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Forecasting of wave energy in Canary Islands based on Artificial Intelligence

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ABSTRACT

In this work two mathematical models based on soft computing techniques for the forecasting of the wave energy in the Macaronesian region are exposed. The intelligent systems proposed for the wave energy prediction are Fuzzy Inference Systems (FIS) and Artificial Neural Networks (ANN). The models were implemented and validated thanks to the dataset of deep waters buoys belonging to Spain's State Ports, in several places near the Canary Islands. The buoys dataset covered a total period of 18 years. Once this research finished, it was possible to conclude that there is an excellent correspondence between annual wave energy predicted by ANN- and FIS-based models with respect to both buoys. These models constitute an effective tool to compute the wave power quickly and accurately at any point in oceanic deep waters, which allows for an optimal use of the dataset from the buoys even with only a few months of measurements.

1. Introduction

The Canary Islands (Spain) are an archipelago formed by eight main volcanic islands (El Hierro, La Palma, La Gomera, Tenerife, Gran Canaria, Fuerteventura, Lanzarote, and La Graciosa) located on the Atlantic Ocean (27.5°N - 29.5°N, 13°W - 18.5°W), near the southern coast of Morocco (Fig. 1). The established population in all the islands is over 2 millions and the more than 13 million tourists visit the islands each year, which has escalated up to 16 millions in the last years. This tourism industry is only possible by the desalination of seawater, because the majority of the islands have scarcity of water, which becomes extreme in the case of Lanzarote and Fuerteventura [1-8]. Another huge problem in the islands is the energy production; more than 98% of primary energy consumption comes from imported fuel and the electrical system is isolated, so that increases the difficulty of its optimization [6,7,9].

The Canarian Archipelago can be considered a reference in the fresh water production from desalination. Currently, desalination produces 19% of the total water consumption required in the islands [5,10,11]. The highest limitation of desalination is its great energy requirements, which is a serious problem due to the increasing environmental pollution caused by the use of fossil fuels required for its production, hence the fact that this is the most extended electrical energy source in the islands, not only for desalination use, but also for the supply of energy in general.

The use of renewable energies results in green technology, which minimizes the environmental impact of the electricity production. The Canary Islands present high renewable energy availability such as solar irradiation, wind speed and, surrounded by the Atlantic Ocean, wave energy is abundant too [2,5].

As reported by [1,2,12,13] the Canary Islands are exposed to energetic seawaters from the North Atlantic Ocean and a substantial wave resource can be found in the west and northern coasts of the archipelago, with an average wave power of 25-30 kW/m, although the resource is less abundant in the east and south of the islands.

Based on these natural resources, special attention should be paid to wave energy; since it is one of the most promising one owing to the ocean renewable energy resources. This type of renewable energy offers an abundant high energy density resource, accessible by most coastal regions and islands; furthermore, it is more predictable than wind or solar energy, with lower environmental and visual impacts [1,12-14]. Ruso and Soares [15] claim that the wave energy resources that usually surround the areas of the archipelagos are abundant, the particular bathymetric of these places generates significant wave energy concentrations. The ones located near the coast may become effective locations for the transformation of the wave energy. In the case of this work, the power calculations for the studied zones show a promising energy source for this region.

As it is known, new prototypes for taking advantage of marine energy are developing in recent years. Furthermore, the energy research

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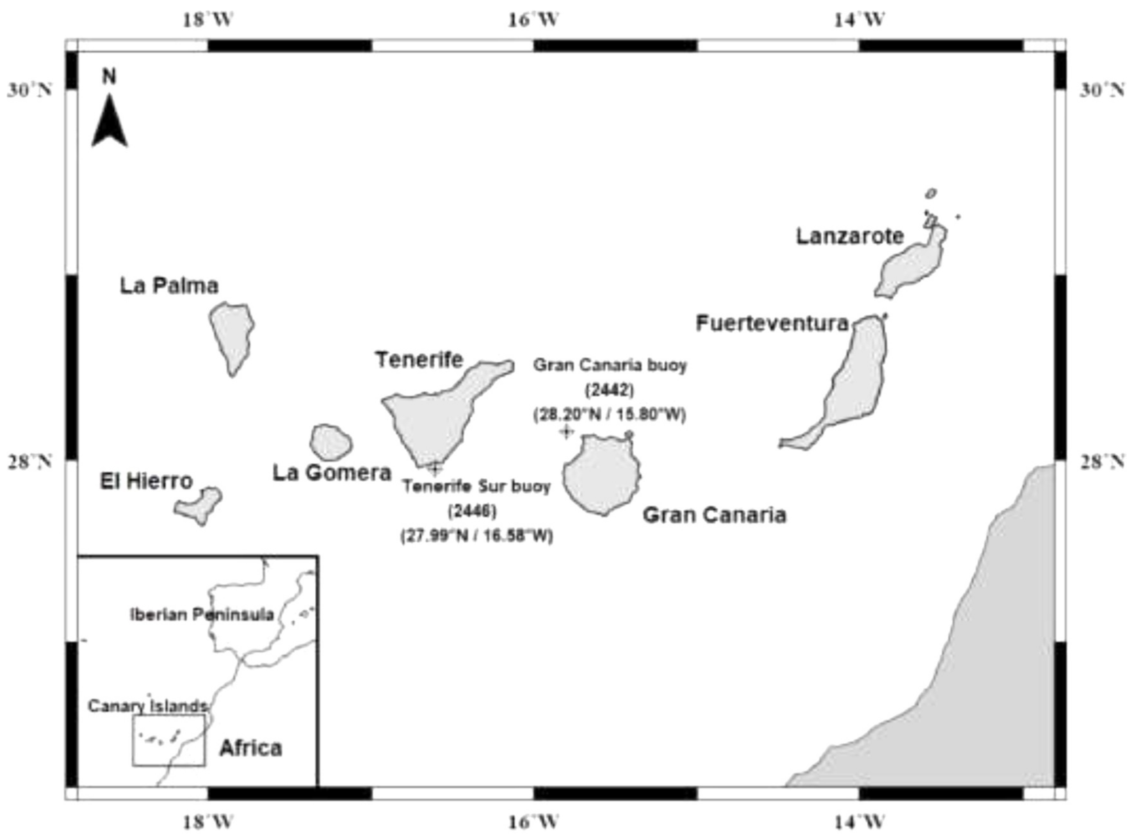

Fig. 1. Geographic location of the studied points.

community is showing much interest in wind offshore energy, one of the most developed ones along with other marine energy sources. The wave energies are one of the less developed ones among them. Because of that a lot of efforts are being made in order to devise new commercial prototypes. In this sense, new prototypes and tools to evaluate this energy are necessary. In fact, it is important to determine the most adequate areas to take advantage of this kind of energy. In the case of this work, the power calculations for the studied zones show a promising energy source for this archipelago. Moreover, it is likely that there will be an extraction growth in the coming decades since this technology is becoming more advanced and specialized [1]. Wave energies are expected to play a significant role in the upcoming years for the reduction of CO_2 and greenhouse gas emission in the world, particularly in the European Union (EU) [12,16].

The European Renewable Energy Council predicts that the ocean energy will represent 0.15% of the electricity consumption at the end of 2020, contributing to the objectives of the European energetics strategy [17]. This renewable energy source, in particular wave energy, has a singular link in the adoption of the Renewable Energy Directive (2009/28/EC), to which the EU has committed to reduce its contaminants gas emissions by 80-95% by 2050 [17-19].

In order to determine, or estimate the potential production of energy from a Wave Energy Converter (WEC) at any place, it is necessary to know the potential of the waves, for this reason it is possible to say that maybe wave energy prediction is not an objective in itself, but it is necessary to lay the foundations of the evaluation of any WEC [1].

In the last decade many projects for the development of Wave Energy Converters (WECs) for its use in energy production, desalination, hydrogen production and pumping of water have been designed and tested in a lot of places around the world, mainly in Europe [12,19-24]. However, most of said technologies still need to be improved before being used on a commercial scale; meanwhile, the industry of Wave Energy Converters (WECs) keeps growing. Therefore, it is important to work on the improvement of wave energy prediction methods. It is necessary to determine the regions in the world where it is feasible to implement wave energy farms in a faster and more inexpensive manner [21,25,26].

Since the early 1960s, buoys have been used for measuring waves due to their good estimates of the sea state. Nevertheless, buoys present a problem when it is necessary to maintain the wave climate estimation in the long term, because it is too costly, except for some key reference sites, for example, near ports [27].

Wave forecasting has come to rely fundamentally on computer hindcast third-generation (3G) wind-wave models, such as WAve Modelling, (WAM) and SWAN, acronym for Simulating WAves Nearshore [27-30]. At present WAM provides global coverage, and has been used in many projects such as WERATLAS for European waters and WorldWaves project to cover the entirety of the globe [27-30,31]. SWAN is a third generation phase-averaged Eulerian numerical wave model, designed to simulate the propagation of random waves ranging from deep to coastal locations [27,32-34].

Currently, several studies and assessments have been implemented making use of 3G wind-wave models in different regions of the world, such as in the Macaronesian Islands, which include the Canary Islands, Cape Verde and the Azores. Some noteworthy research projects are Gonçalves, Martinho and Guedes in [1], which deliver a numerical study of wave power distribution around the Canary Islands. For this study the SWAN model was used to define the transformation of the waves in the archipelago. The model was validated by buoy and satellite data. In El Hierro Island, the wave resource was determined using third generation wave model WAM [2]. A study of the wave energy resources using wave model SWAN in the Cape Verde coast is found in [3]. In this research it is intended to identify potential wave energy hotspots. In the Azores Archipelago a wave energy evaluation was made, for this aim, satellite data and SWAN numerical models were used [23].

Every day more and more researchers use in their studies computing systems different to wave forecasting, for example, the systems based on Artificial Intelligence. These soft computing techniques (SC) are frequently used to model complex relations in databases, not only to relate inputs and outputs, but also to find patterns. Some of the most widely used intelligent computing methods for regression and data classification are: Fuzzy Inference Systems (FIS), Artificial Neural Networks (ANN), Support Vector Machines (SVMs), Bayesian Networks (BNs) and Decision Trees (DTs) [35].

One such example of this is the use of Artificial Neural Networks in wave height prediction in places such as Indian coasts [36], the northern part of the Adriatic Sea, offshore Croatia [37], or the west coast of Portugal [38]. There are many other studies in lakes that can be extrapolated to sea conditions which aim to forecast wave heights based on ANN and other soft computing techniques [28,35]. Other implementations of the intelligent systems are the assessment of the wave energy potential, for example in [21,25,26,39,40].

A key element in the development of renewable energies based on waves is the prediction of such energy resource. In this sense, island regions will be very interested in taking advantage of this resource especially if the characteristics of the wave resources are convenient for the production of a considerable amount of energy. This is the case of the Canary and other islands or archipelagos where these resources are a promising source of energy. Currently, there is not much research based on soft computing techniques for wave height prediction or wave energy forecasting in the North Atlantic Ocean, especially in the Macaronesian region. For this reason, the main objective of this research is to determine the behavior of the intelligent systems Fuzzy Inference System (FIS) and Artificial Neural Network (ANN) for wave energy prediction, in order to demonstrate the advantages entailed by the use of soft computing methods rather than numerical models. As a starting point, the research was done taking wave data buoys belonging to *Puertos del Estado* (Spain's State Ports), located in deep waters near the Canary Islands. Even with a few months of dataset measurements to determine the wave energy forecasting for the evaluation of any Wave Energy Converters (WECs) for energy production or pumping of water for desalination, this document can be considered as the first stage of research for the application of soft computing in regions with wave energy conditions similar to the Canarian Archipelago. The renewable energy produced can be injected directly in the electrical network or can be used in isolated desalination systems.

