Article

Short-Term Load Forecasting for Spanish Insular Electric Systems

Eduardo Caro * and Jesús Juan

Statistics Laboratory, ETSII, University Politécnica de Madrid, C/José Gutiérrez Abascal, 2, 28006 Madrid, Spain

* Correspondence: eduardo.caro@upm.es

Received: 4 June 2020; Accepted: 13 July 2020; Published: 15 July 2020

Abstract: In any electric power system, the Transmission System Operator (TSO) requires the use of short-term load forecasting algorithms. These predictions are essential for appropriate planning of the energy resources and optimal coordination for the generation agents. This study focuses on the development of a prediction model to be applied to the ten main Spanish islands: seven insular systems in the Canary Islands, and three systems in the Balearic Islands. An exhaustive analysis is presented concerning both the estimation results and the forecasting accuracy, benchmarked against an alternative prediction software and a set of modified models. The developed models are currently being used by the Spanish TSO (Red Eléctrica de España, REE) to make hourly one-day-ahead forecasts of the electricity demand of insular systems.

Keywords: short-term electric load forecasting; time series; Seasonal Reg-ARIMA models

1. Introduction

1.1. Motivation and Literature Review

Electric power consumption is omnipresent throughout the world. Among the different types of energy, electricity is crucial for human activity at home, at work, in leisure, in commerce and public activities. Today, electricity cannot be stored in large quantities and must be produced at the same time as it is demanded. This implies that the electric systems operator of any country must be prepared to meet future demand without knowing what it will be in advance. Forecasting of power demand plays an essential role in the electric industry, as it provides the basis for making decisions in power system planning and operation. Having good predictions of hourly electricity demand in the next few hours and for the next few days is crucial for the proper functioning of the electricity system with acceptable costs. The cost of electricity is a determining factor in a country's competitiveness. Improving demand forecasts significantly reduces costs in liberalized electricity markets.

The problem of predicting demand with different time horizons is the subject of a continuous process of improvement. The two pillars of progress are the emergence of new statistical forecasting techniques (e.g., deep learning [1]) and the availability of new data. Improved communications allow quick and convenient access to a large amount of information that substantially changes the mathematical model. For example, new forecasting techniques provide up-to-date information on the weather conditions of a region for the next few days at hourly intervals and with high spatial accuracy. Adding this information to power demand prediction models significantly improves their results. The massive arrival of data requires the development of new techniques, and the combination of new data and new techniques has revolutionized the current systems for predicting electricity demand. This has only just begun, great changes are expected in the electricity sector with the development of new electricity storage systems; with the installation of intelligent meters that provide instantaneous

information on consumption; the integration of the electric vehicles [2], etc. All this directly affects the problem of consumption prediction.

Another aspect to consider is the need to adapt the models to the particular conditions of the electric system. Demand fluctuation is determined by weather effects and human activity, which is conditioned by national habits and the economy. The effect of temperature, humidity, and solar radiation, to mention some of the climatic characteristics that affect demand, can be very different from one country or region to another. Another factor that has been widely analyzed, and that has a great impact on the demand for electricity is public holidays. For example, in Spain, it is very complex to include in the prediction model the different holidays [3], some of a national nature that affect the whole system and others of a regional and local nature that affect only part of it. These holidays usually are associated with a specific date (May 1st, for example) and are celebrated each year on a different day of the week. The impact on the demand for a holiday on a Monday is very different than when the same holiday is celebrated on a Tuesday or Wednesday. Considering all these details is essential and requires the use of hundreds of parameters in the Spanish model of hourly prediction [4].

In this paper, we focus on the short-term prediction of the hourly series of electricity demand. To make the problem more precise, we consider a daily task faced by the operator of an electric system. Every day at ten o'clock in the morning, the operator must decide hour by hour which reserve generation capacity must be available the next day to guarantee the supply of the demand. To do this, it is necessary to have a good prediction of the hourly energy demand for the next day. This is a standard situation that all electrical systems face with a daily routine. These predictions are also useful for companies that make production bids in the daily electricity spot market.

A review of the literature on the subject provides an idea of the wide variety of techniques used to solve the problem of short-term prediction of electricity demand [5]. Within the classical statistical models, multiple regression and multivariate quantile regression [6,7], time series with ARIMA models [4] or state space models should be mentioned. In recent years, many works have appeared that use artificial intelligence and machine learning techniques [1–3,8], such as artificial neural networks [9,10], clustering, support vector regression [11,12], support vector machines [13], reinforcement learning [14], among others. Some authors use algorithms that combine both methodologies. A general and exhaustive review can be found in [15]. More recently, the IEEE Power and Energy Society organized the Global Energy Forecasting Competition to improve the forecasting practices of the utility industry. This competition has attracted hundreds of participants in its three editions GEFCom2012, GEFCom2014 and GEFCom2017 with ingenious proposals that combine a variety of sophisticated techniques with more traditional models, such as the multiple regression model [16]. Although there have been several attempts to elucidate which methodology is best suited to solve the problem of prediction, a consensus is far from being reached. Large electricity companies or electricity system operators, after a great deal of trial and error experience with different methodologies, develop their own hybrid systems adapted to their particular circumstances [17].

Red Eléctrica de España (REE) is the company that operates the different Spanish electric systems. REE is responsible for operating the main Spanish system, the peninsular system (an area of almost 500,000 square kilometers, with more than 45 million people and an average daily demand of 650 GWh) and another 20 smaller systems corresponding to the Canary Islands, the Balearic Islands and the systems of the two Spanish cities in North Africa: Ceuta and Melilla. Over the years, REE has developed a very precise system that combines classic time series models (ARIMA) with complex non-linear regression techniques. The model integrates the knowledge acquired over the last forty years of analysis of Spanish consumption. The current forecasting model in operation performs very well at present, attaining below a 2% mean absolute percentage error in forecasting over a one-day horizon for the Spanish peninsular system.

The objectives of this work are: (i) to describe the adaptation of the model to the ten Spanish small insular systems whose electric load is, on average, lower than the 0.6% peninsular model. Insular demand ranges from 123 MWh on “El Hierro” to 12.402 MWh on “Mallorca”, compared with the

peninsular daily load of 650 GWh; (ii) to analyze in detail the effects of temperature and festivities over electric demand for each system, and (iii) to perform an exhaustive analysis concerning both the estimation results and the forecasting accuracy, benchmarked against a prediction software currently used in those insular systems.

1.2. Contribution

The contribution of this work is threefold. Firstly, ten insular forecasting models are developed to predict the electric consumption of the main systems in the two Spanish archipelagoes: the Canary and Balearic Islands. Secondly, the variables that affect the insular electric load (such as weather, and public holidays) are analyzed in detail for each system. Thirdly, the prediction accuracy is compared with a forecasting software currently used by the TSO, and two alternative ARIMA models. It should be noted that the ten developed models are currently being used by the Spanish TSO to compute forecasts on a real-time basis for the ten insular systems.

1.3. Paper Structure

The rest of this paper is organized as follows. Section 2 briefly describes the forecasting model used in the Spanish mainland. In Section 3, the previous mathematical model is modified to consider the particularities of each insular system, developing the ten insular forecasters. Section 4 provides three illustrative case studies using actual data from the ten Spanish insular systems, and the performance is compared with alternative models. Finally, Section 5 provides relevant conclusions.

2. Initial Reg-ARIMA Forecasting Model

The time series of hourly demand shows a strong daily seasonality. The mean and the autocovariance function of the series depend on the hour of the day. In these circumstances, a single ARIMA model is not flexible enough to consider the complexity of the hourly process. The alternative proposed by several authors is to use different models for each hour of the day [18].

Following this recommendation, the evolution of electric power demand is modeled by means of 24 h Reg-ARIMA models [19]. Let $y_{t,h}$ be the logarithm of the demand for hour h of day t . The Reg-ARIMA model for hour h is determined by the following two equations:

$$y_{t,h} = c_h + \alpha_h^T x_t + \beta_h^T z_t + u_{t,h} \quad (1)$$

$$\phi_h(B)\Phi_h(B^7)\nabla^d\nabla_7^D u_{t,h} = \vartheta_h(B)\Theta_h(B^7)w_{t,h} \quad (2)$$

where (1) represents a multiple linear regression model with non-stationary and correlated disturbances $u_{t,h}$. The vectors of explanatory variables x_t and z_t are assumed to be known and represent the influence of temperature and special days on energy demand, respectively. They are constant throughout all hours of day t , whereas the parameter vectors to be estimated α_h and β_h are different for each hour. The disturbances $u_{t,h}$ follow an autoregressive integrated moving-average process with weekly seasonality as in (2), where B is the backshift operator such that $B^k u_{t,h} = u_{t-k,h}$; $\nabla = (1 - B)$ and $\nabla_7 = (1 - B^7)$ are the regular and seasonal difference operators; d and D are the orders of differencing for both operators; $\phi_h(B)$, $\theta_h(B)$, $\Phi_h(B^7)$ and $\Theta_h(B^7)$ are polynomials in B and B^7 , of order p , q , P and Q , respectively; and $w_{t,h}$ are independent random variables with zero mean and variance σ_h^2 that can be different for each hour of the day.

The estimation of the previous model is made following the Box-Jenkins methodology. The same Reg-ARIMA model with different parameters is valid for 24 h a day, with some exceptions for some hours of the night, where not all parameters are significant. However, in order to simplify the successive updates of the model, it has been decided to maintain the same structure in all the equations. The following sections describe the mathematical model for the influence of temperature and special days, and the hourly update of predictions. More details can be found in [20].

2.1. Model for the Temperature's Influence

It is well-known that temperature has a transcendental impact on energy demand. The problem has great complexity that can be solved in several ways [4,21,22]. Any modeling must consider the following aspects: (i) the effect of temperature on demand changes throughout the year, (ii) in large systems it is necessary to take into account the spatial dimension of the problem and (iii) the effect of the temperature is not instantaneous since the temperature of a day can significantly affect the demand of the subsequent days.

In this work, the use of regression-spline techniques [23] has been used to model the nonlinear relationship between demand and temperature. Basically, it involves dividing the temperature range into sections, defined by a sequence of nodes, and each section fits a polynomial. The employed procedure ensures that the polynomials are jointed smoothly in the nodes $\{x_i^* : i = 1, 2, \dots, r\}$, and the whole function and its first and second derivatives are continuous. The position of the nodes is chosen depending on the shape of the curve to be adjusted. The number of nodes is determined using cross-validation with out-of-sample predictions. In this case, the model implements three nodes, and the regression-spline model for variable x is built using:

$$b_0(x) = 1, \quad b_1(x) = x, \quad b_{i+1}(x) = R(x, x^*) \quad i = 1, 2, \dots, r \quad (3)$$

$$R(x, x^*) = \left[\left(x^* - \frac{1}{2} \right)^2 - \frac{1}{12} \right] \left[\left(x - \frac{1}{2} \right)^2 - \frac{1}{12} \right] \frac{1}{4} - \left[\left(|x - x^*| - \frac{1}{2} \right)^4 - \frac{1}{2} \left(|x - x^*| - \frac{1}{2} \right)^2 + \frac{7}{240} \right] \frac{1}{24} \quad (4)$$

$$x = (T - T_{min}) / (T_{max} - T_{min}) \quad (5)$$

where T is the forecasted temperature of the day for the considered insular system. The location of the forecasted weather variable corresponds to the geographic coordinates of the most populated city of each island. The proposed algorithm considers weather forecasts provided by AEMET (State Meteorological Agency in Spain), not actual observed data.

The model also considers a non-instantaneous effect of temperature over energy demand: it is considered that the effect temperature has on demand persists through several days after the actual value was reached. The model implements a four-day persistence: the temperature reached during day t can affect the demand of days $t, t + 1, t + 2$ and $t + 3$.

