Analysis of Mutriku's OWC performance

Isabel Casas, Jon Lekube

Abstract—**An analysis of oscillating water columns (OWC) at the Mutriku Wave Power Plant to understand their efficiency in transforming ocean energy into electricity. The study aims to estimate the rate of convergence of wave energy flux to kilowatts hour of each OWC and determine whether it is more accurate to estimate for each OWC independently or as part of a system of equations. The dataset includes electricity production data from 7 turbines in the MWPP during 2019, along with ocean measurements such as significant wave height, wave period, wave energy flux, swell direction, and wind direction. All models in the paper have varying coefficients which change with the significant wave height. The methodology includes the use of generalized least squares and local polynomial kernel methodologies for coefficient estimation.**

Index Terms—**Mutriku Wave Power Plant, Functional coefficient SURE, OWC performance**

I. Introduction

OUR planet faces an urgent climate crisis and requires immediate action. The fundamental change to overcome the climate crisis is to reach a net zero, which requires a paradigm shift in our economy, moving from fossil fuel to renewable energy sources, from an extractive to a circular economy, and from a global to a local economy. The main objective of the current article is to contribute to settling wave power plants as renewable energy alternatives. With this goal in mind, we compare several statistical models to analyse the functioning of each oscillating water column (OWC) at the Mutriku Wave Power Plant (MWPP). In particular, we are interested in understanding how efficiently each OWC transforms ocean energy into electricity. This information is essential to maintain the plant in good working condition.

Despite the strong potential for developing wave power plants, only a few hundred kW of wave energy are commercialised globally, compared to GW of offshore wind. Among these, the MWPP has been functioning commercially since July 2011 [1], [2]. Today, the Ente Vasco de Energía (EVE) manages the MWPP and outsources its electricity trading in the Iberian Electricity Market. Although the MWPP does not have the latest wave converters, the availability of its production data from several turbines and years makes it a perfect candidate for this project. Specifically, the MWPP production data from 7 turbines during 2019 will be analysed.

There is a vast literature analysing the performance of OWC where their efficiency and power are analysed in experimental conditions such as in [3] and [4]. Analysing their performance with real production data from the OWC is less frequent due to the limited availability of data from commercial wave power plants. In this paper, we use stochastic models to measure the performance of seven OWCs and obtain their conversion rate from WEF to electricity production.

It is important for wave power plant operators to continually monitor and optimise the performance of individual OWCs to ensure the highest possible correlation in their production levels under varying ocean conditions. The main statistical question in this paper is whether it is more accurate to estimate the production of each OWC in an independent equation or as part of a system of equations. Both cases can be put into the context of seemingly unrelated equations (SURE). Equations in this system might not be directly related but can indirectly influence each other. The potential interdependencies among the equations are considered when estimating the parameters. In any case, we assume that the coefficients may vary depending on the significant wave height.

In this paper, we first describe the dataset and the methodology in Section II. Section III presents the empirical results. Finally, Section IV summarises the results.

II. Data and Methodology

A. Data

This project originally had access to electricity production from 12 turbines, i.e. from Turbines 2-8 and 10-15 of the Mutriku Wave Power Plant (MWPP). The number of kilowatts of nominal power is positive when the turbo generator produces more electricity than it spends and negative when the turbo-generator acts as a motor to maintain the minimum rotation speed so the turbine does not stall. Nominal power is recorded every half a second: its average over one hour is the energy production of that hour (i.e., we denote the dependent variable at hour t of turbine k by kWh_{kt}. The predictors are ocean measurements corresponding to the SIMAR point number 3172032, closest to Mutriku and operated by Puertos del Estado (Spain's State Ports). Specifically, the ocean variables used are the significant wave height (H_t), wave period (T_t), wave energy flux (WEF_t), swell direction ($SwellDir_t$), and wind direction ($WindDir_t$). Puertos del Estado uses the WAM model to predict ocean variables at each SIMAR point from values at the Bilbao Buoy and the HARMONIE-AROME model to predict wind variables. The wave energy flux (WEF) at time t is calculated by $WEF_t = \frac{\rho g^2}{64\pi} H_t^2 T_t = 0.491 H_t^2 T_t$, where g is the acceleration due to gravity and ρ is the water density.

