

# Characterizing the Spanish hydro basins for their use in openTEPES

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The logo for the World openTEPES Conference features a stylized graphic of three overlapping squares in green, blue, and orange above the text. The word "World" is in blue, "openTEPES" is in green, and "Conference" is in a lighter green.

World  
openTEPES  
Conference

The openTEPES logo consists of a stylized graphic of three overlapping squares in green, blue, and orange above the text. The word "open" is in blue and "TEPES" is in a darker blue.

open  
TEPES



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## 1. Introduction

- The Significance of Hydropower Generation
- Challenges in Modeling Hydropower Generation

## 2. Methodology

- Our first approximation: Regression models
- Model Training and Validation

## 3. Results

- Results
- Model Interpretation and Insights

## 4. Conclusions

- Future directions and challenges



## 1. Introduction

2. Methodology

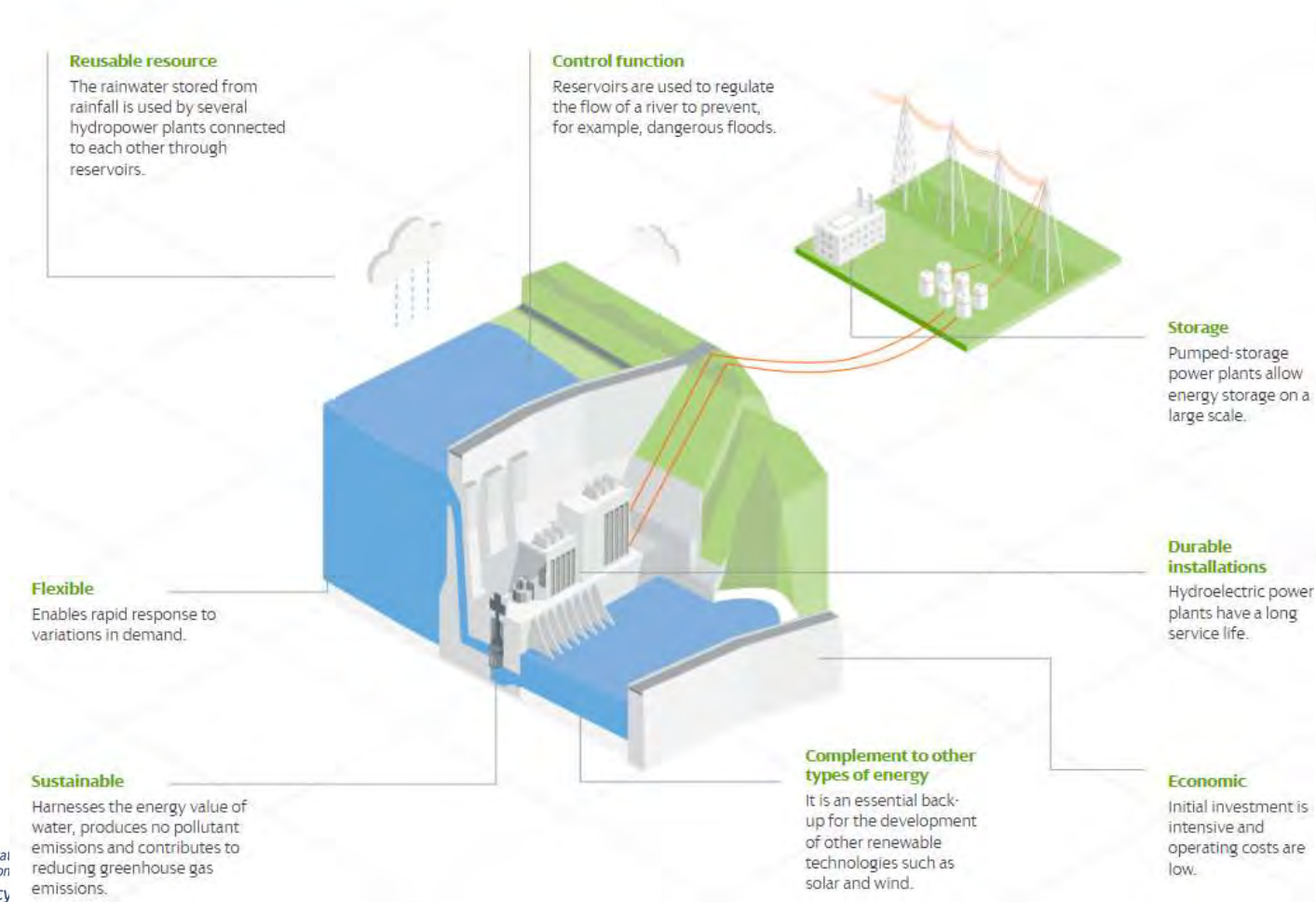
3. Results

4. Conclusions

# The Significance of Hydropower Generation



## Advantages of hydropower



# Challenges in Modeling Hydropower Generation



## REAL LIFE

ENVIRONMENTAL CONSTRAINTS

OPERATIONAL CONSTRAINTS

REGULATORY CONSTRAINTS

## MATHEMATICAL MODEL

- Natural water inflows uncertainty
- Minimum and maximum power and reservoir levels
- Minimum number of units on line
- Upward and downward ramping rates
- Reservoir level restrictions
- Total release volume

And if we want to conduct a planning study, considering the model configured in openTEPES, how can we incorporate these features?



1. Introduction

**2. Methodology**

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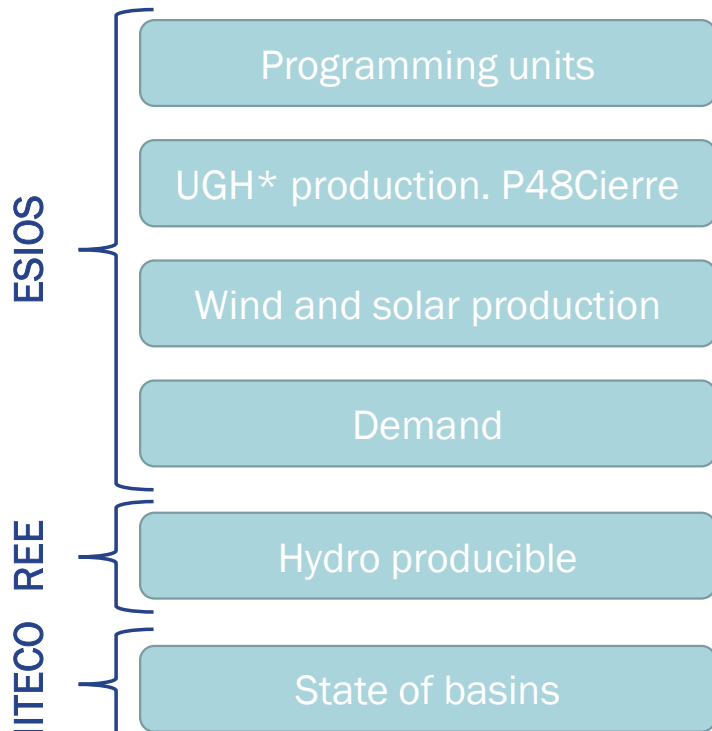
# Our first approximation: Regression models



Modeling dynamic minimum and maximum power and dynamic upward and downward ramping rates as a function of other variables

What do we have?

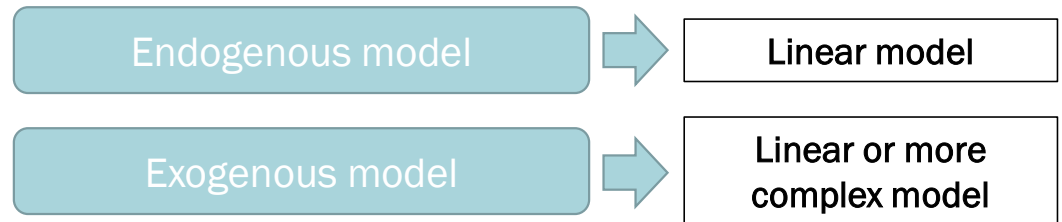
What do we expect?



