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Excitation Forces Estimation for Non-linear Wave Energy Converters: A Neural Network Approach

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Abstract: Investigating optimal control algorithms is a continuing concern within the Wave Energy field. A considerable amount of literature has been published on optimal control architectures applied to Wave Energy Converter (WEC) devices. However, most of them requires the knowledge of the wave excitation forces acting on the WEC body. In practice such forces are unknown and an estimate must be used. In this work a methodology to estimate the wave excitation forces of a non-linear WEC along with the achievable accuracy, is discussed. A feedforward Neural Network (NN) is applied to address the estimation problem. Such a method aims to map the WEC dynamics to the wave excitation forces by training the network through a supervised learning algorithm. The most challenging aspects of these techniques are the ability of the network to estimate data not considered in the training process and their accuracy in presence of model uncertanities. Numerical simulations under different irregular sea conditions demonstrate accurate estimation results of the NN approach as well as a small sensitivity to changes in the plant parameters relative to the case study presented.

Keywords: Wave excitation force, Neural Networks, Estimation, Wave Energy Converter.

1. INTRODUCTION

In the last few decades a wide range of Wave Energy Converter (WEC) concepts have been widely investigated as they represent a powerful source for renewable energy generation. The application of WEC systems to irregular sea states calls for a robust control logic in order to enhance the extracted energy with acceptable efficiencies. Most of the proposed optimal control algorithms in literature require the knowledge of the wave elevation and/or excitation forces acting on the WEC body. Within this context, several approaches have been proposed to address the problem of the wave excitation force estimation. Ling and Batten (2015) used a Kalman Filter (KF) observer assuming that the wave excitation force can be modelled as a linear superposition of fixed and finite harmonic components. In the work of Nguyen and Tona (2018) two approaches are presented: the first approach is based on a KF coupled with a random-walk model of the wave excitation force; the second performs a receding horizon − unknown input estimation. A black-box approach is proposed by Li et al. (2019) that used a Neural Network (NN) to estimate and predict the wave excitation force on a Point-Absorber WEC. Similarly, Desouky and Abdelkhalik (2019) studied the estimation of the wave elevation of a WEC using the measurements from a nearby buoy employing a Non-linear Autoregressive with exogenous input network (NARX). All the mentioned studies showed promising results in terms of estimation accuracy. However, most studies in this field refer to single Degree of Freedom (DoF) linear models. The novelty of this work is to estimate the wave excitation forces on a non-linear multi-DoF WEC. The study is applied to the Inertial Sea Wave Energy Converter (ISWEC) device designed for the Mediterranean Sea. In this context, two different approaches have been applied to the ISWEC device so far. Genuardi et al. (2019) built an unknown state observer with a second order augmented state space representation of the ISWEC for the estimation of the wave excitation force induced on the pitch DoF of the device. However, this work deals with the estimation of the wave excitation force along the pitch DoF only. Sirigu et al. (2018) presented a method to estimate the sea state Power Spectral Density (PSD) of the wave climate by using the device motion; the heave motion measurements was used to estimate the PSD of the incoming wave and the results was compared with the wave PSD acquired by a wave measurement system. In the current study a feedforward NN is proposed to relate the ISWEC motion to the wave excitation forces acting on surge, heave and pitch DoFs. The main challenge consists of consider a non-linear 3-DoF model of the WEC and estimate the wave excitation forces along three degree of motion. The main outcome is to assess the estimation performances in term

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of estimation accuracy and sensitivity in different irregular sea-states as well as in presence of plant uncertineties.

This paper is organized as follows. First, in Section 2 the ISWEC device is presented together with the non-linear 3-DoF model. Second, Section 3 describes the NN approach to estimate the wave excitation forces as well as the network design studied in this work. Then, in Section 4, numerical results are presented and discussed to assess the accuracy of the method presented. Finally, Section 5 reports conclusions and proposed further works on the wave excitation force estimation problem.