Concerning the weather information, the algorithm works as follows: (i) the TSO receives the weather forecasts from the Spanish meteorological agency on a daily basis, (ii) maximum daily temperature forecasts for the most-populated city of each insular system are obtained from the weather forecasts' files, (iii) the obtained temperature information is transformed using the spline-regression model in Equations (3) to (5), (iv) finally, the estimated model in Equations (1) and (2) for each insular system is used to compute the electric load forecasts for each island.

2.2. Model for Special Days

Throughout the year there are several weekdays declared as non-working days or public holidays, for cultural, religious or political reasons. For example, there are six national public holidays during the year in Spain. In addition to the national public holidays, there are a few more days that are also holidays but only in certain cities and/or specific regions. The demand profile for these special days differs considerably from regular days, and, in general, the loads of these days are the most difficult to predict [24]. The existence of a public holiday in the middle of the week may also affect demand on the days before and after the holiday. Also, there is empirical evidence that the decrement in demand for a special day changes depending on the day of the week that is celebrated. The characteristics of each special day have been analyzed considering the information collected over several years. The procedure detects identifiable patterns of behavior that can be used to predict changes in demand for future holidays.

The procedure requires many parameters in order to consider all the features described in the preceding paragraphs. The method has been validated exhaustively by cross-validation, and improvements in predictions are considerable. Due to the vast number of possible situations, the model requires many regressors to model the effect of special days on demand.

Each public holiday is modeled as the dummy variable $Z_t^{w,i}$ where index w represents the day of the week ($w \in \{Su, Mo, Tu, We, Th, Fr, Sa\}$) and index i stands for the public holiday considered (public holidays are described in Section 3.2). Dummy variable $Z_t^{w,i}$ is equal to one if the d -th day corresponds to the i -th public holiday during the w -th day of the week. For example, the national holiday New Year's Day (1st January) is modeled by means of the set of regressors $\{Z_t^{Su,Jan1}, Z_t^{Mo,Jan1}, Z_t^{Tu,Jan1}, Z_t^{We,Jan1}, Z_t^{Th,Jan1}, Z_t^{Fr,Jan1}, Z_t^{Sa,Jan1}\}$. Additionally, to consider the effect of previous/following days, the previous set of regressors are tripled: one set for the actual festivity day, one set for the festivity's previous day, and the third set for the festivity's next day. These regressors are represented by the vector z_t in (1).

Concerning the holidays' information, the algorithm works as follows: (i) every year, at the end of December, the TSO obtains the next year's work calendar based on the information published in the national and regional Official Gazettes, (ii) once the dates of the holidays are known, the binary vector z_t in (1) can be computed for all days of the next year, following the previous guidelines to compute $Z_t^{w,i}$, (iii) once the model is estimated at the end of December, the obtained parameters in Equations (1) and (2) allow for the predicting of the effect of each national/regional holiday over the demand of each insular system, (iv) finally, on a daily basis, this holidays effect is used to compute the electric load forecasts for each island.

2.3. Hourly Update of the Prediction

Each of the 24 h models are used to make predictions from one day to the next. Prediction errors for adjacent hours (i.e., $w_{t,h}$ and $w_{t,h-1}$) are highly correlated. Considering that the demand data are received by the system every hour, each time a new observation is obtained, this information is used to update the predictions of the successive hours. The error $w_{t,h}$ is partially predicted using the observed errors of the previous hours, $w_{t,h-1}, w_{t,h-2}, \dots, w_{t,h-r}$ using the following equation:

$$w_{t,h} = \delta_{h,1}w_{t,h-1} + \delta_{h,2}w_{t,h-2} + \dots + \delta_{h,r}w_{t,h-r} + \varepsilon_{t,h} \quad (6)$$

where parameters $\delta_{h,1}, \delta_{h,2}, \dots, \delta_{h,r}$ are estimated by least squares with the residuals of the 24 Reg-ARIMA models. The number r of terms in the equation is three. To simplify the notation, it has been assumed that all hours correspond to the same day t . In the first hours of the day, it will be necessary to use the previous hours that correspond to the previous day. The parameters $\delta_{h,1}, \delta_{h,2}, \dots, \delta_{h,r}$ are different for different hours. This update greatly improves predictions for the next few hours and its effect significantly reduces prediction errors up to a 48-h horizon.

3. Insular Models

In this chapter, the initial Reg-ARIMA model currently employed in the Spanish mainland electric system is adapted for the main Spanish insular systems.

3.1. Spanish Insular Electric Systems

In this work, the ten most-important Spanish insular systems are studied. Spanish territory includes two archipelagoes: the Canary Islands off the coast of Africa, and the Balearic Islands in the Mediterranean Sea. The Spanish TSO computes the load forecasts for seven islands in the Canary Islands, and three insular systems in the Balearic Islands hourly (<https://demanda.ree.es>).

The names of the analyzed systems are provided in Table 1, as well as the acronyms used hereinafter throughout this document, their approximate geographical location, their population (2019, Spanish Statistical Office), and the average daily electric consumption. It should be noted that the

latitudes of the three Balearic systems are quite different than the latitude of the seven Canary systems, significantly affecting the temperature and climate.

Table 1. List of insular systems.

Archipelago	Acronym	Island Name	Geographical Location	Populat.	Avg. Daily Load
Canary Islands	TENER	Tenerife	28°16′07″ N 16°36′20″ W	917.841	9.591 MWh
Canary Islands	GRCAN	Gran Canaria	27°57′31″ N 15°35′33″ W	851.231	9.500 MWh
Canary Islands	LANZA	Lanzarote	29°02′06″ N 13°37′59″ W	152.289	2.333 MWh
Canary Islands	FUERT	Fuerteventura	28°25′57″ N 14°00′11″ W	116.886	1.899 MWh
Canary Islands	PALMA	La Palma	28°40′00″ N 17°52′00″ W	82.671	737 MWh
Canary Islands	GOMER	La Gomera	28°06′00″ N 17°08′00″ W	21.503	202 MWh
Canary Islands	ELHIE	El Hierro	27°45′00″ N 18°00′00″ W	10.968	123 MWh
Balearic Islands	MALLO	Mallorca	39°37′00″ N 2°59′00″ E	859.289	12.402 MWh
Balearic Islands	MENOR	Menorca	39°58′00″ N 4°05′00″ E	94.559	2.660 MWh
Balearic Islands	IBFOR	Ibiza-Forment.	38°59′00″ N 1°26′00″ E	144.659	1.340 MWh

3.1.1. Meteorological Data

Concerning the weather data, every day Spanish TSO receives from the State Meteorological Agency of Spain (AEMET) both the daily maximum and the daily minimum forecasted temperatures for the most-populated city of each insular system. Figure 1 depicts the annual evolution of these two weather one-day-ahead forecasted variables.

Figure 1. Maximum and minimum temperatures for the Spanish insular systems (Source: AEMET).

From Figure 1 it can be observed that the temperatures in the Canary Islands (red/blue lines) are more regular and stable than the temperatures in the Balearic Islands (orange/purple lines). Due to this characteristic, it is expected that the use of air conditioning and electric heating machines will have a higher impact on the electric load of the Balearic insular systems. Consequently, a higher dispersion of electric demand in Balearic systems is expected.

3.1.2. Electric Consumption Data

Figure 2 provides the hourly electric consumption for the analyzed insular systems. Figure 3 depicts a boxplot of the daily electric load for each insular system during the period between 2016 and 2018. Note that the X-axis is on a logarithmic scale.

Figure 2. Hourly electric load for the nine Spanish insular systems. Time period displayed: from 7 January 2019 until 13 January 2019. Upper plot: Tenerife, Gran Canaria and Mallorca. Lower plot: remaining systems.

Figure 3. Boxplot of daily electric demand for the considered insular systems.

From Figures 2 and 3 it can be observed:

- The systems with lower demand are “El Hierro” (ELHIE) and “Gomera” (GOMER);
- The systems with higher demand are “Mallorca” (MALLO), “Gran Canaria” (GRCAN) and “Tenerife” (TENER);
- Balearic systems present higher load variability than Canary systems. For instance, the interquartile range of “Mallorca” (most-populated island in the Balearic Islands) is 2.8 GWh, whereas the interquartile ranges of “Gran Canaria” and “Tenerife” (most-populated islands in the Canary Islands) are 0.7 and 0.8 GWh, respectively. There is a significant difference in the data dispersion, considering the similarity of average daily demands and populations of the three previous systems.

3.2. National and Regional Holidays

In this section, the developed model for special days in insular systems is detailed. Concerning the holidays’ effect, the mathematical model currently used to predict the electric demand on the Spanish mainland includes a set of regressors for each Spanish national holiday (see Table 2) and an additional regressor ranging from 0 to 1 modeling the percentage of the population affected by regional holidays.

Each special day is modeled considering that: (i) the effect over demand depends on the day of the week and (ii) it influences also the demand of previous and following days. Most of these holidays have a fixed date “month-day”. Other holidays (e.g., Good Friday) are movable, i.e., have no fixed date in the Gregorian calendar and may be aligned with moon cycles or other calendars.

Table 2. List of Spanish national holidays.

Date	Spanish National Holiday
January 1	New Year’s Day
January 6	Epiphany
March or April	Maundy Th., Good Fr. and Easter Mo.
May 1	Labor Day
August 15	Assumption
October 12	National Day
November 1	All Saints Day
December 6	Constitution Day
December 8	Immaculate Conception
December 25	Christmas Day

The model for holidays employed in the forecaster of the Spanish mainland demand, is adapted for the ten insular system. Additionally, for each insular system, the following regional holiday is included: see Table 3.

Table 3. List of regional holidays for Spanish insular systems.

System	Date	Reg. Holiday
Fuertevent.	May 30	Canary Islands’ Day
	October 7	Our Lady of Rosary
Gomera	January 20	Saint Sebastian
	May 30	Canary Islands’ Day
Gran Canaria	May 30	Canary Islands’ Day
	June 24	City Foundation
	September 8	Virgin of Pino
	November 17	Saint Gregorio
El Hierro	May 15	Saint Isidro Labrador
	May 30	Canary Islands’ Day
	June 29	Saint Peter
Lanzarote	May 30	Canary Islands’ Day
	September 15	Our Lady of Sorrows
Palma	May 30	Canary Islands’ Day
	August 5	Holy Virgin of snow
Tenerife	May 3	Feasts of the Cross
	May 30	Canary Islands’ Day
	November 30	Saint Andrew
Ibiza-Form.	January 17	Saint Anthony
	March 1	Balearic Islands’ Day
	August 5	Holy Virgin of snow
Mallorca	January 17	Saint Anthony
	January 20	Saint Sebastian
	March 1	Balearic Islands’ Day
	September 12	Mallorca’s Day
Menorca	January 17	Saint Anthony
	March 1	Balearic Islands’ Day
	June 24	Saint John
	November 30	Saint Andrew

3.3. Insular Temperature Effect

The location of weather stations for electric load forecasting in extensive areas has been studied in state-of-the-art technical literature [25]. The Spanish mainland load forecaster implements the temperature effect using a spline-regression model for the average maximum daily temperature of the ten most representative locations in Spain: Barcelona, Bilbao, Cáceres, Madrid, Málaga, Murcia, Oviedo, Sevilla, Valencia y Zaragoza.

However, considering the comparatively smaller geographical extension of the insular systems, the temperature effect is implemented using just a single local position of the temperature.

4. Estimation Results

Real data from ten Spanish insular electric systems are used. This section details the settings employed for the case study.

The demand data have been provided by the Spanish TSO (REE). This information is public and can be accessed through the TSO website (<https://demanda.ree.es/demanda.html>). The parameters of the Reg-ARIMA model are estimated using twelve years of historical data: hourly demand, temperature forecasts, and past holidays calendar for each system. The temperature information has been provided by the Spanish State Meteorology Agency; each insular model implements the maximum daily temperature for the most-populated city. The calendar information on special days for both national and regional public holidays is obtained from the BOE (National Official Gazette) [26].