$$P_{max} = f(\dots)$$

$$P_{min} = f(\dots)$$

$$\frac{dP}{dt} = f(\dots)$$

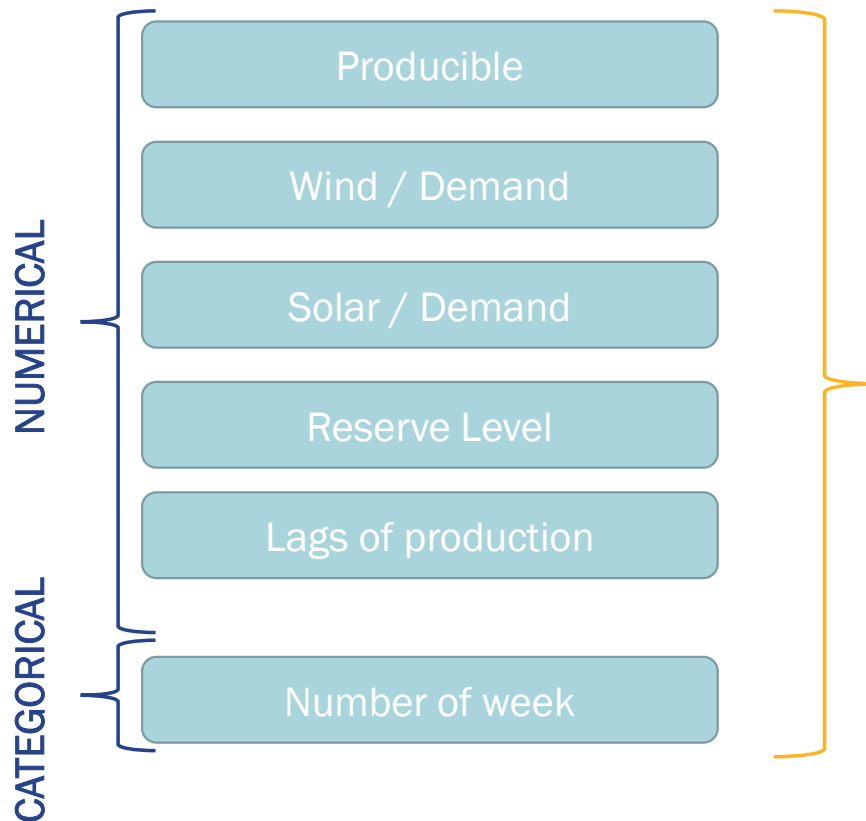


\* UGH: "Unidad de gestión hidráulica" (Hydro management unit)

# Model training and validation



## Predictor variables



## Data set

Production: 2011 – 2019 hourly  
 Producibile: 1991 – 2023 monthly  
 Wind, solar, and demand: 2012 – 2020 monthly  
 Water reserve level: 1988 – 2023 weekly  
 Training set: 70%  
 Test set: 30%

### Linear model

- OLS
- Bayesian linear regression (OLS with Lasso)

### Linear or more complex model

- Neural networks (MLP)