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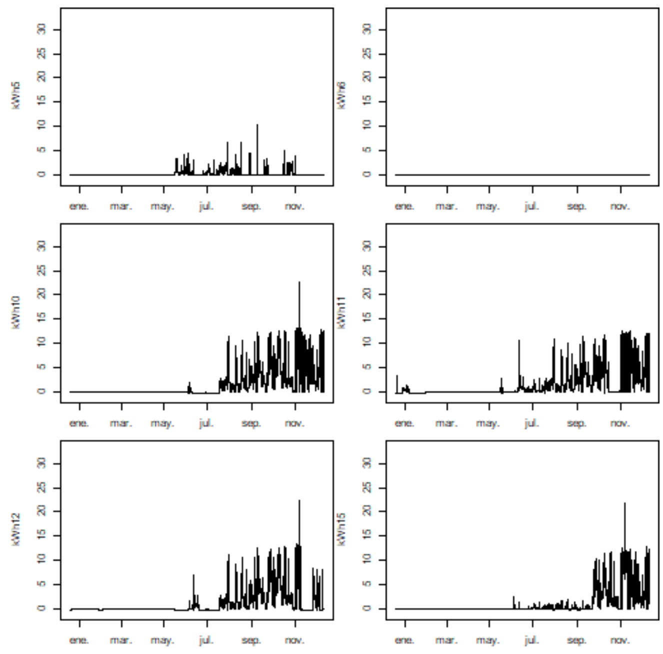

Fig. 1. production of the MWPP turbines that only functioned during part of the period.

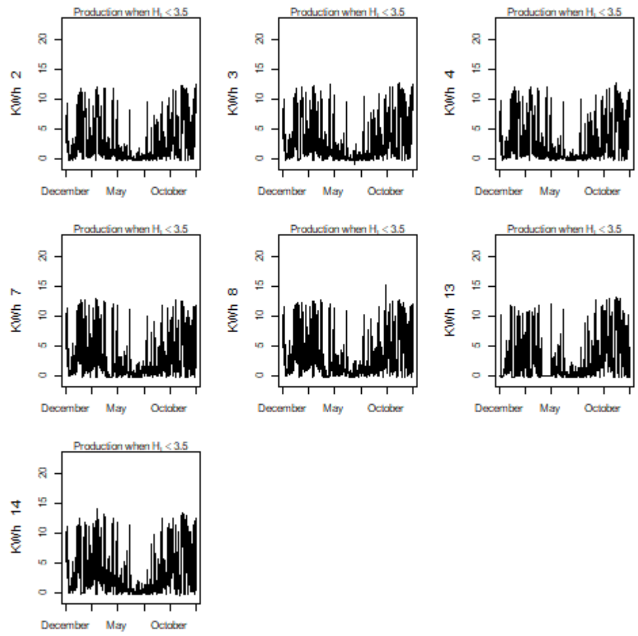

Fig. 2. production of the MWPP turbines that functioned during the whole period.

Missing values of kWh are replaced using the 10-nearest-neighbor algorithm [5], which does not depend on the data time structure. The study period is from the 1st of January 2019 until the 31st of December 2019. In total, we have 8,616 data points.

Unfortunately, some turbines did not function for long periods in 2019. Turbine 6 was off during 2019, and Turbines 4, 5, 10, 11, and 15 only worked for half of 2019; see Figure 2. However, Turbines 2, 3, 7, 8, 13 and 14 produced electricity consistently throughout the year (see Figure 1), and we analyse their production in this study.

B. Methodology

In this section, we analyse the expected conversion rate from WEF to energy of OWCs at MWPP to understand the efficiency of this plant and estimate the plant production. We accomplish this by treating energy production as the dependent variable and analysing the influence of various ocean conditions as explanatory factors.