Concerning the computational specifications, these models have been implemented in MATLAB using a 64-bit eight-core i7 processor (3.6 GHz max.) with 16 GB of RAM. Model estimation requires around two hours of CPU time for each insular system, and the calculation of one-day-ahead predictions requires less than 20 s per system. Note that model estimation should be performed yearly, whereas forecasting computation should be performed every hour.

Once the 24 Reg-ARIMA hourly models in Equations (1) and (2) have been estimated, the residual standard error $\hat{\sigma}_h$ is computed and provided in Table 4 and Figure 4. It should be noted that the residual standard errors quantify the differences between the theoretical mathematical model and the actual data for the estimation period. Consequently, lower standard errors imply higher forecasting accuracy.

Figure 4. Residual standard deviations for the insular models.

From Table 4 and Figure 4, it can be observed that “El Hierro” is the insular system with the lowest consumption and highest residual standard errors. On the other hand, it can be observed that the islands with higher electric demand (such as “Tenerife” and “Gran Canaria”) present lower residual standard error. Additionally, insular systems with higher temperature variability (i.e., Balearic systems) present a higher standard error during the main sunlight hours (from 11 a.m. to 8 p.m.).

Table 4. Residual standard deviations [log (MWh)] for the 24 Reg-ARIMA hourly models.

	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24
TENER	1.47	1.51	1.45	1.44	1.42	1.39	1.55	2.07	1.93	1.76	1.77	1.84	1.90	1.84	1.81	1.87	1.87	1.86	1.76	1.61	1.49	1.31	1.23	1.35
GRCAN	1.61	1.70	1.71	1.73	1.73	1.71	1.77	2.29	2.11	1.96	1.95	1.94	1.95	1.93	1.91	1.98	2.02	1.96	1.84	1.70	1.63	1.42	1.35	1.50
LANZA	1.82	1.94	1.96	2.01	1.99	1.95	1.85	2.10	1.93	1.91	1.93	2.01	2.03	2.04	1.99	2.01	2.02	1.96	1.80	1.70	1.65	1.55	1.59	1.72
FUERT	1.78	1.90	1.92	1.93	1.90	1.83	1.76	1.92	1.89	1.91	2.15	2.32	2.35	2.36	2.37	2.36	2.27	2.10	1.86	1.64	1.59	1.59	1.60	1.72
PALMA	3.85	4.10	4.27	4.27	4.28	4.16	3.87	3.92	3.53	3.30	3.48	3.66	3.86	3.86	3.92	4.08	4.12	4.00	3.75	3.28	3.05	2.91	3.00	3.38
GOMER	3.62	3.97	4.05	4.09	4.13	4.05	3.76	3.65	3.34	3.05	3.45	3.17	3.22	3.18	3.20	3.37	3.47	3.47	3.33	3.13	3.02	2.80	2.88	3.25
ELHIE	6.80	7.22	7.48	7.54	7.70	7.62	7.24	6.66	6.53	6.15	6.05	5.80	5.74	5.66	5.78	6.11	6.21	6.35	6.16	5.94	5.68	5.50	5.70	6.25
MALLO	2.14	2.08	2.04	1.99	1.96	1.91	1.91	2.33	2.48	2.44	2.72	3.08	3.38	3.51	3.57	3.62	3.61	3.45	2.99	2.59	2.28	2.05	2.06	2.17
IBFOR	2.35	2.37	2.42	2.41	2.39	2.38	2.43	2.66	2.61	2.41	2.65	3.04	3.46	3.75	3.93	4.07	4.08	3.92	3.37	2.85	2.51	2.23	2.27	2.38
MENOR	2.61	2.66	2.59	2.64	2.61	2.50	2.45	2.96	2.85	2.79	3.20	3.69	4.11	4.22	4.29	4.37	4.17	3.91	3.42	2.98	2.69	2.44	2.43	2.58

4.1. Temperature Effect

The temperature influence for each system depends on the geographical location. In Figure 5, the average daily electric consumption versus the maximum daily forecasted temperature for “Mallorca” (Balearic Islands) and “Gran Canaria” (Canary Islands) is depicted. Blue, red and orange dots represent weekdays, Saturdays and Sundays, respectively.

Figure 5. Average daily electric demand (measured in MWh) versus maximum daily temperature for insular systems: Mallorca in the Balearic Islands (**left**) and Gran Canaria in the Canary Islands (**right**).

In Mallorca (left plot in Figure 5), a convex non-linear relationship between demand and temperature is observed. On the other hand, in Gran Canaria (right plot), this relationship is less clear.

The set of parameters α_h measures the thermic effect on electric consumption, based on regression-spline models. Once the Reg-ARIMA model (1)–(2) has been estimated, the computed values for these parameters quantify the temperature effect for each hour.

Figure 6 depicts the effect of temperature on the electric consumption for several hours, for the ten insular systems. As expected, the effect of temperature is more marked on the Balearic Island’s systems, whereas the Canary systems do not exhibit a significant nor consistent relationship. Concerning the Balearic systems, it is observed that the thermic effect differs greatly by the time of day: temperature affects demand less at night than during the rest of the day.

Figure 6. Influence of temperature on Spanish insular electricity demand.

4.2. Holidays Effect

The effect of holidays on electric demand is modeled by means of the set of parameters β_h in Equation (1). Once these parameters are computed, its estimated values quantify the percentual reduction of electric consumption for every hour of each special day. For example, the effect of Christmas Day is considered with seven parameters, one for each day of the week. Another seven parameters are used for the previous day (December 24th) and seven more for the following day (December 26th). Consequently, $7 \times 3 = 21$ parameters are required to model the Christmas Day effect for each hour (See Section 2.2 for more details).

Figure 7 shows the effect of Christmas Day on Monday and the two adjacent days (in columns) depending on the insular system analyzed (in rows). Each point corresponds to a parameter, the abscissa indicates the hour of the day, and the ordinate value represents the estimated value. Each value measures the load reduction (in percentage) of the holiday compared with a normal day. When Christmas Day is celebrated, a significant decrease in demand occurs relative to what would be expected for a working day. This plot can also be generated for all the National/Regional Holidays, and for all the days in the week (for reasons of space limitations, all these plots are not provided in this document). Green dots correspond to no-significant effects (p -value > 0.05), orange dots correspond to significant effects (p -value between 0.0001 and 0.05), and red dots correspond to very significant effects (p -value < 0.0001).

Figure 7. Influence of the public holiday on December 25th on Monday for each insular system.

From Figure 7, it can be observed:

- There is a significant reduction (higher than 10%) of electric consumption during Christmas Day on Monday from 7 a.m. until 11 p.m.;
- The maximum reduction is observed at 9 a.m. and 10 a.m., when demand may decrease up to 30–40%. In some systems (e.g., Mallorca and Menorca), there is a second reduction of demand at 4 p.m. and 5 p.m.;
- For Balearic systems, there is a significant effect on demand on Tuesday, December 26th. This is due to the celebration of the regional holiday “St Stephen’s Day”. For Canary systems, the effect over demand on Tuesday is negligible.

The effect of public holidays on hourly electric consumption for each insular system, measured as percentual increment, is provided in Table 5. This table quantifies the average hourly descend of electricity demand for each national or regional holiday that occurs on a weekday.

Table 5. Influence of public holidays on hourly electric consumption for each insular system (in %)