1. Introduction

2. Methodology

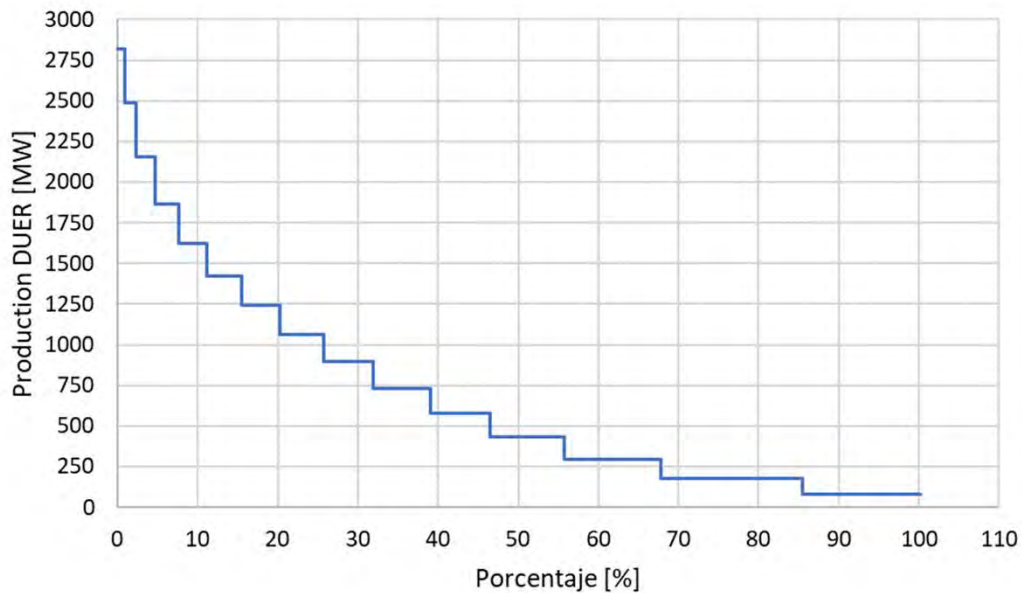
**3. Results**

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# Minimum and maximum power



What production value should we choose to model the minimum and maximum in an operational context?



Procedure (duration curve):

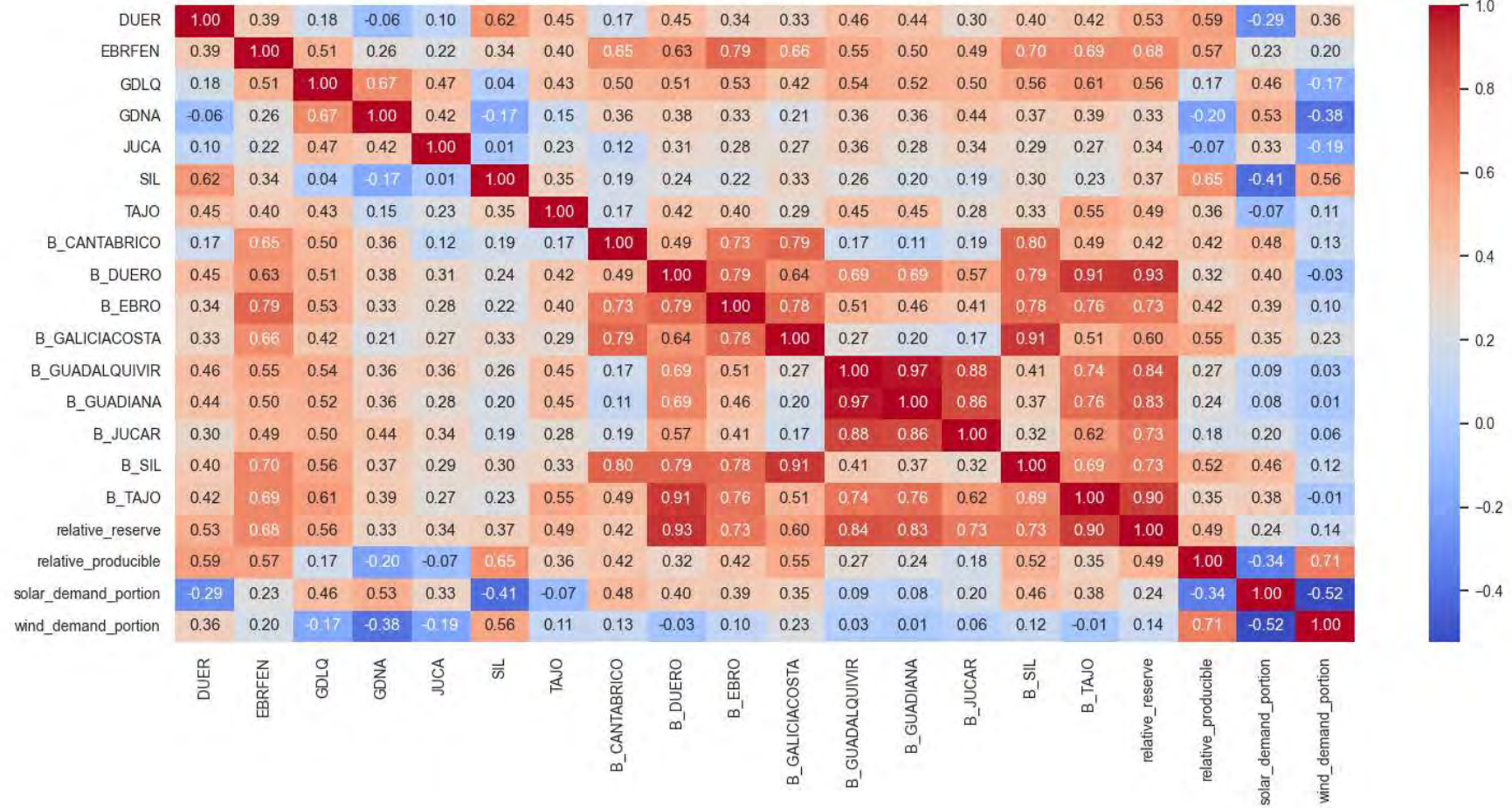
1. The production will be clustered into 15 groups
2. Plot the empirical probability distribution for each centroid
3. Select the first and last clusters as Pmax and Pmin, respectively

