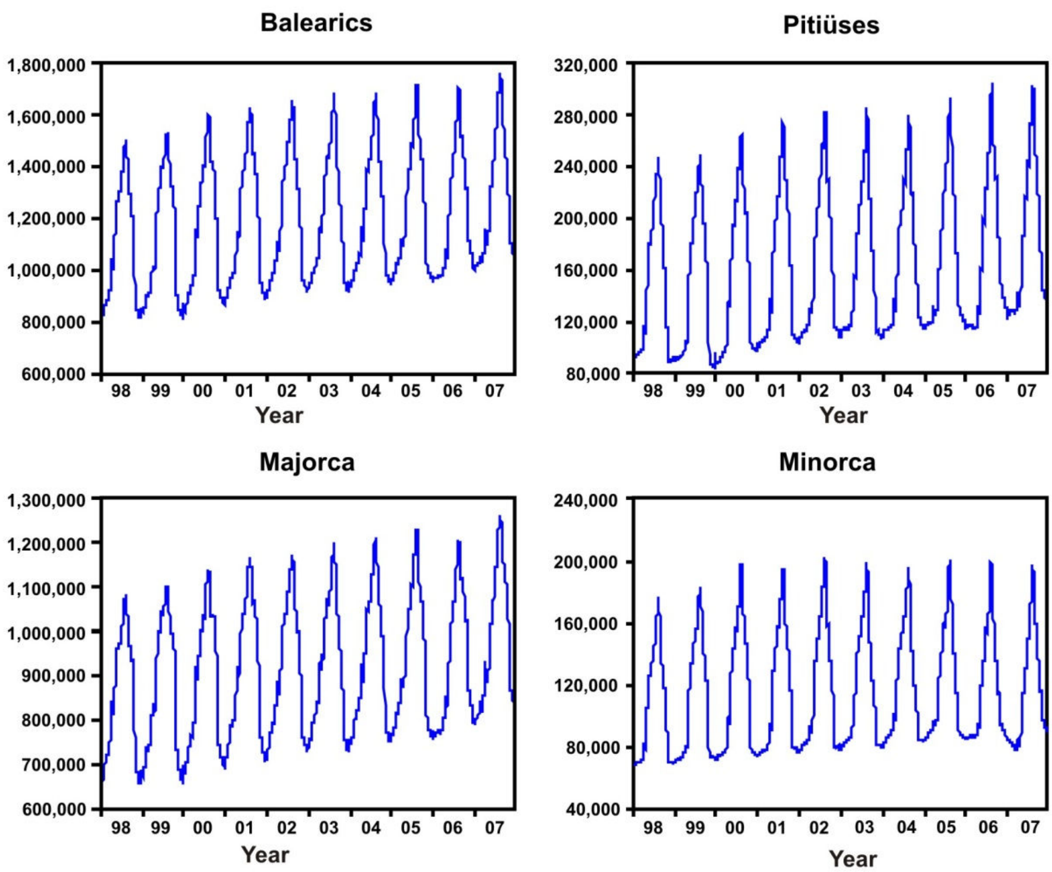
T_t is the weighted average temperature for day t and T_{ref} is a reference temperature that must be adequately selected to separate the hot and cold branches of the demand-temperature relationship. In combination, these functions reflect the number of days on which the temperature falls below or rises above the heating and cooling thresholds and by how many degrees. Since there is no strict quantification of the values of the "threshold" temperatures, there can be many different versions of the HDD and CDD functions. In the context of this study, the selected reference temperature is equal to 17°C for high temperatures and 12°C for low temperatures.

Additionally, because of the particularly high degree of humidity that characterizes the Balearic Islands, a Heat Index (HI) was incorporated as an alternative to the use of the simple mean temperature variable. Measurements have been taken in other studies, based on subjective descriptions of how hot subjects feel for a given temperature and humidity, allowing for the development of an index where a combination of a certain temperature and humidity corresponds to a higher temperature in dry, non-humid conditions. Whatever the case, the most commonly used formulation of an HI was proposed by Steadman (1979) and it is also adopted in this study.[4] For the measurement of the Balearic index, a population-weighted temperature index was constructed from the mean daily temperatures measured separately on the different islands. The population was selected as a weighting factor because climate influences electricity consumption through people's response to the weather; the larger population, the greater the influence of weather conditions on the electricity demand.

Finally, for the case of the population pressure, airport and port data were taken as reference in order to undertake two different measures. First, an estimation of the daily population stock of people on the islands, namely Human Pressure Daily Indicator (HPDI), was used as the most suitable variable from a theoretical point of view, to account the idea of population pressure. The HPDI was developed by Riera and Mateu (2007), and analyzed by Haldrup, Hylleberg, Pons, & Sansó (2007) and Bakhat, Rosselló, & Saenz de Miera (2010). The HPDI is an estimation of the daily people that is on each on of the islands, based on resident population registers and daily arrivals and departures from the airports and ports. Results from the HPDI estimation for our period of analysis can be seen in Figure 2.2, where a positive trend and a clear hard seasonal variation can clearly be observed.

[4] Thus $HI = -42.379 + 2.04901523T + 10.14333127R - 0.22475541TR - 6.83783 \cdot 10^{-3}T^2 - 5.481717 10^{-2}R^2 + 1.22874 \cdot 10^{-3}T^2R + 8.5282 \cdot 10^{-4}TR^2 - 1.99 \cdot 10^{-6}T^2R^2$, with T = ambient dry bulb temperature degrees in Fahrenheit and R = relative humidity.

Figure 2 2 Population stock (HPDI) for the Balearic Islands



The second reference measure for the population pressure was the daily airport arrivals. Although from a theoretical point of view this second measure exhibits different defects, since different tourists' length of stay is not captured by this measure. However, in the Balearics islands more than 90% of arrivals are via airports (less than 10% are via ports) and tourists' length of stay remains relatively similar during the year, hence the variability between HPDI and the airport arrival is significantly reduced. In contrast, taking into consideration the forecasting objective of this work, it should be noted that in practice, forecasts should be implemented to get either daily tourists arrivals or HPDI variable. Hence, prediction for airport daily arrivals are easy to undertake through the slots that airport authorities have engaged, while HPDIs' prediction is comparably complicated due to the the presence of other historical data incorporated in HPDI measure.

2.3.2. Forecasting evaluation strategy

We used 84 months of daily data from 1 January 1999 to 31 December 2005 to estimate model parameters, and 12 months of daily data from 1 January 2006 to 31 December 2006 to evaluate the different forecasting methods. This 12 months period gave 365 days for evaluation period for lead times of 1 to 10 days ahead. Analysis and forecasts of Balearic's electricity consumption has been undertaken for every single island separately and jointly, thus considering Majorca, Minorca and Pitiüses. Models were estimated using the multivariate regression and ARMAX models described above. Their forecasting performances were compared to the set of benchmark models also mentioned in the previous section. Table 2.1 summarizes the benchmark and the rest of models used in the forecasting exercise.

Table 2 1 Models for forecasting evaluation

Model 1	Naive	$\widehat{C}_t = C_{t-7}$
Model 2	Holt Winters Multiplicative	$\widehat{C}_{t+k} = (a(T) + b(T)k)c_{T+k-s}$ where a, b and c are the estimated recursive coefficients
Model 3	Static Model with meteorological variables	From equation 1
Model 4	Dynamic Model with meteorological variables	From equation 2
Model 5	Static Model with meteorological variables and HPDI	From equation 3
Model 6	Dynamic Model with meteorological variables and HPDI	From equation 4
Model 7	Static Model with meteorological variables and daily airport arrivals	From equation 3
Model 8	Dynamic Model with meteorological variables and daily airport arrivals	From equation 4

Comparison of the different sets of forecasts was undertaken using the mean absolute percentage error (MAPE) summary measure, which is used extensively in the electricity demand forecasting literature. It is important to highlight how the performance of the exercise was assessed. On the one hand it was assessed by the whole year while on the other hand because of the special interest for the electric system in providing good accuracy forecasting during the peak seasons the data base of errors was split into three parts: the high season, which comprises June, July, August and September; the low season, which covers January, February, November and December; and the mid season, consisting of March, April, May and October.

2.4. Results and forecast performance

Daily forecasts were used to set up the weekly network outage plan. They were computed by the middle of the week, usually on Wednesday morning, with information up to Tuesday, for the seven-day period beginning the following Saturday. The relevant lead times go from 4 to 10 days ahead, although they are some minor modifications. For example, the origin of the forecast changes when a public holiday falls on Wednesday. We ignore this for the sake of simplicity, and act as if there is a one to one relationship between the day of the week and the lead time. Thus, table 2.2 reports MAPE for the different models used in this study. Bold figures indicate which model attains the lowest MAPE.

Table 2 2 Mean absolute percentage errors (MAPE) in daily forecasting for the entire year

	Naive	Holt Winter	Static 1	Static 2
	Model 1	Model 2	Model 3	Model 5
Majorca	6.024	4.784	6.297	6.209
Minorca	6.470	5.522	7.303	5.392
Pitiüses	6.619	5.096	9.118	7.334
	Using HPDI		Using Tourists' Arrival	
	Dynamic 1	Dynamic 2	Static 2	Dynamic 2
	Model 4	Model 6	Model 7	Model 8
Majorca	2.721	**2.675**	6.615	2.726
Minorca	**2.942**	2.958	6.719	**2.899**
Pitiüses	**2.319**	2.336	7.854	**2.309**

Results show how using the HPDI variable and considering the static models (Model 2 and 3) the forecasting errors have decreased for all the islands (Majorca; Minorca and Pitiüses), whereas in the case of the dynamic models (model 4 and 6) this feature is only observed for Majorca island and not for Minorca or Pitiüses. Secondly, the use of airport's arrival as a substitute to HPDI in our case of study does not improve the MAPE in Majorca for neither of the static or dynamic models. However, in the case of Minorca and I Pitiüses, the MAPEs decrease for static and dynamic models. Particularly, in the dynamic models that include airport's arrival have a better forecasting performance than their correspondent that include HPDI, though the values of the MAPEs are very close (2.899 and 2.30 versus 2.95 and 2.33 for Minorca and Pitiüses respectively). Moreover, the real time performance of the model 6 and model 8 seems to be satisfactory, in the sense that the errors are within the bounds that guarantee the electricity supply security and quality, reflected by MAPEs below 5%, a constant limit suggested as a benchmark in the literature (Ranaweera, Karady, & Farmer, 1997).

Table 2 3 Mean absolute percentage errors (MAPE) in daily forecasting for different seasons

						Using HPDI		Using Tourists' Arrival	
		Naive	Holt Winter	Static 1	Static 2	Dynamic 1	Dynamic 2	Static 2	Dynamic 2
		MODEL 1	MODEL 2	MODEL 3	MODEL 5	MODEL 4	MODEL 6	MODEL 7	MODEL 8
Majorca	LOW SEASON	6.483	5.048	5.688	6.649	3.142	3.118	6.660	3.145
	MED SEASON	5.502	4.374	7.385	5.840	2.583	2.569	7.631	2.588
	HIGH SEASON	6.119	4.953	5.753	6.160	2.448	**2.345**	5.495	2.454
Minorca	LOW SEASON	6.579	5.389	7.182	5.946	3.675	3.657	7.011	3.586
	MED SEASON	6.688	5.799	8.576	4.951	2.503	2.500	7.773	2.479
	HIGH SEASON	6.130	5.363	6.075	5.304	**2.673**	2.744	5.313	**2.658**
Pitiüses	LOW SEASON	6.871	5.885	10.444	8.305	3.014	3.010	8.406	3.013
	MED SEASON	6.641	4.944	10.529	6.893	1.983	2.080	9.704	1.970
	HIGH SEASON	6.343	4.467	6.299	6.828	1.981	**1.933**	5.341	**1.965**

Table 2.3 shows the results of the forecasting performance by season. For Majorca, the inclusion of HPDI variable in the dynamic model improves the forecasting performances for all seasons. However its corresponding model that includes airport arrivals does not perform well and their MAPEs stay practically very close to the MAPEs of the model 4 (Dynamic model that does not include any population stock). In other words, the dynamic model that incorporates HPDI performs better in all seasons than its correspondent that includes airport's arrival. For Pitiüses, the same features are observed in low and high seasons, where the dynamic model that includes HPDI has a better forecasting performance than its correspondent. Particularly, the inclusion of airport arrival as a variable in the dynamic model improves the forecasting performances. However the values of MAPEs are inferior to their correspondent in the HPDI model. Finally, in the case of Minorca which has a different pattern, the forecasts deteriorate during high season when we use HPDI variable, however the use of airport's variable in this particular case improves well the forecasting performances in all seasons.

2.5. Summary and conclusions

Many islands around the world are characterized by small and isolated electric systems and a high level of tourism specialization from an economic point of view. Thus, on the one hand, having an accurate electricity load forecast is of crucial importance to electricity planning in short-term and, on the other hand, variability in population stocks can be incorporated easily to electricity load models using data from port and airport control points. This chapter has investigated these special circumstances studying Balearic Islands as a particular case and forecasting for lead times from 1 to 10 days ahead, which coincide with the forecasting system currently implemented at Red Eléctrica de España, the Spanish system operator.

Using simple multiple regression and time series models, results have evidenced again the usefulness of including meteorological variables in daily electricity forecasting. However, the most significant result has been the usefulness of including daily population measures that is found to be relevant in improving the forecasting accuracy. Thus, the results have shown that the major improvement in error reduction comes from understanding how the load reacts to population stock variable, and integrating its effects together with the weather variables and other specific dummies in an extended model that captures the main determinants of the electricity load. In general, and depending on the particularity of the islands, the inclusion of either HPDI variable or airport's arrival variable improves the forecasting performance of the dynamic model ARMAX.

Use of HPDI variable in the dynamic model in the case of Majorca outperforms the forecasting performances in annual average and in high season. For Pitiüses the same model perform well in annual average and low season, but stands behind in high season, compared to its correspondent that uses airport's arrival variable. Finally, in the case of Minorca the dynamic models that incorporate airport's arrival variable perform better in all seasons and in annual average compared to their correspondent that involves HPDI variable.

Inclusion of tourist variables in forecasting electricity models can be of enormous interest for tourism regions that can star replicating the approach presented in this chapter. However further research would have to consider the inclusion of this variable but using more advanced techniques. We, therefore, conclude that there is strong potential for the use of population stock variable in improving the accuracy and uncertainty assessment of electricity demand forecasts for number of tourist destinations with the same characteristics as Balearics Islands.