1) Comparing OWCs production: All OWCs in the plant share the same ocean site. In a well-designed and maintained plant, we expect energy production between OWCs to be highly correlated. This information is included in the variance-covariance matrix, $\Sigma_t(z_t)$. We assume that this correlation varies depending on a random variable z_t, which in our case is the significant wave height (H_t). The varying variance-covariance matrix is estimated nonparametrically. Given a random process $y_i = (y_{i1}, \ldots, y_{iT})^\top$, such that $E(y_{it}) = 0$ and $E(y_{it}y_{i't'}) = \sigma_{ii't}$ if $t = t'$ and zero otherwise. Given that Σ_t is locally stationary, its local linear estimator is defined by

$$\text{vech}(\tilde{\Sigma}_t) = \sum_{j=1}^{T} \text{vech}(y_j^\top y_j) K_h(z_j - z_t) \frac{s_2 - s_1(\tau - t)}{s_0 s_2 - s_1^2} \tag{1}$$

where $s_i = \sum_{j=1}^{T}(z_t - z_j)^j K_b(z_t - z_j)$ for $i = 0, 1, 2$. Note that a single bandwidth is used for all co-movements, which ensures that $\tilde{\Sigma}_t$ is positive definite.

2) Comparing OWCs conversion rate: We employ the functional coefficients SURE (FCSURE) to model MWPP production. It is a system of regressions whose coefficients depend on the significant wave height, which ensures the system's nonlinearity. Each equation explains the electricity production of one OWC, whose production may or may not be correlated to the other OWCs' production. The equation of the FCSURE is expressed by:

$$\begin{aligned}
kWh_{2t} =& \beta_{0,2}(z_t) + \beta_{1,2}(z_t)\ WEF_t + \\
& \sum_{j=2}^{m} \beta_{j,2}\ X_{jt} + u_{2t} \\
& \vdots \\
kWh_{13t} =& \beta_{0,13}(z_t) + \beta_{1,13}(z_t)\ WEF_t + \\
& \sum_{j=2}^{m} \beta_{j,13}\ X_{jt} + u_{13t} \\
kWh_{14t} =& \beta_{0,14}(z_t) + \beta_{1,14}(z_t)\ WEF_t + \\
& \sum_{j=2}^{m} \beta_{j,14}\ X_{jt} + u_{14t},
\end{aligned} \tag{2}$$

The coefficients $\beta(z_t)_{1,k}$ represent the relationship between the WEF at a given time t and the production of Turbine k. This is the quantity that we define as the **rate of conversion** because it represents the rate of change in energy production given the change of 1 unit in WEF. The conversion rate is an unknown function of a random variable z_t, which, in our problem as before, is the significant weight height (H_t). This means that the rate of conversion might not only be different for different OWCs but also for different values of H_t. The rest of the coefficients, $\beta_{j,k}(z_t)$ with $j = 2, \ldots, m$, represent the relationships between the ocean variables, X_t, and the electricity production, kWh_{kt}. The error vector, $U_t = (u_{1t}, \ldots, u_{kt})$ has variance-covariance matrix $E(U_t U_t^\top) = \Sigma_t$ that may be also a function of H_t. Σ_t represents the interdependencies between the different OWCs production.

The estimation of (2) may be done separately for each equation as if there is no correlation in the error term across equations, $Sigma_t$ is the identity matrix for every H_t. In this case, coefficient estimates are obtained by combining the ordinary least squares (OLS) and the local polynomial kernel estimator, extensively studied in [6]. Roughly, these methodologies fit a set of weighted local regressions with an optimally chosen window size. The size of these windows is given by the bandwidth b_i, and the weights are given by $K_{b_i}(z_t - z) = b_i^{-1} K(\frac{z_t - z}{b_i})$, for a kernel function $K(\cdot)$. The local linear estimator general expression is:

$$\begin{pmatrix} \hat{\beta}_i(z_t) \\ \hat{\beta}_i^{(1)}(z_t) \end{pmatrix} = \begin{pmatrix} S_{T,0}(z_t) & S_{T,1}^\top(z_t) \\ S_{T,1}(z_t) & S_{T,2}(z_t) \end{pmatrix}^{-1} \begin{pmatrix} T_{T,0}(z_t) \\ T_{T,1}(z_t) \end{pmatrix} \tag{3}$$