On the other hand, some particularities such as environmental impact, protected zones, military zones, or bathymetry, have not been taken into consideration in this research.

This paper is organized in five sections. Following this introduction, the used data sources are shown. The third section presents the model based on different intelligent systems and the fourth one showcases the validation and analysis of such models. Finally, the conclusions of the whole research are given in the last section.

2. Used data sources

In order to model the behavior of waves, data from two buoys located near the Canary Islands were taken. The first one is the Gran Canaria buoy (2442), whose position is 28.20 North latitude and 15.78 West longitude, with a mooring depth of 780 m. The other one is the Tenerife Sur buoy (2446), whose position is longitude 16.58° W and latitude 27.99° N, with a mooring depth of 710 m. Both buoys are part of the Deepwater Buoys Network of the State Ports of Spain, which are characterized by being anchored far from the coastline at great depth (more than 200 meters deep). They are SeaWatch buoy type, which measure waves, atmospheric and oceanographic parameters. The buoys have different types of sensors, as well as process units, dataset storage and satellite transmission. The obtained data provide representative observations of large coastal areas [41,42].

The sea surrounding the Canary Islands is characterized by being particularly deep; even near the coast, given the fact that these islands have no continental shelf. Thus, the wave energy in general, is unaffected by refraction or shoaling [1]. Fig. 1 shows the geographic location of the studied buoys. The obtained dataset covers a total period of 18-years (1998 to 2016).

In both buoys, measurements of spectral significant wave height, H, and mean peak period, T, were carried out every three hours. It should be noted that an average value of the analyzed variable is calculated over the data obtained during the first 30 minutes, after every two hours and a half. That is, the data are average values rather than data collected at a very specific point in time. The measurement accuracy was ± 0.05 m and ± 0.05 s, respectively. All this dataset was facilitated by *Puertos del Estado* (Spain's State Ports) through an official request.

3. Modelling

3.1. Data pre-processing

Considering the fact that it is a random phenomenon, a frequency distribution was used to describe wave behavior in order to later obtain the wave power prediction, which depends on the spectral significant wave height (H) and the mean peak period (T). By following the other researchers' recommendations [27,41-44], a two-dimensional Weibull distribution was used, with the expression:

$$f(H,T)=\frac{k_1k_2\left(\frac{H}{c_1}\right)^{k_1-1}\left(\frac{T}{c_2}\right)^{k_2-1}}{c_1c_2(1-c_{12}^2)}exp\left[-\frac{\left(\frac{H}{c_1}\right)^{k_1}+\left(\frac{T}{c_2}\right)^{k_2}}{1-c_{12}^2}\right]B_0\left[\frac{2c_{12}\left(\frac{H}{c_1}\right)^{\frac{k_1}{2}}\left(\frac{T}{c_2}\right)^{\frac{k_2}{2}}}{1-c_{12}^2}\right]; \tag{1}$$

where B_0 is the zero-order Bessel function, whereas c_1, k_1, c_2, k_2 and c_{12} are the obtained distribution coefficients. The fitting process was carried out by using the Simultaneous Maximum Likelihood Estimate method [27,41-44]. Figs. 2 and 3 show the graphical representation of these coefficients for each month and hour in both buoys.

As it can be noted, most of the coefficients appear in similar intervals in both buoys, but the corresponding distribution is remarkably different. An important issue that can be identified is the variation of the coefficient values in relation with the months, while having only minor changes in relation with the hours. This can be explained because the influence of the seasons of the year on wave characteristics is much more important than that of daily behaviors.

3.2. Artificial Neural network (ANN) -based modelling

In order to predict wave power at any instant (month and hour), a model that related the 2D-Weibull coefficients with the month and the hour was established. For this purpose, the first approach used was an Artificial Neural Network (ANN). A multi-layer perceptron (MLP) was selected since this paradigm has universal approximation capability (i.e., it can approximate any function, with arbitrary accuracy, if the proper number of neurons is supplied). Several authors have proposed different architectures, in which the choice of the number of neurons on hidden layers is a key issue [21,28,35,37-39,45-48].

In this paper, the MLP has 15 neurons on a single hidden layer and one neuron on the output layer. In general, this choice is problem dependent. Because of that, this number was selected by trial and error, starting from five and increasing by steps of five, until reaching no decrement in the obtained coefficient of determination. However, the number was kept low enough in order to guarantee fewer model parameters (i.e., weights and biases) than the number of training data, thus avoiding the indetermination of the training process. As for the hidden neurons, the hyperbolic tangent was used as a transfer function, while a linear transfer function was used in the output neuron. In order to facilitate the training process, all the inputs and outputs were normalized to the interval [−1, 1]. The gradient descent with momentum

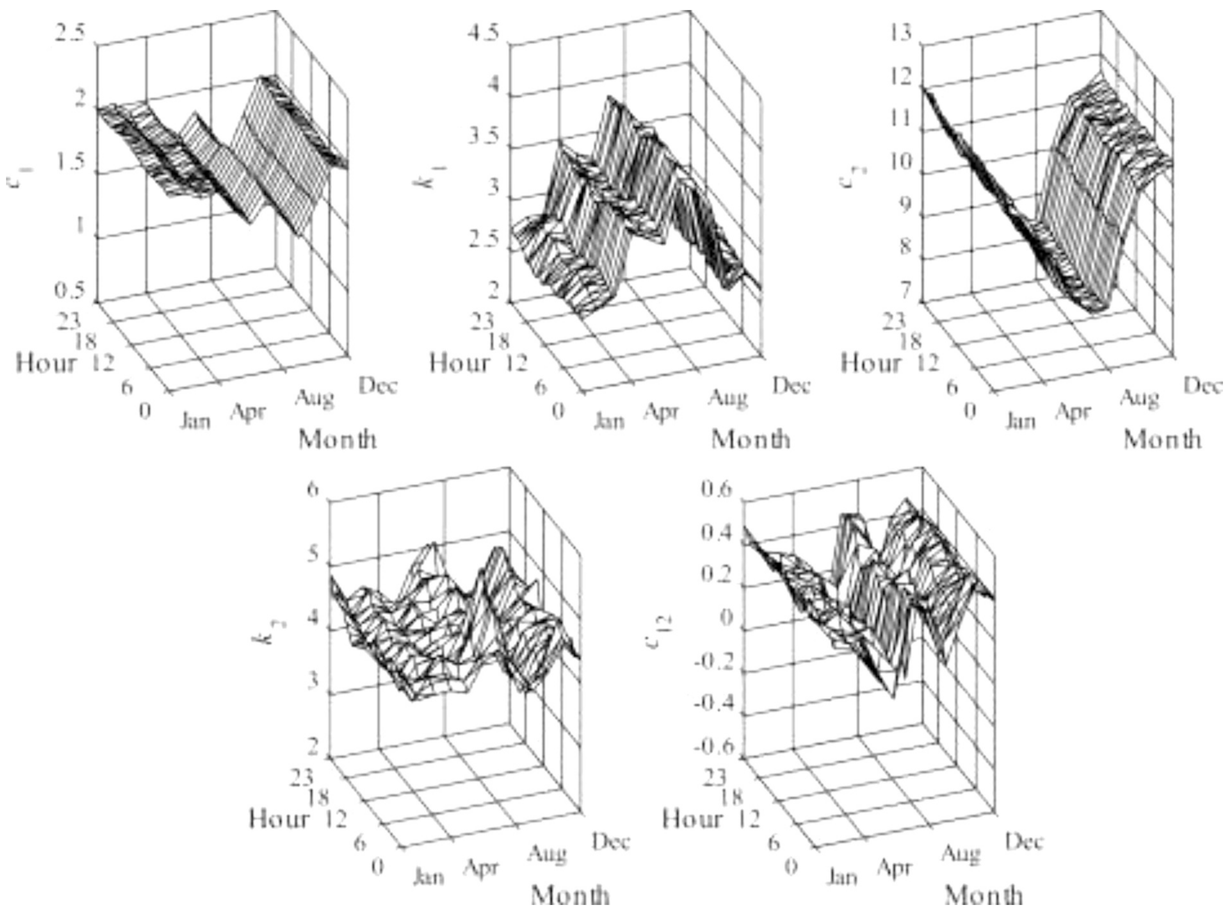

Fig. 2. 2D-Weibull distribution coefficients for Gran Canaria buoy (2442).

and adaptive learning rate backpropagation algorithm were used to train the MLP, with a learning rate of 0.01; the ratio used to increase the learning rate was 1.05; the ratio used to decrease it was 0.70; the maximum performance increase was 1.04; the minimum performance gradient was 10^{-5}; and the momentum constant was 0.90. All the aforementioned values were selected by heuristic recommendations. Most of them match the default values of the training algorithm implemented, and have proved to be effective. The training process was stopped after 5000 epochs in order to avoid overtraining.

Fig. 4 shows the predicted vs. observed values for each coefficient in the 2D-Weibull model for Gran Canaria (2442) buoy, as forecast by the neural network. As it can be seen, there is a higher matching for coefficients c_1 ($R^2 = 0.9241$), k_1 ($R^2 = 0.9579$) and c_2 ($R^2 = 0.9876$), while k_2 ($R^2 = 0.6810$) and c_{12} ($R^2 = 0.8424$) are more scattered.

Graphical representations of Neural Network-based predictions for each coefficient are given in Fig. 5. There is a sound coincidence with the observed values (see Fig. 2), but the graphs are smoother, because the fitted models were capable of eliminating the unavoidable random noise presented in the training data.

Predictions for Tenerife Sur (2446) buoy are shown in Fig. 6, for each 2D-Weibull model coefficient. As for Gran Canaria, coefficients c_1 ($R^2 = 0.9464$), k_1 ($R^2 = 0.9200$) and c_2 ($R^2 = 0.8983$) present a high goodness-of-fit. However, coefficients k_2 ($R^2 = 0.5723$) and, specially, c_{12} ($R^2 \approx 0$) show a lower correlation. Nevertheless, due to the lower values of c_{12}, errors do not propagate to the predicted distribution values (see Eq. 1).

Fig. 7 depicts the models as fitted for each 2D-Weibull coefficient for Tenerife Sur (2446) buoy. A high correspondence with the values shown by Fig. 3 can be noted, which means a high correlation with the observed values.

3.3. Fuzzy inference system (FIS) -based modelling

The second approach tested for modeling the 2D-Weibull coefficients was a Sugeno-type Fuzzy Inference System (FIS), which was fitted through subtractive clustering [35,49-52]. The FIS uses Gaussian membership functions for the inputs, and linear membership functions for the outputs. Radii (i.e., the cluster centre's range of influence in each of the data dimensions) was set to 0.35.

Fig. 8 shows the predicted vs. observed values, forecast by the FIS-based model, for Gran Canaria (2442) buoy.

With this technique, the models for c_1 ($R^2 = 0.9606$), k_1 ($R^2 = 0.9490$) and c_2 ($R^2 = 0.9927$) have high coefficient of determination (even higher than those for the Neural Network-based models). As in the neural models, correlation for coefficients k_2 ($R^2 = 0.7282$) and c_{12} ($R^2 = 0.7816$) are noticeably lower than the other ones.

The graphical representation of the models obtained is depicted in Fig. 9. A great coincidence can be appreciated not only with training data (Fig. 2) but also with values predicted by the Neural Network-based model (Fig. 5).

