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Bayesian optimization of a hybrid system for robust ocean wave features prediction

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ABSTRACT

In the last years, Bayesian optimization (BO) has emerged as a practical tool for high-quality parameter selection in prediction systems. BO methods are useful for optimizing black-box objective functions that either lack an analytical expression, or are very expensive to evaluate. In this paper, we show that BO can be used to obtain the optimal parameters of a prediction system for problems related to ocean wave features prediction. Specifically, we propose the Bayesian optimization of a hybrid Grouping Genetic Algorithm for attribute selection combined with an Extreme Learning Machine (GGA-ELM) approach for prediction. The system uses data from neighbor stations (usually buoys) in order to predict the significant wave height and the wave energy flux at a goal marine structure facility. The proposed BO methodology has been tested in a real problem involving buoys data in the Western coast of the USA, improving the performance of the GGA-ELM without a BO approach.

1. Introduction

The accurate prediction of waves features plays a key role in different ocean engineering-related activities, such as safe ship navigation [1,2], the design of marine structures [3,4], e.g., oil platforms and harbors, and in marine energy management problems [5,6], like the proper operation of wave energy converters [7], among others. Thus, the topic has a clear impact on human safety, economics and clean energy production. One of the most important features to define the severity of a given ocean wave field is the significant wave height, H_{m_0}. H_{m_0} is usually estimated using in-situ sensors, such as buoys, recording time series of wave elevation information. Buoys provide reliable sea state information that characterizes the wave field in a fixed position (i.e., the mooring point). In addition, as buoys are anchored in a hostile media (the ocean), the probability that measuring problems (and therefore missing data) occur in situations of severe weather is very high [8]. Besides this, marine energy [9,10] is currently one of the most promising sources of renewable energy, still minor at a global level, but playing a major role in several offshore islands [11,12]. In this case, the accurate estimation of the wave energy flux P is relevant to characterize the wave energy production from Wave Energy Converters (WECs) facilities [13].

The research work on wave features prediction systems has been intense in the last years, with special incidence in machine learning approaches. One of the first works on this topic was the direct prediction of H_{m_0} using artificial neural networks in [14]. Improvements on this prediction system were further presented in [15]. Neural networks have also been applied to other problems of H_{m_0} and P prediction, such as [16], where H_{m_0} and P are inferred from observed wave records using time series neural networks. In [17], neural networks were applied to estimate the final breaking wave-height for laboratory-scaled and full-scaled ocean waves, showing that neural models are able to improve previously proposed empirical models for breaking waves-height estimation in terms of accuracy. In [18], a neural network was applied to estimate the wave energy resource in the northern coast of Spain. In [19], a hybrid genetic algorithm-adaptive network-based fuzzy inference system model was developed to forecast H_{m_0} and the peak spectral period at Lake Michigan. In [20,21], different hybrid algorithms mixed with an Extreme Learning Machine neural network were proposed for the estimation of H_{m_0} and P, in the context of marine energy applications. Alternative methods based on different computational approaches have been recently proposed. For example, in [22] different soft-computing techniques are tested for H_{m_0} prediction. Support Vector regression (SVR) has also been applied to marine energy related problems such as in [23]. Similarly, Nieto-Borge et al. [24,25] proposed to feed SVR approaches with information from radar sources in order to obtain an accurate prediction of H_{m_0} and P features. Classification approaches have been

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applied in [26] to analyze and predict H_{m_0} and P ranges in buoys for marine energy applications. In [27], the use of Genetic Programming for H_{m_0} reconstruction problems has been proposed. Finally, in [28] fuzzy logic-based approaches were introduced for H_{m_0} prediction problems.

In this paper we test a BO methodology to improve the performance of a hybrid prediction system for wave features (H_{m_0} and P) prediction. Specifically, the prediction system was previously presented in [21], and it is formed by a Grouping Genetic Algorithm for feature selection, and an Extreme Learning Machine for carrying out the final energy flux prediction. This hybrid prediction system has a number of parameters that may affect its final performance, and need to be previously specified by the practitioner. Traditionally, these parameters have been manually tuned by a human expert, with experience in both the algorithm and the problem domain. However, it is possible to obtain better results by an automatic fine tuning of the prediction system's parameters. In this case, the parameters of GGA-ELM approach include the probability of mutation in the GGA or the number of neurons in the ELM hidden layer, among others. We propose then to use a Bayesian optimization (BO) approach to automatically optimize the parameters of the whole prediction system (GGA-ELM), with the aim of improving its performance in wave energy prediction problems. BO has been shown to obtain good results in the task of obtaining good parameter values for prediction systems [29]. In the paper, we detail the basic prediction system considered and the BO methodology implemented, along with the improvements obtained in real problems of H_{m_0} and P prediction in the Western coast of the USA.