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CHAPTER 3

SEASONAL FUEL TAX IN TOURIST REGIONS

Chapter 3 Seasonal fuel tax in tourist regions

Abstract:

This chapter formulates and estimates diesel oil and gasoline demands in a representative tourist region (Balearic Islands) which is characterized with a high level of seasonality. Using conventional fuel demand models, and including variable to account for the human pressure, results confirm conventional wisdom that fuel consumption responds positively to changes in income and negatively to changes in prices. This study discusses the appropriateness of fuel tax when it is applied only in the high season. Furthermore, using estimated elasticities, different price policies are evaluated with special reference to a seasonal fuel tax.

Keywords: Diesel oil demand, gasoline demand, tourism, fuel tax.

3.1. Introduction

Petroleum products demand has received a great deal of attention as a research topic during the last decades. Initially, since the 1973 oil crisis, a growing number of studies modeled demand for gasoline addressing concerns about the availability of this non-renewable resource. Most of those studies focus on the demand for motor gasoline for automobiles since the segment was relatively important and represented one of the highest growth rates. The quantification of price and income elasticities of fuel demand was of paramount interest in order to project future trends of oil markets in order to plan infrastructures and strategic reserves.

Whereas last late century scientific research was fueled mainly by the threat of energy scarcity, nowadays environmental problems like the potential global warming change are becoming increasingly important. Recently, studies have directed the various environmental consequences of petrol consumption, particularly with respect to the emission of greenhouse gases (Raux and Lee-Gosselin, 2010). In this new context, accurate estimations of petrol demand are also important because of the wide range of fiscal instruments that are worldwide applied.

The need for mechanisms that promote more efficient use of transport has encouraged the use of fuel taxes or charges, given their considerable benefits in terms of the achievement of a ‘‘double dividend’’ through the improved efficiency of the tax system (Bovenberg and Mooijr, 1994) and efficient compliance with the ‘‘Polluter Pays Principle’’. These principles have led to different purposes aimed to directly tax those activities less environmentally respectful, being the increase of fuel prices one of the last options that have recently emerged in the context of tourism policy (Tol, 2007; Mayor and Tol, 2010; Rothengatter, 2010; Zhang et al. 2010) and more specifically the taxation of gasoline and diesel oil during high season months (Aguiló et al. 2011).

The arguments for a temporal discriminatory fuel tax during the year include the high exportability of the tax (an important part of the revenues from taxes come from non-residents and, then, by non voters) and discouraging private road transport during the high season, one of the most important tourist externalities (Palmer et al., 2007). The key objective of this chapter therefore is to model and estimate diesel oil and gasoline demand with the aim of deriving the role of human pressure in these demands and find more robust estimates of price and income elasticities that could be used in the design of a fuel tax applied exclusively during some months.

This study is structured as follows. In Section 2 the relationship between gasoline demand and their determinants is discussed, with reference to the seasonal contribution of tourism sector. In Section 3 methodological considerations and model specification are introduced Data with results and discussions are presented in Section 4. Section 5 discuss results and policy implications and concludes.

3.2. Fuel demand from road transport and tourism

Tourism sector remains a controversial issue in the sustainable development. Although tourism is considered an important source of foreign currency and contributes to the economic growth and the generations of jobs, the interest for their environmental consequences has been increased recently. Awareness about environmental impacts, their contribution to environmental degradation and climate change because of the large quantities of fossil fuels that are required to operate has centered the most recent literature. Lundie, et al. (2007) researched an environmental measure of tourism yield by input-output analysis showing how the major driving factor for energy input is accommodation, causing 16-29% of the total energy demand. Becken et al. (2003) also observed key tourism industry subsectors with the highest energy demand, notably transportation, accommodation, and activity in tourist attractions. Other studies suggested the relevance to research these three subsectors in terms of their onsite impact by energy consumption and transportation (Dubois and Ceron, 2006; Kelly and Williams, 2007).

Air transportation is a primary form of frequent, long-distance travel and is often criticized for causing large quantities of greenhouse gas emissions (Becken, 2002). The Environment Protection Agency (EPA), estimated that 76.5% of greenhouse gas emissions of the tourism and recreation sector were caused by transportation (against 15% for lodging, 2.7% for restaurants, 1% for retail, and 4.8% that are activity-specific) for the United States, and this largely due to the longer air travel distance involved in attending conventions (EPA, 2000).

However, recent studies on social trend showed that tourism is highly influenced by income-driven lifestyles that increase auto-utility and energy use for pleasure and leisure, and thus, people tend to be more concerned with personal convenience than with environmental protection (Becken, 2004). With the significant increase of non-package holidays tourist habits worldwide seem to favor a higher number of shorter breaks to short-distance, short-haul destinations, which in turn leads to increased mobility. Therefore, the continued growth of low-cost airlines and the increasing use of the Internet will sustain this trend and give more extension to ‘‘self-service’’ tourism (Palmer et al., 2007).

New trends in tourism point towards an increase in tourist mobility in the host country or region, with a subsequent rise in externalities associated with the use of hire cars like atmospheric and noise pollution, congestion and greater numbers of accidents (Rosselló and Saenz-de-Miera, 2011). Consequently, transportation demand management strategies have become a central issue in regarding sustainable tourism policies in multiple destinations being the analysis of the fuel demands one of the key issues to be determined previous to the design of any policy.

To our knowledge, none of the fuel demand studies or tourism studies so far has used monthly time-series data to capture the effect of tourism on fuel demand meanwhile oil and gasoline demand price elasticities are estimated. Thus, the chapter is a contribution to the literature, first, to formally test the relationship between tourism and the demand of road transportation fuels and, second, to providing a first evaluation of the effects of a seasonal fuel tax.

3.3. Model and empirical specification

The reviewed literature revealed that the demand for fuel has been modeled in variety of ways. The lagged endogenous model has been used extensively in the literature. The most common variables that have been included in the estimation of the fuel demand models include real income, real price of fuel type, price of substitute energy sources and vehicle fleet. Given data constraints on most of these variables we estimate a simple model of fuel demand. We specify fuel demand as function of income and the real price of fuel type, including the price of substitute fuel when appropriate. We do not include vehicle fleet because of data unavailability. Following the specifications of Bentzen (1994), Alves and Bueno (2003), Ramanthan (1999), and Polemis (2006), we specify our model of fuel (Diesel and Gasoline) demand in log-linear form. To account in the model for the monthly seasonality temperature, eleven dummy variables Mjt were introduced, each representing one of the months in a year and taking January as the base month. Thus, j refers to February, March, April, May, June, July, August, September, October, November and December, and Mjt equals 1 if in the t observation the month j is found, and 0 otherwise. In this study in addition to these variables, demographic variables reflecting the human pressure both from residents (*HP_R*) and from tourists (*HP_T*) are also used as explanatory variables, since significant fluctuations over the year can be expected influencing fuel demand. Therefore the long-run fuel demand takes the following form:

$$\ln(G_t) = \alpha + T + \beta_1 \ln(P_t) + \beta_2 \ln(IN_t) + \beta_3 \ln(HP\_R_t) + \beta_4 \ln(HP\_T_t) + \sum_{j=2}^{12} \lambda_j M_{jt} + \varepsilon_t \qquad (1)$$

Where $ln(G_t)$ is the natural log of the monthly fuel consumption at time t, $ln(P_t)$ is the natural log of the monthly real fuel price at time t, $ln(IN_t)$ is the natural log of the monthly real income at time t, $ln(HP\_R_t)$ and $ln(HP\_T_t)$ are the natural log of the monthly human pressure indicator for residents and tourists respectively, M_{jt} are dummies that capture the month of the year, T stands for the trend that could be present in the time series, and α, βi ($1 \leq i \leq 4$) λ_j ($2 \leq j \leq 12$) are parameters to be determined, and ε is a random error which is assumed to be white noise and normally and identically distributed. According to economic theory β_1 and β_2 are expected to be positive and negative respectively. Higher real income will increase purchases of motor vehicles and hence increase fuel consumption.

Assuming that the fuel demand followed the traditional in Eq. (1), the change in price postulated by the hypothetical question should have led to change fuel consumption. Because only the price changes in the hypothetical case, Eq. (1) suggest that the rest of the variables should have dropped out. That is, the βi (2≤i≤4) from Eq. (1) should equal zero given a change just in prices. However, there is a possibility that different people behavior would result in different responses to the proposed changes in price, making βi (2≤i≤4) different from zero for some variables. Thus, we propose a modification of the Eq. (1) to analyze the influence of annual change in explanatory variables on the annual change of fuel consumption:

$$\Delta_{12}\ln(G_t) = \alpha + \beta_1\Delta_{12}\ln(P_t) + \beta_2\Delta_{12}\ln(IN_t) + \beta_3\Delta_{12}\ln(HP\_R_t) + \beta_4\Delta_{12}\ln(HP\_T_t) + \varepsilon_t \quad (2)$$

where $\Delta_{12} = (1 - L^{12})$ and L is the backshift operator, the model could be extended when appropriate with different interaction terms.

The basic double-log model assumes that elasticities are constant over each analysis period. However, factors such as the level and change in fuel price as well as to different behavioral responses may lead to differences in price elasticity estimated during different periods of the year. To investigate these issues, two dummies HS (High-season) and LS (Low-season) are included in Equations 1 and 2 to separate the effect of price changes. HS includes May, June, July and August whereas LS gather the rest of the months, and will have the following extended models:

$$\ln(G_t) = \alpha + T + \beta_{1,HS}\ln(P_t) * HS + \beta_{1,LS}\ln(P_t) * LS + \beta_2 \ln(IN_t) + \beta_3 \ln(HP\_R_t) + \beta_4 \ln(HP\_T_t) + \sum_{j=2}^{12} \lambda_j M_{jt} + \varepsilon_t \quad (3)$$

$$\Delta_{12}\ln(G_t) = \alpha + \beta_{1,HS}\Delta_{12}\ln(P_t) * HS + \beta_{1,LS}\Delta_{12}\ln(P_t) * LS + \beta_2\Delta_{12}\ln(IN_t) + \beta_3\Delta_{12}\ln(HP\_R_t) + \beta_4\Delta_{12}\ln(HP\_T_t) + \varepsilon_t \quad (4)$$

The most common form used in this chapter, is the log-log specification, largely used because it can reduce the potential heteroscedasticity and because it gives direct estimate of the relevant elasticities. We performed an initial estimation of the system using the log-linear form and conducted RESET tests for functional misspefication. All the models passed the Reset test.

The models were estimated both individually using ordinary least squares (OLS) and simultaneously using the seemingly unrelated regression equations method (SURE). SURE provides more efficient estimates than OLS when the error terms in different equations are contemporaneously correlated. Specific factors associated with each country that are not accounted for in the model, such as cultural influences or government policies, could give rise to contemporaneous correlation. On the other hand, the different functional forms of the equations could mean that such correlation may not exist. For this reason, we conducted a Lagrangian multiplier test for the hypothesis that no correlation exists in errors across equations and we found this to be insignificant implying that OLS may be more efficient than SURE. However, the Lagrangian multiplier test is not definitive, especially for a small sample such as the one used in this analysis. We have thus included both an OLS and SUR model in the results that follow, which also useful for comparative purposes.

3.4. Empirical application

The fuel (diesel oil and gasoline) demands in the Balearic Islands (Spain), a 5,000 sq. kilometer archipelago situated in the eastern Mediterranean, are used as case study. The Balearic Islands can be qualified as one of the most important tourist regions in the world, with 1 million of inhabitants and receiving 13 millions of tourist yearly. Since beaches and climate are often mentioned as the most central attractors, as in other tourist areas around the world, a high degree of seasonality characterizes the Balearics with an 80% of tourist arrivals registered during the May-October semester. The suitability of the Balearic archipelago as a case study is also supported by the location characteristics that makes easy to control periodically the amount of people (tourists and residents) on the islands.

3.4.1. Data

The database gathered covers the monthly demand in thousands of liters for the automobile diesel oil from January 1986 to November 2009 and for gasoline from January 1999 to August 2009. The data is sourced from CHL Company (Compañía Logística de Hidrocarburos) and provided by Economic Research Center of the Balearics islands (CRE). Fuel consumer prices after taxes in Euros were available from official statistics (MITYC, 2010) and can be downloaded free of charge.

Figure3.1 shows the diesel prices and consumptions in the Balearics Islands between 1999 and 2009. During this period diesel consumption in average has increased almost 4 times with a growing particularly quick between 1999 and 2006. Between 2006 and 2009, the growth rate slowed down with a less dramatic fashion than in the period before. With respect to Diesel oil price there has been considerable variation between 1999 and 2009, with a minimum value of 0.523€ per liter in February of 1999 and a maximum value of 1.313€ per liter in July 2008. During the period between 1999 and 2004, the diesel oil price was relatively stable. After 2004 the price increased till reaching its maximum in July of 2008, and then returned to a relative stability on 2009.

Figure 3 1(a) Diesel oil price (Euros/liter) and monthly diesel oil consumption (thousands liters) between 1999 and 2009, (b) Gasoline price (Euros/liter) and monthly gasoline consumption (thousands liters) between 1999 and 2007

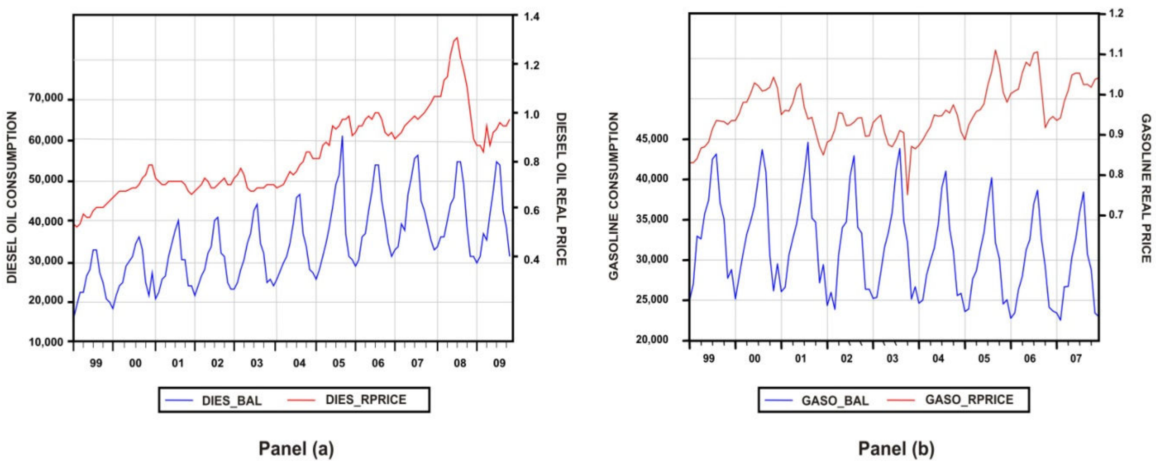


Figure 3.1 depicts also the price and the consumption of gasoline in the Balearics islands between 1999 and 2008. The demand curve follows a negative trend with a fall of 7 % in average during the period of analysis. As far as prices are concerned, it is shown the fluctuation of gasoline prices between 1999 and 2007 with the minimum value of 0.75€/liter and the maximum value of 1.16€/liter that were reported on October 2003 and July 2008 respectively.

