A Machine Learning Approach for Model-free Control of PeWEC

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***Abstract*—Among the devices aimed to the conversion of the wave energy source, PeWEC (Pendulum Wave Energy Converter) stands out for his ability to reliably absorb power by exploiting the relative rotation between its hull pitching and the oscillation of an internal pendulum. The conversion process is performed by the PTO (Power Take-Off), a generator aimed of damping the pendulum motion. By regulating the PTO torque, PeWEC can adapt to different sea states and maximize the absorbed power. However, the control adopted for the definition of this action follows a model-based approach, affected by uncertainties and unable to conform to system changes. To solve these issues, this work presents a model-free control strategy that is based on learning a metamodel from real data and optimizing its action through it.**

Keywords—Wave Energy Converter, Artificial Neural Networks, Deep Learning, Model-free control, Genetic Algorithm.

I. PeWEC and State of the Art of its Control

In the field of renewable energy, one of the most promising branches is wave energy. The amount of energy potentially available from the motion of waves in seas and oceans is high. Only a small part of this energy is currently converted and exploited. Systems used to extract wave energy are called WECs (Wave Energy Converters). One of these, PeWEC (Pendulum Wave Energy Converter), uses the relative rotation of a pendulum with respect to the device hull to convert the energy of sea waves motion into electrical energy [1] [2]. It is composed of an anchored hull capable of orienting itself with respect to the incident wave. The energy conversion is performed by damping the pendulum oscillations on its rotational axis. This conversion process is actuated inside the hull by the Power Take-Off (PTO) system [1]. In Figure 1, a simple scheme of the PeWEC is shown.

The wave resource is variable in time and space. Its characteristics can be expressed through various parameters, including the energetic wave period *Te* and significant height *Hs*, which affect the amount of energy available, the way the system will be stimulated and how it will respond in terms of conversion. These parameters define the sea state, and they are estimated from the measures of hull motion [3]. It is therefore clear that the control system of WECs must be able to adapt to the sea state changes to maximize the extracted energy.

The control system that is currently adopted on PeWEC generates a torque that is a linear combination of the position and velocity on the PTO axis. The parameters of the control law are computed through a lookup table built offline using a model of the system. For each sea state, the lookup table returns the optimized combination of control parameters. The applied control torque can be formulated as:

$$T_{control} = c\dot{\varepsilon} + k\varepsilon \qquad (1)$$

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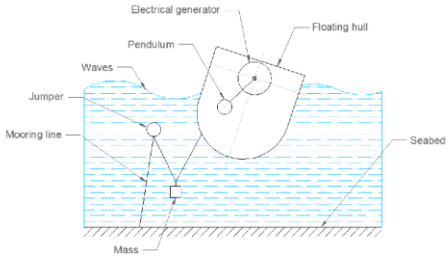

Fig. 1 Scheme of PeWEC device.

In (1), c and k are the control gains, while ε and $\dot{\varepsilon}$ are respectively the position and velocity on the PTO axis.

II. Proposed Machine Learning Control Strategy

The actual control system is unfortunately affected by uncertainties due to the differences between the theoretical model on which the simulations are based and the actual device. Moreover, the proportional control parameters do not change with the variation in time of the real plant, but it is chosen in the design phase based on simulations of the theoretical system with ideal waves. Therefore, the control action is unable to adapt to the ageing of the device or to the changes that could happen due to phenomena like biofouling or system faults. For these reasons, the conversion process efficiency is affected and the amount of energy extractable from the wave motion is reduced. For the above motivations, to improve the plant and maximize its productivity, a different approach should be pursued. In the field of wave energy, the most popular model-free control strategies are based on artificial neural networks (ANNs) [4], reinforcement learning [5] and extremum seeking [6]. This work analyzes different aspects of the development of a model-free control for PeWEC based on ANNs and on a machine learning strategy.

The aimed controller should be independent from the parameters of the system model, and it should be able to tune itself, adapting over time and finding an optimal configuration on the basis only of the history of previous values of applied inputs and obtained outputs. Moreover, having to compute an optimal conversion, among the considered inputs, some parameters related to the sea-state must be considered to take care of the wave energy source.
The solution proposed in this work can be summarized by the following points.