		h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24
TENER	01-JAN	−7.60	−6.18	−4.72	−4.17	−3.81	−3.08	−2.26	−3.25	−2.79	−2.31	−2.23	−2.39	−2.38	−2.01	−1.72	−1.46	−1.77	−2.40	−2.47	−1.95	−1.29	−0.83	0.05	−0.11
	06-JAN	−3.47	−2.75	−2.36	−1.88	−1.60	−1.37	−2.67	−5.85	−4.68	−1.79	−0.94	−0.71	−0.57	0.66	0.63	0.56	0.06	−0.54	−0.63	−0.51	−0.33	0.05	0.18	−0.11
	02-FEB	−3.56	−3.17	−2.87	−2.67	−2.37	−2.14	−1.61	−1.43	−0.62	−0.22	0.17	−0.11	−0.17	0.27	0.75	0.71	0.68	0.25	0.10	0.58	0.73	0.96	1.19	0.45
	01-MAY	−3.80	−3.54	−3.13	−2.98	−2.82	−2.54	−2.58	−3.33	−2.66	−2.61	−3.06	−2.51	−2.86	−2.10	−1.51	−1.42	−1.39	−0.97	−0.73	−0.36	−0.59	−0.80	−0.34	−0.89
	03-MAY	−1.35	−1.25	−1.14	−1.09	−1.27	−1.30	−1.20	−1.11	−0.91	−1.16	−0.98	−1.36	−1.49	−1.52	−0.77	−0.60	−0.46	−0.16	0.02	−0.23	−0.14	−0.10	−0.01	−0.40
	30-MAY	−2.67	−1.91	−1.70	−1.71	−1.30	−1.09	−1.12	−1.58	−1.27	−0.89	−0.61	−1.02	−0.68	−0.56	−0.32	−0.67	−0.61	−0.69	−0.63	−0.77	−0.13	0.29	0.43	0.02
	15-AUG	−3.99	−3.65	−3.39	−2.98	−2.92	−2.24	−2.28	−2.20	−1.73	−1.49	−1.05	−0.84	−1.00	−0.84	−0.19	0.04	0.21	0.17	0.01	0.18	0.44	1.02	1.24	1.40
	12-OCT	−2.47	−1.94	−1.90	−1.69	−1.28	−0.97	−0.41	−1.07	−0.59	−0.50	−0.33	−0.18	−0.18	0.01	0.33	0.18	−0.26	−0.07	0.18	0.35	0.43	0.20	−0.33	−0.53
	01-NOV	−4.17	−3.31	−2.63	−2.63	−2.10	−1.57	−1.89	−2.64	−1.77	−1.38	−1.26	−1.40	−1.03	−0.57	−0.30	−0.47	−0.29	−0.37	−0.22	−0.04	0.27	0.13	−0.16	−0.51
	06-DEC	−2.15	−2.15	−2.08	−1.94	−1.80	−1.95	−3.11	−6.31	−4.39	−2.11	−1.51	−1.88	−1.60	−0.95	−1.02	−1.70	−2.25	−2.22	−2.41	−2.64	−2.88	−2.84	−2.31	−1.48
	25-DEC	−6.27	−4.96	−4.22	−3.75	−3.42	−3.06	−3.15	−5.03	−4.04	−2.51	−1.92	−1.63	−1.48	−0.72	−0.65	−0.89	−1.37	−1.30	−1.78	−1.34	−1.13	−0.98	−0.86	−0.88
GRCAN	01-JAN	−6.55	−5.04	−4.11	−3.60	−2.72	−2.13	−2.26	−3.13	−1.91	−1.53	−1.74	−2.07	−2.06	−1.63	−1.58	−1.74	−2.16	−1.96	−1.97	−1.76	−1.14	−0.52	0.58	0.56
	06-JAN	−3.98	−3.70	−3.30	−3.21	−2.99	−2.78	−4.37	−6.83	−4.81	−1.65	−0.67	0.28	0.48	1.40	0.92	0.27	0.15	−0.16	0.18	−0.02	0.17	0.32	0.91	0.65
	01-MAY	−3.69	−3.43	−3.19	−2.99	−2.60	−1.98	−1.35	−2.07	−1.48	−0.85	−0.75	−1.17	−1.71	−1.38	−1.39	−1.34	−0.89	−0.61	−0.43	−0.64	−0.43	0.12	0.18	0.14
	30-MAY	−3.18	−3.28	−3.43	−3.33	−3.32	−2.79	−2.73	−3.47	−2.44	−1.22	−1.02	−0.73	−0.75	−0.56	−0.20	−0.57	−0.85	−0.65	−0.57	−0.33	0.77	0.49	0.13	−0.78
	24-JUN	−1.67	−1.42	−1.77	−1.71	−1.28	−0.69	−0.98	−2.10	−0.68	0.32	−0.27	−0.64	−0.69	−0.50	−0.32	−0.20	−0.60	−0.70	−0.33	0.04	0.17	0.41	0.44	−0.03
	15-AUG	−3.31	−3.29	−3.03	−2.88	−2.59	−1.99	−1.63	−1.48	−0.87	−0.47	−0.51	−0.52	−0.50	−0.29	−0.01	0.20	−0.06	0.02	−0.18	−0.23	0.08	0.39	0.27	0.20
	08-SEP	−2.37	−2.26	−2.17	−1.83	−1.65	−1.73	−1.62	−1.98	−0.84	−0.33	−0.57	−0.56	−0.83	−0.04	−0.13	0.47	0.74	0.77	0.67	0.62	0.81	1.06	0.93	0.61
	12-OCT	−3.42	−3.36	−2.73	−2.97	−2.62	−2.30	−2.10	−2.41	−1.23	−0.86	−0.61	−0.29	−0.32	−0.33	−0.38	−0.24	−0.12	−0.06	0.13	0.10	0.43	0.59	−0.16	−0.93
	01-NOV	−4.02	−3.93	−3.88	−4.11	−3.88	−3.15	−2.96	−3.71	−2.30	−1.40	−1.22	−1.23	−0.96	−0.89	−0.40	−0.44	−0.58	−0.15	0.02	−0.20	0.15	0.27	0.07	−0.41
	17-NOV	−0.05	0.19	0.01	0.04	0.21	0.72	0.72	0.87	0.53	0.04	0.02	0.04	−0.13	−0.06	−0.29	0.05	0.48	0.61	0.56	0.43	0.49	0.32	0.58	0.31
	06-DEC	−2.69	−2.38	−2.23	−2.12	−1.77	−1.56	−3.20	−6.33	−4.14	−2.03	−1.37	−1.94	−2.27	−1.72	−1.87	−1.67	−1.42	−1.47	−2.20	−2.33	−2.47	−2.16	−0.59	0.99
	25-DEC	−4.60	−3.74	−3.32	−3.16	−2.76	−2.38	−2.42	−4.04	−3.14	−1.70	−1.35	−1.21	−0.92	−0.65	−1.18	−1.29	−1.49	−1.52	−1.28	−1.17	−1.12	−1.19	−0.85	−1.52
LANZA	01-JAN	−3.76	−2.58	−1.90	−1.38	−1.18	−0.82	−1.07	−2.13	−2.23	−2.41	−2.92	−3.02	−2.52	−2.19	−2.10	−2.38	−2.45	−3.44	−2.56	−2.30	−1.61	−0.74	−0.33	−0.57
	06-JAN	−0.86	−0.22	0.28	−0.14	0.15	0.58	−0.64	−3.88	−2.39	0.01	0.40	−0.54	−0.53	−0.13	−0.91	−1.18	−0.55	−0.43	−0.55	−0.12	−0.21	−0.09	−0.45	−0.56
	01-MAY	−1.90	−0.91	−0.46	−0.72	−0.82	−0.59	−0.81	−1.26	−1.08	−0.70	−0.54	−0.78	−0.96	−0.85	−0.78	−0.41	−0.53	−0.30	−0.36	0.00	0.18	0.01	0.13	−0.18
	30-MAY	−1.16	−1.07	−1.21	−1.39	−1.35	−0.68	−0.47	−1.00	−1.22	−1.59	−0.85	−0.78	−0.70	−1.06	−0.78	−0.73	−1.03	−1.67	−1.50	−0.97	−0.61	−0.28	−0.22	−1.00
	15-AUG	−0.51	−0.21	−0.50	0.12	0.17	0.00	0.13	−0.37	0.00	−0.53	−0.50	−0.53	−0.39	0.11	0.47	0.79	0.57	0.50	0.33	−0.01	0.41	0.17	−0.18	−0.13
	25-AUG	−0.59	−0.51	−0.87	−1.27	−1.25	−0.81	−0.30	−0.11	−0.31	0.48	0.25	0.41	0.69	0.77	0.78	0.66	0.39	0.05	−0.11	−0.26	−0.27	−0.13	0.18	0.53
	15-SEP	−1.44	−1.12	−1.05	−1.20	−1.44	−0.93	−0.69	−0.59	0.09	−0.67	−0.56	−0.96	−0.86	−0.54	−0.30	−0.31	−0.15	0.09	−0.44	−0.44	−0.14	−0.13	0.65	0.31
	12-OCT	−1.12	−1.28	−1.58	−1.36	−1.12	−0.53	−0.22	−0.65	−0.62	−0.28	−0.50	−0.28	−0.56	−0.59	0.09	−0.35	−0.22	−0.36	−0.04	0.18	0.17	0.47	0.04	0.05
	01-NOV	−1.84	−0.20	−0.16	−0.31	−0.40	−0.60	0.01	−0.45	−1.07	−1.51	−1.98	−1.28	−1.17	0.42	0.67	0.45	0.13	−0.04	−0.13	−0.03	0.03	0.09	−0.42	−0.83
	06-DEC	−1.38	−1.20	−1.63	−1.24	−1.04	−0.91	−2.02	−5.12	−2.93	−0.40	0.03	−0.61	−0.75	−0.36	−0.94	−1.43	−1.45	−1.25	−1.03	−1.32	−1.25	−1.12	−0.47	0.40
	25-DEC	−1.84	−1.52	−1.66	−1.79	−1.51	−1.86	−2.44	−3.80	−3.72	−2.41	−1.17	−0.86	−0.58	−0.46	−0.64	−1.24	−1.83	−2.44	−2.45	−2.28	−1.43	−1.33	−1.11	−1.55

Table 5. Cont.

		h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24
FUERT	01-JAN	−3.28	−2.67	−1.98	−1.60	−1.32	−1.14	−1.68	−2.87	−2.52	−2.21	−3.02	−2.85	−2.70	−2.45	−2.14	−2.91	−3.55	−3.36	−2.39	−2.05	−1.54	−1.32	−1.37	−1.38
	06-JAN	−2.12	−1.65	−1.09	−0.71	−0.85	−0.67	−1.87	−3.55	−2.10	−0.38	−0.35	−0.58	−0.97	0.56	0.15	−0.62	−0.40	−0.89	−0.84	−0.53	−0.52	−0.32	−0.22	−0.24
	01-MAY	−1.30	−1.10	−1.17	−0.73	−0.36	−0.48	−0.96	−2.17	−1.41	−1.45	−1.54	−1.32	−1.87	−0.47	−0.88	−0.98	−2.00	−2.18	−0.82	−0.36	−0.14	0.09	−0.01	−0.44
	30-MAY	−0.39	−0.22	−0.18	−0.39	−0.18	0.15	−0.11	−0.55	0.32	1.76	1.96	1.54	1.02	−0.09	0.53	0.52	0.26	0.03	−0.22	0.19	0.15	0.70	1.18	1.05
	15-AUG	−1.32	−1.25	−0.97	−0.94	−1.02	−0.82	−0.73	−0.90	−0.33	−0.48	−0.53	−0.59	−0.13	0.18	0.09	−0.06	−0.16	−0.30	−0.14	−0.22	−0.05	0.39	0.50	0.42
	07-OCT	−1.42	−1.42	−1.29	−1.39	−1.23	−1.32	−1.27	−1.15	−0.52	−0.67	−1.28	−1.10	−0.64	−0.20	0.06	0.19	0.28	0.47	0.17	−0.29	−0.09	0.28	0.30	0.43
	12-OCT	−1.18	−1.00	−0.99	−0.68	−0.61	−0.83	−1.15	−2.52	−2.63	−1.81	−1.79	−1.56	−1.81	−1.53	−1.95	−1.08	−0.87	−1.11	−1.26	−1.51	−0.96	−0.95	−1.15	−1.23
	01-NOV	−1.39	0.44	0.42	0.19	0.20	−0.09	−0.23	0.27	−0.25	−1.35	−2.14	−2.14	−1.72	−0.60	−1.09	−1.31	−1.22	−0.27	1.08	1.11	1.48	1.19	0.30	−0.02
	06-DEC	−0.13	−0.13	−0.50	−0.61	−0.47	−0.23	−0.82	−3.01	−2.13	−0.35	0.07	0.33	−0.14	0.67	−0.31	−1.04	−1.33	−1.14	−1.19	−1.19	−1.13	−1.33	−0.52	−0.19
	25-DEC	−2.47	−2.47	−2.43	−2.44	−2.29	−2.30	−2.93	−4.58	−3.81	−2.59	−1.76	−1.57	−0.58	−0.20	−0.80	−1.46	−2.06	−2.32	−2.10	−2.13	−1.98	−1.83	−1.71	−1.39
ELHIE	01-JAN	−1.45	−0.16	−1.72	−2.91	−3.46	−4.99	−4.51	−2.84	−0.58	2.04	3.98	0.99	−0.84	−2.03	−1.50	−3.07	−1.94	−1.96	−2.83	−1.39	−2.57	−3.26	−1.20	−1.40
	06-JAN	−0.04	2.17	−0.21	−0.50	−0.32	0.33	−1.48	−5.18	−6.95	−4.40	−4.13	−1.36	0.77	0.48	0.52	−1.88	−0.30	0.19	−2.13	−1.72	−1.27	−1.32	−2.04	0.89
	01-MAY	−2.68	−1.00	−0.75	−0.76	−1.51	−1.21	−1.35	−1.46	−1.85	−2.10	0.11	2.04	0.30	0.32	0.28	−1.60	−2.93	−1.15	1.46	−0.52	−1.11	0.55	0.32	0.32
	15-MAY	1.91	1.39	2.42	3.26	−0.02	0.94	0.72	−0.95	−1.10	−2.42	0.85	0.25	0.27	−0.90	0.19	0.27	−0.36	0.13	2.11	0.35	−0.30	−0.68	0.35	0.99
	30-MAY	−0.68	−0.20	−1.77	−1.69	−2.20	−2.22	−1.60	0.54	0.96	3.56	3.03	0.32	0.88	1.42	1.68	1.55	−0.66	1.77	1.82	2.25	1.91	2.81	0.05	0.39
	29-JUN	0.76	0.87	1.53	1.71	1.09	1.71	0.96	2.12	2.78	4.15	4.96	4.07	3.15	3.39	2.42	3.01	3.41	3.76	4.04	3.12	3.22	3.24	4.98	1.98
	15-AUG	−2.60	−4.23	−3.93	−2.71	−2.92	−2.18	−2.46	−4.04	−2.86	−2.98	−1.69	−2.34	−1.93	0.09	1.51	−0.50	0.20	−1.59	−1.19	−0.29	−0.62	1.21	0.70	−0.52
	24-SEP	−5.87	−5.93	−4.45	−4.08	−3.58	−3.22	−3.40	−3.76	−2.87	−2.18	−1.58	0.36	−0.71	−1.19	−1.49	−2.08	−1.90	−0.72	1.01	1.47	2.20	1.54	−0.76	−0.46
	12-OCT	0.80	1.36	1.56	1.61	1.83	−0.55	−0.69	0.61	0.02	1.76	2.26	−0.29	1.28	1.49	3.17	3.11	2.83	−0.06	0.38	1.08	2.04	1.10	0.69	0.27
	01-NOV	−3.48	−3.38	−1.62	−3.27	−5.40	−3.60	−3.29	−1.78	−0.36	2.22	1.04	2.30	1.89	−0.45	−3.68	−3.01	−0.98	−0.66	1.71	1.25	0.62	1.80	0.68	−1.01
	06-DEC	−1.88	−2.55	−2.76	−2.11	0.39	−2.27	−3.89	−5.17	−7.51	−3.83	−2.04	−2.59	−1.36	−0.30	−1.46	0.96	−2.11	1.12	−0.40	0.82	1.33	−0.78	−0.07	2.66
	25-DEC	−6.96	−6.39	−7.27	−6.76	−5.18	−3.95	−6.51	−4.86	−5.71	−1.78	−0.82	0.88	3.29	3.63	2.03	2.42	0.22	0.28	−0.57	−0.64	0.25	−0.33	0.37	1.38
GOMER	01-JAN	−2.46	−2.36	−1.87	−1.05	−0.97	−1.29	−1.33	−2.78	−2.24	−1.41	−0.87	−0.68	−0.02	0.19	−0.05	0.41	−0.29	−1.35	−1.99	−0.70	−0.08	0.03	−0.11	0.10
	06-JAN	−0.67	−0.06	0.19	0.76	−0.10	0.62	−1.01	−5.05	−5.29	−2.42	2.83	0.25	0.72	0.87	0.20	−0.60	−0.80	−0.65	−0.64	0.33	0.04	0.85	0.75	0.35
	20-JAN	−2.33	−1.18	−1.82	−1.37	−1.19	−0.83	−0.54	−0.64	−0.84	−1.16	2.13	0.30	0.34	0.37	0.13	−0.82	−0.63	−0.23	0.31	0.64	0.27	0.10	0.94	0.68
	01-MAY	1.81	2.14	2.16	1.90	2.21	2.65	1.44	−0.54	0.36	0.58	0.25	−0.58	−0.74	−0.89	0.40	0.08	0.46	0.37	0.02	0.35	1.22	1.62	1.19	1.03
	30-MAY	0.64	0.45	−0.71	−1.03	−0.72	−0.25	−1.66	−2.74	−0.19	−0.43	−1.04	0.76	0.33	0.90	1.27	0.93	0.32	1.25	0.97	−0.74	−0.33	0.04	−0.07	−1.20
	15-AUG	−0.61	−1.18	−1.93	−2.54	−2.22	−0.55	−0.76	−1.27	−0.82	−0.83	−0.12	−0.12	−0.72	−0.40	−0.49	−0.59	−0.78	−1.17	−1.55	−0.58	−0.59	0.16	0.93	1.26
	12-OCT	0.99	0.16	−0.04	−0.65	−0.70	−0.67	−0.42	−1.61	−0.52	0.88	2.98	0.88	0.52	0.55	0.39	−0.65	−0.57	0.21	0.05	0.62	0.92	1.15	0.49	−0.19
	01-NOV	2.00	1.37	1.07	0.68	0.72	0.64	−1.03	−1.55	0.28	1.29	1.99	0.10	−0.25	0.40	1.27	−0.51	−2.01	−1.34	0.93	0.35	1.17	0.51	−0.39	−1.02
	06-DEC	2.27	2.92	3.15	2.08	1.99	1.45	−1.21	−2.99	−1.11	1.11	1.62	0.44	0.31	0.51	0.22	0.20	0.25	−0.28	−0.27	−0.47	−0.24	0.21	0.70	1.83
	25-DEC	−3.20	−3.58	−3.52	−2.42	−2.64	−2.08	−2.88	−5.60	−5.23	−2.70	−3.01	0.36	0.37	−0.85	−1.13	−0.85	−1.98	−2.21	−1.86	−1.37	−1.19	−1.38	−1.49	−0.96