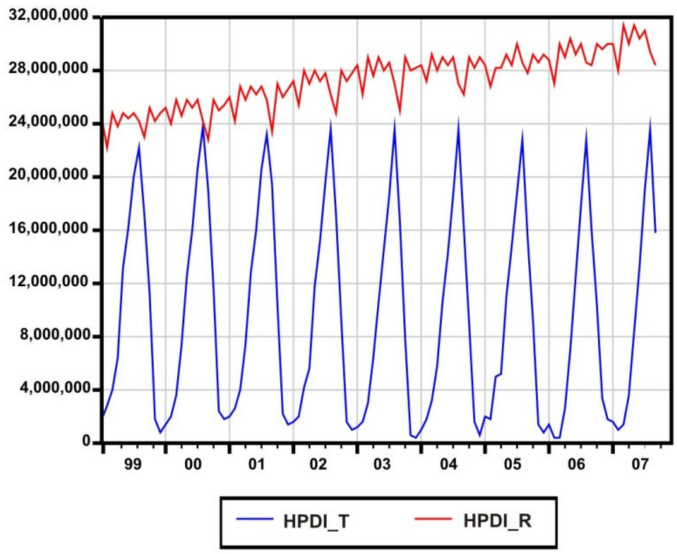
In reference to the economic activity, since income monthly observations are not available at a monthly basis, quarterly data on real gross domestic product (GDP) provided by CRE were taken and transformed to monthly data using the cubic spline interpolation method.

For the case of the tourism impact variable, different alternatives were initially considered. Since tourism is not traditionally measured in public national accounts, and its economic situation and impact must be evaluated through satellite accounts that are often elaborated with significant delays and at annual level, the statistics of tourist arrivals, which are often used as the real tourism demand (Crouch, 1994), is presented as one of the most appropriate indicator to compute tourism pressure.

Although tourist arrivals constitute a first real alternative to compute the contribution of tourism on fuel use, two main drawbacks should be pointed out. First, the presence of time lag between arrival date and the day when tourist is effectively consuming fuel could result in a bias, and particularly when including tourists arriving at the end of the month. Second, and due to tourism pattern which may change during years, length of stay could be affected and hence its omission in the analysis could largely affect the estimated results.

In order to overcome these problems Riera and Mateu (2007) developed a Human Pressure Daily Indicator (*HPDI*) for the Balearic Islands that, based on resident population registers and daily arrivals and departures from the airports and ports was able to the daily stock of people on the islands. The daily indicator was split between residents (*HP_R*) and tourists (*HP_T*) using data from the Spanish domestic tourist survey (*Familitur*) in Bakhat et al. (2010). Results, on monthly averages, are presented in Figure 3.2.

Figure 3 2 Monthly HPDI for the residents and for the tourists in the Balearics



Thus, one of the most important results that can be derived from this analysis is the fact that, on annual average, tourists account for a 25% of the total population pressure in the archipelago, although for the high season months tourist population pressure is much close to the resident one. Otherwise, although it should be admitted that the monthly average of the *HP_T* do not differ significantly from the tourist arrival data, the split between tourist and residents provides further knowledge about the presence of both populations that can be useful for the design and implementation of policy measures.

3.4.2. Results and Discussions

The results of the models are reported in the tables 3.1 to 3.6, and for each model the estimates of the parameters associated with the explanatory variables are given. The adjusted R-squared, Akaike Info Criterion (*AIC*) and Schwarz Criterion (*SC*) were also considered for models specification. In addition, the F-test was used for the overall significance of the model and a t-test for testing the strength of each of its individual coefficients. The Lagrangian multiplier (*LM*) test of order 2 has been used to check the presence of correlation between residuals in both static and dynamic models. Furthermore, stability tests were implemented showing no distortion in the parameter estimates. Thus, the results obtained allow concluding that the explanatory variables considered are globally significant in explaining the behavior of the endogenous variable. The adjusted R-squared of the estimated models can be qualified as good, being higher than 0.93 for diesel oil and gasoline models. In addition, a subset of variables in the models was tested for statistical significance to examine whether they could be omitted. Each of the insignificant variables was sequentially deleted, using the general-to-specific-model strategy, while significant parameters at a 1%, 5% and 10% level were retained.

Table 3.1 presents the results of the Equation 1 estimation. Using either OLS or SUR models, the results indicate that resident human pressure, real price and income all influence the long-run demand for diesel. Both, real price and GDP are significant with an expected negative sign for the price parameter estimate, and both estimates are consistent with the economic theory. The price and income elasticity estimate of diesel demand are -0.693 and 0.842 respectively (-0.684 and 0.834 with SURE).

Table 3 1Estimated models for diesel and gasoline consumption in the Balearics

Dependent variable	Level of diesel consumption		Level of gasoline consumption	
	OLS	SUR	OLS	SUR
LOG(HP_R)	0.469**	0.470***	0.028	0.048
LOG(HP_T)	0.009	0.009	-0.002	-0.003
LOG(RP_GAS	0.038	0.030	-	-
LOG(RP_DIE	-0.693***	-	-	-
LOG(RGDP)	0.842**	0.834***	0.186	0.358
C	-1.876	-1.840	-	-
T	-		9.128**	8.002**
M2	0.107***	0.107***	0.036*	0.035*
M3	0.172***	0.172***	0.145**	0.141**
M4	0.211***	0.212***	0.218**	0.215**
M5	0.329***	0.329***	0.303**	0.301**
M6	0.425***	0.426***	0.368**	0.368**
M7	0.536***	0.537***	0.487**	0.487**
M8	0.584***	0.585***	0.555**	0.556**
M9	0.439***	0.439***	0.369**	0.372**
M10	0.267***	0.267***	0.278**	0.280**
M11	0.098***	0.098***	0.063**	0.066**
M12	0.091***	0.091***	0.095**	0.097**
Equation Statistics				
Adjusted R-Squared	0.933686	0.933684	0.97561	0.97557
Log likelihood	173.3798		213.009	
Durbin-Watson stat	2.117341	2.117407	2.10665	2.10388
AIC	-2.895922		-	
SC	-2.473735		-	
F-statistic	95.15885		268.542	
Proba(F-Statistic)	0.000000		0.00000	
LM(13)	0.233176		0.39228	

Note: *** significant at 1%, ** significant at 5%, * significant at 10%

As for population stock variables, the estimate of resident human pressure is significant with an expected positive sign, whereas tourist human pressure variable is not significant. All the coefficients for the dummy variables related to the monthly seasonality are positive and significant. These results imply that July and August are the months when more diesel is consumed. For the disturbance terms, no presence of serial autocorrelation in the residuals of the dynamic model has been detected.

Similarly, the same analysis was conducted for gasoline and the results are reported in table3.1. In the case of gasoline demand, GDP and resident human pressure variable are no more significant. As expected, and with concordance with the literature(Sterner, 1990), the price elasticity estimate in gasoline (-1.074 and -1.081 with OLS and SURE respectively) model have a negative sign and is greater in magnitude than its correspondent in diesel oil model, showing that consumers in the long-run are more sensitive to price changes of gasoline than that of diesel oil. In addition, the negative trend present in the gasoline models is more likely due to the adoption of the dieselization policy in Spain during the last decade. In other words, the numerous incentives for diesel vehicles along with higher fuel efficiency could have boosted sales of diesel, independently of changes in income. Different simulations were undertaken in order to evaluate two general alternative tourist policy measures related to, first, the implementation of additional fuel taxes (with special reference to a seasonal fuel tax) and, second, to the promotion of additional tourists to the destination.

The results from Table 3.2, present the “seasonal price elasticity” for both diesel and gasoline. The low and high seasons price elasticities for diesel are -0.642 and -0.805, respectively. For gasoline, the estimates are -1.077 and -1.057, which again are consistent with the literature. Again, for each season demand is more price elastic for gasoline than diesel. In addition, price elasticities for gasoline demand are almost similar in low and high seasons, for diesel, as we shift from low to high season it seems that people become more sensitive to price changes.

Table 3 2 Price elasticity results of fuel demand in high and low seasons

Dependent variable	Level of diesel consumption		Level of gasoline consumption	
	OLS	SUR	OLS	SUR
LOG(HP_R)	0.522***	0.528***	0.024	0.047
LOG(HP_T)	0.010	0.010	-0.002	-0.003
LOG(RP_GASOLINA)	0.060	0.062		
LOG(RP_DIESEL)			-0.017	-0.013
LOG(RGDP)	0.769**	0.760**	0.198	0.397
C	-2.447	-2.514	9.137***	7.832***
T		-	-0.005***	-0.005***
M2	0.111***	0.112***	0.035*	0.035*
M3	0.170***	0.170***	0.145***	0.141***
M4	0.210***	0.210***	0.217***	0.215***
M5	0.298***	0.294***	0.303***	0.301***
M6	0.395***	0.391***	0.368***	0.368***
M7	0.505***	0.501***	0.487***	0.488***
M8	0.556***	0.553***	0.555***	0.557***
M9	0.436***	0.436***	0.368***	0.372***
M10	0.261***	0.260***	0.278***	0.280***
M11	0.096***	0.096***	0.064***	0.066***
M12	0.090***	0.090***	0.095***	0.097***
LOG(RP_DIESEL)*LS	-0.648***	-0.642***		-
LOG(RP_DIESEL)*HS	-0.793***	-0.805***		-
LOG(RP_GASOLINA)*L	-	-	-1.063***	-1.077***
LOG(RP_GASOLINA)*H	-	-	-1.046***	-1.057***
Equation Statistics				
Adjusted R-Squared	0.934227	0.934209	0.975079	0.979222
Log likelihood	174.4184		213.0381	
Durbin-Watson stat	2.110295	2.106155	2.10747	2.102903
AIC	-2.896637		-3.593298	
SC	-2.449615		-3.121442	
F-statistic	90.39999		233.583	
Proba(F-Statistic)	0		0	
LM(13)	0.269502		0.398608	

Note: *** significant at 1%, ** significant at 5%, * significant at 10%

Table 3.3 summarizes the results for the null hypotheses tested for analyzing whether price elasticity changes when we shift from high to low season. The obtained P-values reveal that for both diesel and gasoline, the equality hypothesis for the price elasticity coefficients for high and low seasons is accepted for high probability levels. Thus, price elasticities corresponding to low and high seasons cannot be considered statistically different. In addition, horizontal hypothetical tests for price elasticity equality have been computed by season, to compare if price elasticity in particular season differs statistically between fuel types. Results show that during high season price elasticity of diesel is statistically not different from its correspondent of gasoline, whereas in low season, there is uncertainty to accept the equality hypothesis for the price elasticity coefficients.

Table 3 3 Results for the different seasonal elasticity homogeneity tests (variables in level)

	Monthly elasticity		
	H_0 Hypothesis	F-statistic	P-value
Diesel	$\beta_{D,HS} = \beta_{D,LS}$	1.747730	0.1895
Gasoline	$\beta_{G,HS} = \beta_{G,LS}$	0.022438	0.8813
		χ^2-statistic	P-value
Diesel vs Gasoline, in Low -season	$\beta_{D,LS} = \beta_{G,LS}$	3.599842	0.0578
Diesel vs Gasoline, in High -season	$\beta_{D,HS} = \beta_{G,HS}$	1.142044	0.2852

Using Equation (2), table 3.4 represents the results of the change in fuel (Diesel and Gasoline) consumption in Balearic Islands. The respective price elasticity estimates for diesel and gasoline are -0.754 and -1.097, which are consistent with the literature. Based on Equation (4), the results from Table 3.5, present the “seasonal price elasticity” for both diesel and gasoline. For diesel, the low and high seasons price elasticities are -0.725 and -0.916, respectively. Whereas, for gasoline, the estimates are -1.074 and -1.171, again are consistent with the literature. Again, for each season demand is more price elastic for gasoline than diesel. In addition, price elasticities for gasoline demand are almost similar in low and high seasons, for diesel, as we shift from low to high season (and vice versa) it seems that people become more sensitive to price changes.

Table 3 4 Estimated models for diesel and gasoline consumption in the Balearics

Dependent variable	Change in diesel consumption		Change in gasoline consumption	
	OLS	SUR	OLS	SUR
Δ_{12}LOG(HP_R)	0.558**	0.557**	0.007	0.007
Δ_{12}LOG(HP_T)	0.012	0.012	-0.001	-0.001
Δ_{12}LOG(RP_GASOLINA)	0.114	0.110	-1.097***	-1.097***
Δ_{12}LOG(RP_DIESEL)	-0.754***	-0.752***	-	
Δ_{12}LOG(RGDP)	0.419	0.426	0.742	0.742
C	0.804**	0.769**	-0.067***	-0.067***
Equation Statistics				
Adjusted R-Squared	0.493369	0.493318	0.757343	0.757343
Log likelihood	119.6546		151.8104	
Durbin-Watson stat	2.033304	2.039041	2.052914	2.052914
AIC	-2.346971		-3.05855	
SC	-2.159987		-2.92499	
F-statistic	16.41887		75.12481	
Proba(F-Statistic)	0		0	
LM(13)	1.321293		2.294577	

Note: *** significant at 1%, ** significant at 5%, * significant at 10%

Similarly, Table 3.5 summarizes the results for the null hypotheses tested for analyzing whether a shift from low season to high season (and vice versa) would affect price elasticity of fuel demand. The results from P-values reveal that for both diesel and gasoline, the equality hypothesis for the price elasticity coefficients for high and low seasons is accepted for high probability levels. Thus, price elasticities corresponding to low and high seasons cannot be considered statistically different. To compare if price elasticity in a particular season differs statistically between fuel types, we found that during high season price elasticity of diesel is statistically not different from its correspondent of gasoline, whereas in low season, the equality hypothesis for the price elasticity coefficients is rejected at 5% significance level.