DUER:

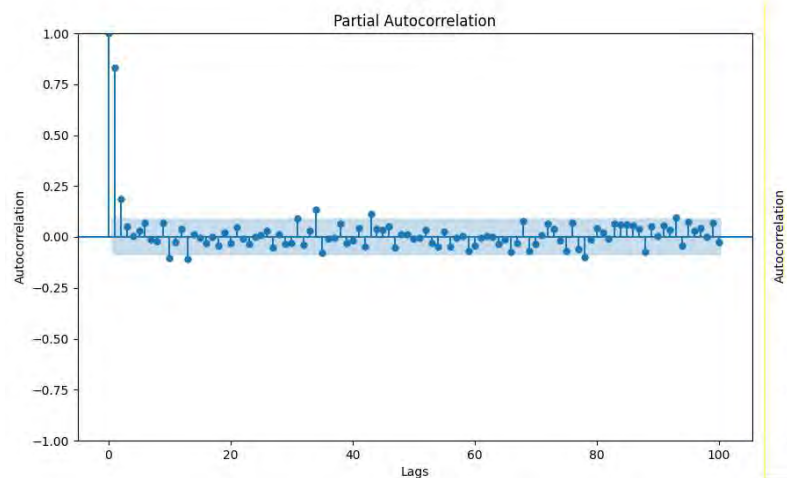
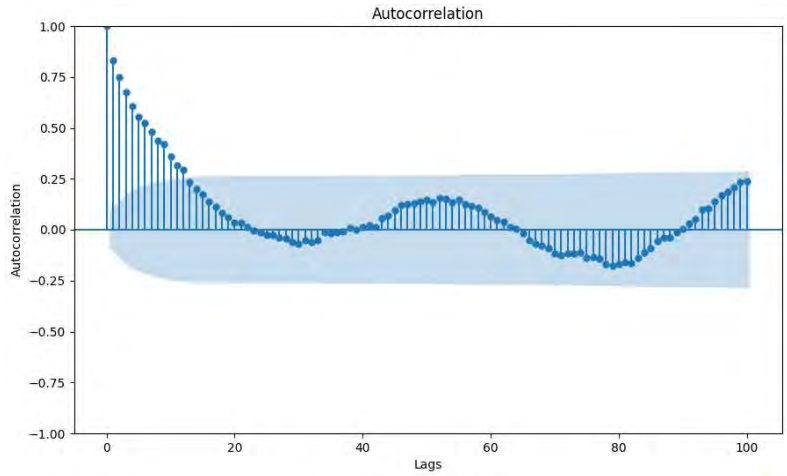
Pmax = quantil 99