Table 5. Cont.

		h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24
PALMA	01-JAN	−5.00	−3.99	−3.05	−2.61	−2.27	−1.63	−1.53	−3.01	−1.86	−0.84	−1.61	−1.41	−1.10	−1.53	−1.20	−1.18	−2.35	−2.53	−2.67	−2.13	−1.02	−0.52	0.49	0.96
	06-JAN	−0.41	0.32	1.16	0.64	0.55	0.42	−1.97	−5.00	−3.88	−2.01	−2.16	−1.85	−1.43	−0.58	−0.92	−2.27	−3.12	−2.21	−2.34	−1.20	−1.55	−1.35	−1.40	−2.39
	01-MAY	−0.09	−0.42	−0.01	0.16	0.52	0.01	−0.15	0.69	1.52	2.02	1.53	1.21	1.63	1.47	1.55	1.62	2.55	2.61	2.49	2.48	1.58	0.68	−0.05	0.39
	30-MAY	−1.95	−2.77	−3.64	−3.87	−3.48	−2.82	−2.70	−2.44	−0.57	1.04	1.61	1.06	0.07	2.18	2.30	1.85	1.56	2.05	2.11	1.96	2.12	1.40	−0.09	−0.44
	05-AUG	−1.17	−0.68	−0.34	−1.08	−0.81	0.19	−0.76	−1.04	−0.38	−0.64	−0.95	−1.52	−0.82	−0.53	0.04	0.78	0.18	0.09	−0.53	−0.27	0.58	1.28	1.47	0.33
	15-AUG	−3.03	−1.90	−1.26	−1.29	−1.63	−0.62	0.00	−0.25	−0.11	0.00	0.23	−0.80	−1.18	−0.57	−0.07	−0.37	0.10	0.45	0.74	0.13	−0.25	1.08	1.89	0.59
	29-SEP	−1.05	−1.62	−1.89	−1.74	−2.03	−1.75	−1.08	0.29	0.94	0.13	−0.31	−1.52	−0.68	−0.90	−0.97	−0.98	−1.15	−0.63	−0.49	−0.68	−0.24	0.34	−0.09	−0.08
	12-OCT	−3.41	−3.70	−3.07	−3.73	−3.71	−3.09	−2.20	−3.16	−2.03	−0.35	−0.45	−1.19	−1.23	−1.51	−0.33	−0.30	0.24	0.64	0.81	1.08	1.30	1.53	0.50	0.54
	01-NOV	−3.73	−3.72	−3.39	−2.97	−2.95	−2.62	−2.80	−3.04	−2.25	−2.16	−1.29	−2.29	−2.50	−1.43	−0.95	−0.86	−1.14	0.05	0.34	0.31	1.09	1.92	0.96	−0.24
	06-DEC	−1.22	−1.28	−0.43	−0.87	−1.76	−1.79	−3.63	−7.77	−5.94	−3.33	−3.06	−4.50	−4.69	−3.23	−3.18	−3.12	−3.34	−3.93	−2.32	−2.28	−2.65	−2.83	−1.88	−0.61
	25-DEC	−6.24	−5.69	−4.61	−4.70	−4.95	−4.17	−3.87	−4.63	−3.87	−2.17	−1.03	−1.78	−1.00	−0.57	−1.76	−2.14	−1.85	−1.09	−0.84	−0.73	−1.06	−0.29	−0.69	−1.28
MALLO	01-JAN	−2.51	−2.18	−1.43	−1.16	−1.10	−0.98	−1.53	−2.55	−2.27	−1.31	−0.90	−0.37	−0.04	1.26	1.82	1.07	0.71	0.34	−0.30	−0.02	0.60	0.95	1.15	0.60
	06-JAN	−2.64	−2.54	−2.68	−2.64	−2.73	−2.21	−3.06	−5.12	−3.77	−0.78	0.42	0.68	0.67	0.91	1.14	0.45	−0.13	−0.87	−1.33	−1.45	−1.30	−1.27	−1.21	−1.41
	17-JAN	−1.44	−1.44	−1.15	−1.00	−1.20	−1.25	−0.95	−1.21	−1.20	−0.72	−0.77	−0.46	−0.37	−0.56	−0.74	−0.88	−1.06	−1.24	−1.17	−0.85	0.34	1.07	0.62	−0.30
	20-JAN	−2.47	−1.89	−1.44	−1.52	−1.53	−1.63	−1.09	−1.08	−1.35	−1.60	−1.98	−2.35	−1.80	−1.72	−1.98	−2.02	−2.11	−2.68	−2.03	−0.82	0.32	1.00	1.11	0.38
	01-MAR	−2.37	−2.15	−2.13	−2.02	−1.72	−2.05	−2.18	−3.11	−2.85	−2.13	−1.74	−1.43	−1.33	−0.90	−0.96	−0.73	−0.94	−1.27	−1.03	−0.35	0.10	0.48	0.15	−0.42
	01-MAY	−1.41	−1.30	−1.38	−1.35	−1.25	−0.87	−0.98	−1.98	−2.41	−1.83	−1.57	−1.62	−1.64	−1.23	−0.87	−1.02	−1.04	−1.30	−1.20	−0.92	−0.68	−0.61	−0.42	−1.05
	15-AUG	−1.07	−0.60	−0.73	−0.60	−0.40	−0.21	0.08	−0.06	−0.10	−0.17	−0.45	−0.65	−0.55	−0.42	−0.70	−1.00	−1.32	−1.68	−1.80	−1.54	−0.99	−0.87	−0.67	−0.92
	12-SEP	−0.16	−0.49	−0.75	−1.18	−0.85	−0.84	−0.76	−0.40	−0.33	−0.92	−0.78	−0.60	−0.45	−0.18	−0.32	−0.37	−0.33	−0.12	−0.16	−0.16	0.16	−0.26	−0.39	−0.53
	12-OCT	−2.38	−2.10	−1.86	−1.82	−1.53	−1.26	−1.41	−1.76	−1.07	−0.42	−0.19	−0.13	−0.18	0.06	0.30	0.27	0.36	0.62	0.48	0.52	0.64	0.57	0.60	−0.25
	01-NOV	−3.17	−2.34	−2.01	−1.68	−1.42	−1.33	−1.80	−4.01	−3.09	−1.76	−1.74	−1.86	−1.59	−1.50	−1.55	−2.29	−2.67	−2.51	−1.83	−0.88	−0.42	−0.13	−0.50	−1.42
	06-DEC	−0.42	−0.38	−0.24	−0.50	−0.54	−0.70	−2.23	−4.91	−3.33	−1.13	−1.16	−1.94	−2.39	−2.28	−2.24	−2.52	−2.80	−2.43	−2.49	−2.79	−2.58	−2.22	−1.22	−0.07
	25-DEC	0.10	0.48	0.04	−0.76	−1.55	−3.23	−9.61	−21.00	−27.11	−22.68	−15.59	−10.07	−7.20	−6.95	−11.47	−15.01	−16.06	−15.34	−13.44	−11.86	−9.74	−8.11	−5.25	−4.16
MENOR	01-JAN	−3.79	−3.91	−3.09	−2.50	−2.42	−1.81	−1.90	−3.28	−2.27	−0.93	−0.69	−0.33	−0.93	−0.68	1.06	0.56	1.02	1.37	0.03	−0.52	0.12	0.79	0.69	−0.08
	06-JAN	−4.62	−4.99	−4.59	−4.15	−3.89	−3.91	−4.34	−6.70	−5.19	−0.90	0.37	0.59	0.41	0.78	1.50	0.60	−0.04	−0.25	−0.98	−0.78	−0.51	−0.57	−1.14	−1.45
	17-JAN	−4.53	−4.00	−3.58	−3.46	−3.28	−3.18	−3.28	−3.23	−2.12	−0.83	−0.37	0.54	0.83	1.04	0.34	0.06	−0.43	−0.78	−1.13	−1.36	−0.86	−0.40	−0.62	−1.15
	01-MAR	−3.40	−2.62	−2.50	−2.55	−2.17	−1.60	−2.12	−4.02	−2.73	−1.56	−1.17	−0.90	−1.29	−0.98	−0.58	−0.99	−1.17	−1.32	−1.15	−0.41	0.05	0.11	−0.06	−0.17
	01-MAY	−2.01	−1.71	−1.60	−1.28	−1.26	−1.09	−1.54	−2.13	−1.71	−0.99	−1.22	−1.55	−1.80	−1.09	−1.14	−1.95	−1.78	−1.45	−0.96	−0.37	0.00	−0.17	−0.22	−0.86
	24-JUN	−1.47	−0.46	−0.49	−0.10	−0.08	−0.64	−2.79	−6.04	−6.25	−5.47	−4.55	−3.69	−3.61	−2.48	−1.20	−2.14	−2.48	−2.68	−1.88	−0.11	1.18	1.27	0.02	−1.23
	15-AUG	0.48	0.55	−0.06	−0.17	0.06	0.35	0.82	0.36	−0.36	−1.13	−0.69	−0.68	−0.87	−0.76	−0.69	−1.07	−1.42	−1.86	−2.33	−2.30	−2.21	−2.04	−1.62	−2.28
	12-OCT	−3.20	−3.44	−3.08	−3.14	−2.91	−2.32	−1.71	−1.06	−0.75	−0.47	−0.70	−1.41	−0.52	−0.57	−0.87	−0.45	−0.38	−0.04	0.08	0.76	0.59	0.65	0.38	−0.67
	01-NOV	−4.04	−3.31	−3.64	−3.57	−3.82	−3.22	−3.20	−4.82	−4.20	−2.45	−2.23	−2.35	−2.74	−2.66	−2.10	−2.58	−3.20	−3.08	−1.91	−1.10	−0.62	−0.52	−0.98	−1.62
	06-DEC	−0.70	−0.47	−1.02	−1.52	−1.83	−2.26	−4.04	−6.74	−5.33	−2.56	−3.33	−4.71	−6.01	−4.82	−4.40	−4.74	−4.23	−3.47	−2.76	−2.66	−2.33	−1.63	−0.54	0.67
	25-DEC	0.48	−0.42	−1.34	−2.10	−2.38	−3.23	−10.05	−22.12	−24.60	−17.99	−12.72	−9.34	−8.62	−6.88	−8.00	−12.95	−13.75	−14.80	−13.03	−11.17	−8.79	−6.89	−5.73	−5.41