1. The actual main parameters of the sea-state are forecasted from the values of previous time instants with a model based on historical data.
2. A metamodel is built from data to link the sea-state (*Te* and *Hs*) and the adopted control action (*c*, *k* parameters of the PTO torque action) with the average absorbed power in the time span in which the control action is applied.

3. Depending on the amount of the experiences of the system, the control action is chosen aiming to explore the control space or to optimize the power absorption.

The first issue related to the model-free control problem that has to be faced is the forecast of the parameters that describe the actual sea state. To obtain an information about the current condition, a prediction of the actual sea state given its previous values is needed. To do that a model able to describe the behaviour of *Te* and *Hs* is necessary. Indeed, these two parameters are the only information that the aimed control strategy has about the wave conditions in which the system is placed. Different methodologies based on time-series and neural networks have been explored. The selected approaches have been analyzed and tested with a dataset of two years of sea state parameters computed every 30 minutes. The dataset is composed by real data measured by RON (*Rete Ondametrica Nazionale*) in the site of Alghero in northwestern Sardinia, Italy. From the results comparison, two promising candidates, based on autoregressive (AR) models and vector autoregressive neural networks (VAR-NN), have been identified as potential solutions to the sea-state forecasting issue.

The development of the proposed control strategy is based on the concept of building a metamodel and optimize the control gains through it. A metamodel is a model built from real experiences (replaced in this work by simulations) and it is used to map the inputs (sea state and control gains) with the obtained outputs (average extracted power within 5 or 20 minutes). To build this metamodel, different strategies based on neural networks have been adopted. A deep analysis of several different metamodel architectures has been performed in the design stage. The possible candidates have been evaluated in terms of ability to approximate the data, of quality of optima representation and of the needed computational effort in training and optimization phases. Each architecture has been extensively analyzed through the usage of three different test problems (an equivalent mass-spring-damper system and the linearized models of PeWEC that consider respectively one and three degrees of freedom of the hull). A promising metamodel architecture has been found for the aimed application. It is based on neural network composed of three layers, 30 neurons each. The activation function adopted for all the neurons is the Rectified Linear Unit function (ReLU). Additionally, the problem of the choice of the optimization algorithm to be used during the computation of the optimal control action has been faced. In the evaluations made in this work, the optimal gains have been computed by means of a genetic algorithm.

The final issue considered in this work is related to the exploration and optimization strategies. The decision of the control action indeed, not only influences the power absorption, but also the metamodel development and the learning process. An exploration strategy has been elaborated for the development of the metamodel. This strategy is composed of a first stage of pre-learning and a second one based on the concept of exploration/exploitation policy. In the first phase, the aim of the control system is not the maximum extraction of energy but the pure exploration of some possible combinations of the control inputs and of their effects in the power absorption. In the second phase, once enough experience has been obtained and the metamodel has been built, the control action to be adopted is managed by a designed greedy function. This function is used to define the percentage of exploration actions (that are a random control) and optimization ones (which are generated by optimizing the control gains using the metamodel in the actual sea-state). This greedy function is also referred to as greedy policy because, for each sea-state, based on the number of times that wave condition has been actually faced, it sets the probability of applying one of the two approaches. Since the need of exploring decreases with the number of experiences in the training dataset, the greedy function decreases too. To improve the results, the metamodel is continuously re-trained also considering the new additional knowledge. The possibility of updating the model with less frequent further explorations is also addressed. Moreover, a strategy has been defined to forget properly the oldest experiences and enable in this way the model to adapt to the changing real system.

III. Preliminary Results and Conclusions

The proposed solution has been preliminarily analyzed through some learning simulations with two test problems (equivalent mass-spring-damper system and the linearized model of PeWEC that consider one degree of freedom of the hull). The learning simulations have been performed with 15 different sea states, each one 60 minutes long and with different occurrences percentage. The preliminary results are satisfactory. With a control configuration applied every 5 minutes, the proposed strategy reaches the performances of the simulation-based control in less than 3 days in the equivalent mass-spring-damper case. For the PeWEC system, the analyzed strategy can perform quite similarly to the actual control after 12 days. To reduce this learning time, a solution based on collaborative learning [7] could be explored if an array of converters is considered, or the time span in which each control combination is applied could be lowered.

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