Pmin = quantil 15

# Linear regression analysis



# Exogenous model



### Linear model

OLS Regression Results

```

Dep. Variable:          DUER      R-squared:                0.730
Model:                  OLS      Adj. R-squared:           0.726
Method:                 Least Squares   F-statistic:              173.4
Date:                   Mon, 17 Jul 2023   Prob (F-statistic):       6.09e-89
Time:                   19:32:11         Log-Likelihood:           -248.89
No. Observations:      327             AIC:                      509.8
DF Residuals:          321             BIC:                      532.5
DF Model:               5
Covariance Type:       nonrobust
    
```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0958	0.059	0.281	0.881	-0.051	0.063
relative_producible	0.2339	0.050	4.714	0.000	0.136	0.331
wind_demand_portion	-0.0751	0.044	-1.690	0.092	-0.162	0.012
solar_demand_portion	-0.0990	0.034	-2.954	0.003	-0.165	-0.033
DUERlag1	0.5742	0.056	10.258	0.000	0.464	0.684
DUERlag2	0.1491	0.054	2.737	0.007	0.042	0.256

Omnibus: 7.515 Durbin-Watson: 1.946  
 Prob(Omnibus): 0.023 Jarque-Bera (JB): 12.267  
 Skew: 0.031 Prob(JB): 0.00217  
 Kurtosis: 3.947 Cond. No. 4.32

Notes:  
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.  
 R^2 score linear regression in the test set: 0.7525112471393269

- R<sup>2</sup> Training set: 0.73
- R<sup>2</sup> Test set: 0.75

Significant variables:

- Producible
- Solar/demand
- Lag 1
- Lag 2

Wind/demand (p-value > 0.05)

### Bayesian linear model (Lasso)

```

R^2 lasso: 0.7091400496239069
R^2 lasso in the test set: 0.7417066642015798
coefficients lasso: [ 0.14425389  0.          -0.00234461  0.55955267  0.10291472]
intercept lasso: 0.008730207738090592
    
```

- R<sup>2</sup> Training set: 0.709
- R<sup>2</sup> Test set: 0.742

### Neural Networks (MLP)

```

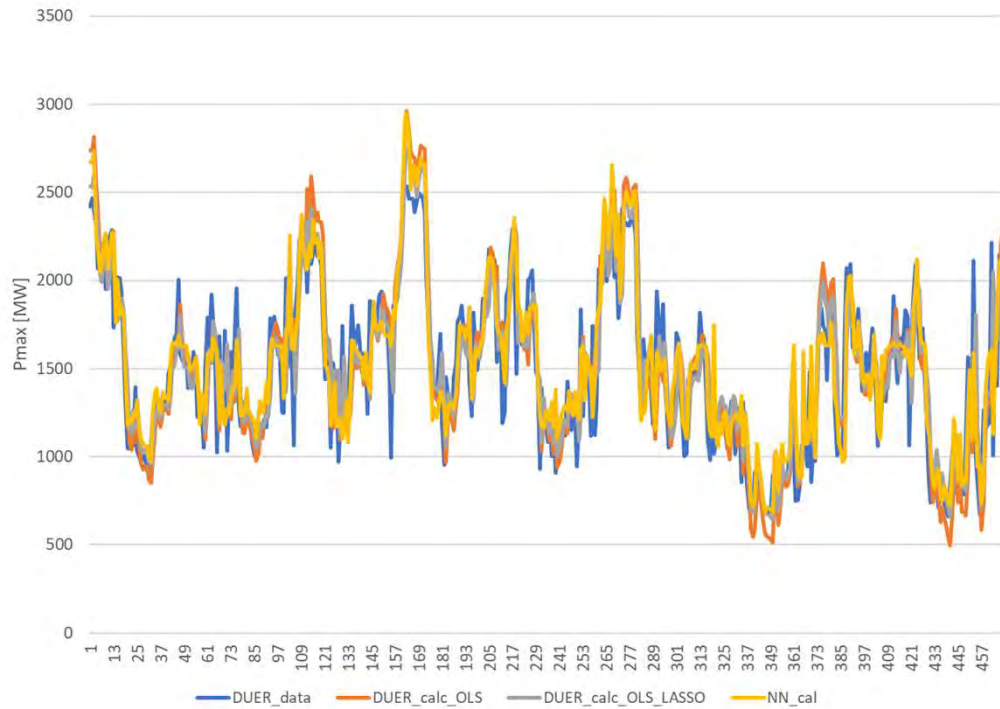
R^2 score neural network: 0.8451768864529361
5/5 [=====] - 0s 750us/step
R^2 score neural network in the test set: 0.6718192231708278
    
```