Table 5. Cont.

		h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24
	01-JAN	−3.12	−1.97	−1.17	−0.58	−0.40	−0.27	−0.88	−2.36	−2.29	−0.78	−0.10	−0.19	−0.82	−0.44	0.74	0.95	0.55	0.05	−0.67	−0.78	−0.82	−0.49	−0.26	−0.58
	06-JAN	−2.62	−2.14	−2.14	−1.99	−1.99	−2.08	−2.47	−4.44	−3.81	−0.82	0.31	0.45	−0.01	0.28	−0.19	−1.12	−1.81	−2.53	−2.53	−2.12	−1.75	−1.52	−1.56	−1.59
	17-JAN	−0.23	−0.04	−0.03	−0.07	−0.19	−0.44	−0.38	−0.40	−0.50	−0.86	−1.05	−1.49	−1.82	−1.57	−0.76	0.00	−0.32	−0.53	−0.96	−1.56	−1.56	−1.51	−1.84	−1.90
	01-MAR	−1.54	−0.73	−0.58	−0.67	−0.68	−0.45	−0.54	−1.54	−1.68	−1.14	−1.24	−1.51	−1.83	−2.35	−1.97	−1.92	−2.22	−2.86	−3.03	−1.62	−0.43	0.26	0.21	−0.18
	01-MAY	−0.99	−0.67	−0.57	−0.50	−0.44	−0.36	−0.21	−1.04	−1.34	−1.30	−0.85	−0.91	−1.03	−0.57	−0.40	−0.82	−1.14	−0.97	−0.88	−0.38	−0.21	0.05	0.09	−0.43
IBFOR	05-AUG	−0.83	−0.25	0.04	0.01	0.25	0.20	0.13	−0.43	−0.66	−0.13	0.41	0.35	0.32	0.42	0.72	0.74	0.75	0.65	0.68	0.63	0.35	0.72	0.95	0.80
	08-AUG	−3.75	−3.03	−3.70	−4.79	−4.95	−4.95	−4.77	−4.41	−3.75	−2.66	−2.31	−1.93	−1.95	−2.20	−2.40	−2.63	−1.63	−0.56	−0.36	−0.49	−0.13	0.20	0.28	1.69
	15-AUG	−1.54	−0.32	−0.08	−0.09	−0.56	−0.79	−0.98	−1.12	−1.33	−1.60	−1.58	−1.48	−1.06	−1.21	−0.89	−0.79	−0.50	−0.27	−0.61	−0.70	−0.57	−0.46	−0.45	−0.82
	12-OCT	−2.06	−2.10	−1.90	−1.68	−1.71	−1.87	−2.07	−3.14	−2.23	−1.06	−0.23	0.29	0.22	0.20	0.12	−0.14	−0.17	−0.38	−0.51	−0.21	−0.35	−0.35	−0.64	−1.08
	01-NOV	−2.59	−1.28	−0.90	−1.04	−0.66	−0.60	−1.26	−2.50	−2.38	−1.81	−2.04	−2.42	−2.25	−1.77	−1.55	−1.85	−1.81	−1.86	−0.97	−0.23	0.26	0.40	0.33	−0.13
	06-DEC	0.77	1.37	1.29	1.36	1.45	1.04	0.36	−1.42	−0.91	0.36	−0.01	−0.65	−1.88	−1.70	−1.98	−2.12	−2.23	−1.90	−1.14	−0.75	−0.76	−0.32	0.39	1.72
	25-DEC	−1.36	−0.93	−0.85	−1.26	−1.57	−2.34	−4.70	−11.41	−16.50	−13.12	−9.00	−5.30	−3.26	−2.13	−2.86	−5.36	−7.09	−8.13	−8.07	−7.31	−5.99	−5.09	−4.12	−3.05

4.3. Accuracy Performance

In order to evaluate the accuracy of the developed insular models, two forecasting situations are analyzed: (1) predictions made at noon for 24 h of the next day, and (2) predictions made at 10 a.m. for 24 h of the next day. In both cases, electric load forecasts are computed from June 1st, 2018 until June 30th, 2019 (i.e., 13 months). Consequently, the performances of the different insular models are tested using the 395 days of the considered period. The performance metric employed in this work is the Root Mean Square Percentage Errors (RMSPE) for each hour h , computed as:

$$RMSPE_h = \sqrt{\frac{1}{n} \cdot \sum_{t=1}^n \left(\frac{y_{t,h} - \hat{y}_{t,h}}{y_{t,h}} \right)^2} \quad (7)$$

where $y_{t,h}$ and $\hat{y}_{t,h}$ are the observed and forecasted demands for hour h of day t , respectively; and n is the number of days for the analyzed time period.

4.3.1. Forecasting Situation 1: Predictions Made at Noon

In this first situation, electric load forecasts are computed at midnight of day d , generating the 24 h load predictions for day $d + 1$. It should be noted that these 24 values are one-step-ahead predictions due to the use of 24 h Reg-ARIMA models. Table 6 provides the global RMSPE and the hourly RMSPE for the ten insular models.

From Table 6 it is observed that the insular model with higher forecasting error coincides with the less-populated island (“El Hierro”); whereas the model with the lowest prediction error corresponds with the most-populated island (“Tenerife”). On the other hand, insular electric systems with higher temperature variation along the year (i.e., islands from the Balearic archipelago), usually obtains less accurate forecasts.

These deductions can be graphically visualized by means of the scatter plot between the following variables: population, average consumption and forecasting error. From Figure 8 it is observed that population and electricity consumption are strongly linearly correlated ($R^2 = 0.979$), whereas the average yearly error is negatively correlated with population and consumption. Additionally, it is observed that the forecasting error is augmented for systems with higher temperature ranges (Balearic Islands).

Figure 8. Relationship between forecasting accuracy, population and average hourly consumption.

Table 6. Forecasting situation 1: Hourly RMSPE for the test period for the insular models.

	RMSPE	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24
TENER	1.41	0.81	0.93	0.96	1.02	1.01	1.07	1.39	2.02	1.98	1.68	1.52	1.51	1.50	1.49	1.49	1.55	1.61	1.64	1.60	1.42	1.39	1.20	1.07	1.12
GRCAN	1.66	0.98	1.26	1.27	1.27	1.28	1.35	1.70	2.27	2.26	2.01	1.80	1.76	1.83	1.74	1.78	1.85	1.85	1.82	1.70	1.73	1.67	1.32	1.18	1.31
LANZA	1.87	1.05	1.37	1.50	1.53	1.72	1.77	2.17	2.19	2.01	2.00	1.95	2.06	2.07	2.17	2.12	2.09	2.00	1.91	1.77	1.75	1.69	1.64	1.77	2.00
FUERT	1.71	1.04	1.49	1.53	1.55	1.59	1.49	1.44	1.70	1.59	1.81	1.80	1.93	1.96	2.01	1.97	1.98	2.01	1.89	1.87	1.75	1.63	1.52	1.56	1.67
PALMA	2.55	1.91	2.27	2.43	2.49	2.52	2.55	2.43	2.73	2.77	2.75	2.53	2.51	2.57	2.49	2.51	2.62	2.86	2.94	2.67	2.43	2.50	2.31	2.55	2.76
GOMER	3.27	2.79	3.11	3.11	3.38	3.42	3.23	3.09	3.22	3.21	3.07	3.31	3.30	3.35	3.26	3.30	3.51	3.61	3.65	3.43	3.31	3.20	2.97	3.09	3.47
ELHIE	5.66	3.62	4.50	5.30	5.57	5.51	5.83	5.68	5.52	5.71	5.88	5.46	5.52	5.67	5.70	5.73	6.30	6.63	6.27	6.12	5.98	5.64	5.04	5.58	6.34
MALLO	2.49	1.36	1.37	1.42	1.38	1.39	1.66	1.84	2.40	2.45	2.34	2.48	2.80	3.09	3.19	3.34	3.40	3.43	3.26	2.87	2.62	2.46	2.26	2.25	2.43
IBFOR	2.60	1.23	1.40	1.52	1.49	1.54	1.54	1.58	1.94	2.17	1.96	2.30	2.86	3.29	3.57	3.83	3.82	3.87	3.72	3.28	2.89	2.50	2.16	2.10	2.18
MENOR	2.88	1.71	1.85	2.04	2.14	2.11	2.04	2.05	3.36	3.30	2.47	2.77	3.21	3.50	3.56	3.72	3.80	3.74	3.66	3.21	2.79	2.65	2.51	2.49	2.54

4.3.2. Forecasting Situation 2: Predictions Made at 10 a.m.

The Spanish electricity market is organized as a “day ahead market”: each day prior to 10 a.m., all the energy bids for the following day must be presented by the agents to the Market Operator. Thus, for planning reasons, each day d at 10 a.m. the Spanish TSO obtains the 24 h electricity forecasts for the day $d + 1$. It should be noted that ten values correspond to one-step-ahead predictions, and fourteen correspond to two-step-ahead predictions.

In order to compare the accuracy of predictions, the Spanish TSO provided reference forecasts from the currently working forecasting software at their facilities. Thus, in this second case study: (i) 24 h forecasts for day $d + 1$ are computed each day d at 10 a.m., and (ii) the accuracy results are compared with another forecasting model. The reference model is based on a hybrid algorithm that combines neural networks and time series models used by the Spanish TSO in its daily predictions. For reasons of space and confidentiality, no details are provided. The aim of this article is to describe how prediction errors vary depending on the size and climate characteristics of the electricity systems. The effects described in this paper do not depend so much on the prediction algorithm used as on the characteristics of the electrical system itself.

Tables 7 and 8 provide the global, hourly and monthly RMSPEs for the developed insular models (labeled as “final”) and the reference forecaster outputs (labeled as “refer”). Additionally, Tables 9 and 10 provide the percentual improvement for the global, hourly, and monthly RMSPEs for the proposed insular models.

To check if the proposed algorithm provides forecasts with significantly lower errors than the reference predictions, the Diebold-Mariano inference test [27,28] has been used for each system, computing the DM test statistic and its p -value. If the p -value is lower than 0.05, as usual, it can be stated that the accuracy of the proposed method is higher than the reference forecaster.