with

$$S_{T,s}(z_t) = \frac{1}{T} \sum_{i=1}^{T} X_i^\top X_i (z_i - z_t)^s K\left(\frac{z_i - z_t}{b_i}\right) \tag{4}$$

$$T_{T,s}(z_t) = \frac{1}{T} \sum_{i=1}^{T} X_i^\top (z_i - z_t)^s K\left(\frac{z_i - z_t}{b_i}\right) y_i \tag{5}$$

and $s = 0, 1, 2$. We denote (3), the functional coefficients OLS (FCOLS) estimator.

Assuming interdependency between the production of all OWCs because they share the same ocean site, Σ_t is used in the estimation of (6), generating the functional coefficients generalised least squares (FCGLS) estimator. The expression of the FCGLS is the same as in (3), but its terms include the covariance matrix:

$$\begin{aligned} S_{T,s}(z_t) &= \frac{1}{T} \sum_{i=1}^{T} X_i^\top K_{B,it}^{1/2} \Sigma_i^{-1} K_{B,it}^{1/2} X_i (Z_i - z_t)^s \\ T_{T,s}(z_t) &= \frac{1}{T} \sum_{i=1}^{T} X_i^\top K_{B,it}^{1/2} \Sigma_i^{-1} K_{B,it}^{1/2} Y_i (Z_i - z_t)^s, \end{aligned} \tag{6}$$

where $K_{B,it} = diag(K_{b_1,it}, ..., K_{b_N,it})$ and $K_{b_i,it} = (Tb_i)^{-1} K((Z_i - z_t)/(Tb_i))$ is the matrix of weights introducing smoothness according to the vector of bandwidths, $B = (b_1, \ldots, b_N)^\top$.

The FCGLS assumes that Σ_t is known. In practice, this is unlikely and must be estimated as we explained above.

3) Forecasting plant production: When the study's main objective is to understand the plant's production process, often knowing the production one hour ago gives an accurate estimation of current production. Adding lagged terms of production to (2) that carry this information produces the following model:

$$\begin{aligned} kWh_{2t} =& \beta_{0,2}(z_t) + \beta_{1,2}(z_t)\ WEF_t + \sum_{j=2}^{m} \beta_{j,2}\ X_{jt} + \\ & \sum_{k=1}^{p} \delta_{k,2}(z_t)\ kWh_{2,t-k} + u_{2t} \\ & \vdots \\ kWh_{13t} =& \beta_{0,13}(z_t) + \beta_{1,13}(z_t)\ WEF_t + \sum_{j=2}^{m} \beta_{j,13}\ X_{jt} + \\ & \sum_{k=1}^{p} \delta_{k,14}(z_t)\ kWh_{14,t-k} + u_{13t} \\ kWh_{14t} =& \beta_{0,14}(z_t) + \beta_{1,14}(z_t)\ WEF_t + \sum_{j=2}^{m} \beta_{j,14}\ X_{jt} + \\ & \sum_{k=1}^{p} \delta_{k,14}(z_t)\ kWh_{15,t-k} + u_{14t}. \end{aligned} \tag{7}$$

Coefficients $\delta_{kj}(\cdot)$ represent the relationships between lagged production and current production. In our study, we use only one lag (p=1). We denote this model as the functional coefficient vector autoregressive model, FCVAR(1)—H, whose estimation is done with the FCOLS.

III. Empirical results

A. Comparing OWCs production

Analysing the correlation between all OWCs in MWPP can provide valuable insights into the plant's functioning and performance. If the correlation is high, the devices react similarly to ocean conditions, showing a good design and consistent plant maintenance. However, if the correlation is low, showing the differences in performance between several OWCs might indicate a possible design or operational flaw. We expect a strong correlation between the production of all OWCs in our analysis. We also expect a different correlation for different ocean conditions. In particular, we expect a different correlation value for different significant wave heights.