In summary, using either Equation (1) or (2), demand of diesel oil is in general less elastic compared to gasoline demand. The long-run price elasticities range between -0.68 and -0.75 for diesel and range between -1.08 and -1.09 for gasoline. Again, these results tally with the literature which shows that many gasoline consumers are price sensitive than diesel consumers. In addition, homogeneity tests for price elasticities show that seasonal fuel price elasticities estimates are statistically equal. On the other hand we found that, in high season, consumer price elasticity estimates are statistically not different for either diesel or gasoline.

Table 3 5 Price elasticity results of fuel demand in high and low seasons (variables in difference)

	Diesel		Gasoline	
	OLS		OLS	
Δ_{12}LOG(HP_R)	0.564**	0.563**	0.015	0.015
Δ_{12}LOG(HP_T)	0.011	0.010	-0.001	-0.001
Δ_{12}LOG(RP_GASOLINA)	0.094	0.094	-	
Δ_{12}LOG(RP_DIESEL)	-	-	-	
Δ_{12}LOG(RGDP)	0.710	0.710	0.794	0.793
C	0.001	0.001	-0.068	-0.067
Δ_{12}LOG(RP_DIESEL)*LS	-0.725***	-0.725***	-	
Δ_{12}LOG(RP_DIESEL)*HS	-0.916***	-0.916***	-	
Δ_{12}LOG(RP_GASOLINA)*LS	-		-1.074***	-1.074***
Δ_{12}LOG(RP_GASOLINA)*HS	-		-1.171***	-1.171***
Equation Statistics				
Adjusted R-Squared	0.493369	0.493318	0.757343	0.757343
Log likelihood	119.6546		151.8104	
Durbin-Watson stat	2.033304	2.039041	2.052914	2.052914
AIC	-2.346971		-3.05855	
SC	-2.159987		-2.92499	
F-statistic	16.41887		75.12481	
Proba(F-Statistic)	0		0	
LM(13)	1.612907		2.317552	

Note: *** significant at 1%, ** significant at 5%, * significant at 10%

Table 3 6 Results for the different seasonal elasticity homogeneity tests (variables in difference)

	Seasonal elasticity		
	H_0 Hypothesis	F-statistic	P-value
Diesel	$\beta_{D,HS} = \beta_{D,LS}$	1.239864	0.2685
Gasoline	$\beta_{G,HS} = \beta_{G,LS}$	0.457452	0.5006
		χ^2-statistic	P-value
Diesel vs Gasoline, in Low -season	$\beta_{D,LS} = \beta_{G,LS}$	3.904231	0.0482
Diesel vs Gasoline, in High -season	$\beta_{D,HS} = \beta_{G,HS}$	1.175909	0.2782

3.5. Policy implications and conclusion

In this study diesel oil and gasoline demands have been estimated in the context of a tourist region characterized by high seasonal fluctuations of population on the territory. The case study of the Balearic Islands is undertaken confirming that fuel consumption responds positively to changes in income and negatively to changes in prices, a consistent result with literature. In addition, results show that resident human pressure is also a significant factor in explaining diesel oil demand.

Estimated elasticities have been used to analyze different price and tourist policies. Thus, from the tax analysis, the relatively low price-elasticity shows how the internalizing mechanism that could be argued for introducing the tax in order to reduce transport externalities does not work. Although, an increase in fuel prices should be used as an effective tax collection instrument, that would benefit for a high level of exportability (taxes would be paid in a high rate by non-residents, that is, by non-voters) the homogeneity tests for price elasticities in low and high seasons show that applying these taxes regularly and only during the high season is an inadequate measure. Our results indicate that if an environmental surcharge is added to gasoline taxes, then the additional tax will decrease gasoline consumption only slightly and, therefore, will have little effect. For example, the price elasticity estimates suggest that a 17% increase in gasoline prices (a 0.20€ per liter) would decrease gasoline consumption by only 18%., and the growth rate would happen if we apply the tax only in high season. Therefore, as far as this analysis is concerned, we think that it is not apparent that it would be worth pursuing such an inappropriate tax for a small improvement in the environment.

New trends in tourism point towards an increase in tourist mobility in the host region. Thus, findings of this study appear to be significant policy implications for specialized tourist economies, particularly with respect to the way in which taxation could help government increase fiscal revenues and regulate the level/structure of fuel consumption from a temporal point of view. In any case, as a limitation of this study, it should be noted how price elasticities have been estimated, considering both resident and tourist population jointly. Although, results are valid in mean terms, future research will have to focus in trying to estimate if different price elasticities characterize these two fuel consumers groups. An additional limitation of this study arise in the fact that a complex relationship do exist between tourism, income and fuel demand. Changes in GDP could be due to the changes in the tourism activity which is the main economic sector in a tourist area. Thus, we assume in this study, that tourism has a direct effect on diesel oil demand, whereas the effect of other sectors is induced by the GDP variable in the specification model.

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CHAPTER 4

SEASONALITY AND TRENDS OF MONTHLY TOURIST ARRIVALS AND ELECTRICITY LOAD TIME SERIES

Chapter 4 Seasonality and trends of monthly tourist arrivals and electricity load time series

Abstract:

This chapter presents empirical evidence on the non-stationary seasonal patterns in several monthly time series related to tourist arrivals and electricity consumption in Balearics islands, Spain. The seasonal integration and periodic models are investigated. The analysis implemented in this chapter is selected on the basis of a battery of parametric and non-parametric tests. The outcome of the applied tests indicates that periodically or conventionally integrated process best captures the movements in the tourist arrivals and total electricity consumption series in Balearics islands.

Keywords: tourist arrivals, electricity consumption, seasonality, periodic and seasonal integration.

4.1. Introduction

The reliability of empirical studies is often endangered by the nonstationarity of the analyzed variables. When data of higher frequency (monthly or quarterly) are analyzed problems may reappear as consequence of neglecting seasonality in the series. This is because many time series models widely used in practice require a pre-knowledge of statistical properties of trend and seasonality. Treating stochastic seasonality (trend) as deterministic, or *vice versa,* is a misspecification and may have some adverse effect on the performance of a time series model. It is well-known that some of the macroeconomic time series display stochastic trends, moreover, when working with seasonally observed data stochastic seasonal cycles may exist as well. When these components, trend and seasonality, do not evolve independently, traditional differencing filters may not be suitable. According to periodic autoregressive time series models, a seasonally varying autoregressive parameters and a periodic differencing filter are proposed for that case. Though the latter embeds the former, the two models exhibit different characteristics, both univariate and multivariate. In the case of monthly data, seasonal integration is defined in relation to the twelve unit roots implied by the annual difference operator $(1 - L^{12})$ where L is the lag operator, with one underlying stochastic trend implicitly associated with each of these unit roots (twelve stochastic trends).

On the other hand, for the observed series $y_{s\tau}$,where $s(1,2,\ldots,12)$ and $\tau\ (1,2,\ldots,N)$ refer to the season and the year respectively, the periodic approach views these series, as twelve separate $I(1)$ processes with eleven cointegrating relationship between them. Therefore, a process is said to be periodically integrated when it has a single stochastic trend.

A number of studies show that periodic processes can arise naturally from the application of economic theory to modelling decisions in an economic context, and their role should not be ignored as unimportant. Gersovitz and Mac kinnon (1978) and Osborn (1988) argue that a process of this type arises when modelling the seasonal decisions of consumers, while Hansen and Sargent (1993) suggest that it could also arise from seasonal technology.

Once it is admitted that the underlying economic driving forces such as preferences or technologies may vary seasonally, and then subtle periodic seasonal effects may come into play. The finding of Ghysels and Nerlove (1988) in investigating seasonality in consumer expectations, show that sometimes consumers appear to have difficulties in disentangling seasonal and trend patterns.The implication of periodic integration is that the stochastic trend and the seasonal fluctuations are not independent, in the sense that accumulations of shocks can change the seasonal pattern and that the time series cannot be decomposed in two strictly separate trend and seasonal components. Periodically integrated model for a univariate time series can yield a useful description of the correspondence that may exist between seasonal and nonseasonal fluctuations.

On the other hand, our empirical study is motivated by the fact that in many international tourist destinations and particularly Balearics islands (Spain) the intra-year variations of tourist arrivals are evident. The islands currently constitute one of the Mediterranean leading destinations with an annual volume of foreign arrivals that represent more than 1% of world tourism. Tourists, who usually visit the Islands are often referred to as mass “sun and sand” tourists. In addition, they are also characterized by a high repeat rate, about 75% in this category. Another characteristic that must be highlighted is the predominance of international arrivals with (domestic only 13% of the total), particularly from Germany and United Kingdom, which together represent about 80% of all arrivals. This Balearics islands market segment has led it to an extreme seasonality shape, with more than 80% of total arrivals during the May-September period. Moreover, over the past few years, holiday preferences seem to be changing, with more tourists inclined to separate their holidays into several sub-periods, as this give them the opportunity to take summer and winter breaks (Rosselló et al., 2004).

Although the economic benefits generated by arrivals and revenues is highly significant, tourism sector, unfortunately, is considered a major source of environmental impacts and resources consumption, particularly, energy (Becken & Simmons, 2002; Gossling, 2000). In this general context, the close correlation between energy demand and population pressure is highly significant, because it illustrates and justifies, beyond questions of efficiency, the increasing pressure on energy resources. For instance, between June and September sales of electricity account for an average of 38,2% of the total sales in Balearics (Aguiló and Riera, 2009). Therefore, a better analysis of energy consumption will provide an opportunity to better understand the emerging trends and seasonality patterns of this vital sector, and thus, for better decision making in terms of overall regional marketing and promotion, touristic product development, investment attraction and infrastructure provision.

In the present article our running example assumes data sampled monthly, for which a high degree of over-parameterization is likely to occur in a periodic context. The sample comprises 29 years of observations of monthly arrivals at the airports of Balearics islands, 26 years of monthly total electricity consumption in the Balearics and 18 years of the disaggregated electricity consumption per sector. The data of tourist arrivals and total electricity consumption exhibit a strong degree of periodic variation over the months of the year, as well as a strong seasonal variation over the year. Similar pattern is also observed for electricity consumption for some economic sectors.

Thus, the objectives of this study are to summarize the intra-year variation in the series and to explain long-term changes in yearly pattern of data analyzed exploring seasonal and periodic integration. For this purpose, stochastic seasonality is tested using the standard HEGY test and another efficient version called HEGY-GLS proposed by Rodrigues and Taylor (2007). For periodic integration, we use the test proposed by Boswijk and Franses (1996). However, due to the presence of high degree of parameterization involved in the analysis of periodic integration, and especially for monthly data, we extend our analysis with two additional nonparametric test proposed by del Barrio Castro and Osborn (2011). Finally, we apply Johansen method to the vector autoregressive model (*VAR)* to estimate the number of cointegration relations between the annual series (Johansen, 1988).

It has been found that the movements in German tourist arrivals, British tourist arrivals, international tourist arrivals and total electricity consumption are best captured by a periodically integrated process, which means that for each of these series, the seasons share the same stochastic trend. None of the other variables exhibits periodically varying dynamics. The finding of periodic integration for these time series has an important implication. The importance of periodic integration is present in the fact that a shock to a season, for instance January, is transmitted to all the seasons (all the months) of the year, and particularly, the shocks' effect is different in each season. Whereas, the existence of seasonal integration implies a varying seasonal pattern where "summer may become winter" see Osborn (1991). In most cases, such a situation is not feasible and the finding of seasonal unit roots should be interpreted with care and taken as an indication of a varying seasonal pattern.

The rest of the chapter is structured as follows. Section 2 describes the characteristic features of the dataset. Section 3 exposes the econometric methodology used in the chapter. Section 4 presents the results and a discussion of the empirical data, and the chapter concludes with Section 5.

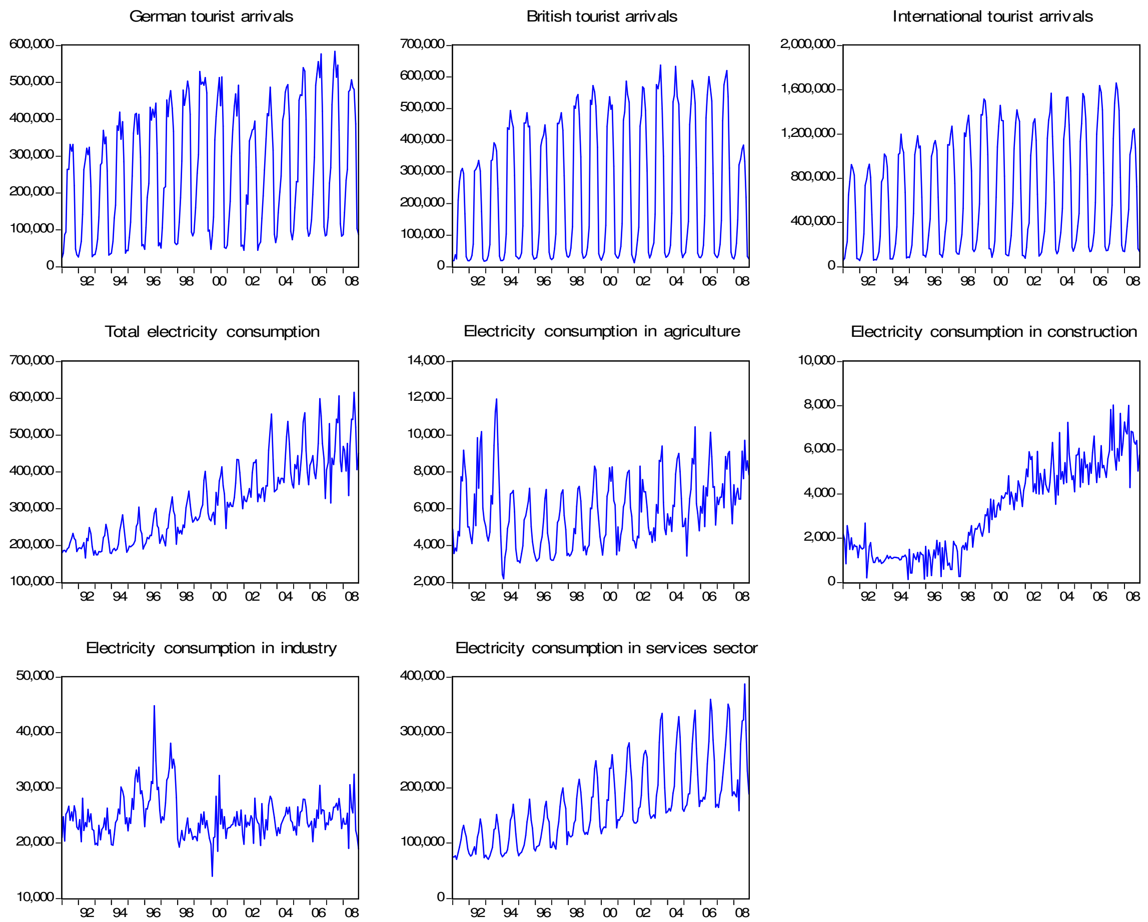
4.2. The dataset

We start by presenting some properties about the data to be examined later to motivate some of the empirical analyses to be undertaken. The data used in the article comprises of German and British arrivals, international tourist arrivals, and total and sectoral electricity consumption in Balearic Islands. There are many explanations to support the suitability of the Balearics airports data. First due to locations characteristics, tourists arriving by boat (4%) are in a minority compared to those who come by plane (96%). This constitutes an advantage over other regions, which must estimate arrivals using road transport. Second, for many decades the islands have had a high presence of international sun-and-sand mass tourism and, consequently, the same typology has remained stable over the course of time. Finally, another factor was the certainty that the data had been correctly gathered, without changes in the compilation method. The data are taken from the official statistics for air passengers to airports to airports in the Balearics and it is compiled periodically by Aeropuertos Españoles y Navigación Aérea (Spanish

Airports and Air Navigation), whereas for electricity data it was compiled by the Spanish System Operator Red Electrica de España with no missing observations were present.