2. ISWEC DEVICE

2.1 Working principle

The ISWEC system has been considered as the case study of this work. A schematic representation of the device is showed in figure 1.

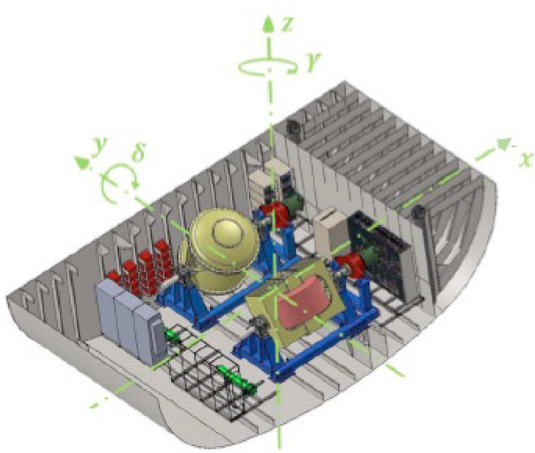

Fig. 1. ISWEC device architecture

It consists of a sealed hull with two gyroscopic units. The waves induce the pitching angular motion of the hull that is converted into an inner precession oscillation of the gyroscopes by the gyroscopic effect. The gyroscope is composed of a spinning flywheel that rotates around the z_1 axis with a speed $\dot{\varphi}$. The flywheel is supported by a frame allowing the rotation of the gyroscope around its precession axis x_1. A mechanical gearbox and an electrical generator, connected to the gyroscopic frame, compose the electrical Power Take-Off (PTO). The electrical generator extracts electricity acting as a linear damper braking the precession motion of the gyroscope. The possibility to regulate the flywheel speed and the torque of the electrical generator allow the system to adapt to different wave conditions. An accurate description of the internal components of the device and its working principle can be found in the work of Bonfanti et al. (2018).

2.2 ISWEC model equations

The ISWEC mathematical model consists of coupling the hull hydrodynamics and the gyroscope dynamics. Under the linear potential flow theory assumptions and according to the well-known Cummins' equation (Cummins (1962)), the dynamic behaviour of a floating body can be derived in the time domain. Furthermore, some non-linear effects are considered: the non-linear viscous forces, the drift forces in the surge direction, the mooring action and the gyroscopic reaction on the hull. The ISWEC device extract energy from the sea exploiting only the motion around the pitch axis. Moreover, the hull is symmetrical with respect to its longitudinal and transversal plane. Under these assumptions, a planar 3-DoF model of the hull has been considered in this work. The reference plane is identified by the vertical gravity axis z and the horizontal direction of the incoming wave x as showed in figure 1.

Let X be the vector containing the three DoFs of the hull:

$$X = [x \;\; z \;\; \delta]^T \tag{1}$$

Then, $\dot{X}$ and $\ddot{X}$ are the first- and second-time derivative of X, respectively. In this planar reference frame, x represents the surge motion, z the heave motion and δ the pitch motion. Following the notation of equation 1, the time-domain equation of the hull can be written as:

$$M\ddot{X} + F_\beta + F_r + KX = F_w + F_d + F_m + F_g \tag{2}$$

Where M represents the mass matrix of the hull including the added mass contribution evaluated for infinite oscillation frequency, F_r are the radiation forces, F_β the non-linear viscous forces, K the linear hydrostatic stiffness, F_w the wave forces, F_d the non-linear wave drift forces, F_m the mooring line actions and F_g the gyroscopic reactions on the hull. For the sake of clarity, the subscripts x, z and δ will be used in the next sections to specify the DoF to which the forces or parameters refers. The gyroscope dynamics can be derived from the Newton's law and the conservation of the flywheel angular momentum. Through a linearization of the angular momentum of the gyroscope around the y_1 axis, the expression of the gyroscopic reaction discharged on the the hull can be determined:

$$T_\delta = J\dot{\varphi}\dot{\varepsilon}cos(\varepsilon) \tag{3}$$

Where J is the flywheel moment of inertia, $\dot{\varphi}$ the flywheel speed around its spinning axis z_1, $\dot{\varepsilon}$ the precession velocity of the gyroscope and ε its angular position. This torque acts on the pitch axis of the hull, so it represents the third component of the F_g term in eqaution 2.