Tables 7–11 show the following:

- The proposed insular models outperform the reference forecaster. For the Balearic systems the global RMSPE improvement ranges from 22 to 30%; whereas the improvement for the Canary Islands is minor: from 2 to 8% (Gran Canaria);
- Comparing the prediction errors using the Diebold-Mariano test, it is observed that the proposed method provides statistically significant lower errors than the reference forecaster for all insular systems except Tenerife and Palma (with a 95% confidence level);
- Concerning the Balearic Islands, the proposed method provides a higher improvement during night and morning hours: from 8 p.m. to 11 a.m. For the three considered systems, the average hourly improvement during these hours is 32% (ranging from 22 to 47%). During the rest of the day, the average hourly improvement is 19% (ranging from 13 to 28%);
- Concerning the Canary Islands, the proposed method does not provide a significant enhancement from 7 a.m. to 10 p.m. (the average hourly improvement is 1%) for the seven insular systems. During the rest of the day, the average hourly accuracy increment is 9%, ranging from −1 to 20%;
- In general terms, the monthly prediction errors are higher in winter months (November, December and January), and lower in summer: June and July;
- For systems with higher temperature variation (i.e., Balearic systems), both forecasters present higher hourly error from 11 a.m. to 10 p.m. On the other hand, Canary systems exhibit a more regular hourly error, for both forecasting models.

Table 7. Case study 2: hourly RMSPE for the test period for the insular models.

		RMSEh1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24	
TENER	final	1.57	1.17	1.23	1.19	1.22	1.19	1.23	1.54	2.17	2.08	1.76	1.63	1.65	1.65	1.64	1.66	1.74	1.80	1.80	1.82	1.61	1.60	1.30	1.20	1.26
	refer	1.60	1.44	1.54	1.48	1.46	1.41	1.40	1.55	1.92	1.67	1.76	1.72	1.74	1.69	1.68	1.63	1.67	1.77	1.77	1.79	1.56	1.53	1.30	1.31	1.36
GRCAN	final	1.85	1.52	1.66	1.61	1.59	1.58	1.62	1.90	2.42	2.33	2.05	1.90	1.89	1.98	1.90	1.98	2.05	2.02	1.95	1.84	1.86	1.87	1.47	1.35	1.53
	refer	2.00	1.88	2.04	1.94	1.91	1.88	1.81	1.95	2.47	2.23	2.19	2.07	2.05	2.06	2.08	2.13	2.21	2.19	2.15	2.00	1.97	1.87	1.52	1.52	1.69
LANZA	final	2.12	2.09	2.16	2.11	2.10	2.19	2.12	2.39	2.34	2.13	2.11	2.10	2.19	2.20	2.28	2.23	2.18	2.16	2.08	1.99	1.94	1.85	1.78	1.94	2.15
	refer	2.19	2.15	2.27	2.32	2.33	2.36	2.29	2.54	2.46	2.15	2.29	2.25	2.24	2.19	2.28	2.16	2.17	2.18	2.11	2.10	1.93	1.87	1.80	1.92	2.07
FUERT	final	1.93	1.54	1.82	1.83	1.83	1.78	1.69	1.59	1.81	1.69	1.94	2.00	2.14	2.16	2.19	2.15	2.19	2.25	2.12	2.13	2.01	1.85	1.71	1.75	1.85
	refer	2.04	1.83	2.09	2.12	2.06	2.00	1.86	1.82	2.30	1.91	2.08	2.10	2.15	2.14	2.23	2.14	2.11	2.17	2.15	2.16	1.98	1.83	1.86	1.86	1.83
PALMA	final	2.95	2.85	3.04	3.18	3.20	3.13	3.11	2.93	3.05	2.93	2.88	2.67	2.68	2.80	2.84	2.89	2.99	3.26	3.23	2.98	2.69	2.79	2.61	2.78	3.07
	refer	2.99	3.10	3.46	3.60	3.59	3.56	3.51	3.23	3.46	2.72	2.76	2.56	2.39	2.47	2.54	2.63	2.76	3.07	3.10	2.89	2.65	2.80	2.58	2.80	2.99
GOMER	final	3.46	3.13	3.26	3.39	3.50	3.48	3.46	3.37	3.40	3.41	3.27	3.41	3.45	3.53	3.45	3.52	3.71	3.88	3.92	3.72	3.52	3.32	3.08	3.22	3.55
	refer	3.64	3.37	3.50	3.59	3.85	3.89	3.93	3.76	3.86	3.62	3.48	3.29	3.41	3.50	3.45	3.47	3.72	4.03	4.14	3.87	3.72	3.64	3.12	3.33	3.65
ELHIE	final	6.69	6.82	7.27	7.80	8.06	7.66	7.84	7.05	6.61	6.62	6.49	6.21	6.11	6.16	6.17	6.20	6.66	6.95	6.56	6.49	6.24	5.92	5.26	5.97	6.74
	refer	6.85	7.37	7.91	8.26	8.52	8.17	8.18	7.38	6.63	6.77	6.67	6.07	6.21	6.19	6.27	6.17	6.63	6.89	6.77	6.12	5.93	5.61	5.47	6.00	6.84
MALLO	final	2.83	2.03	2.00	2.00	1.92	1.86	2.02	2.15	2.60	2.67	2.56	2.78	3.07	3.34	3.44	3.64	3.74	3.78	3.60	3.25	2.99	2.83	2.61	2.61	2.80
	refer	3.64	3.33	3.16	2.99	2.97	2.87	2.94	3.08	3.33	3.42	3.19	3.40	3.66	3.94	4.17	4.20	4.33	4.47	4.37	4.25	3.90	3.68	3.55	3.63	3.67
IBFOR	final	3.05	2.02	2.08	2.09	2.02	2.04	2.03	2.07	2.24	2.36	2.16	2.59	3.20	3.65	3.96	4.28	4.32	4.38	4.24	3.84	3.51	3.07	2.72	2.67	2.71
	refer	4.38	3.79	3.57	3.52	3.51	3.47	3.50	3.65	3.85	3.80	3.76	4.07	4.46	4.69	4.85	5.06	5.29	5.48	5.35	5.15	4.82	4.74	4.60	4.37	4.52
MENOR	final	3.24	2.29	2.33	2.42	2.50	2.45	2.35	2.29	3.39	3.32	2.60	3.04	3.53	3.85	3.94	4.11	4.21	4.22	4.20	3.81	3.33	3.13	2.94	2.95	2.95
	refer	4.34	3.68	3.62	3.56	3.55	3.47	3.37	3.56	4.70	4.08	4.01	4.19	4.59	4.98	4.98	4.94	5.37	5.35	5.13	4.65	4.46	4.24	4.21	4.21	4.23

Table 8. Case study 2: monthly RMSPE for the test period for the insular models.

		JUN-18	JUL-18	AUG-18	SEP-18	OCT-18	NOV-18	DEC-18	JAN-19	FEB-19	MAR-19	APR-19	MAY-19	JUN-19
TENER	final	1.080	1.108	1.360	1.124	1.496	1.305	2.227	2.688	1.165	1.453	1.306	1.758	1.314
	refer	1.216	1.241	1.339	1.450	1.720	1.405	2.239	1.793	1.441	1.725	1.386	1.747	1.662
GRCAN	final	2.446	1.426	1.642	1.684	1.823	1.693	2.234	2.708	0.951	1.684	1.383	1.886	1.807
	refer	2.707	1.639	2.101	2.681	2.225	1.803	2.017	1.766	1.045	2.423	1.374	1.737	1.947
LANZA	final	1.804	1.557	1.619	1.631	2.505	2.277	2.152	2.181	2.872	2.113	2.288	2.326	1.835
	refer	2.120	1.813	1.893	1.833	2.480	2.287	2.028	2.022	2.761	2.263	2.307	2.504	1.981
FUERT	final	1.700	1.396	1.624	1.436	2.330	1.890	2.820	2.066	1.791	1.864	1.998	1.934	1.689
	refer	1.852	1.355	1.746	1.842	2.715	1.971	2.788	2.369	1.827	1.947	2.101	1.835	1.536
PALMA	final	2.402	2.124	2.336	1.840	3.558	3.435	3.093	3.683	2.412	3.116	3.571	3.469	2.170
	refer	2.608	1.926	2.155	1.979	4.171	4.250	3.173	2.944	2.482	2.804	3.783	2.866	2.440
GOMER	final	4.807	2.523	2.827	3.834	3.688	3.069	3.277	3.929	3.346	3.728	4.607	2.282	2.304
	refer	4.967	2.625	3.149	3.695	3.735	2.918	3.236	3.488	3.092	3.772	6.239	2.486	2.355
ELHIE	final	6.497	5.194	5.763	6.357	6.438	8.240	6.639	6.542	6.920	6.755	6.931	6.976	7.382
	refer	7.057	4.936	6.051	6.012	6.938	8.138	7.139	5.612	8.254	7.381	6.784	7.308	6.825
MALLO	final	1.921	2.775	3.352	2.510	2.341	2.743	4.055	3.215	2.143	2.535	3.074	1.793	3.329
	refer	2.174	2.792	4.870	3.007	3.147	3.988	3.835	3.858	2.359	3.323	5.087	3.211	4.215
IBFOR	final	1.754	2.816	3.699	2.350	2.811	3.291	3.248	3.725	2.882	3.576	4.214	2.213	1.790
	refer	2.914	2.795	6.910	3.468	3.657	3.939	3.947	4.758	3.673	3.840	7.487	3.181	3.310
MENOR	final	2.085	3.067	3.022	3.231	3.878	3.498	3.512	4.166	3.710	3.143	2.940	2.468	2.803
	refer	3.004	3.138	4.654	4.388	3.839	5.786	4.121	5.623	4.567	4.246	4.303	3.371	4.420

Table 9. Case study 2: global and hourly percentual improvement for RMSPE.

	Per. Im.	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24
TENER	2%	19%	20%	19%	17%	16%	12%	0%	−13%	−25%	0%	5%	6%	3%	2%	−2%	−4%	−1%	−2%	−2%	−3%	−5%	0%	9%	8%
GRCAN	8%	19%	19%	17%	17%	16%	10%	2%	2%	−5%	7%	8%	8%	4%	9%	7%	7%	7%	10%	8%	6%	0%	3%	11%	9%
LANZA	3%	3%	5%	9%	10%	7%	8%	6%	5%	1%	8%	6%	2%	0%	0%	−3%	0%	1%	1%	5%	−1%	1%	1%	−1%	−4%
FUERT	5%	16%	13%	13%	11%	11%	9%	13%	21%	12%	7%	5%	0%	−1%	2%	0%	−4%	−4%	2%	1%	−2%	−1%	8%	6%	−1%
PALMA	2%	8%	12%	12%	11%	12%	11%	9%	12%	−8%	−4%	−4%	−12%	−13%	−12%	−10%	−8%	−6%	−4%	−3%	−1%	0%	−1%	1%	−3%
GOMER	5%	7%	7%	5%	9%	11%	12%	10%	12%	6%	6%	−3%	−1%	−1%	0%	−2%	0%	4%	5%	4%	5%	9%	1%	3%	3%
ELHIE	2%	7%	8%	6%	5%	6%	4%	5%	0%	2%	3%	−2%	2%	1%	2%	−1%	−1%	−1%	3%	−6%	−5%	−6%	4%	0%	1%
MALLO	22%	39%	37%	33%	36%	35%	31%	30%	22%	22%	20%	18%	16%	15%	18%	13%	14%	15%	18%	24%	23%	23%	27%	28%	24%
IBFOR	30%	47%	42%	41%	42%	41%	42%	43%	42%	38%	43%	36%	28%	22%	18%	15%	18%	20%	21%	26%	27%	35%	41%	39%	40%
MENOR	25%	38%	36%	32%	29%	29%	30%	35%	28%	19%	35%	27%	23%	23%	21%	17%	22%	21%	18%	18%	25%	26%	30%	30%	30%

Table 10. Case study 2: percentual improvement for monthly RMSPE.