The data for tourist arrivals (German, British and International) span the period from January 1980, to December 2008, and the period from January 1991 to December 2008 for sectoral electricity consumption, whereas for total electricity consumption the data start from January 1983 and end on December 2008. This corresponds to 348 months (29 years) for tourist arrivals, 216 months (18 years) for sectoral electricity consumption, and 312 months (26 years) for total electricity consumption.

Figure 4 1 The time series processes

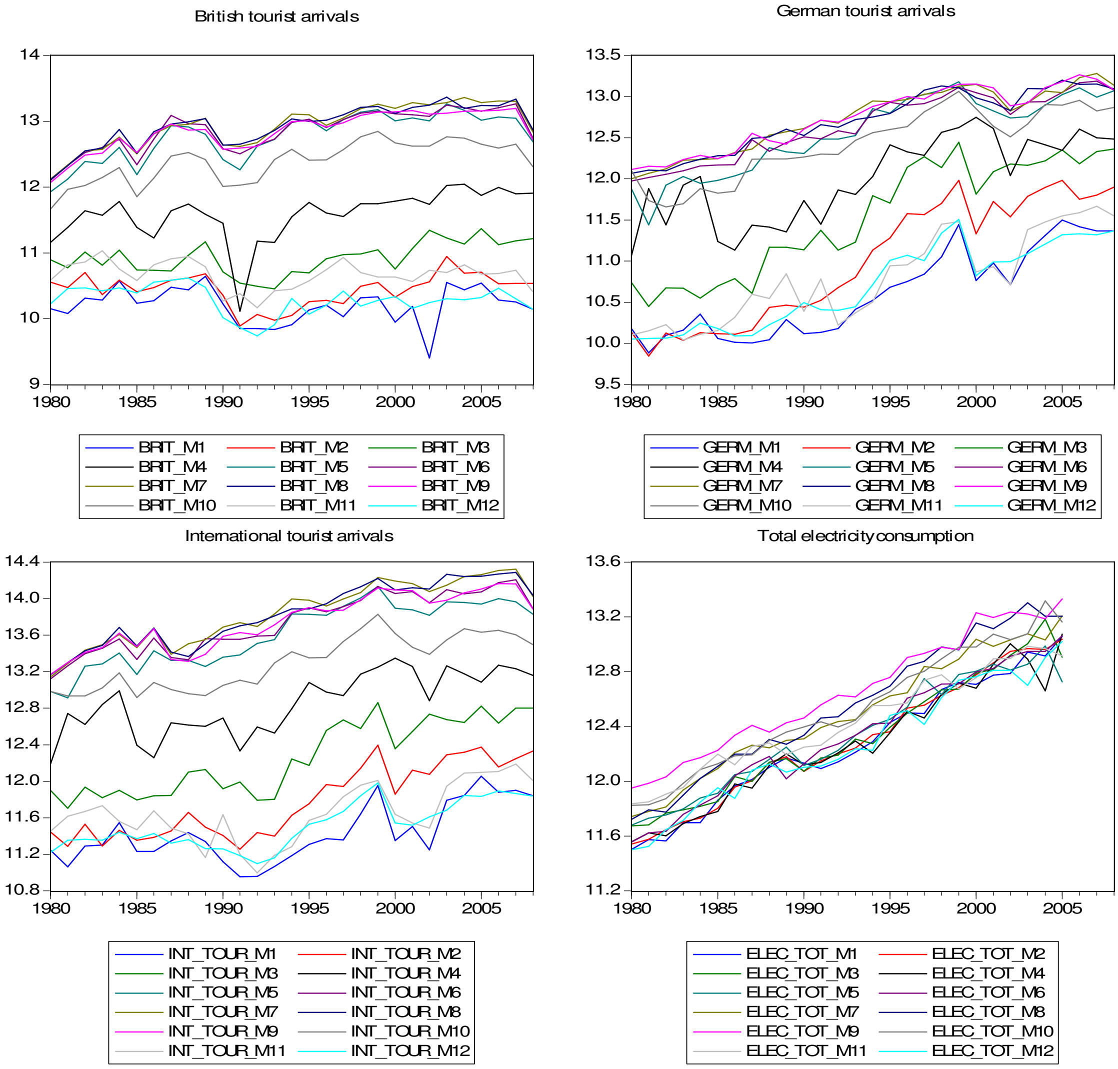


From Figure 4.1, the yearly variation of tourist arrivals data and electricity consumption data is most obvious. Particularly, international tourist arrivals and total electricity consumption time series exhibit a strong seasonal pattern with peaks in high season.

For instance, the four series of tourist arrivals in Figure 4.1 show significant seasonality fluctuations in addition to a trending pattern which is clearer in the case of international tourist arrivals. Similarly, electricity consumption series exhibit marked seasonal variations, and almost all of them are trending upward except for the case of electricity consumption in industry. For example, total electricity consumption series show a clear upward trend and pronounced seasonal fluctuations during the whole sample period.

A further aspect of the present dataset concerns the possibility to represent a process y_{st} in a multivariate process for the (12x1) vector $\boldsymbol{y}_{\tau}$ containing the annual series $y_{s\tau}$, where $y_{s\tau}$ is the observation in season s in year τ. The annual index τ runs from 1 to *N* where *N*=n/12 is the number of the years in the data. As shown in the Figure 4.2 which represents the graphs of the $y_{s\tau}$ series for German tourist arrivals; British tourist arrivals; international tourist arrivals and the total electricity consumption, to which we applied a log transformation. It can be seen that for each of the series, the patterns of the twelve seasons seem to evolve similarly over time. Hence, there seems to be visual evidence for the presence of a co-movement between the elements of $\boldsymbol{y}_{\tau}$. This property can indicate to the presence of periodic integration or non-periodic integration, a further insight to this type of series will be explained in depth in the next sections.

Figure 4 2 Monthly series of British/ German/ International tourist arrivals and total electricity consumption



4.3. Econometric methodology

Periodic models have frequently been criticized, because such models require estimating numerous parameters. Further, we applied nonparametric tests, which are explained in the next sections, to alleviate this problem. The periodic model formulation has a number of advantages. One implication is that models with fixed parameters and standard seasonal ARIMA processes, including seasonal unit root processes, are encompassed within the periodic model for certain restrictions on the parameters, and hence these restrictions can be tested. Thus, the model framework is rather flexible. First we review some known properties of periodic models.

It is clear that periodic models are the most general models which embed both seasonal integration and simple integration (or non-periodic integration), as special cases. The neglect of periodicity, on the other hand, not only leads to misspecification of the models but its hide some important information relating to periodic variation in the parameters of interest. Similarly, the presence of seasonal unit roots, even in non-periodic models, invalidates the analysis which is based on the assumption that the seasonality can be taken care of by simply including seasonal dummies in the relevant equations (see, Abeysinghe (1991,1994) and Franses et al. 1995, among others). It would be better to start with periodic models and then move to simpler models if the characteristic of data permit. This the strategy followed in the present study.

The periodic autoregressive process of order p, PAR(p), is defined by the equation

$$y_{s,\tau} = \alpha_s + \beta_s \tau + \phi_{1s}\, y_{s-1,\tau} + \phi_{2s}\, y_{s-2,\tau} + \cdots + \phi_{ps}\, y_{s-p,\tau} + e_{s\tau}, \qquad (1)$$

$$s = 1,2,3,\ldots,12 \qquad \tau = 1,2,\ldots,N$$

in which $e_{s\tau}$is white noise. Including α_s and β_s in the equation we allow for periodically varying intercepts and trends. Note, however, that all the coefficients in this process may vary over seasons $s = 1,2,3,\ldots,12$. The conventional (nonperiodic) AR (p) process is a special case where $\phi_{is} = \phi_i$ $(s = 1,2,3,\ldots,12)$ for all $i = 1,2,3,\ldots,p$. However, in the presence of seasonality, it is important to consider the possibility that the process may be periodic, with at least some of the *AR* coefficients in (1) varying over the year.

It is more convenient to consider the notation of Boswijk and Franses (1996) to a *PAR*(p) model, assuming $y_{s,\tau}$ is integrated of order 1, equation (1) is written as

$$(y_{s,\tau} - \varphi_s\, y_{s-1,\tau}) = \alpha_s^{**} + \beta_s^{**}\tau + \sum_{i=1}^{p-1} \psi_{i,s}\,(y_{s-i,\tau} - \varphi_{s-i}\, y_{s-1-i,\tau}) + e_{s\tau}, \qquad (2)$$
$$s = 1,2,3,\dots,12 \qquad \tau = 1,2,\dots,N$$

With $\varphi_{s-12k} = \varphi_s$ and $\prod_{s=1}^{12}\varphi_s = 1$. $\psi_{i,s}$ is a nonlinear function of $\alpha_s; \beta_s$ and ϕ_s. $\alpha_s^{**}; \beta_s^{**}$ capture the varying intercepts and trends. In the special case $\varphi_s = 1 (s = 1,2,\dots,12)$, (2) may be a periodic *I*(1) process, such that the first difference is a stationary *PAR*(p-1) process. On the other hand, when $\prod_{s=1}^{12}\varphi_s = 1$ but not all $\varphi_s = 1 (s = 1,2,\dots,12)$ in (2), $y_{s,\tau}$ is periodically integrated, or *PI*(1), see Ghysels and Osborn (2001, pp. 153-155) for more discussions of these possibilities.

The periodic process described by model (1) is nonstationary as the variance and autocovariances are time-varying within the year. For some purposes a more convenient representation of a *PAR* (p) process is given by rewriting it in a vector of seasons form (see Tiao and Grupe (1980), Osborn (1991), Franses (1994), among others), this utilize the vector $\boldsymbol{y}_{\boldsymbol{\tau}} = (y_{1\tau}, y_{2\tau}, y_{3\tau}, \dots y_{12\tau})'$ and the disturbance process $\boldsymbol{e}_{\boldsymbol{\tau}} = (e_{1\tau}, e_{2\tau}, e_{3\tau}, \dots e_{12\tau})'$. The corresponding vector representation to (1) is given by

$$\boldsymbol{\Phi_0 y_\tau} = \boldsymbol{A} + \boldsymbol{B\tau} + \boldsymbol{\Phi_1 y_{\tau-1}} + \boldsymbol{\Phi_2 y_{\tau-2}} + \dots + \boldsymbol{\Phi_P y_{\tau-P}} + \boldsymbol{e_\tau} \qquad (3)$$
$$\tau = 1,2,\dots,N$$

where the vector autoregression (VAR) has order $P = \left\lfloor {(p+1)}/{12} \right\rfloor + 1$ and $\lfloor . \rfloor$ indicates the integer part of the expression in the brackets. Including

$\boldsymbol{A} = (\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_{12})'$ and $= (\beta_1, \beta_2, \beta_3, \ldots, \beta_{12})'$, which $\boldsymbol{A}$ and $\boldsymbol{B\tau}$ represent vectors of seasonal intercepts and seasonal trends respectively.

The unit root properties of the multivariate process $\boldsymbol{y_\tau}$ determine those of the monthly process $y_{s,\tau}$. Define the matrix lag polynomial

$$\boldsymbol{\Phi(L^{12}) = \Phi_0 - \Phi_1 L^{12} - \cdots - \Phi_P L^{12P}}$$

where $Ly_{s,\tau} = y_{s-1,\tau}$ (with $Ly_{1,\tau} = y_{12,\tau-1}$) and $L^{12}y_{s,\tau} = y_{s,\tau-1}$. When all the roots are of the characteristic equation $\left|\boldsymbol{\Phi(L^{12})}\right| = \boldsymbol{0}$ lie outside the unit circle, the process $\boldsymbol{y_\tau}$ is stationary. It is usual to express the regression in (3) in the vector autoregressive (VAR) representation. The multivariate representation can be used to select among the different types of unit roots by means of cointegration analysis (Johansen 1991). This procedure was proposed by Franses (1994) for quarterly data. The same method can be used to test for periodic integration of monthly series. For a monthly process the model is expressed as

$$\Delta_{12}\boldsymbol{y}_\tau = \boldsymbol{A} + \boldsymbol{B\tau} + \boldsymbol{\Pi y}_{\tau-1} + \sum_{j-1}^{P} \boldsymbol{\Phi}_j \Delta_{12}\boldsymbol{y}_{\tau-j} + \boldsymbol{e_\tau} \qquad 4)$$

where $\boldsymbol{e_\tau} \sim idd(0, \Sigma)$ is a white noise vector with Σ being positive definite. The different types of unit roots in the monthly processes are associated with different properties of the impact matrix $\boldsymbol{\Pi}$. Following Osborn (2000), we then have the following three definitions:

$y_{s\tau}$ is *Integrated*, $y_{s\tau} \sim I(1)$, if rank($\boldsymbol{\Pi}$) = 11 and the eleven cointegrating relations are $y_{2\tau} - y_{1\tau}, y_{3\tau} - y_{2\tau}, \ldots, y_{12\tau} - y_{11\tau}$ i.e. the monthly changes are the cointegrating relations.