It is beyond the scope of this study the derivation and experimental validation of the model equations and details can be found in the studies of Bracco et al. (2016), Pozzi et al. (2018a), Pozzi et al. (2018b), Sirigu et al. (2020a) and Sirigu et al. (2020b).

3. WAVE EXCITATION FORCE ESTIMATION WITH NEURAL NETWORK

In this section, the estimation problem is formulated introducing the NN used to models the relation between the motion of the hull and the wave excitation forces. Then, once the framework of the estimator is defined, the training data are presented as well as the training process.

3.1 Neural Network design

When the system definition is based only on observed data the model is called black-box model as the input-output behaviour is characterized with no information about its architecture. In a black-box model the parameters are tuned to fit the input-output data, without reference to the physical background. Artifical NNs represent powerful tools to map non-linear relations from sets of input-output data. In this work a feedforward neural network with one hidden layer is considered as showed in figure 2.

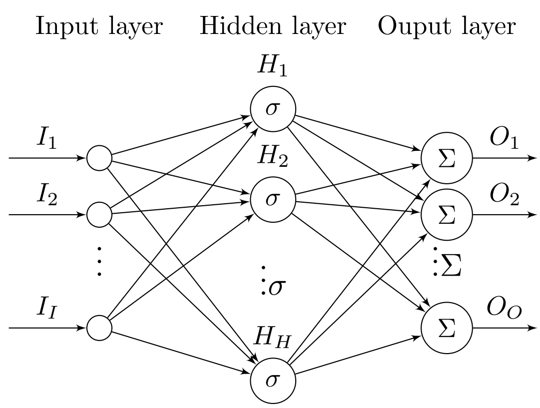

Fig. 2. Structure of a feedforward Neural Network

The NN is composed of linked neurons arranged in discrete layers: the input layer receive a set of inputs I_I and connect all the available information multiplying them by a set of weights, assigned to the data on the basis of their relative importance to other inputs. At this stage the hidden neuron H_H apply an activation function σ to the weighted sum of their inputs. Then, the output of each hidden neurons is combined by the output functions Σ to produce the network outputs O_O.

In general mathematical terms, the wave excitation force for each DoF can be expressed as a non-linear function $f(\bullet)$ such that:

$$\hat{F}_w(t) = f(Y(t), ..., Y(t-k)) \tag{4}$$

Where $\hat{F}_w$ are the estimated excitation forces and $Y(t)$, ..., $Y(t-k)$ are a set of known measurements at the current and past time instants. Equation 4 highlights that the values of the wave excitation force at time t is, at least in principle, based on a series of system measurements collected from time $t-k$ to time t. Considering the equation 2, the wave excitation forces relative to the three DoFs of interest at time instant t are estimated considering the set of measurements available from the ISWEC on-board sensors and the gyroscopic reaction torque on the pitch DoF. The measures are provided by an Inertial Unit of Measurement (IMU) Xsens MTi-30 AHR fixed inside the floater and a digital encoder mounted on the gyroscope shaft. The measurements avaiable from the sensors are: the linear acceleration along the heave and surge directions ($\ddot{x}$ and $\ddot{z}$), the angular position and velocity of the hull (δ and $\dot{\delta}$), the flywheel speed ($\dot{\varphi}$) and the angular speed of the gyroscope ($\dot{\varepsilon}$). The velocity $\dot{z}$ and position z of heave DoF are numerically integrated from the acceleration $\ddot{z}$. These two inputs were included to enanche the estimation performaces of the wave excitation force in heave direction. The gyroscopic reaction torque on the pitch DoF is computed considering the equation 3. The input-output architecture of the NN is shown in figure 3.