	JUN-18	JUL-18	AUG-18	SEP-18	OCT-18	NOV-18	DEC-18	JAN-19	FEB-19	MAR-19	APR-19	MAY-19	JUN-19
TENER	11%	11%	−2%	22%	13%	7%	1%	−50%	19%	16%	6%	−1%	21%
GRCAN	10%	13%	22%	37%	18%	6%	−11%	−53%	9%	30%	−1%	−9%	7%
LANZA	15%	14%	14%	11%	−1%	0%	−6%	−8%	−4%	7%	1%	7%	7%
FUERT	8%	−3%	7%	22%	14%	4%	−1%	13%	2%	4%	5%	−5%	−10%
PALMA	8%	−10%	−8%	7%	15%	19%	3%	−25%	3%	−11%	6%	−21%	11%
GOMER	3%	4%	10%	−4%	1%	−5%	−1%	−13%	−8%	1%	26%	8%	2%
ELHIE	8%	−5%	5%	−6%	7%	−1%	7%	−17%	16%	8%	−2%	5%	−8%
MALLO	12%	1%	31%	17%	26%	31%	−6%	17%	9%	24%	40%	44%	21%
IBFOR	40%	−1%	46%	32%	23%	16%	18%	22%	22%	7%	44%	30%	46%
MENOR	31%	2%	35%	26%	−1%	40%	15%	26%	19%	26%	32%	27%	37%

Table 11. Case study 2: accuracy comparison using the Diebold-Mariano test.

System	D-M Test	<i>p</i> -Value
TENER	−1.24	$1.08 \cdot 10^{-01}$
GRCAN	−5.39	$3.45 \cdot 10^{-08}$
LANZA	−3.75	$8.90 \cdot 10^{-05}$
FUERT	−4.22	$1.22 \cdot 10^{-05}$
PALMA	1.27	$0.89 \cdot 10^{+00}$
GOMER	−4.78	$8.75 \cdot 10^{-07}$
ELHIE	−2.81	$2.45 \cdot 10^{-03}$
MALLO	−17.54	$3.36 \cdot 10^{-69}$
IBFOR	−19.03	$4.43 \cdot 10^{-81}$
MENOR	−17.94	$2.72 \cdot 10^{-72}$

4.3.3. Third Case Study: Temperature and Holidays Effects

To analyze the effect of temperature and holidays on prediction accuracy, the results obtained have been compared with two simplified versions of the model:

- Proposed approach without the temperature effect, where the thermal information is not included in the model;
- Proposed approach with a basic model for holiday effect, which considers only the influence of holidays on demand depending on the hour of the day, assuming a similar response from Monday to Friday for all festivities and neglecting the weekend effect. Thus, just a set of 24 regressors has been employed.

Figure 9 provides the hourly RMSPE for the previous methods, using the same forecast settings described in Section 4.3.2.

Figure 9. Case study 3: hourly RMSE for the prediction period, compared with alternative models.

Table 12 provides the global percentual improvement of the proposed method compared with the alternative modified forecasters, for the ten insular systems.

Table 12. Case study 3: global percentual improvement for RMSPE.

		TENER	GRCAN	LANZA	FUERT	PALMA	GOMER	ELHIE	MALLO	IBFOR	MENOR
Percen.	no Temp	19%	17%	16%	15%	0%	3%	−3%	45%	39%	39%
Improv.	no Fest.	29%	25%	6%	5%	4%	3%	−5%	17%	4%	7%

Concerning the temperature effect: it can be observed that the model that does not consider the temperature effect provides a higher-error forecast, especially during sun hours, in Balearic systems (Mallorca, Menorca, and Ibiza-Formentera) and the Canary systems with a higher population (Tenerife, Gran Canaria, Lanzarote and Fuerteventura). The forecasting accuracy for smaller systems (El Hierro, La Gomera and La Palma) does not exhibit a significant variation in the case of temperature removal.

Concerning the holidays' effects: the proposed model of holidays provides a significant improvement compared with the forecaster with a basic model for holidays for Tenerife and Gran Canaria during the whole day, whereas the effect in the rest of the systems can be observed between 7 a.m. and 11 a.m. For smaller systems (El Hierro and La Gomera) the differences are almost negligible due to their large hourly errors.

5. Discussion

In any electric power system, the load forecasting plays a key role in the appropriate management and efficient administration of energy resources. A lack of prediction accuracy leads to an increment in operating costs.

In this work, a mathematical Reg-ARIMA model is developed to predict the electric consumption for ten insular systems located in the two Spanish archipelagos: the Canary and Balearic Islands. Once the ten models have been estimated, the temperature's influence and the effect of special days have been quantified and analyzed.

- The performance of the proposed algorithm has been tested using real data from the years 2018 and 2019, and the forecasting accuracy has been compared with alternative modified models and another prediction software currently used at the Spanish TSO facilities. The developed models prove to be more accurate, robust, and reliable.
- The percentual improvement of accuracy of the proposed method for each Balearic system ranges from 22 to 30%; whereas the average improvement for the Canary Islands is 11% (compared with the reference model).
- The proposed method provides a higher improvement during the night and morning hours: from 8 p.m. to 11 a.m. in the Balearic systems. For the three considered systems, the average hourly improvement during these hours is 32% (ranging from 22 to 47%).
- The temperature effect is very significant in Balearic systems. On the other hand, the festivities effect is significant in the most-populated islands: Gran Canaria, Tenerife and Mallorca.

Future work will focus on including additional weather variables in the developed insular models (e.g., solar radiation, wind speed and direction, cloudiness, etc.); and forecasting the electric consumption of Spanish mainland regional systems.

Author Contributions: J.J. conceived and designed the experiments; E.C. and J.J. analyzed the data, E.C. performed the experiments, E.C. and J.J. wrote the paper. All authors have read and agreed to the published version of the manuscript.

Funding: This work has been funded by Red Eléctrica de España (REE) as an R&D project.

Acknowledgments: The Authors would like to thank to Jesus Rupérez, Carlos Rodríguez, Ana Rodríguez and Juanjo Abellán for their help and technical support.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Pramono, S.H.; Rohmatillah, M.; Maulana, E.; Hasanah, R.N.; Hario, F. Deep Learning-Based Short-Term Load Forecasting for Supporting Demand Response Program in Hybrid Energy System. *Energies* **2019**, *12*, 3359. [\[CrossRef\]](#)
2. Zhu, J.; Yang, Z.; Mourshed, M.; Li, K.; Zhou, Y.; Chang, Y.; Wei, Y.; Feng, S. Electric Vehicle Charging Load Forecasting: A Comparative Study of Deep Learning Approaches. *Energies* **2019**, *12*, 2692. [\[CrossRef\]](#)
3. López, M.; Sans, C.; Valero, S.; Senabre, C. Classification of Special Days in Short-Term Load Forecasting: The Spanish Case Study. *Energies* **2019**, *12*, 1253. [\[CrossRef\]](#)
4. Cancelo, J.R.; Espasa, A.; Grafe, R. Forecasting the electricity load from one day to one week ahead for the Spanish system operator. *Int. J. Forecast.* **2008**, *24*, 588–602. [\[CrossRef\]](#)
5. Weron, R. Electricity price forecasting: A review of the state-of-the-art with a look into the future. *Int. J. Forecast.* **2014**, *30*, 1030–1081. [\[CrossRef\]](#)
6. Bracale, A.; Caramia, P.; De Falco, P.; Hong, T. Multivariate Quantile Regression for Short-Term Probabilistic Load Forecasting. *IEEE Trans. Power Syst.* **2020**, *35*, 628–638. [\[CrossRef\]](#)
7. He, F.; Zhou, J.; Mo, L.; Feng, K.; Liu, G.; He, Z. Day-ahead short-term load probability density forecasting method with a decomposition-based quantile regression forest. *Appl. Energy* **2020**, *262*, 114396. [\[CrossRef\]](#)
8. Candelieri, A.; Archetti, F. Global optimization in machine learning: The design of a predictive analytics application. *Soft Comput.* **2018**, *23*, 2969–2977. [\[CrossRef\]](#)
9. Kong, W.; Dong, Z.Y.; Jia, Y.; Hill, D.J.; Xu, Y.; Zhang, Y. Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network. *IEEE Trans. Smart Grid* **2017**, *10*, 841–851. [\[CrossRef\]](#)
10. Pham, M.-H.; Vu, T.-A.-T.; Nguyen, D.-Q.; Dang, V.-H.; Nguyen, N.-T.; Dang, T.-H.; Nguyen, T.V. Study on Selecting the Optimal Algorithm and the Effective Methodology to ANN-Based Short-Term Load Forecasting Model for the Southern Power Company in Vietnam. *Energies* **2019**, *12*, 2283. [\[CrossRef\]](#)
11. Zhang, G.; Guo, J. A Novel Method for Hourly Electricity Demand Forecasting. *IEEE Trans. Power Syst.* **2020**, *35*, 1351–1363. [\[CrossRef\]](#)
12. Candelieri, A. Clustering and Support Vector Regression for Water Demand Forecasting and Anomaly Detection. *Water* **2017**, *9*, 224. [\[CrossRef\]](#)
13. Ahmad, W.; Ayub, N.; Ali, T.; Irfan, M.; Awais, M.; Shiraz, M.; Glowacz, A. Towards Short Term Electricity Load Forecasting Using Improved Support Vector Machine and Extreme Learning Machine. *Energies* **2020**, *13*, 2907. [\[CrossRef\]](#)
14. Park, R.-J.; Bin Song, K.; Kwon, B.-S. Short-Term Load Forecasting Algorithm Using a Similar Day Selection Method Based on Reinforcement Learning. *Energies* **2020**, *13*, 2640. [\[CrossRef\]](#)
15. Hong, T. Short Term Electric Load Forecasting. Ph.D. Dissertation, North Carolina State University, Raleigh, NC, USA, 2010.
16. Hong, T.; Pinson, P.; Fan, S. Global energy forecasting competition 2012. *Int. J. Forecast.* **2014**, *30*, 357–363. [\[CrossRef\]](#)
17. Cho, H.; Goude, Y.; Brosat, X.; Yao, Q. Modelling and Forecasting Daily Electricity Load via Curve Linear Regression. In *Modeling and Stochastic Learning for Forecasting in High Dimension*; Lecture Notes in Statistics; Springer Science and Business Media LLC: Berlin/Heidelberg, Germany, 2014.
18. Cancelo, J.R.; Espasa, A. *Forecasting Daily Demand for Electricity with Multiple-Input Nonlinear Transfer Function Models: A Case Study*; Working Paper 91-05; Universidad Carlos III de Madrid: Madrid, Spain, 1991.
19. Box, G.; Jenkins, G. *Time Series Analysis: Forecasting and Control*; Holden-Day: San Francisco, CA, USA, 1970.
20. Caro, E.; Juan, J.; Cara, J. Periodically correlated models for short-Term electricity load forecasting. *Appl. Math. Comput.* **2020**, *364*, 124642. [\[CrossRef\]](#)
21. Dordonnat, V.; Koopman, S.J.; Ooms, M.; Dessertaine, A.; Collet, J. An hourly periodic state space model for modelling French national electricity load. *Int. J. Forecast.* **2008**, *24*, 566–587. [\[CrossRef\]](#)
22. Wang, Y.; Bielicki, J.M. Acclimation and the response of hourly electricity loads to meteorological variables. *Energy* **2018**, *142*, 473–485. [\[CrossRef\]](#)

23. Hastie, T.J.; Tibshirani, R.J. *Generalized Additive Models*; Chapman and Hall: New York, NY, USA, 1990.
24. López, M.; Valero, S.; Rodríguez, A.; Veiras, I.; Senabre, C. New online load forecasting system for the Spanish Transport System Operator. *Electr. Power Syst. Res.* **2018**, *154*, 401–412. [[CrossRef](#)]
25. Sobhani, M.; Campbell, A.; Sangamwar, S.; Li, C.; Hong, T. Combining Weather Stations for Electric Load Forecasting. *Energies* **2019**, *12*, 1510. [[CrossRef](#)]
26. Spanish Government—Agencia Estatal Boletín Oficial del Estado. Available online: <https://www.boe.es/> (accessed on 1 February 2020).
27. Diebold, F.X.; Mariano, R.S. Comparing Predictive Accuracy. *J. Bus. Econ. Stat.* **1995**, *13*, 253–263. [[CrossRef](#)]
28. Harvey, D.I.; Leybourne, S.; Newbold, P. Testing the equality of prediction mean squared errors. *Int. J. Forecast.* **1997**, *13*, 281–291. [[CrossRef](#)]

© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).