$y_{s\tau}$ is *Periodically Integrated*, $y_{s\tau} \sim PI(1)$, if rank($\mathbf{\Pi}$) = 11 and the eleven cointegrating relations are $y_{2\tau} - \varphi_1 y_{1\tau}, y_{3\tau} - \varphi_2 y_{2\tau}, \dots, y_{12\tau} - \varphi_{11} y_{11\tau}$with not all $\varphi_s = 1 (s = 1,2, \dots, 12)$.

$y_{s\tau}$ is *Seasonally integarted*, $y_{s\tau} \sim SI(1)$, if rank($\mathbf{\Pi}$) = 0 which implies $\mathbf{\Pi}$ = 0. Hence, there is no cointegration between the series for the individual seasons.

When $\mathbf{\Pi}$ has rank $0 \leq r < 12$, and proper restrictions on the cointegration space apply (see, Franses 1994), $y_{s\tau}$ is a integrated at some frequencies (see Hylleberg et al.1990; Ghysels and Osborn 2001; Del Barrio Castro, 2007).

To test periodic integration Boswijk and Franses (1996) analyze the distribution of the likelihood Ratio with the restriction $\prod_{s=1}^{S} \varphi_s = 1$. versus the alternative $\prod_{s=1}^{S} \varphi_s < 1$ in (2), with this statistic defined by

$$LR = N \ln \left[\frac{RSS_0}{RSS_1} \right] \tag*{5)}$$

where RSS_0 and RSS_1 denote the sum of the squared residuals of the estimated *PAR* (p) model under the restriction of periodic integration and without this restriction respectively. The latter can be obtained directly from the estimated residuals of the regression model (1). To obtain the residuals under the null, one has to estimate the *PAR*(p) model under the nonlinear restriction of periodic integration using nonlinear least squares

(NLS). As this restriction may be complex in higher order *PAR* models, it is more convenient to consider the *PAR* model in (2).

Although Boswijk and Franses (1996) consider the case of quarterly data, it is evident that the test can be performed to data at other periodicities, such as monthly. However, from a practical perspective, it may be difficult to implement for seasonal data with higher periodicity than quarterly, as the analysis is highly parameterized in such cases. In addition, estimation of (2) subject to the restriction $\prod_{s=1}^{S} \varphi_s = 1.$ requires the use of non-linear methods. Del Bario Castro and Osborn (2011), proposed two nonparametric methods to test the null hypothesis of periodic integration that avoids these difficulties. The proposed methods are a generalization of the variance ratio test of Breitung (2002) and the Sargan and Bhargava (1983) test, with the latter in the modified form suggested by Stock (1999).

The variance ratio statistic for a given season s is given as

$$VR_s = N^{-2} \frac{\sum_{\tau=1}^{N} \widehat{U}_{s\tau}^2}{\sum_{\tau=1}^{N} \hat{u}_{s\tau}^2} \; s = 1, \dots S \qquad 6)$$

where is the season-specific partial sum $\hat{u}_{s1} + \hat{u}_{s2} + \cdots + \hat{u}_{s\tau}$ with $\hat{u}_{s\tau}$obtained as the OLS residuals $\hat{u}_{s\tau} = y_{s\tau} - \boldsymbol{\beta}_s^{'} \boldsymbol{z}_\tau$ from a regression of observations for season s, $y_{s\tau}(\tau = 1, .., N)$ on $\boldsymbol{z}_\tau = (1, \tau)'$. In order to test the $PI(1)/I(1)$ null hypothesis, the proposed average variance ratio statistic is $VR_A = S^{-1} \sum_{s=1}^{S} VR_s$where each $VR_s$is defined in (6).

In addition, for a $PI(1)$ or $I(1)$ process the overall statistic VR_A have the same asymptotic distribution as that in Breitung (2002). Therefore, the critical values of Breitung (2002, Table 5) can be used in order to implement the test based on VR_A.

The season-specific modified Sargan and Bhargava (MSB) test statistic proposed by del Bario Castro and Osborn (2008) is based on the works of Stock (1999) and Sargan and Bhagava (1983), and is defined as

$$MSB_s = \left(\frac{N^{-2}\sum_{\tau=1}^{N}\hat{u}_{s,\tau-1}^2}{\hat{\gamma}_{sl}}\right)^{\frac{1}{2}} \quad s = 1,..;S \tag{7}$$

which requires an appropriate long-run variance estimator $\hat{\gamma}_{sl}$ for the annual difference $\Delta u_{s\tau} = u_{s\tau} - u_{s,\tau-1}$ relating to season *s*. To obtain a consistent estimator, the approach of Newey and West (1994) is followed using two sets of weights, Barlett kernel and the quadratic spectral kernel (See del Bario Castro and Osborn, 2008). Analogously to the test in the previous sub-section the average MSB statistic $MSB_A = S^{-1}\sum_{s=1}^{S} MSB_s$ is proposed for testing the null hypothesis of an $I(1)$ or $PI(1)$ process. For both $PI(1)$ and $I(1)$ processes, the MSB_A statistic follows the same asymptotic distribution as that in Stock (1999).

The HEGY regression, if we consider the seasonal dummies and deterministic trends, takes the following form:

$$\begin{aligned}\Delta_{12}y_{s,\tau} = \gamma_s^{**} + \delta_s^{**}\tau + \pi_0^* y_{s,\tau-1}^0 + \pi_6^* y_{s,\tau-1}^6 \\ + \sum_{k=1}^{5}\pi_{k,\alpha}^* y_{k,s,\tau-1}^{\alpha} + \sum_{k=1}^{5}\pi_{k,\beta}^* y_{k,s,\tau-1}^{\beta} + \sum_{j=1}^{P}\phi_j^* \Delta_S y_{s,\tau-1} + \varepsilon_{s,\tau}\end{aligned} \quad 8)$$

where P is the order of augmentation and in practice it is determined using the AIC and SC information criterion, for other methods used to determine the lag augmentation polynomial in the HEGY test regression, see del Barrio et al. (2010). and $\Delta_{12} = 1 - L^{12}$ with L the usual backshift operator ($Ly_{s\tau} = y_{s-1,\tau}$), and the auxiliary variables are specified as

$y^0_{s,\tau}$=$\sum_{j=0}^{11} y_{s,\tau-j}$, $y^6_{s,\tau}$=$\sum_{j=0}^{11} \cos[(j+1)\pi]\, y_{s,\tau-j}$,

$y^{\alpha}_{k,s,\tau}$=$\sum_{j=0}^{11} \cos[(j+1)w_k]\, y_{s,\tau-j}$, $y^{\beta}_{k,s,\tau}$=$-\sum_{j=0}^{11} \sin[(j+1)w_k]\, y_{s,\tau-j}$

$$w_k = \frac{2\pi k}{12}, \quad k = 1, 2, \ldots, 5, \qquad s = 1, .., 12, \qquad \tau = 1, \ldots, N.$$

To test the null of unit root at the zero, Nyquist and harmonic seasonal frequencies imply that $\pi_0^* = 0, \pi_6^* = 0$ and $\pi_k^* = \pi_k^{**} = 0, k = 1, \ldots, 5$. Therefore, we use the usual regression statistics: $\hat{t}_0$ (left-tailed) for the exclusion of $y^0_{s,\tau-1}$, $\hat{t}_6$(left-tailed) for the exclusion of $y^6_{s,\tau-1}$ and $\hat{F}_k$for the exclusion of both $y^{\alpha}_{k,s,\tau-1}$and $y^{\beta}_{k,s,\tau-1}$. Multiple frequency unit root test is also considered, using the F-statistics, $\hat{F}_{1,..,6}$, for the exclusion of $\{y^{\alpha}_{j,s,\tau-1}\}_{j=1}^{6}$and $\{y^{\beta}_{j,s,\tau-1}\}_{j=1}^{6}$, and $\hat{F}_{0,..,6}$ for the exclusion of $\{y^{\alpha}_{j,s,\tau-1}\}_{j=0}^{6}$and $\{y^{\beta}_{j,s,\tau-1}\}_{j=1}^{6}$

The overall HEGY null hypothesis of seasonal integration, $y_{s,\tau} \sim SI(1)$ implies the presence of unit roots at zero frequency (captured through π_0^*) and at the seasonal frequencies (captured through $\pi_6^*, \pi_k^*, \pi_k^{**}$), so that that $\pi_0^* = 0, \pi_6^* = 0$ and $\pi_k^* = \pi_k^{**} = 0, k = 1, \ldots, 5$.

One of the problems of Standard HEGY test is encountered in its low power, especially in small sample, therefore, and in order to circumvent this problem we apply the HEGY-GLS test proposed by Rodrigues and Taylor (2007) built upon the approaches of Gregoir (2006) and Elliot, Rothenberg and Stock (1996). This test is based on the following auxiliary regression equation,

$$\Delta_{12}\hat{y}_{s,\tau} = \pi_0^*\hat{y}_{s,\tau-1}^0 + \pi_6^*\hat{y}_{s,\tau-1}^6 + \sum_{k=1}^{5}\pi_{k,\alpha}^*\hat{y}_{k,s,\tau-1}^{\alpha} + \sum_{k=1}^{5}\pi_{k,\beta}^{**}\hat{y}_{k,s,\tau-1}^{\beta} + \sum_{j=1}^{P}\phi_j^*\Delta_S\hat{y}_{s,\tau-1} + \varepsilon_{s,\tau} \quad 9)$$

$$s = 1,..,12, \qquad \tau = 1, \dots, N.$$

For more details concerning the construction of the local GLS de-trended data $\hat{y}_{s,\tau}$ see Rodrigues and Taylor (2007). $\hat{y}_{s,\tau}^0, \hat{y}_{s,\tau}^6, \hat{y}_{k,s,\tau}^{\alpha}$ and $\hat{y}_{k,s,\tau}^{\beta}$ are the usual HEGY transformations.

Similarly, the unit root at the zero, Nyquist and harmonic seasonal frequencies imply that $\pi_0^* = 0, \pi_6^* = 0$ and $\pi_k^* = \pi_k^{**} = 0, k = 1, \dots, 5$. Therefore, we use the usual regression statistics: $\hat{t}_0$ (left-tailed) for the exclusion of $\hat{y}_{s,\tau-1}^0$, $\hat{t}_6$(left-tailed) for the exclusion of $\hat{y}_{s,\tau-1}^6$ and $\hat{F}_k$for the exclusion of both $\hat{y}_{k,s,\tau-1}^{\alpha}$and $\hat{y}_{k,s,\tau-1}^{\beta}$. Multiple frequency unit root test is also considered, using the F-statistics, $\hat{F}_{1,..,6}$, for the exclusion of $\left\{\hat{y}_{j,s,\tau-1}^{\alpha}\right\}_{j=1}^{6}$and $\left\{\hat{y}_{j,s,\tau-1}^{\beta}\right\}_{j=1}^{6}$, and $\hat{F}_{0,..,6}$ for the exclusion of $\left\{\hat{y}_{j,s,\tau-1}^{\alpha}\right\}_{j=0}^{6}$and $\left\{\hat{y}_{j,s,\tau-1}^{\beta}\right\}_{j=1}^{6}$.

Given the unavailability of the critical values for the F-statistics, $\hat{F}_{1,..,6}$ and $\hat{F}_{0,..,6}$, some Monte Carlo experiments were conducted for this purpose. The number of replications in the Monte Carlo experiment was set to 100.000, and the critical values of the small sample distributions are displayed for the following different combinations of deterministic terms: 1) zero- and seasonal frequency intercepts, 2) zero- and seasonal intercepts and trends. The critical values of the one-tailed t-test and the F-test statistics were generated for 18, 26 and 29 years of monthly observations. All in all, 0.01; 0.025; 0.05; 0.10; 0.90; 0.95; 0.975; 0.99 percentiles were obtained for the different sample sizes (See Appendix 2).

4.4. Results and discussions

In this section the tests will be applied to eight data series. The first set refers to tourist arrivals to Balearics islands represented in three series, German, British and international tourists respectively, and cover the period from January 1980 till December 2008. The second set is composed of total electricity consumption in Balearics islands which covers the period from January 1983 till December 2008, and four series that represent electricity consumption in the main economic sectors of Balearics islands (Agriculture, industry, construction and services), which cover the period from 1991 till December 2008, see Figure.4.1.

Table 4.1 displays the results of HEGY tests for the eight time series when seasonal dummies and trends are considered. The fourth column shows the lags that are included in the test equation (8), which are determined using AIC or SIC (in both cases the model is estimated with a maximum lag of 12).

For tourist arrivals, we reject unit roots at the 5% level at all the seasonal frequencies except for German and international tourist arrivals at frequencies $\pi/2$, at which the degree of significance depend on whether the order of augmentation employed is selected using AIC or SIC. For agriculture, industry, services, and total electricity consumption, we reject unit roots at 5% level at all the seasonal frequencies, whereas for construction electricity consumption we reject unit roots at 5% level at all the seasonal frequencies except at frequency π and frequencies $\pi/2$ at which the results depend on whether the order of augmentation employed is selected using AIC or SIC.