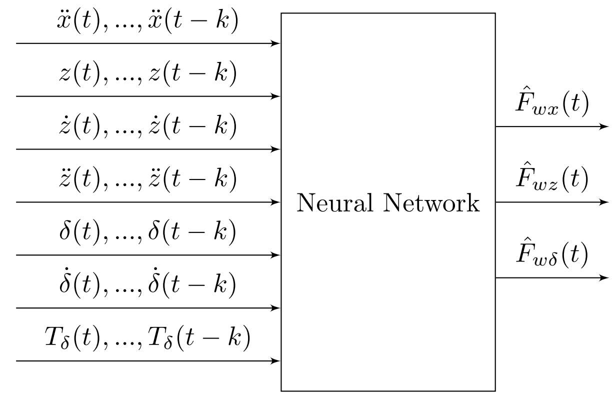

Fig. 3. Neural Network architecture for ISWEC

For the design of the network a structure with 35 inputs (7 system variables each one delayed 5 time steps in the past) and one hidden layer composed by 60 neurons are considered. An hyperbolic tangent (sigmoid) function and a linear function were used for the hidden and output layers, respectively. The choice of the network inputs and neurons has been justified through a sensitivity analysis. Results are presented in section 4.

3.2 Neural Network setup

In order to generate the training data, four different sea states are defined according to the operating conditions of the ISWEC device. In this work, the JONSWAP spectrum (Hasselmann et al. (1973)) is considered to model the wave spectra. In table 1 are reported the wave data used for the network training: T_e represents the energy period and H_s the significant wave height.

Table 1. Training wave data

Id	T_e (s)	H_s (m)
1	4.03	0.75
2	4.98	1.25
3	5.84	1.75
4	6.78	2.25

Four wave profiles are generated to obtain the wave excitation forces for each of the DoF considered. Then, the time-series of the wave excitation forces are concatenated and applied to the non-linear ISWEC numerical model to obtain the WEC motion. All the time-series are normalized in the [-1,1] range to avoid problems due to different magnitude between signals. In order to avoid over-fitting risk, the data obtained from the waves in table 1 are randomly divided into three parts for the different phases of the network design: 50% for training phase, 30% for validation phase and 20% for performance phase. The Levenberg-Marquardt back propagation algorithm is used to train the network as is one of the fastest avaiable. The single wave time-serie is chosen 1200s long with a sample time of 0.1s.

4. NUMERICAL RESULTS AND DISCUSSIONS

In this section the effectiveness of the proposed method is showed, evaluating the estimation performances of the feedforward NN designed. First, the NN is trained in order to obtain the weights and bias. A sensitivity analysis is carried out to evaluate both the number of delay steps and neurons. Second, the network is applied to the non-linear 3-DoF ISWEC model comparing the real and estimated wave excitation force for each DoF considered. Then, a sensitivity analysis is performed considering a variation of the inertia M and stiffness K matrix of the system in respect to the one considered during the training phase.

4.1 Neural Network training

An appropriate investigation of the network inputs and neurons is performed to restrict the network dimension guaranteeing the best fitting results. Different values of these parameters are evaluated:

(1) 1, 3, 5, and 10 delay steps. The number of neurons is fixed to 60.
(2) 30, 60, 90 and 120 neurons. The number of delay steps is fixed to 5.

The estimation accuracy is measured with the *Goodness-of-Fit* (*GoF*) index, defined as follows (Laurent (2016)):

$$GoF_i = 1 - \frac{\sqrt{\sum_{t=0}^{T}[F_{wi}(t) - \hat{F}_{wi}(t)]^2}}{\sqrt{\sum_{t=0}^{T}[\hat{F}_{wi}(t)]^2}} \tag{5}$$

In equation 5, F_{wi} and $\hat{F}_{wi}$ are the true and estimated excitation force for the $i-th$ DoF, respectively. After training, the performance of the NN are carried out for the the wave Id 2. As shown in figure 4 the average scores of GoF are compared in order to evaluate the effect of both delay steps and neurons. There is a clear trend of increasing accuracy in respect to the number of delay steps. 5 delay steps are chosen to have a balance between estimation accuracy and network complexity; there is not a significant improvemet increasing the number of delay steps over 5. On the other hand, no significant increase of GoF is associated with the number of neurons. Further tests showed that 60 neurons well classify the input data not considered in the training process. Therefore, the following numerical tests are performed using 35 inputs and one hidden layer of 60 neurons.