- R<sup>2</sup> Training set: 0.845
- R<sup>2</sup> Test set: 0.672

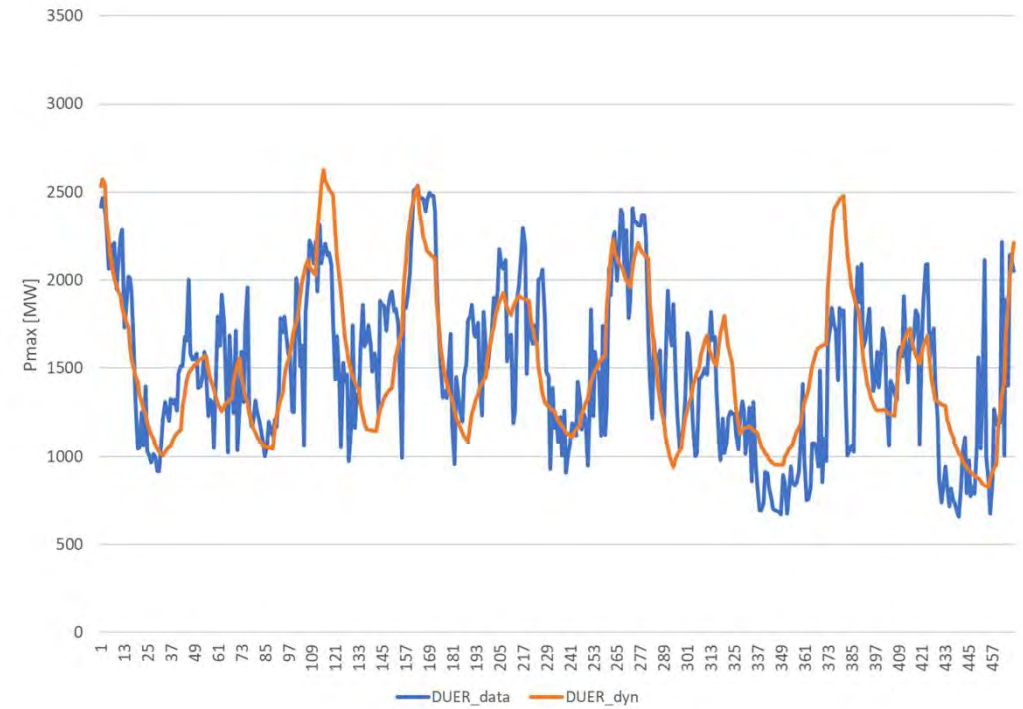
# Model interpretation and insights



### Different models

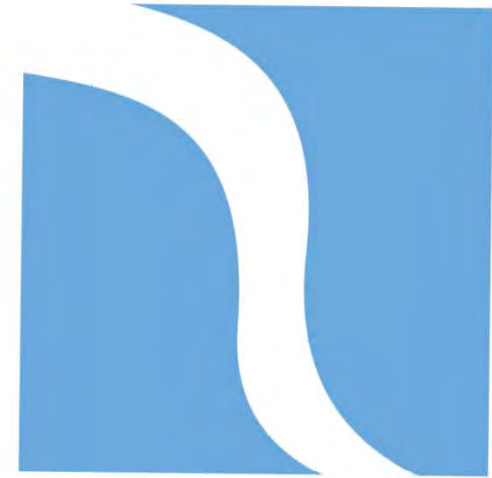


### Lasso (Dynamic)





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# Conclusions

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- Modeling the time-dependent maximum and minimum power, as well as the ramp-up and ramp-down rates, is a first approximation to capture many of the constraints of hydropower
- The duration curve is a useful tool to determine the percentile associated with the minimum and maximum values of a variable
- Linear models adequately represent the objective of this study
- *How to improve the prediction of models that considers temporal correlation?*

# Thank you

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**Break 10 min**

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