Table 4 1 Tests for seasonal unit roots: HEGY tests

Seasonal and Zero frequency Unit Root Tests

with SD and trend

Variable	Years		Aug.	t_0	t_π	$F_{\pi 3 \pi 4}$	$F_{\pi 5 \pi 6}$	$F_{\pi 7 \pi 8}$	$F_{\pi 9 \pi 10}$	$F_{\pi 11 \pi 12}$	F_{SUR}	F_{All}
German	29	AIC	6	-1.940	-4.706 ***	9.165 *	14.918 ***	12.090 ***	19.813 ***	9.428 **	15.807***	17.261***
German	29	SC	5	-1.701	-4.323 ***	11.926 ***	12.774 ***	15.681 ***	17.409 ***	13.190 ***	15.816***	16.826***
Brits	29	AIC	4	-3.136*	-4.386 ***	5.498	14.539 ***	13.520 ***	23.395 ***	14.940 ***	14.672***	17.091***
Brits	29	SC	1	-2.553	-4.355 ***	9.706 **	23.143 ***	12.640 ***	28.083 ***	18.390 ***	20.308***	20.339***
inter	29	AIC	6	-2.151	-4.923 ***	5.254	12.527 ***	14.477 ***	21.359 ***	5.682	13.349***	15.420***
inter	29	SC	1	-1.915	-4.037 ***	7.132	21.212 ***	21.455 ***	19.376 ***	13.068 ***	16.942***	16.963***
Agriculture	18	AIC	2	-1.8794	-3.667 **	15.483 ***	16.187 ***	18.693 ***	15.441 ***	12.192 ***	17.072***	18.199***
Agriculture	18	SC	0	-1.573	-4.303 ***	13.278 ***	16.450 ***	21.494 ***	14.122 ***	16.644 ***	21.828***	23.638***
construction	18	AIC	6	-1.759	-2.272	9.640 **	11.199 **	10.939 **	11.606 ***	6.312	12.024***	12.273***
construction	18	SC	0	-2.214	-3.110 ***	15.904 ***	14.471 ***	14.184 ***	7.533	8.526 *	12.708***	13.737***
Industry	18	AIC	0	-2.078	-3.563 **	11.727 ***	19.533 ***	16.317 ***	13.005 ***	14.680 ***	23.712***	23.296***
Industry	18	SC	0	-2.078	-3.563 **	11.727 ***	19.533 ***	16.317 ***	13.005 ***	14.680 ***	23.712***	23.296***
Services	18	AIC	7	-0.475	-4.117 ***	12.915 ***	17.701 ***	10.918 **	4.947	6.168	14.455***	16.970***
Services	18	SC	0	-0.949	-4.685 ***	17.682 ***	21.018 ***	16.755 ***	11.013 **	19.348 ***	18.196***	18.183***
Total_elec	26	AIC	0	-1.788	-5.715 ***	16.385 ***	19.459 ***	20.268 ***	26.082 ***	28.645 ***	24.570***	24.182***
Total_elec	26	SC	0	-1.788	-5.715 ***	16.385 ***	19.459 ***	20.268 ***	26.082 ***	28.645 ***	24.570***	24.182***

*** sig at 1%; **sig at 5%; * sig at 10%. The Critical values are obtained using a Monte Carlo analysis with 100,000 replications for a sample size of 18, 26 and 29 respectively.

According to the results of F_{All} statistics, none of the series appears to be seasonally integrated, in addition results from F_{SUR} and t_0 show that the rejection of seasonal integration can be assigned to the lack of evidence of seasonal unit roots. It is worth to mention that for the case of British tourist arrivals, the results of zero frequency unit root test depend on whether the order of augmentation employed is selected using AIC or SIC.

Table 4.2 gathers the results of HEGY-GLS considering seasonal intercepts and trends in the deterministic components. For German tourist arrivals we reject unit roots at 5% level at frequencies $\pi, {}^{5\pi}/_{6}$, for the frequencies ${}^{\pi}/_{2}$ the null hypothesis is not rejected, and for the rest of frequencies we reject unit roots at 5% level depending on whether the order of augmentation employed is selected using AIC or SIC. For British tourist arrivals we reject unit roots at 5% level at frequencies $\pi, {}^{5\pi}/_{6}$, and ${}^{\pi}/_{6}$, for the frequencies ${}^{\pi}/_{2}$ the null hypothesis is not rejected, and for the rest of frequencies we reject unit roots at 5% level depending on whether the order of augmentation employed is selected using AIC or SIC. For international tourist arrivals we reject unit roots at 5% level at frequencies π, ${}^{\pi}/_{3}$ and ${}^{5\pi}/_{6}$, for the frequencies ${}^{\pi}/_{2}$, ${}^{\pi}/_{6}$ and ${}^{2\pi}/_{3}$ the null hypothesis is not rejected. For agriculture electricity consumption we reject unit roots at 5% level at all the seasonal frequencies except at frequency ${}^{\pi}/_{2}$. For construction electricity consumption we reject unit roots at 5% level at the seasonal frequencies ${}^{2\pi}/_{3}$, ${}^{\pi}/_{3}$ and ${}^{5\pi}/_{6}$. For industry and services electricity consumptions we reject unit roots at 5% level only at frequencies$\left(\pi, {}^{\pi}/_{6}\right)$ and $\left(\pi, {}^{\pi}/_{3}\right)$ respectively. For total electricity consumption we reject unit roots at 5% level at all the seasonal frequencies except at frequency ${}^{\pi}/_{2}$ and ${}^{2\pi}/_{3}$. The F_{All} statistic rejects the overall *SI* null hypothesis for the all eight series, and the null hypothesis of a zero frequency unit root is not rejected for all the eight series

Table 4 2 Tests for seasonal unit roots: HEGY-GLS tests

				Seasonal and Zero frequency Unit Root Tests								
				Zero-and seasonal intercepts and trends								
Variable	Years		Aug.	t_0	t_π	$F_{\pi3\pi4}$	$F_{\pi5\pi6}$	$F_{\pi7\pi8}$	$F_{\pi9\pi10}$	$F_{\pi11\pi12}$	F_{SUR}	F_{All}
German	29	AIC	12	2.926	-3.370**	0.051	2.486	5.794*	9.095***	4.424	4.181	5.885
German	29	SC	5	3.328	-4.472***	0.571	6.564**	11.668***	15.232***	8.796***	8.440***	10.639***
Brits	29	AIC	4	1.770	-4.317***	0.646	5.178	6.052*	20.738***	10.814***	8.255***	10.010***
Brits	29	SC	1	2.917	-4.094***	1.066	10.002***	5.723	26.987***	12.031***	11.067***	12.568***
inter	29	AIC	6	2.948	-5.077***	0.516	6.086*	7.749**	17.525***	4.028	7.038***	9.757***
inter	29	SC	6	2.948	-5.077***	0.516	6.086*	7.749**	17.525***	4.028	7.038***	9.757***
Agriculture	18	AIC	0	2.292	-3.297**	5.657	16.923***	18.037***	12.114***	15.433***	18.577***	23.454***
Agriculture	18	SC	0	2.292	-3.297**	5.657	16.923***	18.037***	12.114***	15.433***	18.577***	23.454***
construction	18	AIC	6	0.466	-2.540	5.812*	10.397***	10.349***	9.336***	4.792	9.091***	9.064***
construction	18	SC	0	0.832	-2.847*	11.359***	10.044***	14.037***	7.667**	7.342**	10.703***	11.120***
Industry	18	AIC	2	2.754	-3.314**	3.014	6.308*	4.741	6.354*	7.057**	5.045*	6.616***
Industry	18	SC	2	2.754	-3.314**	3.014	6.308*	4.741	6.354*	7.057**	5.045*	6.616***
Services	18	AIC	8	2.039	-5.478***	0.599	2.891	10.184***	3.202	2.098	3.805***	8.025***
Services	18	SC	6	2.465	-4.484***	0.260	5.368	10.865***	5.451	3.487	5.252***	7.434***
Total_elec	26	AIC	4	3.925	-4.458***	2.387	3.534	13.860***	9.620***	10.879***	7.897***	11.283***
Total_elec	26	SC	2	5.447	-4.776***	4.306	4.739	12.092***	7.904**	13.273***	7.894***	13.568***

*** sig at 1%; **sig at 5%; * sig at 10%

Further, the F_{SUR} statistic shows the rejection of the seasonal unit roots for all the electric consumption series, though with low significance level (10%) for the series of industry electricity consumption. However, in the case of tourist arrivals series, the F_{SUR} test rejects the presence of seasonal unit roots for the British tourist arrivals and international arrivals respectively. Whereas, the series of German depend on whether the order of augmentation employed is selected using AIC or SIC. As it is shown by del Barrio Castro and Osborn (2008), Periodic integrated processes do not contain seasonal unit roots. However, the transformed variables used in the HEGY seasonal unit root test do not remove the nonstationarity in a periodic process. Consequently, the use of these variables in a seasonal unit root test regression may lead to the conclusion that seasonal unit roots are present in the process. Thus, complementary tests are implemented and gathered in Table 4.3. The F_{NP} statistics tests the null hypothesis that all the autoregressive coefficients of equation (1) are the same over the seasons, i.e., $\phi_{js} = \phi_j, s = 1, .., 12,\ j \leq p$. On the other hand, and based on the same equation (1), *LR* test statistic is performed to test for the presence of periodic integration. The lag order selection is performed using AIC and SIC, with a maximum lag of 4.

From the results of the F_{NP}, the nonperiodic null hypothesis is rejected at 1% for the German tourist arrivals, British tourist arrivals and total electricity consumption, and also at 5% for international tourist arrivals. However, the nonperiodicity null hypothesis is not rejected for agriculture electricity consumption, industry electricity consumption and services electricity consumption. The *LR* test indicates the rejection of periodic integration for all the series, with the exception of construction electricity consumption. However, in the performance of *LR* test, high number of parameters is required for the estimation of restricted and non-restricted models. Therefore, the results of *LR* test should be considered with a certain degree of caution.

Table 4 3 Periodicity and LR Unit Root Tests

Variable	Years		Order.	F_{NP}	LR
German	29	AIC	3	3.104***	74.258586***
German	29	SC	3	3.104***	74.258586***
Brits	29	AIC	2	2.780***	29.471191***
Brits	29	SC	1	2.802***	40.479471***
inter	29	AIC	1	2.052**	51.199776***
inter	29	SC	1	2.052**	51.199776***
Agriculture	18	AIC	1	0.953	38.934456***
Agriculture	18	SC	1	0.953	38.934456***
construction	18	AIC	1	2.915***	9.0354829
construction	18	SC	1	2.915***	9.0354829
Industry	18	AIC	2	1.292	14.37757**
Industry	18	SC	2	1.292	14.37757**
Services	18	AIC	1	0.841	60.335665***
Services	18	SC	1	0.841	60.335665***
Total_elec	26	AIC	2	2.137***	151.83633***
Total_elec	26	SC	2	2.137***	151.83633***

*** sig at 1%; **sig at 5%; * sig at 10% The Critical values are obtained using a Monte Carlo analysis with 100,000 replications for a sample size of 18, 26 and 29 respectively

The nonparametric tests for periodic integration developed by del Barrio Castro and Osborn (2011) bypass the limitations of the LR statistic which needs a nonlinear estimation. Using either the VR_A or MSB_A test statistic, the null hypothesis of a (periodic or non-periodic) unit root is not rejected in Table 4.4 at the 1% level for any of the eight series, with the exception of the total electricity series with VR_A test at 10% level, though the MSB_Atest do not reject the presence of a non/periodic unit root.

Table 4 4 Table 4 Nonparametric Periodic Integration Tests

Variable	VR_A	MSB_A Bartlett weights	MSB_A Quad Spectral weights
German	0.009929169	0.19800857	0.20484095
Brits	0.006898955	0.17663027	0.1795973
inter	0.007447734	0.21152936	0.21815013
Agriculture	0.010905806	0.26786522	0.26799491
construction	0.008161821	0.24719495	0.25271943
Industry	0.005870161	0.18822891	0.20380886
Services	0.010118341	0.23358369	0.2212275
Total_elec	0.0040442671*	0.18920834	0.20141753

*** sig at 1%; **sig at 5%; * sig at 10% The Critical values are obtained using a Monte Carlo analysis with 100,000 replications for a sample size of 18, 26 and 29 respectively

This test is applied to a VAR model, which is constrained with a high number of parameters when the VAR order increases, additionally to lose of observations for conditioning on the past. It is relevant to mention that using the general VAR with 12 variables in order to capture cointegration is marked with over-parameterization as all the coefficient matrices in the VAR representation are of dimension 12×12, while the maximum number of years of data available for this empirical study is 29 years. Thus, to reduce the number of parameters in the VAR specification we consider data on four quarters of the year. The order $P = 2$ of the VAR model has been chosen according to the Akaike information criterion, which performs reasonably in high-dimensional systems (Gonzalo and Pitarakis, 2002. Table 4.5 gathers the results of trace statistic for the quarterly series of German tourist arrivals, British tourist arrivals, international tourist arrivals and total electricity consumption. When considering the equivalent seasonal intercepts and seasonal trends in the "vector of quarters" representation, the results indicate the presence of three cointegration relationship for German tourist arrivals and total electricity consumption, and one cointegration relationship for both British and international tourist arrivals. Therefore, the trace statistics point toward more evidence of periodic/non-periodic integration for German tourist arrivals and total electricity consumption, whereas, some degree of ambiguity remains present for the two series British and international tourist arrivals. It is relevant to mention that though the use of 4-diemntional VAR alleviates the problem of over-parameterization present in a 12-dimentional VAR (Monthly data), however the number of VARs' parameters to be determined is still high. Therefore, the results from the trace statistics should be taken with more carefulness.

Table 4 5 Table 5 Johansen Trace test for Cointegration

	Number of cointegrating equation(s)	**International**	**German**	**Brit**	**Elec_total**
With cte & trend	0	82.920**	99.045**	75.680**	90.884**
	1	37.825	55.475**	42.665	54.403**
	2	21.180	29.612**	25.975	25.970**
	3	9.930	5.3097	10.265	10.139

* for 10%,** for 5%, *** for 2.5%, **** for 1% degrees of significance

Finally, we conclude that each of the four series is periodically integrated or non-periodically integrated (*PI* (1) or *I* (1)), in other words, that for each quarterly series the four series of annual observations have the same stochastic trend, which implies that the series cannot have any monthly seasonal unit roots. It is relevant to mention that, for total electricity consumption or to international tourist arrivals series, shocks occurring on a particular month of the year are transmitted to the other months of the year.

4.5. Conclusions:

The chapter represents evidence on the seasonal patterns of some tourist arrivals time series, additional to processes that reflect electricity consumption in the economic sectors of Balearic Islands. The methods used are parametric and nonparametric test procedures which allow parameters to vary over the seasons.