The rest of the paper is organized as follows: the next section details the calculation of the features of interest in ocean wave characterization, H_{m_0} and P in this case. Section 3 describes the main characteristics of the hybrid system to be optimized, which is formed by a GGA and an ELM for prediction. Section 4 presents the Bayesian optimization methodology applied in this case to optimize the prediction system considered. Section 5 presents the experimental part of the paper, where the Bayesian hybrid GGA-ELM approach is tested in a real problem of P prediction in the Western coast of the USA. Finally, Section 6 closes the paper exposing the conclusions of this work.

2. Wave features of interest: calculation of H_{m_0} and P

In the evaluation of marine systems it is essential to previously characterize as accurately as possible the wave features of the zone under study. For example, in a wave energy facility, it is necessary to characterize the amount of wave energy available at a particular location, which is given by features such as H_{m_0} and P. In order to obtain these features, it is necessary to focus on the water surface, and within the framework of the linear wave theory, the vertical wave elevation, $\eta(\mathbf{r}, t)$, at a point $\mathbf{r} = (x, y)$ on the sea surface at time t can be assumed as a superposition of different monochromatic wave components [30,31]. This model is appropriate when the free wave components do not vary appreciably in space and time (that is, statistical temporal stationarity and spatial homogeneity can be assumed [31]).

In the model described, the concept of "sea state" refers to the sea area and the time interval in which the statistical and spectral characteristics of the wave do not change considerably (statistical temporal stationarity and spatial homogeneity). The features of a given sea state are then the combined contribution of all features from different sources. For example, the "wind sea" occurs when the waves are caused by the energy transferred between the local wind and the free surface of the sea. The "swell" is the situation in which the waves have been generated by winds blowing on another far area (for instance, by storms), and propagate towards the region of observation. Usually, sea states are the composition of these two pure states, forming multi-modal or mixed seas. In a given sea state, the wave elevation $\eta(\mathbf{r}, t)$ with respect to the mean ocean level can be assumed as a *zero-mean Gaussian stochastic process*, with statistical symmetry between wave maxima and minima. A buoy deployed at point $\mathbf{r}_B$ can take samples of this process, $\eta(\mathbf{r}_B, t_j)$ $j = 1, 2, \ldots, t_{\mathrm{MAX}}$, generating thus a time series of empirical vertical wave elevations. The Discrete Fourier Transform (DFT) of this sequence, using the Fast Fourier Transform (FFT) algorithm, allows for estimating the *spectral density S(f)*. Its spectral moments of order n can be computed as follows:

$$m_n = \int_0^{\infty} f^n S(f) df. \tag{1}$$

The Significant Wave Height (SWH) is defined as the average (in meters) of the highest one-third of all the wave heights during a 20-min sampling period [32], and it has been widely studied. It can be calculated from the moment of order 0 in Eq. (1), as follows:

$$H_{m_0} = 4 \cdot (m_0)^{1/2}. \tag{2}$$

On the other hand, the wave energy flux is a first indicator of the amount of wave energy available in a given area of the ocean. Wave energy flux P, or power density per meter of wave crest [33] can be computed as

$$P = \frac{\rho g^2}{4\pi} \int_0^{\infty} \frac{S(f)}{f} df = \frac{\rho g^2}{4\pi} m_{-1} = \frac{\rho g^2}{64\pi} H_{m_0}^2 \cdot T_e, \tag{3}$$

where ρ is the sea water density (1025 kg/m^3), g is the acceleration due to gravity, $H_{m_0} = 4\sqrt{m_0}$ is the spectral estimation of the significant wave height, and $T_e \equiv T_{-1,0} = m_{-1}/m_0$ is an estimation of the mean wave period, normally known as the period of energy, which is used in the design of turbines for wave energy conversion. Expression (3) (with H_{m_0} in meters and T_e in seconds) leads to

$$P = 0.49 \cdot H_{m_0}^2 \cdot T_e, \tag{4}$$

measured in kW/m, which helps engineers estimate the amount of wave energy available when planning the deployment of WECs at a given location.

3. The hybrid prediction system considered

In this paper we will optimize a hybrid prediction system for marine energy applications described in [25]. In this section, we describe the main characteristics of this approach, in order to better explain later on the Bayesian optimization carried out on it. The prediction system is a hybrid wrapper approach, formed by a Grouping Genetic Algorithm for feature selection, and an Extreme Learning Machine to carry out the final prediction of H_{m_0} or P from a set of input data.

3.1. The grouping genetic algorithm

The grouping genetic algorithm (GGA) [34,35] is a type of evolutionary algorithm especially suited to tackle grouping problems, i.e., problems where a number of items must be assigned to a set of predefined groups. The GGA has shown very good performance on different real applications and problems [36–41]. In the GGA, the encoding, crossover and mutation operators of traditional GAs are modified to better deal with grouping problems. In this paper we use the GGA to obtain a reduced set of features (feature selection) in a context of H_{m_0} and P prediction. We structure the description of the GGA in Encoding, Operators and Fitness Function calculation (Extreme Learning Machine).