4.2 Estimation results

The numerical experiments are carried out adding eight waves to the four considered in the training process. These sets of data were chosen to be representative sea states for the Mediterranean Sea, in Italy. As showed in table 2, the NN performs an accurate estimation for each wave excitation force component considered. The first four wave profiles have been used for training, validation and performance, while profiles 5-12 have been used to investigate further the performance of the network out of the training domain. It is demonstrated that the NN performs well for different sea states because of the variety of data used during the traning phase and the number of past variables in the model. The *GoF* is always greater or equal than 0.92 for all the wave excitation force components.

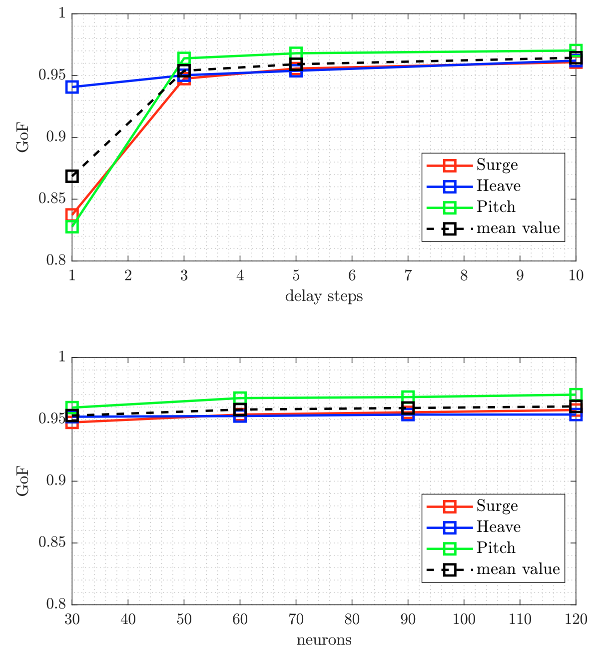

Fig. 4. Delay steps and neurons sensitivity analysis

Table 2. Estimation results

Id	T_e (s)	H_s (m)	GoF_x	GoF_z	GoF_δ
1	4.03	0.75	0.93	0.93	0.94
2	4.98	1.25	0.94	0.95	0.96
3	5.84	1.75	0.95	0.96	0.96
4	6.78	2.25	0.96	0.96	0.96
5	5.84	1.25	0.94	0.96	0.94
6	4.97	1.75	0.92	0.94	0.95
7	7.64	1.75	0.95	0.96	0.95
8	4.98	2.55	0.92	0.94	0.94
9	9.44	2.75	0.96	0.94	0.95
10	5.84	3.25	0.92	0.92	0.94
11	10.39	3.25	0.96	0.93	0.96
12	7.66	4.25	0.94	0.95	0.95

Including the delays was the the key factor of this work: the input variables and their delays represent a sort of dynamic memory of the system; the output of a generic dynamical system at a given time instant t depends on both the input at current time and previous behavior of the system itself. In this regards, the estimated wave excitation force at current time is related with the dynamics of the ISWEC device at present and past time instants. As assessed by Ablameyko et al. (2003), one way to consider the dynamics of a system using static neurons is to store past values of the inputs and/or apply a feedback from the output data. In this work the first approach was considered showing good performances in term of estimation accuracy and robustness to different wave conditions.