In this chapter we have applied several tests for a unit root in autoregressions, first the seasonal integration was tested using the HEGY-test and HEGY-GLS test. Considering seasonal intercepts and seasonal trends in the deterministic part, the former test shows no seasonal integration for each of the time series considered, the latter shows also the same result with the exception of German tourist arrivals that depends on whether the order of augmentation employed is selected using AIC or SIC. Secondly, we test the periodic variation and applied the parametric likelihood ratio (*LR*) test for periodic integration. Thirdly, we applied the nonparametric tests proposed by del Barrio Castro and Osborn (2011) which have the advantage over the *LR* test of not requiring nonlinear estimation and are more appropriate for monthly data. The results revealed the presence of *PI* (1) or *I* (1) for the three time series of tourist arrivals and also for the total electricity consumption time series. Finally and using the annual vector representation, the application of Johansen Cointegration method reinforces the finding of *PI*(1) or *I*(1) for German tourist arrivals and total electricity consumption, whereas, some degree of ambiguity remains present for the two series British and international tourist arrivals which is due to the high number of parameters required for the VAR estimation.

It worth nothing to say that the outcome of the periodic integration or conventional integration present in these processes is in line with the common result of the rejection of seasonal integration in economic time series. Moreover, an important implication of *PI*(1) or $I(1)$ lies in the fact that, for total electricity consumption and German tourist arrivals series, shocks occurring on a particular month of the year are transmitted to the other months of the year. For instance, a shock in Germany in January would be transmitted to the underlying seasonal tourist arrivals (tourist arrivals in January,.., December), in addition, a shock in Spain in January would be transmitted to the underlying seasonal electricity consumption. We believe that these finding will fill the gap of the empirical studies of seasonality presents in tourism and electricity demand in Balearics islands, and will open the door for future research in periodic autoregressive models.

4.6 Reference

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III. CONCLUSIONS

1 Main findings and general conclusions

The interrelationships between tourism, energy use and climate change are presenting a significant policy dilemma for many destinations and tourism businesses. Climate change is a key development issue, while tourism has potential to contribute to economic development. However, tourism also contributes to environmental degradation and is strongly affected by climate change, leading to significant challenges with respect to its management and regulation and long-term development prospects. At a global scale tourism is an extremely significant economic activity; nevertheless, there has also long been substantial criticism of what has been perceived as the negative impacts of tourism as sector. Tourism has been associated with substantial environmental change and degradation, in addition of being considered an energy-intensive sector.

In order to understand the intertwined relationship between tourism, energy use and environment, it is important that the various elements that comprise the tourism marketplace must be considered. It is vital to understand the potential impacts of international and national climate change mitigation regimes on tourism flows and destinations, in parallel with the importance of environmental attributes that are significant in destination choice. Several influential papers have enhanced our understanding of the high complex and interconnected issues of tourism, energy use and green house gases emissions (GHG). Some authors suggested that tourism issues must be incorporated into the wider debate about sustainable development. However, local studies are important too, as the analysis of local issues are place and context specific but may have implications at a larger scale.

Measuring the impacts of tourism on energy demand requires a quantitative appraisal of the relationship between tourism demand and energy use as well as other natural attractions. In the young and the growing research on tourism and energy use, quantitative studies are scarce. To go some way to reduce scarcity and so improve the basis impact of tourism-induced energy consumption, this thesis examines how energy use induced by tourism sector will affect environment. The realisation of the aims of this thesis is summarised below.

In chapter 2, a review of the historical evidence and the recent scientific literature on the importance of tourism and its concomitant contribution to GHG emissions is met. A review of studies shows that, despite the economic importance of tourism, the sector is a major source of environmental degradation and resource consumption. Contemporary studies show that tourism is energy intensive sector and its contribution to GHG emissions is highly significant. However, there are fewer studies on tourism and energy use, mainly, because tourism is not consider as sector in the national accounts, and due to the mix mature of some sub-sectors of tourism such as leisure and catering and so on. Literature reveals that the costs associated with tourism have been evaluated from a sectoral perspective, given the non-recognition of the tourist sector in conventional public economic accounting. However a need to assess the environmental costs of tourism activities arises when different development policies are considered from a regional point of view.

In chapter 2, the demand for energy is posited to be function of some socioeconomic variables and macroeconomic indicators such as real personal income, in addition to weather variables. Isolated territories, such as Balearics Islands, are fortunate to have the possibility of estimating the population pressure in a very accurate manner, even at a daily level. This variable once included to the models reveals to be highly significant. For instance, the independent variables collectively explain more than 96% of the variation of daily electricity demand in all regressions. In all the cases of electricity demand, both weather variables and the population stock are highly significant indicating their importance to determine daily electricity consumption. Strong evidence was found to show that the daily electricity load can be characterized by GARCH models. In addition, the analysis showed that the sensitivity of the electricity load to the population stock variable increased across the time period for residents and non-residents, with a higher sensitivity in the case of the resident population. This result coincides with the idea that residents' financial status has grown at a higher level than that of tourists, implying a higher growth level in electricity consumption

Furthermore, three different approaches were taken in the sensitivity analysis. First the population effect was evaluated through a hypothetical increase in absolute values in the non-resident populations, results in an increase of electricity consumption, with annual rates ranging between 1.4% and 3% for the three simulations. Second, an assessment of the seasonality effect showed a growth in electricity consumption by non-residents of between 2.3% and 2.4% during the high season in the case of a 10 % increase in the population stock, contrasting with a growth rate of 0.2% during the low season. Finally, the marginal effect of an additional tourist is found to be 6.5% lower than a marginal effect of an additional resident.

In chapter 3, the models estimated in the previous chapter were used to design and implement a medium-run forecasting model for daily system loads, and to evaluate the forecast performance of the Balearic Islands electric system. It is relevant to mention that forecasting 10 days ahead is crucial for outage planning for any electric system operator. The results from chapter 03 have shown that the major improvement in error reduction comes from understanding how the load reacts to population stock variable, and integrating its effects together with the weather variables and other specific dummies in an extended model that captures the main determinants of the electricity load. In general, and depending on the particularity of the islands, the inclusion of either HPDI variable or airport's arrival variable improves the forecasting performance of the dynamic model ARMAX. By forecasting energy more precisely, the electricity production can more cost-effectively and can reduce the impact on the environment, including reducing greenhouse gas emissions. In the spirit of Davos declaration (Davos, 2007), this result is of crucial importance because it permits the implementation of energy-efficiency concept at the energy source and not only at the end user.

In chapter 4 quantitative relationships was established between fuel demand and the relevant independent variables, for a purpose to evaluate the effectiveness of a seasonal tax instrument, with the focus on demand for diesel and gasoline. Thus, from the tax analysis, the relatively low price-elasticity shows how the internalizing mechanism that could be argued for introducing the tax in order to reduce transport externalities does not work. For instance, the long-run price elasticities range between -0.68 and -0.75 for diesel and range between -1.08 and -1.09 for gasoline. Again, these results tally with the literature which shows that many gasoline consumers are price sensitive than diesel consumers. However, homogeneity tests for price elasticities show that seasonal fuel price elasticities estimates are statistically equal. On the other hand we found that, in high season, consumer price elasticity estimates are statistically not different for either diesel or gasoline.

Tourism will continue to face a range of short- and long-term external shocks and challenges, as evidenced in major international reports. The main measures to raise the challenges of GHG emissions in tourism are included in Davos declaration, insisting on the complementary role of governments and international institutions of the tourist sector and destinations of consumers and research and communication networks. Through enhancing awareness of environmental protection and sustainability, and ensuring proper management of natural assets, governments have the opportunity to counteract negative consumer perceptions and purchasing behaviors, and to gain significant economic, social and cultural benefits from sustainable tourism. In the short- to long-term, government environmental policy reforms will have associated flow through costs that will affect the tourism industry and broader service sectors. Governments can provide a framework to help businesses prepare for a carbon-constrained future and move to a low-pollution economy, but for this to be effective, a prior analysis of the general trends and stationarity of tourism demand and energy use is for essential importance.

In chapter 5 the trends and periodicities are analyzed of tourist arrivals time series, additional to processes that reflect electricity consumption in the economic sectors of Balearic Islands. The results show that international tourist arrivals and total electricity consumption time series are periodically (or conventionally integrated), but not seasonally integrated. This means that a shock to the total electricity consumption or international tourist arrivals series occurred in particular season can transmit its effects to the rest of the seasons. For instance, a shock in Germany in January would be transmitted to the underlying seasonal tourist arrivals (tourist arrivals in January,.., December), in addition, a shock in Spain in January would be transmitted to the underlying seasonal electricity consumption. I believe that these finding will fill the gap of the empirical studies of seasonality presents in tourism and electricity demand in Balearics islands, and will open the door for future research in periodic autoregressive models.

Tourism development has considerable environmental, economic and social impacts at the local level. The task for tourism planning, to balance the positive and negative impacts of development, requires demand forecasts at local and regional levels. These results are of considerable importance for tourism planners in helping to mitigate the effect of high energy consumption on the environment. The role of policymakers is to avoid hampering and, if possible, to facilitate the adjustment in the Balearic energy market. The diversification into alternative sources of energy, such as solar, wind, geothermal, biomass and ethanol ect, can help to ensure a sufficient supply of energy in the future. Furthermore, to encourage energy conservation, the state government should implement educational programs that promote energy conservation by both the tourism and residential sector. Tourism currently contributes to roughly 5% of CO_2 emissions (Gössling, 2002), and the bulk of this comes from emissions from transport both to and at the destination. Results show that energy demand will continue to grow, which implies a growth in gas emissions from transport and other activities. Nevertheless, the reduction on potential emissions will depend on the model of transport that is used for domestic tourism. The assessment of the impact of transport demand will be needed for both transport and tourism planning as well as mitigation policies. Tax credits can be introduced for the installation of energy saving devices and equipments. However, a prior analysis should be undertaken to assess its effectiveness on a specific destination. Efficiency in energy use can be promoted by providing incentives for the design and the construction of energy-efficient housing and public infrastructure, as well as the use of more energy-efficient production equipment and power transmission by utility companies.

There are some limitations that need to be acknowledged and addressed regarding the present thesis. The main one is that available data do not always match the most appropriate data to perform the analysis. Further research will be aimed to explore new models, at the moment; attention is addressed to periodic autoregressive models. The periodic regression framework points out avenues for future research for modeling and forecasting energy demand and tourism data. To investigate possible cointegration relationship between energy consumption and tourist arrivals in Balearic Islands, as well as exploring the possibility of extending these models to other type of resources such as water. Future research will also have to explore evaluations of tourism's share of the electricity load in other regions, assuming that the outcome of this research can be used for other regions.

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APPENDIX

Appendix 1 Unit root test for electricity consumption series

Null Hypothesis: "Electricity consumption" has a unit root
Exogenous: Constant, Linear Trend, weekly dummies
Lag Length: 2(Automatic based on SIC, MAXLAG=10)

Augmented Dickey-Fuller test statistic		t-Statistic	Prob.
		-7.2201	0.0000
Test critical values:	1% level	-3.96	
	5% level	-3.41	
	10% level	-3.13	

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Appendix 2 Simulated Critical values for HEGY-GLS test

		Zero-and seasonal frequency intercepts				Zero-and seasonal intercepts and trends			
Years	Statistics	1%	2.5%	5%	10%	1%	2.5%	5%	10%
18	t(pi1)	-2.9981724	-2.6980515	-2.4493314	-2.1746727	-3.6158864	-3.323408	-3.0856268	-2.8228137
	t(pi2)	-2.9889444	-2.68699	-2.441476	-2.16861	-3.6124156	-3.3225257	-3.0815149	-2.819256
	F34	5.146869	4.2779345	3.6107351	2.9283597	8.3999344	7.3593526	6.5335957	5.7001705
	F56	5.2884348	4.3815894	3.7220388	3.0396027	8.6256889	7.5537689	6.7254923	5.8879069
	F78	5.3577118	4.4683843	3.7794712	3.0920987	8.7067289	7.649702	6.8439789	5.9593448
	F910	5.2380165	4.3835678	3.7144967	3.0353853	8.6063753	7.5766194	6.7411022	5.8843621
	F1112	5.2003675	4.3003628	3.6157161	2.9315096	8.3909512	7.3044483	6.5006357	5.669871
	F2-12	3.0780732	2.7746475	2.5445109	2.2828543	6.0074205	5.6401972	5.315098	4.9605721
	F1-12	3.0890912	2.7957162	2.5665597	2.3178576	5.9991983	5.621317	5.3168874	4.9742699
26	t(pi1)	-2.8927253	-2.6025901	-2.356387	-2.0701166	-3.513301	-3.2350196	-2.9977585	-2.7345625
	t(pi2)	-2.8920084	-2.606956	-2.3530475	-2.0661703	-3.5090995	-3.2356327	-3.0015452	-2.7362881
	F34	5.1550269	4.219824	3.530583	2.8320837	8.1624365	7.1387412	6.343868	5.5172036
	F56	5.2790573	4.3360376	3.6409256	2.9321552	8.4406956	7.3942964	6.5429523	5.7041461
	F78	5.3027798	4.3799629	3.6694573	2.9600825	8.4940597	7.470218	6.6467804	5.7988128
	F910	5.2308813	4.3141421	3.6212113	2.9133988	8.3868891	7.3544736	6.5357231	5.6979836
	F1112	5.0528089	4.1576666	3.5025144	2.8013322	8.1378028	7.1285272	6.3420633	5.4956612
	F2-12	2.8935759	2.6058279	2.3711503	2.122298	5.6702136	5.3049355	5.0021356	4.6781749
	F1-12	2.8735783	2.6020274	2.38109	2.139088	5.6359898	5.2838938	4.9980922	4.6793609
29	t(pi1)	-2.884229	-2.5743558	-2.316216	-2.0333462	-3.5000966	-3.211082	-2.9745266	-2.7143066
	t(pi2)	-2.8654351	-2.5620096	-2.3169314	-2.0317844	-3.4940718	-3.208962	-2.9739617	-2.7155647
	F34	5.0717964	4.1720593	3.4782542	2.7749813	8.1330367	7.0674136	6.2889612	5.4551689
	F56	5.1176918	4.2810648	3.5866572	2.8803569	8.3299431	7.2863591	6.5128818	5.6687046
	F78	5.2428675	4.3363997	3.6346072	2.9242646	8.4915691	7.4186058	6.5938586	5.7471526
	F910	5.1525518	4.2830647	3.5663199	2.8718567	8.3091437	7.2797517	6.4932149	5.6533084
	F1112	5.0953862	4.1708888	3.4905604	2.7784284	8.0761695	7.065333	6.2804523	5.4502863
	F2-12	2.8395138	2.5424293	2.3200133	2.0737375	5.5778708	5.2168927	4.9165561	4.5964842
	F1-12	2.8139159	2.5440376	2.3275753	2.0913498	5.5477768	5.1976029	4.9049551	4.5934722