Fig. III-A shows that the correlation between the production of Turbine 13 and the other MWPP turbines is close to one for small waves and decreases to 0.2 for bigger ones. This behaviour change might happen because Turbine 13 is more or less efficient than the rest at converting ocean energy to electricity for large waves.

We see the varying correlation between the production of Turbine 2 and the other turbines in Fig. III-A. The correlation has value one between the production of Turbines 2 and 4, independently of the wave height. These two turbines are placed near each other in the plant, which might explain their similar performance. However, other factors should be involved in their equal performance because the correlation between the production of Turbines 2 and 3 is one for waves up to 1.5 m but decreases to 0.4 for higher waves. Similar behaviour appears between the production of Turbines 2 and 8.

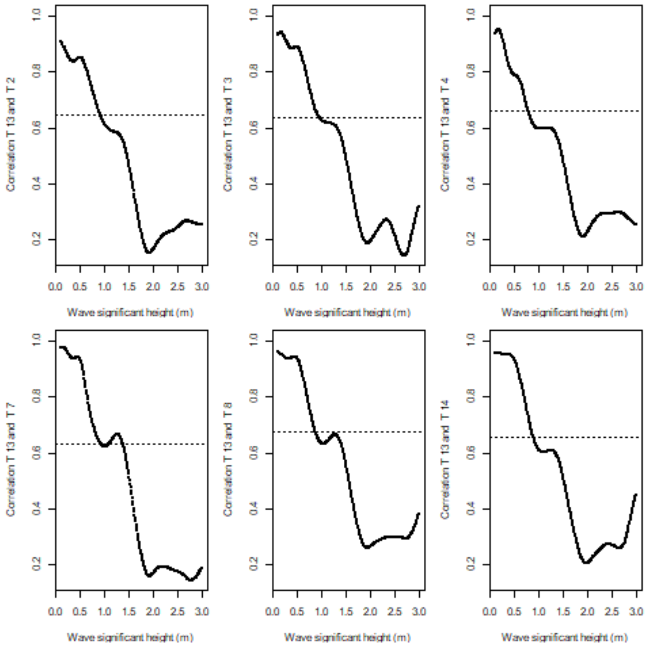

Fig. 3. Varying correlation between Turbine 13 and the other turbines.

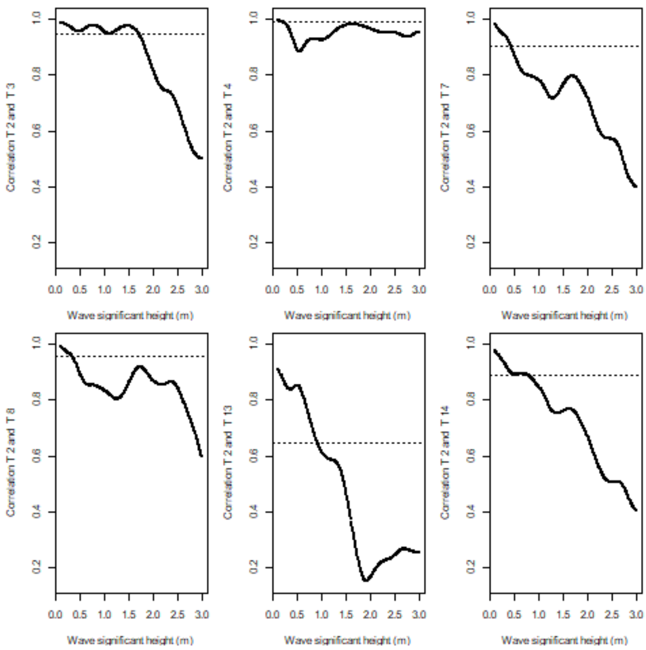

Fig. 4. Varying correlation between Turbine 2 and the other turbines.

The correlations between the production of Turbine 4 and the other turbines in Fig. III-A vary, having values close to 1 for small wave heights and decreasing as the wave height increases.

In summary, electricity production of all OWC for small waves is highly correlated, and this correlation decreases quickly for larger waves. This shows a difference in the behaviour of OWC at MWPP for different ocean conditions, which indicates the need to consider this information when we analyse each OWC's conversion rate.