Fig. 10 shows the Fuzzy Inference System predicted vs. observed values, in the Tenerife Sur buoy (2446).

As in all the previously obtained models, the correlation for coefficients c_1 ($R^2 = 0.9369$), k_1 ($R^2 = 0.8617$) and c_2 ($R^2 = 0.9377$) is very high, while it is lower for coefficient k_2 ($R^2 = 0.5909$) and extremely low for c_{12} ($R^2 = 0.1122$). However, this issue does not significantly affect the accuracy of the overall predictions as coefficient c_{12} appears squared and subtracted from one in the expression for the distribution probability (Eq. 1), which means that lower c_{12} values have very small influence in the equation outcome.

Fig. 11 shows the graphical representation of the model predictions

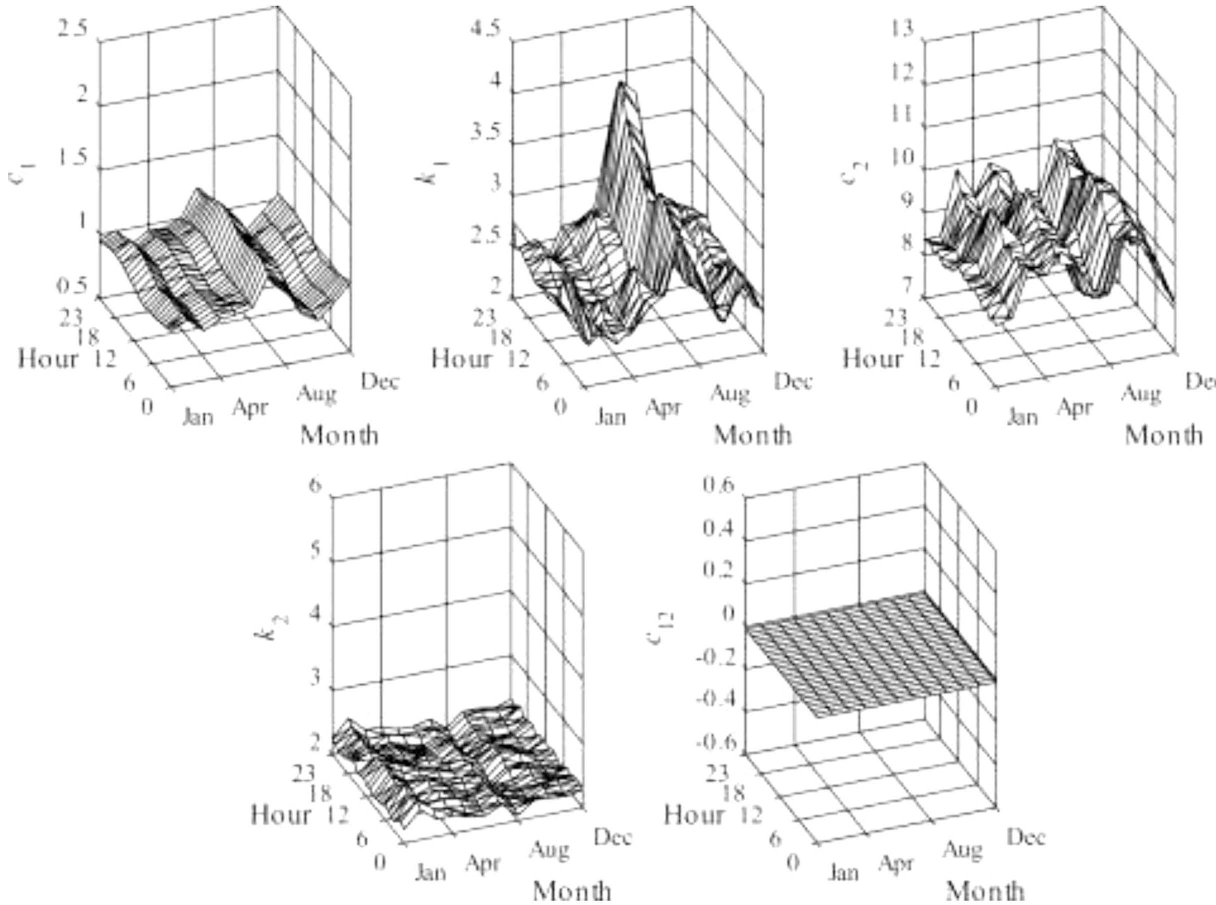

Fig. 3. 2D-Weibull distribution coefficients for Tenerife Sur buoy (2446).

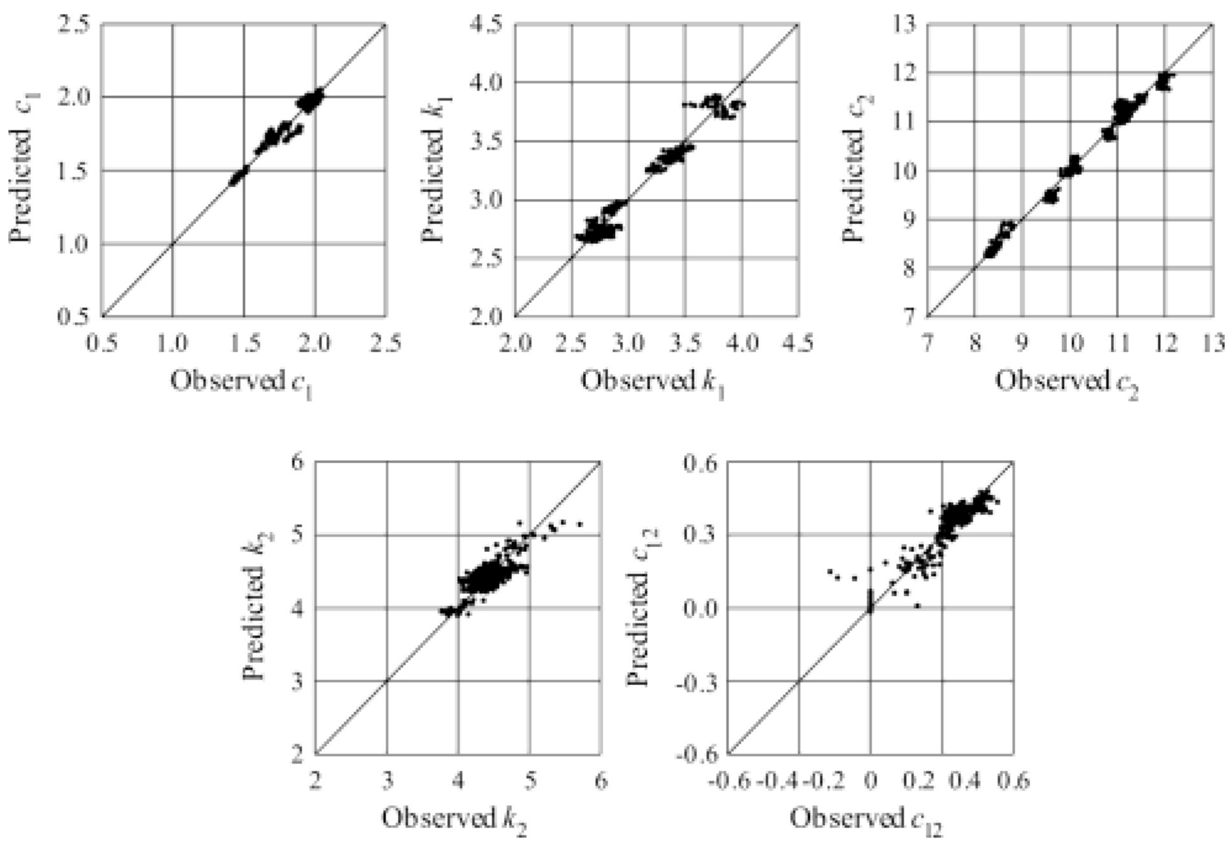

Fig. 4. Predicted vs. observed values for the neural network model of Gran Canaria (2442) 2D-Weibull coefficients.

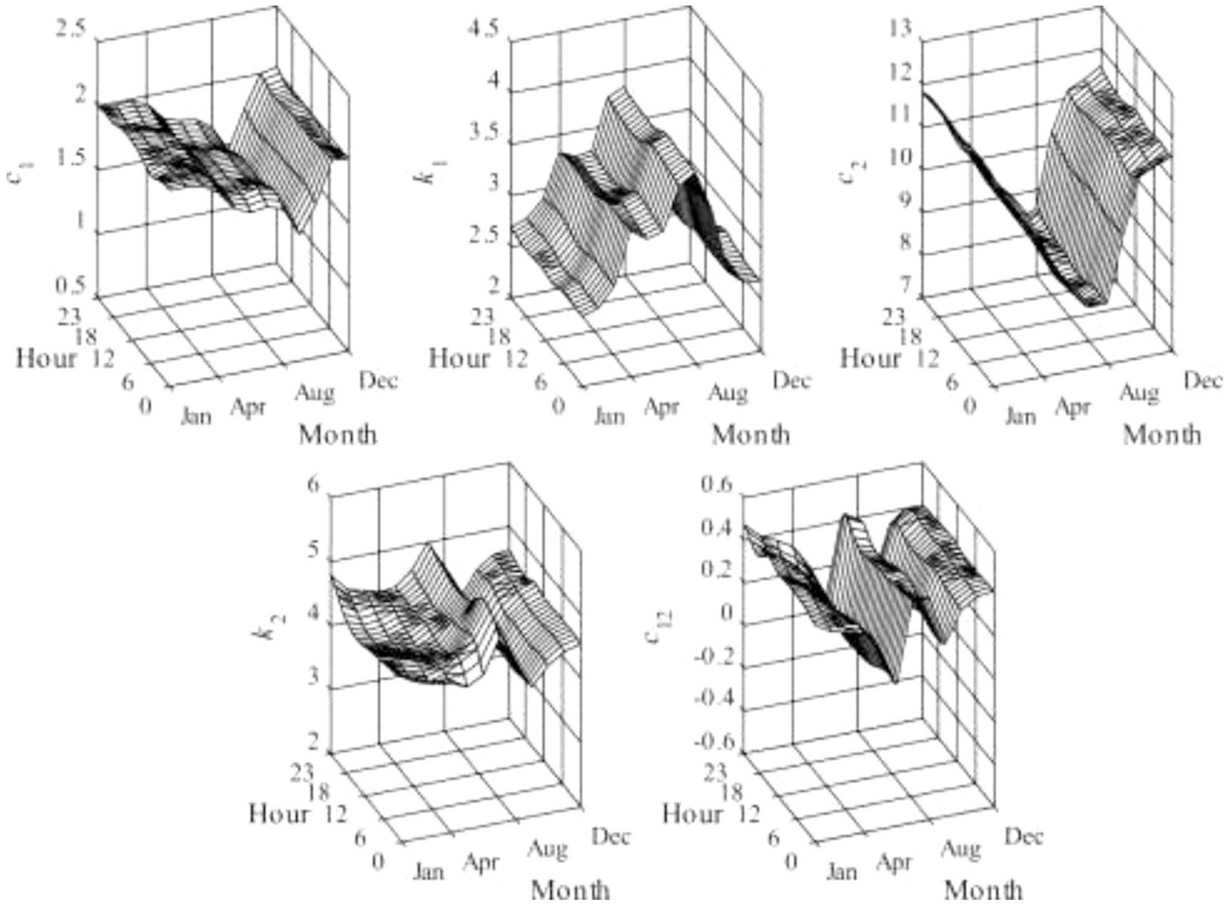

Fig. 5. Neural network-based predictions for Gran Canaria (2442) 2D-Weibull coefficients.