The figure 5 compares the estimated excitation force with the real one for each of the DoF considered. This comparison refers to the wave Id 2.

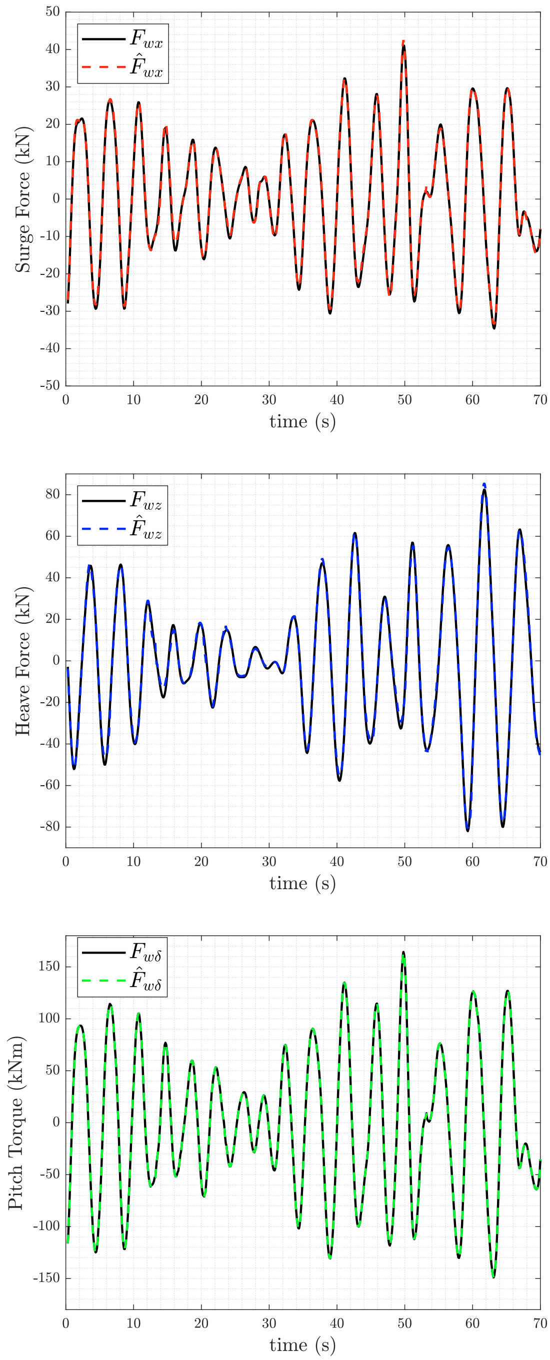

Fig. 5. Wave excitation force estimation results

4.3 Sensitivity to plant variations

In order to evaluate more the performance of the NN architecture, the network is tested considering a typical case may happen in the passage between the theoretical design of the device and its construction in the shipyard: variation of the physical properties of the floater. In this regards, a further analysis has been carried out, testing the behavior of the network for different values of the mass matrix M and stiffness matrix K. An iterative method is used varying both the mass and stiffness matrix in the rage of $\pm 10\%$ in respect to the value considered during the training phase. At this point the effectiveness of the NN is showed in figures 6 and 7 in term of GoF. The results refers to the wave Id 2.