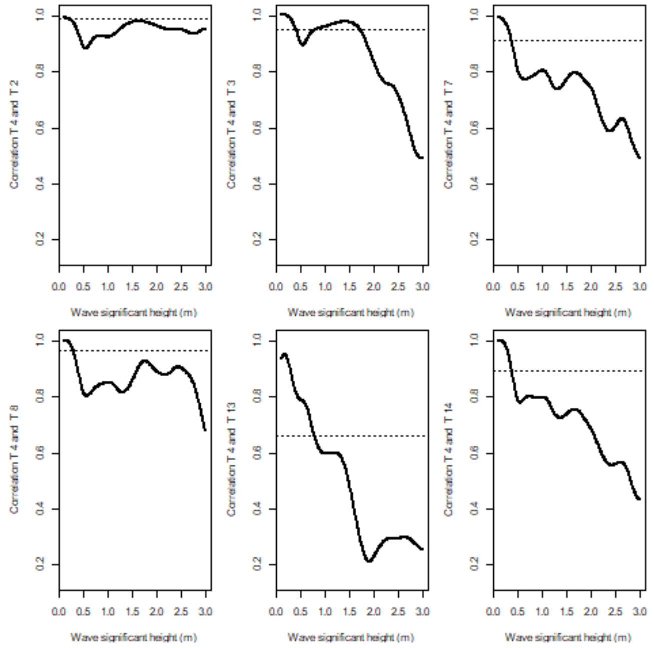

Fig. 5. Varying correlation between Turbine 4 and the other turbines.

B. *Comparing OWCs conversion rate*

We are interested in the coefficient of the WEF for each OWC. It represents the conversion rate of WEF into electricity. Optimally, all OWCs have the same conversion rate, indicating a well-designed and consistently maintained plant. Fig. III-B shows the conversion rate of WEF into kWh for each turbine in the analysis. The blue line is the conversion rate estimated by the FCOLS not considering the interdependencies of all OWCs' production. The black line is the conversion rate estimate by the FCFGLS, which uses a non-parametric estimate of Σ_t to link the production of every OWC in the system. Fig. III-B shows that the OWCs are more efficient in converting WEF into energy for smaller than larger waves. Second, there are apparent differences between the FCOLS and FCFGLS conversion rate estimates for turbines 7-14 and small waves. The FCOLS conversion rate estimates are about double the FCFGLS conversion rate estimates for those turbines and small waves. Thus, the FCOLS describes a picture in which Turbines 2-4 are less efficient than Turbines 7-14, while the FCFGLS estimates are roughly the same for all turbines. The FCFGLS estimates say that keeping all other conditions equal, we can expect an increase of 0.4 kWh in energy production for every additional 1 kW/m of WEF for every turbine and small waves. This rate decreases almost linearly until 3 m waves when the conversion rate is zero.

C. *Forecasting plant production*

Each OWC at Mutriku has an electrical generator of 18.5 kW. Therefore, the seven turbines in our study yield 129.5 kW. In 2019, its annual generation was 193579.3 kWh during 8616 hours, leading to a capacity factor of 17.35%. In comparison, the FCOLS estimated a capacity factor of 17.39%, the FCFGLS of 17.33% and the FCVAR(1) estimated a capacity factor of 17.34%.