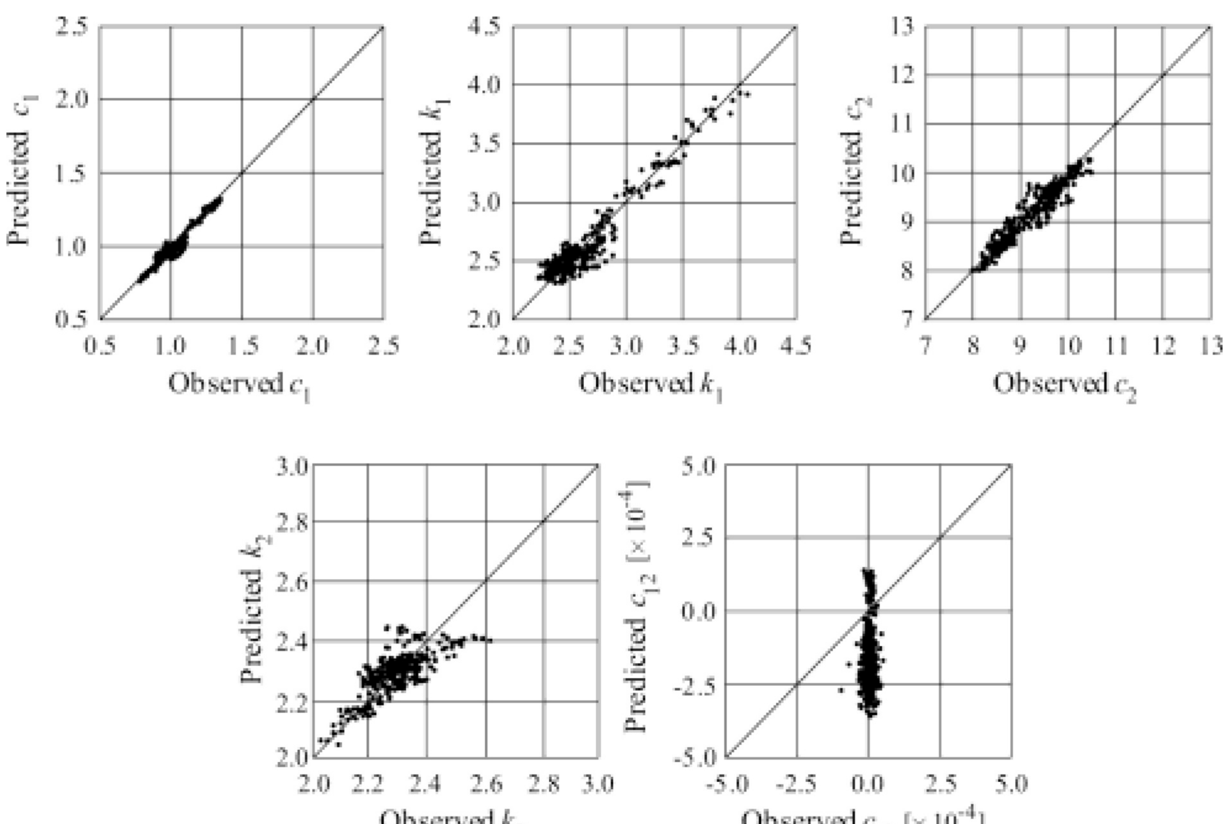

Fig. 6. Predicted vs. observed values for the neural network model of Tenerife Sur (2446) 2D-Weibull coefficients.

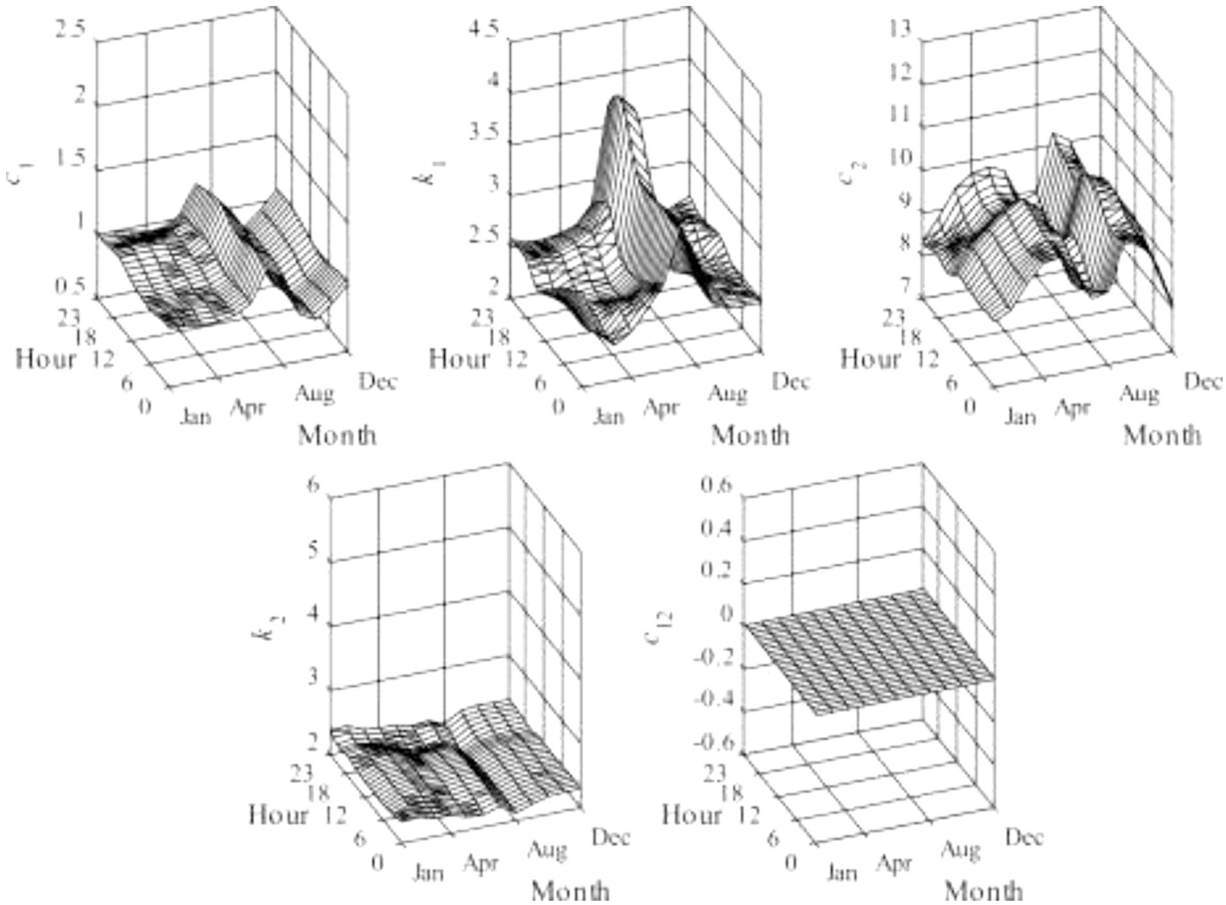

Fig. 7. Neural network-based predictions for Tenerife Sur (2446) 2D-Weibull coefficients.

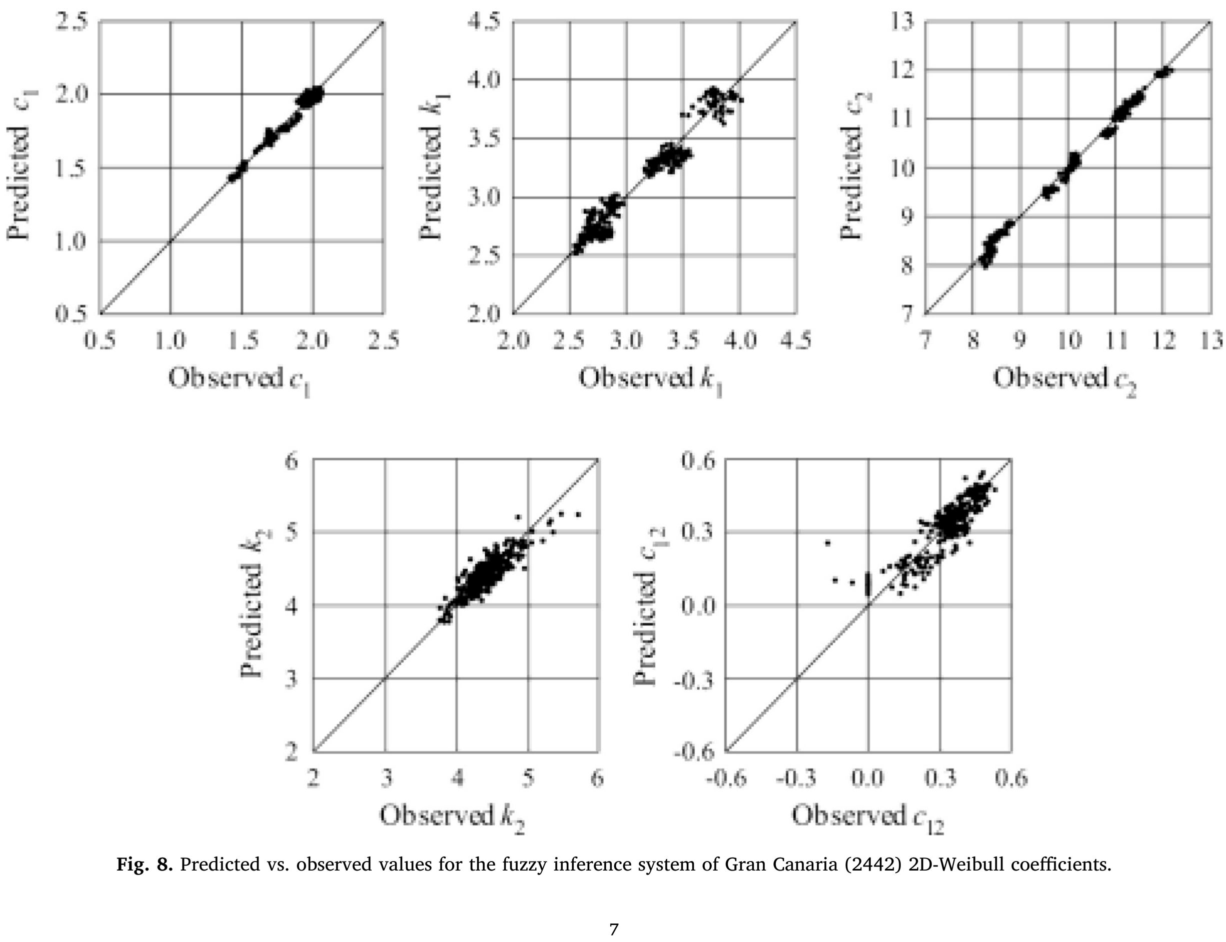

Fig. 8. Predicted vs. observed values for the fuzzy inference system of Gran Canaria (2442) 2D-Weibull coefficients.