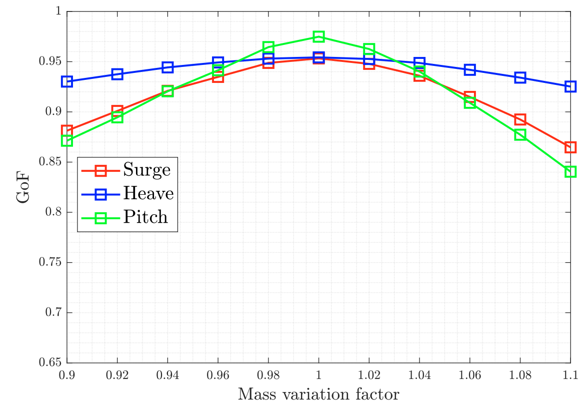

Fig. 6. Stiffness matrix influence on the estimation

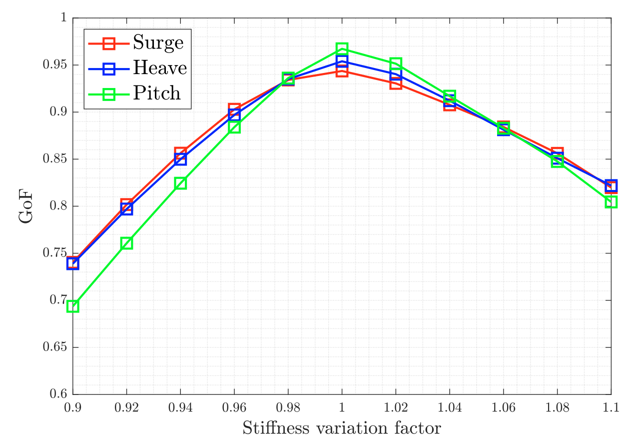

Fig. 7. Stiffness matrix influence on the estimation

As to the mass matrix, the GoF value is always greater than 0.92 for the heave force component. Instead, the performances are lower for the surge and pitch DoFs. In the ISWEC system, the heave DoF is decoupled from the others DoFs because of the device symmetry properties. On the other hand, pitch-surge modes are coupled so the estimation of the wave excitation force along these DoFs is influenced both by the diagonal and off-diagonal terms of M; this leads to the conclusion that, since all the mass matrix is modified for each simulation, the pitch and surge force estimation are more influenced than the heave one because more terms of the mass matrix are modified at once. For what concern the stiffness matrix, the figure 7 shows that the GoF decreases more in the presence of variations of the matrix K than in presence of variations of the matrix M. In this case, the reduction of estimation performances are equal for surge and heave DoFs and slighty greater for the pitch DoF. In the worst case, the GoF of the wave exctitation force for the pitch DoF approaches 0.7.

5. CONCLUSIONS

In this paper, a methodology for designing a NN estimating the wave-induced forcing terms acting on a non-linear WEC during its operating condition is proposed.

The estimation of such functions results to be a key step for the implementation of an optimal controller for the power absorption.

As a first step, a feedforeward NN is designed according to the hydrodynamic equation of the ISWEC hull. Considering the wave excitation forces as a function of the system dynamics both at the current and past time instants was proven to be effective. In this regards, the dynamic memory of the plant is taken into account using static neurons with no feedback data. Successively, the training process is performed obtaining a GoF greater than 0.93 for all the wave excitation force components. Then, the network is validated for eight more wave conditions assessing its accuracy getting out the training set. The GoF index is always greater the 0.92 for all the twelve wave profiles. Moreover, a performance analysis of the NN is carried out changing the simulation conditions, iterating the computation of input data sets considering different mass and stiffness matrices. Even if the range of variation considered is quite wide, the results are promising since the GoF is always greater than 0.80 in presence of a variation of the mass matrix M. On the other hand, a variation the stiffness matrix K produce a GoF of 0.7 in the worst case. This allows to the conclusion that the NN guarantees good performances with variations in the parameters around $\pm 4\%$ of the nominal value, since in this range the GoFs remain around 0.9.

Future works will study the problem of the wave excitation forces estimation considering more uncertanities on the ISWEC plant (e.g un-modelled hydrodynamics phenomena). Moreover, further analysis will be conducted to assess the network robustness in presence of real sensors with disturbance. Model-based approaches (e.g. Kalman Filter, Extended Kalman Filter, etc.) will be considered and compared with this black-box approach. Model-based techniques are expected to be more effective in a wide range of sea-states in respect to a black-box observer. The aim will be comparing the estimation results between model-free and model-based approaches in term of estimation performances. The best estimation approach will be used for the implementation of a Model Predictive Control strategy on the ISWEC.

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