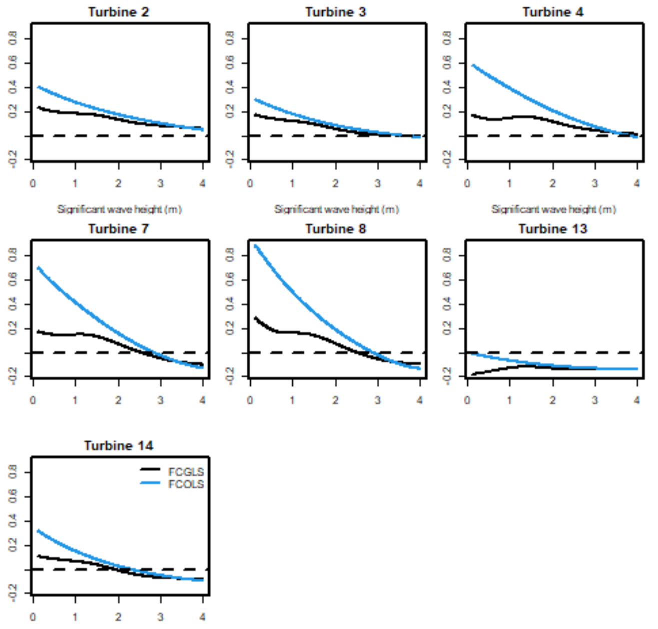

Fig. 6. Estimation of conversion rate of WEF into kWh for each turbine in the analysis. There are differences in the conversion rate estimation between Turbines 2-4 and Turbines 7-14 when using the FCOLS. Not considering the interdependencies between OWCs' production in the estimation model suggests that turbines 7-14 are more efficient than turbines 2-4 at converting ocean energy.

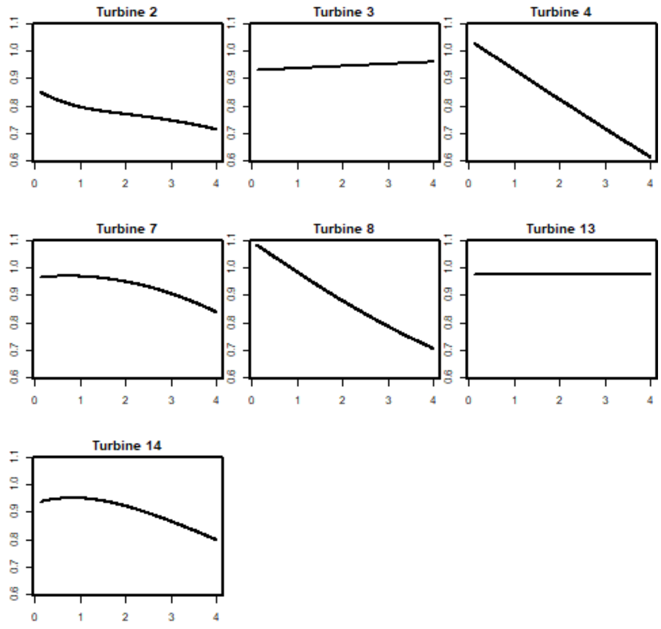

Fig. 7. Estimation of relationship between kWh_t and kWh_{t-1} for each OWC. We see a constant relationship for most OWC independently of the wave height. However, Turbines 4 and 8 behave differently.

TABLE I
PRODUCTION ESTIMATION PERFORMANCE OF THE THREE MODELS IN OUR ANALYSIS.

capacity factor	MSE	MAE	
FCOLS	17.39	27.69	9.42
FCFGLS	17.33	38.22	9.63
FCVAR(1)	17.34	3.94	2.44

The FCVAR(1) also has the smallest mean squared and mean absolute error of the three models (see Table III-C). So, we suggest the use of lagged production values to estimate production.

Fig. III-C displays the coefficient estimates of kWh_{t-1} for all OWCs from (7). As expected, these coefficients are almost constant and close to one, meaning these relationships are the same for every ocean condition. However, we see a discrepancy in this result for Turbines 4 and 8, whose relationship between the one-hour ago and current production decreases rapidly as the significant wave height increases. We do not have any answers for this erratic behaviour, and a deeper investigation is needed on the functioning of these two turbines in 2019.

IV. Conclusions

This paper aims to model a system of OWC that conforms to a wave power plant. The easiest way is to model them independently, and we show that this approach can produce biased estimates of the conversion rate when there is a correlation between all OWC production. We propose using a system of equations linked by their variance-covariance matrix to correct this bias. Results from the seven MWPP's OWCs during 2019 in our dataset show that they all function similarly, having their most significant convergence rate for small waves.

On the other hand, we propose to use autoregressive terms when the aim is to model the production process. In this case, the focus is not on knowing how the OWC is functioning at different ocean conditions but on getting an accurate estimation of the whole plant production, and autoregressive terms carry most of this information.

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