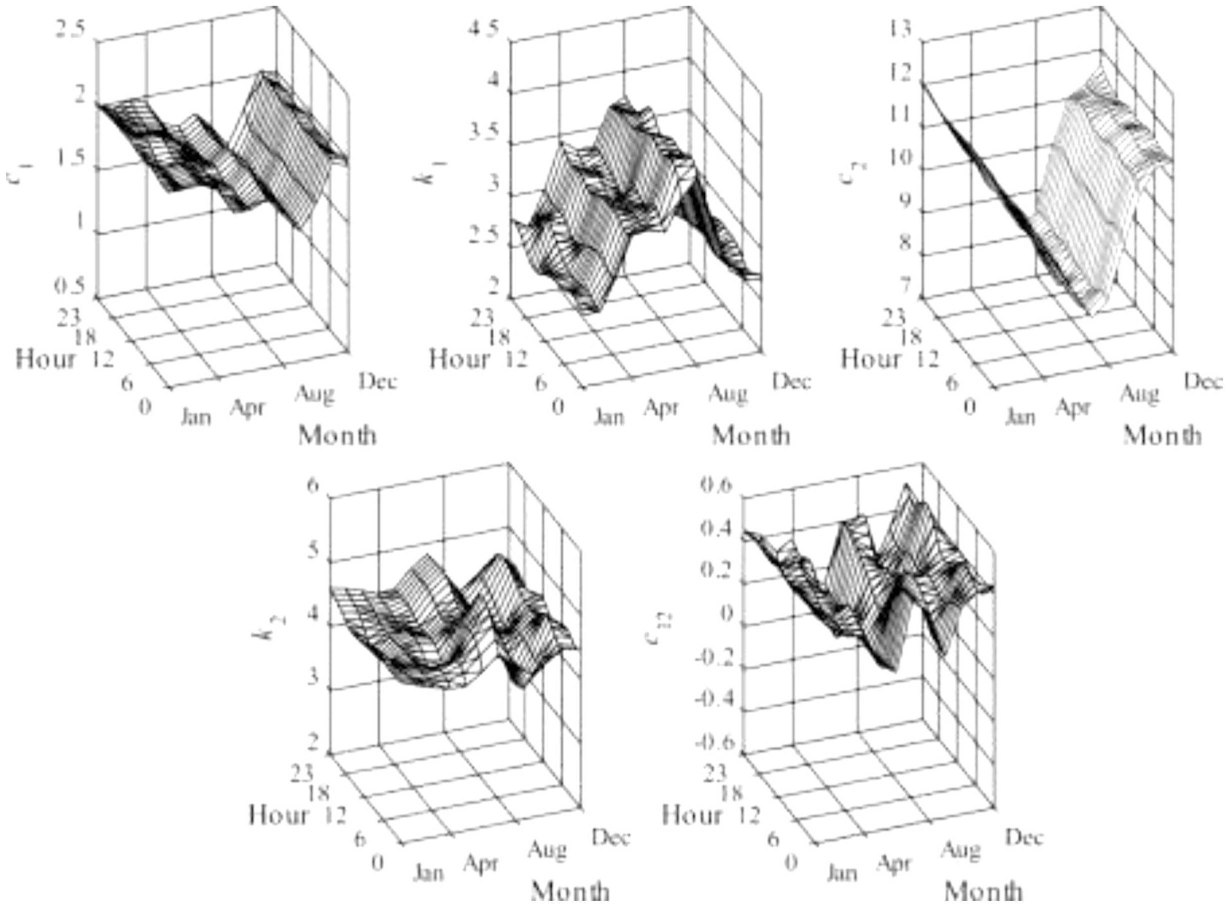

Fig. 9. Fuzzy inference system-based predictions for Gran Canaria (2442) 2D-Weibull coefficients.

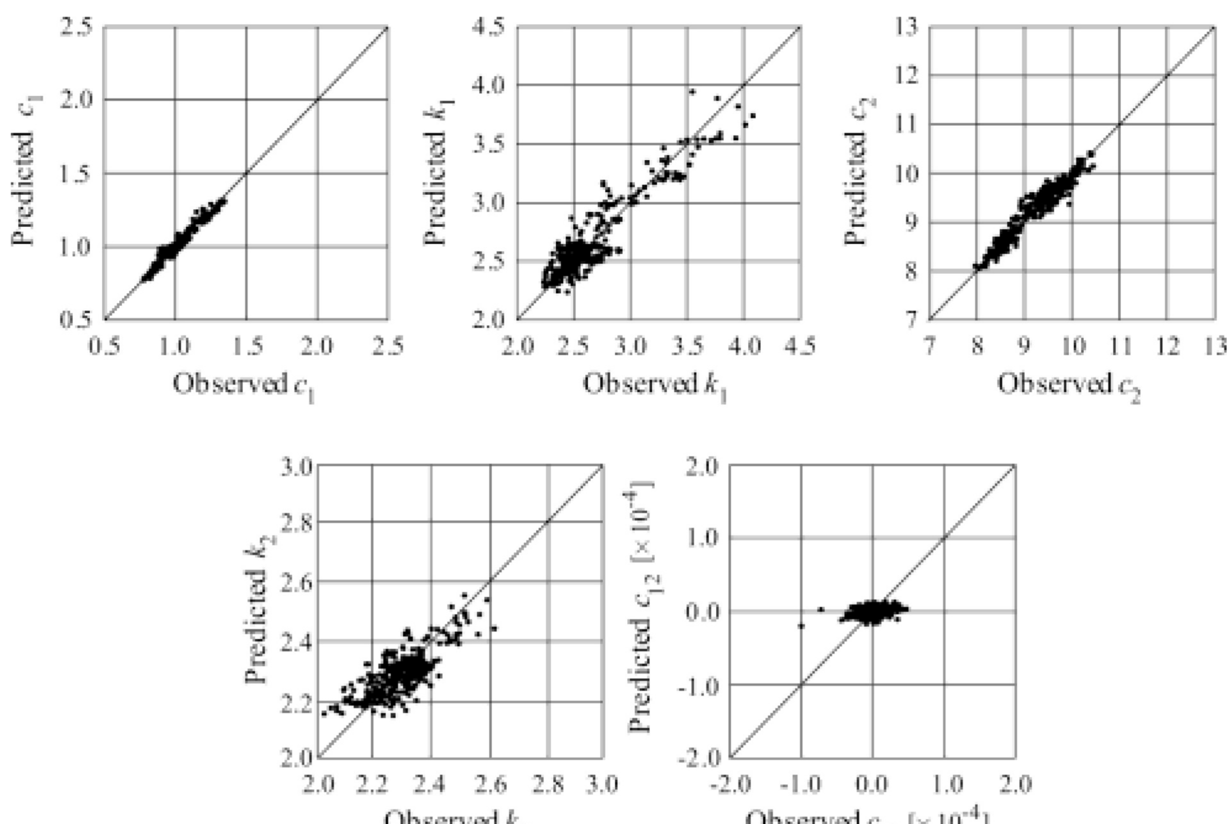

Fig. 10. Predicted vs. observed values for the fuzzy inference system of Tenerife Sur (2446) 2D-Weibull coefficients.

vs. the independent variables (month and hour). The coincidence with observed data (Fig. 3) and outcomes from neural network-based models (Fig. 7) can be noted.

A noteworthy issue brought up from all the previously fitted models, is the high influence of the year period (month) on the 2D-Weibull distribution coefficient value, while the influence of the specific moment (hour) is significantly lower.

4. Validation and analysis

A preliminary validation was carried out by comparing the predicted 2D-Weibull distribution coefficients with those observed for 2015 and 2016. Fig. 12 shows the mean absolute errors of the distribution coefficient predictions. The most remarkable point is the coincidence in prediction on both models.

In order to analyze the forecasting capability of the previously obtained models, the power predicted for each year was computed in the period used for training such models (1998 to 2014), which represent approximately 88.9% of the total dataset. That is, a high percentage of samples are used in the training phase as usual. Validation set was selected outside the period of time used in the training process (2015 and 2016), which represent 11.1% of total datasets. The validation was carried out by extrapolating the model predictions (which is a very rigorous method for testing the generalization capability of a soft-computing based model).

In all the cases, the power, $P_{H,T}$, was computed from the 2D-Weibull probability distribution, $f_{W2D}(H, T)$, which is characterized by the parameters, k_1, c_1, k_2, c_2, c_{12}, through the equation:

$$P_{H,T} = \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} tAH^2(0.8571T) f_{W2D}^{cdf}(H, T) dH \right] dT \tag{2}$$

where t is the period considered and A is a factor (this study considered $A = 0.49$). For given values of ΔH and ΔT, eq. (2) was numerically integrated by using the expression:

$$P_{H,T} \approx 0.8571At \sum_{H=0}^{H_{max}-\Delta H} \sum_{T=0}^{T_{max}-\Delta T} \left(H^2 Tp \middle| \begin{matrix} H+\Delta H,\, T+\Delta T \\ H,\, T \end{matrix} \right) \tag{3}$$

In Eq. (3), $p|\begin{matrix} H+\Delta H,\, T+\Delta T \\ H,\, T \end{matrix}$ is the cumulative probability of the 2D Weibull distribution in the interval bound by $[H, H + \Delta H]$ and $[T, T + \Delta T]$.

This paper does not include the analyses of wave direction, because the main purpose of this work at this first stage is the prediction of the total wave power at any point oceanic deep waters near the coast with island conditions.

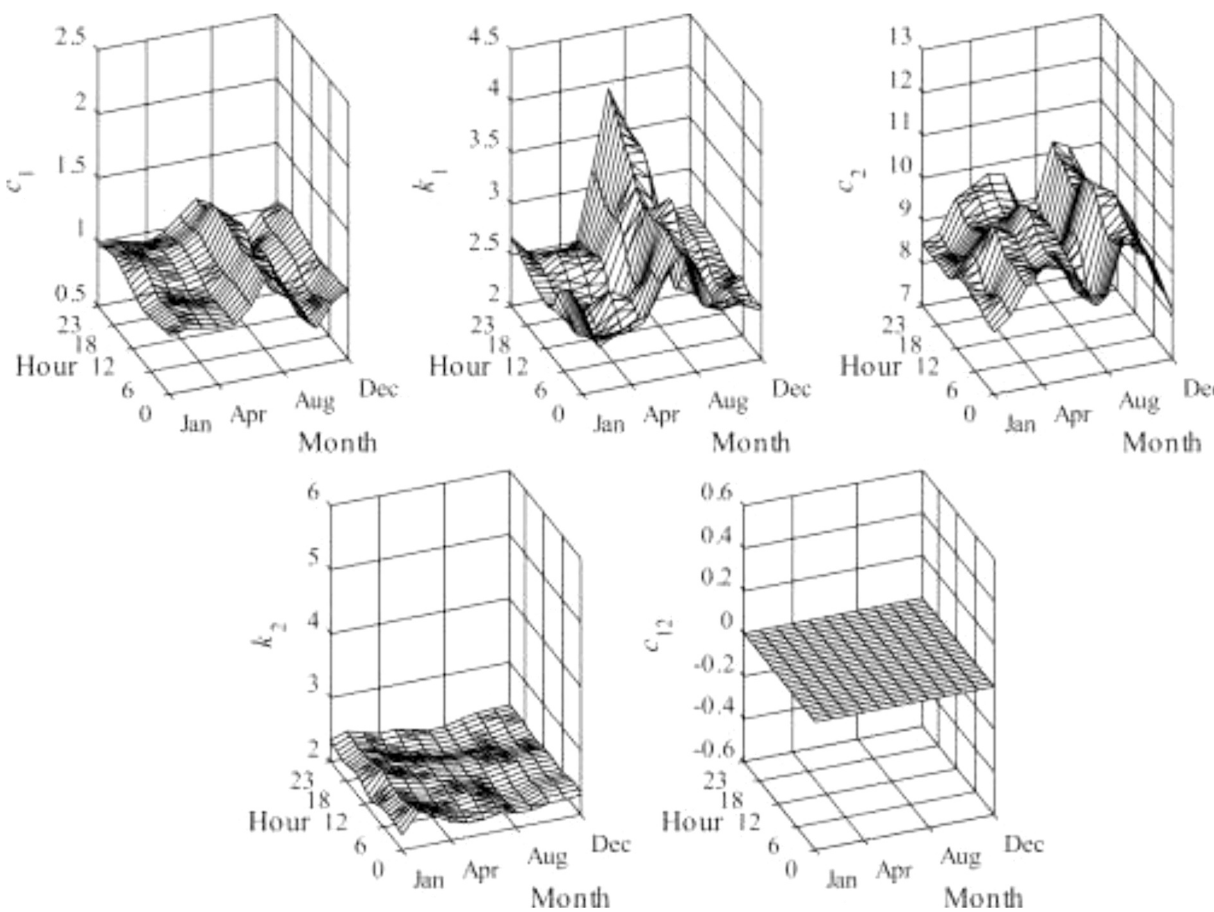

Fig. 11. Fuzzy inference system-based predictions for Tenerife Sur (2446)2D-Weibull coefficients.

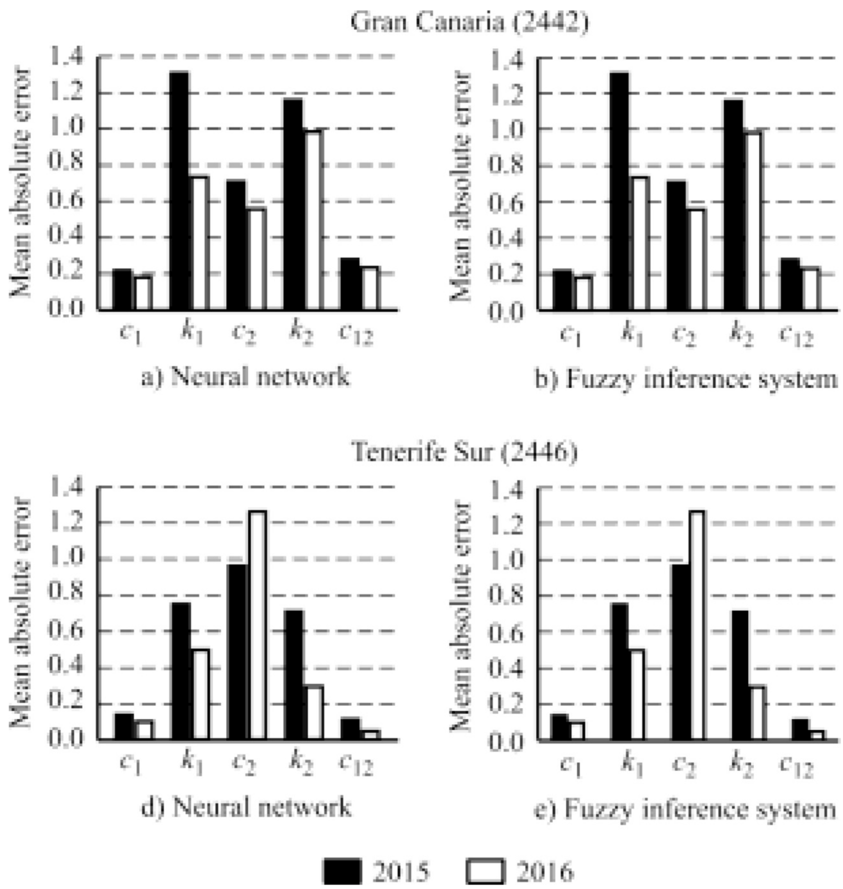

Fig. 12. Mean absolute errors for distribution coefficient predictions compared with observed data from 2015 and 2016.

Fig. 13 and 14 show the behaviour of Gran Canaria (2442) and Tenerife Sur (2446) buoys. The white bars represent the value of the actual power in the period from 1998 up to 2014. In both figures, solid lines represent mean values and dotted lines indicate the corresponding 95% confidence interval. The black bars represent the models, fitted with data up to 2014. It should be noted that predictions from both models, Artificial Neural Network (ANN) and Fuzzy Inference System (FIS), fall into the confidence intervals for all the months. Actually, they are close to the respective mean values.

For validating the models proposed, the forecasting data were compared with those measured in 2015 and 2016 for every month. As it can be noted (see Fig. 15 and 16), there is a good matching between predicted and observed values.

For Gran Canaria buoy (2442), the mean relative errors were 23.1% for ANN-based model and 24.2% for FIS-based model. The maximum forecasting relative error, with values of 85.6% and 91.2%, respectively, takes place in April 2015.

Mean relative errors, for Tenerife Sur (2446) buoy were 36.3% and 36.0%, for ANN- and FIS-based models, respectively. The maximum error, with respect to the observed values was 101.1%, for ANN, and 96.8% for FIS, both corresponding to October 2016.

Model divergences can be explained on the one hand, by weather variability, which can result in outliers; and on the other hand, by the shade projected by the island of Tenerife. In the future it will be necessary to investigate to make corrections in the models for these particular cases.

Table 1 summarizes the total annual power forecast by both models, and a comparison with the respective observed value for the period 1998-2014 (training data) and for 2015 and 2016 (validation data).

As it can be inferred from this table, there is an excellent correspondence between annual power predicted by ANN- and FIS-based models for both buoys. On the other hand, mean relative errors are in all the cases lower than 25%.

5. Conclusions

In the future, oceanic energies could play an important role regarding renewable energies for the enhancement of electric power systems, especially wave energies, which will contribute greatly to the reduction of greenhouse gas emissions.

The Canary Islands and other similar archipelagos are isolated zones from the energy point of view and this issue is of particular interest when it comes to searching new ways of producing energy. In this sense, this work proposes new methods to predict the amount of energy and how this energy is distributed throughout the year in a faster and more inexpensive way. In fact, a soft computing approach has been used based on several artificial intelligence techniques applied in a wide range of engineering problems.

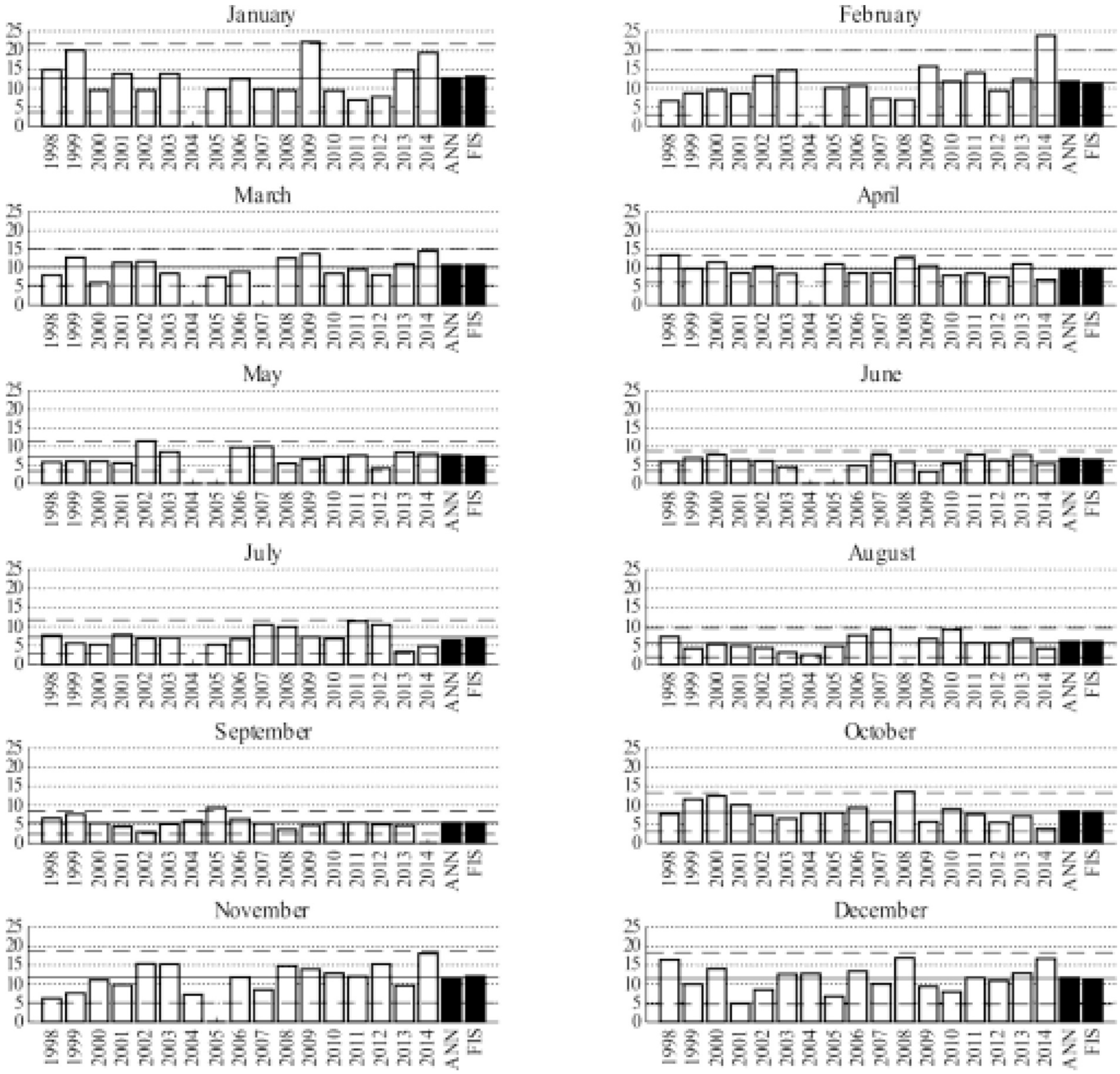

Fig. 13. Modelled power [MW•h/(m•month)] for Gran Canaria buoy (2442).

Moreover, two alternative approaches have been taken. One of them was based on Artificial Neural Networks (ANN) and it focused on learning properties; whereas the another one was based on Fuzzy Inference Systems (FIS) in which rule extraction is a possibility. One of the singularities of this work is the opportunity of having a very wide range of data over a long period of time in the training stage. This has allowed for the testing of the proposed methods in a more adequate way, both approaches have achieved satisfactory results. The model was implemented and validated with and by datasets from two different buoys located near the Canary Islands: the Gran Canaria buoy (2442) and the Tenerife Sur buoy (2446), both in deep waters.

The coefficient of determination (R^2) for distribution coefficients c_1, k_1 and c_2 in all the previously obtained models for both buoys is very high, while it is lower for coefficients k_2 and c_{12}. However, this issue does not significantly affect the accuracy of the overall predictions. Taking this observation into consideration, it is possible to affirm that in this study there are very high correlation coefficients for both training and testing data.

Once this study has finished, it can be concluded that there is an excellent correspondence between annual power predicted by ANN- and FIS-based models with respect to both buoys, with mean relative errors less than 25% in both cases.

The developed models based on the Artificial Neural Network and the Fuzzy Inference System in this work constitute an efficient tool to compute wave power quickly and accurately at any point near coastal oceanic deep waters, which reaches an optimal use of the data obtained for the wave monitoring systems in the buoys. These two mathematical models will allow us to obtain an annual wave power prediction

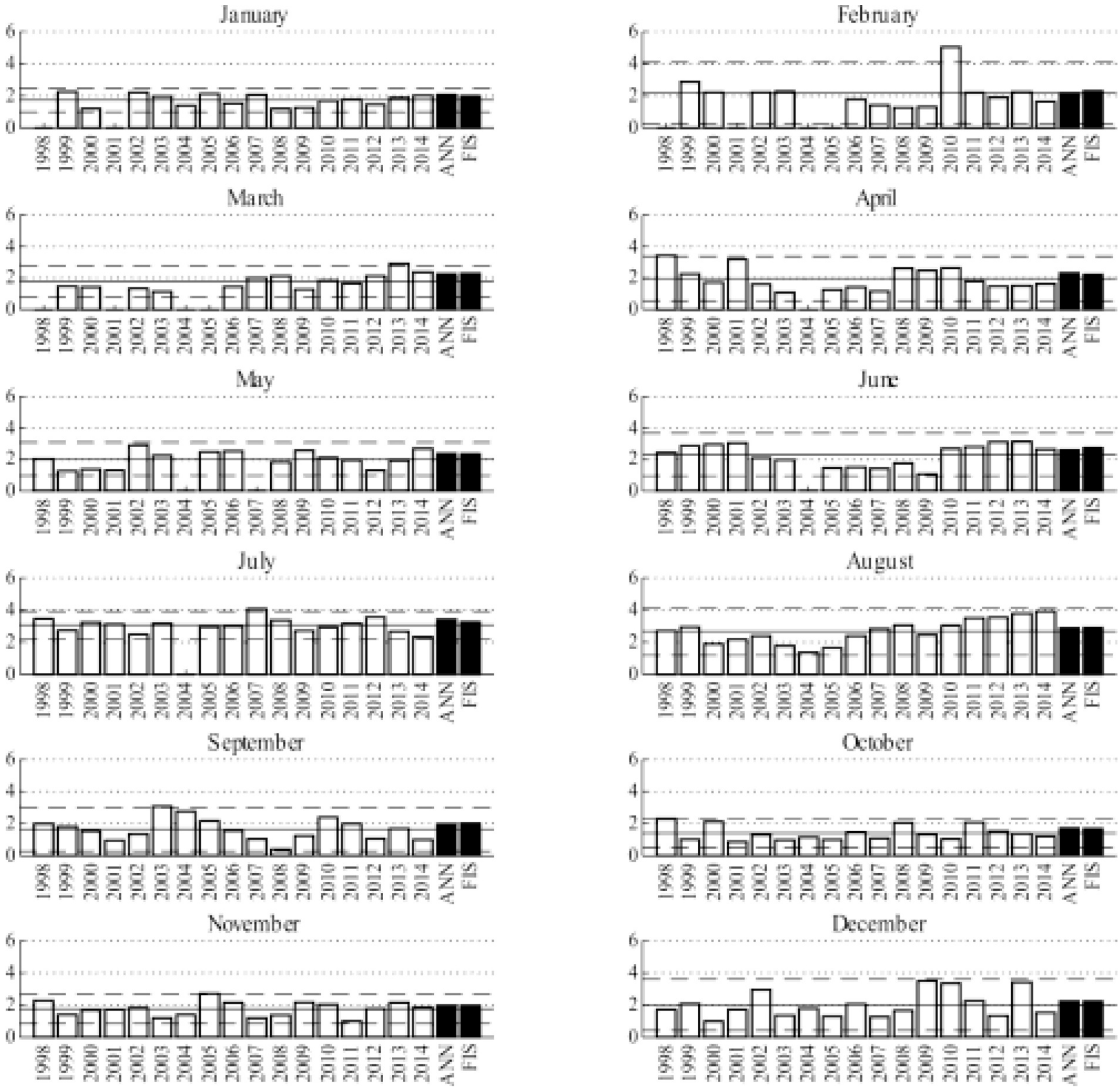

Fig. 14. Modelled power [MW•h/(m•month)] for Tenerife Sur buoy (2446).

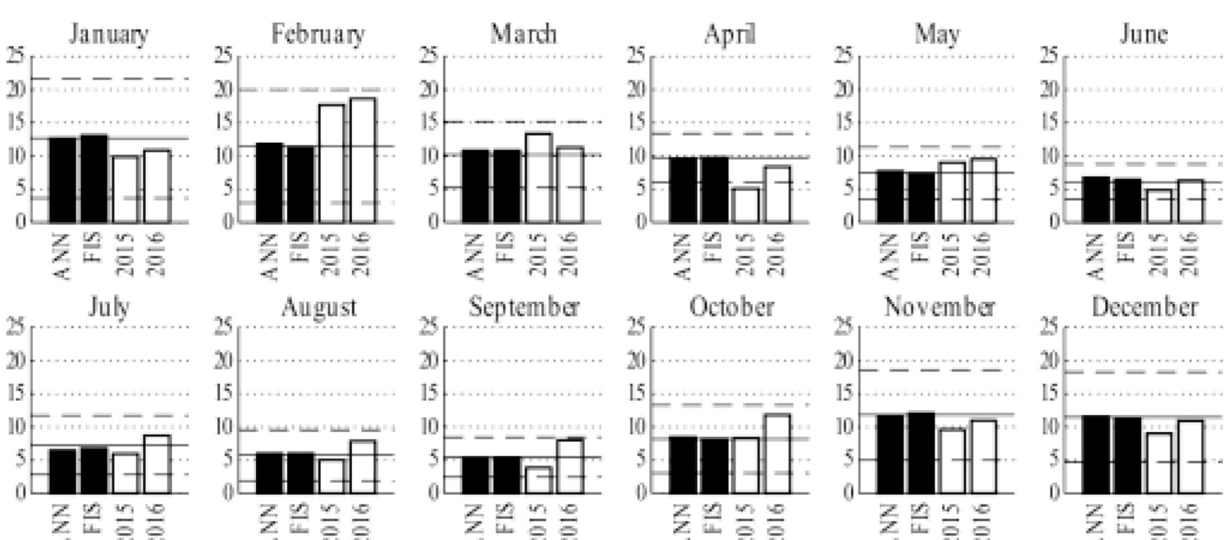

Fig. 15. Comparison of forecasting and observed power [MW•h/(m•month)] data for Gran Canaria buoy (2442).

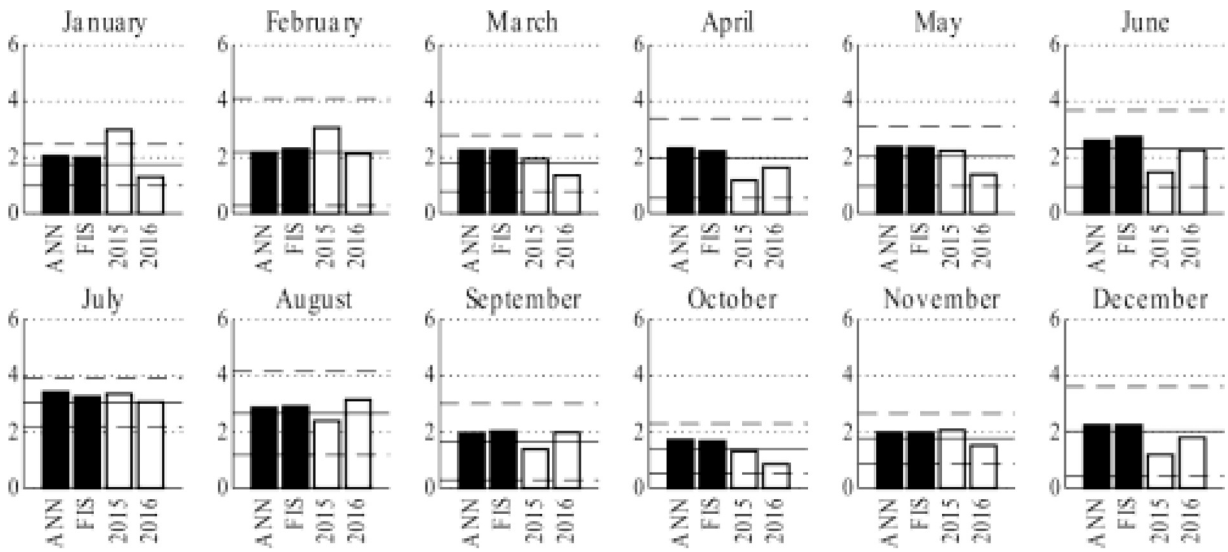

Fig. 16. Comparison of forecasting and observed power [MW•h/(m•month)] data for Tenerife Sur buoy (2446).

Table 1
Forecast total annual power.

Buoy	Period	Total annual power [MW•h/(m•year)] (error)		
		Observed	Predicted ANN	Predicted FIS
Gran Canaria (2442).	1998… 2014	140.37	150.74 (7%)	150.73 (7%)
	2015	141.28	150.74 (7%)	150.73 (7%)
	2016	171.26	150.74 (15%)	150.73 (15%)
Tenerife Sur (2446).	1998… 2014	31.68	38.89 (23%)	38.90 (23%)
	2015	34.15	38.89 (15%)	38.90 (15%)
	2016	31.23	38.89 (24%)	38.90 (24%)

without needing a base data of many years in a particular place, which is of great importance for the evaluation of the WECs to produce renewable energy for desalination, hydrogen production or for its injection into the electric power network.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.apor.2020.102189.

References

[1] M. Gonçalves, P. Martinho, C. Guedes, Assessment of wave energy in the Canary Islands, Renew. Energy 68 (2014) 774–784 https://doi.org/10.1016/j.renene.2014.03.017.
[2] G. Iglesias, R. Carballo, Wave resource in El Hierro - an island towards energy self-sufficiency, Renew. Energy 36 (2011) 689–698, https://doi.org/10.1016/j.renene.2010.08.021.
[3] M. Bernardino, L. Rusu, C. Guedes, Evaluation of the wave energy resources in the Cape Verde Islands, Renew. Energy 101 (2017) 316–326, https://doi.org/10.1016/j.renene.2016.08.040.
[4] T.E. Cropper, E. Hanna, An analysis of the climate of Macaronesia, 1865-2012, Int. J. Climatol 34 (3) (2014) 604–622, https://doi.org/10.1002/joc.3710.
[5] I. Padrón, D. Avila, G.N. Marichal, J.A. Rodríguez, Assessment of Hybrid Renewable Energy Systems to supplied energy to Autonomous Desalination Systems in two islands of the Canary Archipelago, Renew. and Sustain. Energy Rev. 101 (2019) 221–230, https://doi.org/10.1016/j.rser.2018.11.009.
[6] J. Schallenberg, J.M. Veza, A. Blanco, Energy efficiency and desalination in the Canary Islands, Renew. Sustain. Energy Rev. 40 (2014) 741–748, https://doi.org/10.1016/j.rser.2014.07.213.
[7] HCh. Gils, S. Simon, Carbon neutral archipelago-100% renewable energy supply for the Canary Islands, Appl. Energy 188 (2017) 342–355, https://doi.org/10.1016/j.apenergy.2016.12.023.
[8] Canarian Statistic Institute (ISTAC). http://www.gobiernodecanarias.org/istac, 2018 (accessed 15 September 2018).
[9] A. González, J.C. Pérez, J.P. Díaz, F.J. Expósito, Future projections of wind resource in a mountainous archipelago, Canary Islands, Renew. Energy 104 (2017) 120–128, https://doi.org/10.1016/j.renene.2016.12.021.
[10] Canarian Agency for Research, Innovation and Information Society (ACIISI), Evaluación de tecnologías potenciales de reducción de la contaminación de las aguas de canarias. Proyecto Tecnoagua. Informe final. https://issuu.com/cienciacanaria/docs/evaluaci_n_de_tecnolog_as_potenci, 2011 (accessed 18 October 2018).
[11] Canary Islands Institute of Technology (ITC)Plan de ECOGESTIÓN en la producción y distribución de agua de Canarias (2014-2020). pp. 7-30. http://oic.itccanarias.org/files/PLAN_ECOGESTIoN_DEL_AGUA.pdf, 2013 (accessed on 3 September 2018).
[12] G. Lavidas, V. Venugopal, D. Friedrich, Wave energy extraction in Scotland through an improved nearshore wave atlas, Int. J. Mar. Energy 17 (2017) 64–83, https://doi.org/10.1016/j.ijome.2017.01.008.
[13] Institute for the Diversification and Saving of Energy (IDEA), Wave energy evaluation, Technical Study. (2011) PER 2011-2020 http://www.idae.es/uploads/documentos/documentos_11227_e13_olas_b31fcafb.pdf (accessed 10 September 2018).
[14] AFO. Falcão, Wave energy utilization: a review of the technologies, Renew. and Sustain. Energy Rev. 14 (2010) 899–918, https://doi.org/10.1016/j.rser.2009.11.003.
[15] E. Ruso, G. Soares, Wave energy pattern around the Madeira Islands Energy45 (2012) 771–785, http://dx.doi.org/10.1016/j.energy.2012.07.013.
[16] D. Magagna, A. Uihlein, Ocean energy development in Europe: Current status and future perspectives, Int. J. Mar. Energy 11 (2015) 84–104 http://dx.doi.org/10.1016/j.ijome.2015.05.001.
[17] European Renewable Energy Council (EREC), Mapping Renewable Energy Pathways towards 2020: EU Roadmap, http://www.eufores.org/fileadmin/eufores/Projects/REPAP_2020/EREC-roadmap-V4.pdf, 2011(accessed 15 October 2018).
[18] European Commission, Blue Energy Action needed to deliver on the potential of

ocean energy in European seas and oceans by 2020 and beyond, https://eur-lex.europa.eu/legalcontent/EN/TXT/PDF/?uri=CELEX:52014DC0008&from=EN, 2014(accessed 8 June 2018).
[19] O. Molina, F. Castro, L. Rusu, Efficiency assessments for different WEC types in the Canary Islands, in: S. Guedes, P. López (Eds.), Developments in Maritime Transportation and Exploitation of Sea Resources, Eds., Taylor & Francis Group: London, UK, 2014, pp. 879–887 ISBN 978-1-138-00124-4.
[20] A. Babarit, J. Hals, M.J. Muliawan, A. Kurniawan, T. Moan, J. Krokstad, Numerical benchmarking study of a selection of wave energy converters, Renew. Energy 41 (2012) 44–63, https://doi.org/10.1016/j.renene.2011.10.002.
[21] A. Castro, R. Carballo, G. Iglesias, JR. Rabuñal, Performance of artificial neural networks in nearshore wave power prediction, Appl. Soft Comput. 23 (2014) 194–201 http://dx.doi.org/10.1016/j.asoc.2014.06.031.
[22] Ch.W. Zheng, Q. Wang, C.Y. Li, An overview of medium- to long-term predictions of global wave energy resources, Renew. and Sustain. Energy Rev. 79 (2017) 1492–1502, https://doi.org/10.1016/j.rser.2017.05.109.
[23] L. Rusu, G. Soares, Wave energy assessments in the Azores Islands, Renew. Energy 45 (2012) 183–196, https://doi.org/10.1016/j.renene.2012.02.027.
[24] F.J. Vivas, A. De las Heras, F. Segura, J.M. Andújar, A review of energy management strategies for renewable hybrid energy systems with hydrogen backup, Renew. and Sustain. Energy Rev. 82 (2018) 126–155, https://doi.org/10.1016/j.rser.2017.09.014.
[25] Z.Huang C.Xu, Three-dimensional CFD simulation of a circular OWC with a nonlinear power-takeoff: Model validation and a discussion on resonant sloshing inside the pneumatic chamber, Ocean Eng. 176 (2019) 184–198, https://doi.org/10.1016/j.oceaneng.2019.02.010.
[26] Z.Huang C.Xu, Y. Yao, A wave-flume study of scour at a pile breakwater: Solitary waves, Appl. Ocean Res. 82 (2019) 89–108, https://doi.org/10.1016/j.apor.2018.10.026.
[27] S.F. Barstow, G. Mørk, D. Mollison, J. Cruz, The Wave Energy Resource, in: J. Cruz (Ed.), Ocean Wave Energy. Current Status and Future Perspectives, Eds., Springer Series in Green Energy and Technology, 2008, pp. 116–132 ISBN 978-3-540-74894-6.
[28] R.M. Puscasu, Integration of artificial neural networks into operational ocean wave prediction models for fast and accurate emulation of exact nonlinear interactions, Procedia Comput. Sci. 29 (2014) 1156–1170, https://doi.org/10.1016/j.procs.2014.05.104.
[29] WAMDIG Group, The WAM model - a third generation ocean wave prediction model, J. Phys Oceanogr 18 (1988) 1775–1810 https://doi.org/10.1175/1520-0485(1988)0181775:TWMTGO2.0.CO;2.
[30] SWAN Team, SWAN Scientific and technical documentation. http://swanmodel.sourceforge.net/download/zip/swantech.pdf (accessed 13 September2018).
[31] E. Sandvik, O.J.J. Lønnum, B.E. Asbjørnslett, Stochastic bivariate time series models of waves in the North Sea and their application in simulation-based design, Appl. Ocean Res. 82 (2019) 283–295, https://doi.org/10.1016/j.apor.2018.11.010.
[32] S.F. Barstow, G. Mørk, L. Lønseth, P. Schjølberg, U. Machado, G. Athanassoulis, K. Belibassakis, T. Gerostathis, C.N. Stefanakos, G. Spaan, WorldWaves: Fusion of data from many sources in a user-friendly software package for timely calculation of wave statistics, global coastal waters. Proc 13th ISOPE Conf. Oahu, Hawaii, USA, 2003 https://www.researchgate.net/publication/258491685 (accessed 23 October 2018).
[33] G. Reikard, B. Robertson, B. Buckham, J.R. Bidlot, C. Hiles, Simulating and forecasting ocean wave energy in western Canada, Ocean Eng 103 (2015) 223–236, https://doi.org/10.1016/j.oceaneng.2015.04.081.
[34] D.I. Malliouri, C.D. Memos, N.D. Tampalis, T.H. Soukissian, V.K. Tsoukala, Integrating short- and long-term statistics for short-crested waves in deep and intermediate waters, Appl. Ocean Res. 82 (2019) 346–361, https://doi.org/10.1016/j.apor.2018.11.004.
[35] I. Malekmohamadi, M.R. Bazargan-Lari, R. Kerachian, M.R. Nikoo, M. Fallahnia, Evaluating the efficacy of SVMs, BNs, ANNs and ANFIS in wave height prediction, Ocean Eng 38 (2011) 487–497, https://doi.org/10.1016/j.oceaneng.2010.11.02.
[36] D.I. Gopinath, G.S. Dwarakish, Wave prediction using neural networks at New Mangalore Port along west coast of India, Aquat. Procedia 4 (2015) 143–150, https://doi.org/10.1016/j.aqpro.2015.02.020.
[37] J. Berbić, E. Ocvirk, D. Carević, G. Lončar, Application of neural networks and support vector machine for significant wave height prediction, Oceanologia 59 (2017) 331–349, https://doi.org/10.1016/j.oceano.2017.03.007.
[38] O. Makarynskyy, A.A. Pires, D. Makarynska, C. Ventura, Artificial Neural Networks in wave predictions at the west coast of Portugal, Computers & Geosciences 31 (2005) 415–424, https://doi.org/10.1016/j.cageo.2004.10.005.
[39] A. Santos, D. Arruda, R. Maia, M. Fernandes, R. Araújo, E. Andrade, Wave resource characterization through in-situ measurement followed by artificial neural networks' modeling, Renew. Energy 115 (2018) 1055–1066, https://doi.org/10.1016/j.renene.2017.09.032.
[40] H. Sanaz, A. Etemad-Shahidi, K. Bahareh, Wave energy forecasting using artificial neural networks in the Caspian Sea, Maritime Eng 167 (1) (2013) 42–52, https://doi.org/10.1680/maen.13.00004.
[41] Harbors of State, Waves average. Buoy of Gran Canaria (2442). *(Clima medio de oleaje. Boya de Gran Canaria (2442))*, 2017, http://calipso.puertos.es/BD/informes/medios/MED_1_2_2442.pdf(accessed 4 June 2018).
[42] Harbors of State, Waves average. Buoy of Tenerife Sur (2446). *(Clima medio de oleaje. Boya de Gran Canaria (2446))*, 2017, http://calipso.puertos.es/BD/informes/medios/MED_1_2_2446.pdf(accessed 4 June 2018).
[43] R.M. Sorensen, Basic Coastal Engineering, Springer-Verlag, US, 2006, pp. 11–52 pp.ISBN: 978-0-387-23332-1.
[44] M.A.A. Desouky, O. Abdelkhalik, Wave prediction using wave rider position measurements and NARX network in wave energy conversion, Appl. Ocean Res. 82 (2019) 10–21, https://doi.org/10.1016/j.apor.2018.10.016.
[45] S.N. Londhe, S. Shah, P.R. Dixit, T.M. Balakrishnan, P. Sirisha, R. Jain, A Coupled Numerical and Artificial Neural Network Model for Improving Location Specific Wave Forecast, Appl. Ocean Res. 59 (2016) 483–491, https://doi.org/10.1016/j.apor.2016.07.004.
[46] R. Hecht-Nielson, Kolmogorov's mapping neural network existence theorem, Proceedings of the First IEEE International Joint Conference on Neural Networks, New York, 3 1987, pp. 11–14.
[47] L.L. Rogers, F.U. Dowla, Optimization of groundwater remediation using artificial neural networks with parallel solute transport modeling, Water Resour. Res. 30 (2) (1994) 457–481.
[48] W. Sha, Comment on “Modeling of tribological properties of alumina fibrereinforced zinc–aluminum composites using artificial neural network”by K. Genel et al. [Mater. Sci. Eng. A 363 (2003) 203], Mater. Sci. Eng. A 372 (2004) 334–335, doi:10.1016/j.msea.2004.01.001.
[49] G. Sylaios, F. Bouchette, V.A. Tsihrintzis, C. Denamiel, A fuzzy inference system for wind-wave modeling, Ocean Eng 36 (2009) 1358–1365, https://doi.org/10.1016/j.oceaneng.2009.08.016.
[50] M.P. Schoen, J. Hals, T. Moan, Wave prediction and fuzzy logic control of wave energy converters in irregular waves, 16th Mediterranean Conference on Control and Automation: MED'08, Ajaccio, Corsica, France, 2008, pp. 25–27 , https://doi.org/10.1109/med.2008.4602036 JuneCongress Centre.
[51] M. Özger, Prediction of ocean wave energy from meteorological variables by fuzzy logic modeling, Expert Systems with Applications 38 (2011) 6269–6274, https://doi.org/10.1016/j.eswa.2010.11.090.
[52] A. Akpınar, M. Özger, M.I. Kömürcü, Prediction of wave parameters by using fuzzy inference system and the parametric models along the south coasts of the Black Sea, Journal of Marine Science and Technology 19 (2013) 1–14, https://doi.org/10.1007/s00773-013-0226-1.