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# Digitalization in hydropower generation: development and numerical validation of a model-based Smart Power Plant Supervisor

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**Abstract.** The paper presents the development of a model-based Smart Power Plant Supervisor, a digital tool targeting the optimization of the operation and maintenance of hydroelectric units to improve ancillary services provision to the power system. The paper focuses on a control-oriented modelling methodology which allows integrating the operational parameters of the hydroelectric unit in an optimization algorithm steering the advanced control of the units. The technique to develop analytical functions representing the behaviour of the hydropower plant is presented and validated by comparing numerical simulations with measurements of the real time operation of the run-of-river hydropower plant Vogelgrun. The results show a good performance of the modelling technique able to correctly predict the power generation of the power plant over one month of operation.

## 1. Introduction

The European Energy Strategy 2050 is prescribing a very ambitious rise in annual production of renewable energy sources, and grid regulation services are increasingly important in the course of a massive integration of intermittent renewable energy sources.

Nowadays, in Europe, hydropower already plays a key role in the generation mix by counting for the 16.8% of the total electricity production [1] and providing to the power system several ancillary services for frequency regulation. However, in the foreseen scenario of high share of volatile renewable energy supply, the hydropower sector is facing enormous challenges: it has to be ready to support the needs of the future power system by implementing a profound modernization to push the hydraulic machine operation at its limits in terms of both extension of the operating range and hours of operation [2, 3]. For a successful modernization, it is crucial to have a comprehensive knowledge of the critical operation limits and to optimize the predictive maintenance to exploit the machine flexibility at its maximum by guaranteeing its availability and safety.

The existing predominant maintenance philosophy in the hydropower sector is the periodic maintenance. It requires to stop the hydroelectric unit at regular intervals, depending on the hours of operation and to repair a certain component when a damage is found. This approach results in arbitrary, unforeseen and costly outages of generating units. Since a few years, Maintenance 4.0 is providing new tools for improving asset management towards the early detection of the changes in the behaviour of the monitored parameters by establishing various health indices in real time, and processing them in advanced algorithms to anticipate problems and plan ahead.

Nowadays, digitalization and artificial intelligence have a profound impact on the power sector and hydropower is not an exception. Recent studies have shown the interest of applying data-driven methods such as multivariate regressive methods and artificial neural network to the data collected during the



hydropower plants operation or reduced scale model tests to predict critical phenomena during operation and condition monitoring [5, 6, 7], such as oil leakage [8], cavitation erosion [9], fatigue [10] and performance degradation [11]. Survival models have been implemented to predict hydraulic turbine failures [12] in case the system is characterized by a high failure rate allowing the training of the models. Nevertheless, digitalization in hydropower generation is still at the dawn of its development, and it certainly requires deeper research activities to implement effective forecasting and decision-making tools to assess the health of the hydroelectric system, suggest maintenance, and optimize the operation [13, 14, 15, 16].

This paper presents the development and the numerical validation of a model-based digitalization tool, the Smart Power Plant Supervisor (SPPS), within the framework of the EU-H2020 project XFLEX HYDRO. The goal of the SPPS is to improve the flexibility and lifespan of the hydropower plant by optimizing its operation and maintenance thanks to a model-based advanced control. In this work, a control-oriented modelling tool is proposed, while the advanced control and the integrated optimization algorithm are out of scope for the study. The SPPS contributes to the digitalization of the hydropower generation, and in particular to the Maintenance 4.0 asset, as it integrates the conversion of the deep knowledge of the hydroelectric units behaviour and operational parameters into meta-models which can be read and leveraged by an advanced automatic control, which can improve both operation and maintenance strategies. This can provide relevant benefits for by the power plant operators by maximizing the availability of the unit and the efficient power production.

The paper is structured as follows: the SPPS methodology is presented in Section 2, while Section 3 present a first case study application. The numerical validation of the modelling technique is presented in Section 4 and followed by the conclusions in Section 5.

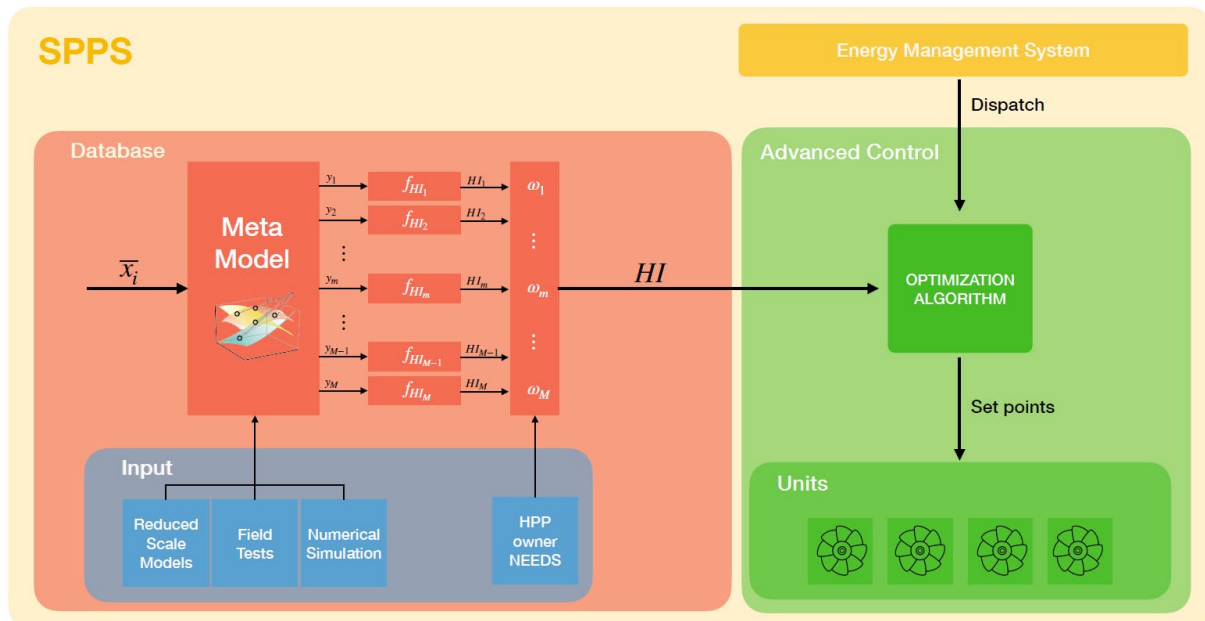
## 2. Methodology

### 2.1. The Smart Power Plant supervisor

Within the XFLEX HYDRO project framework, the Smart Power Plant Supervisor (SPPS) is defined as a system integration methodology of hydroelectric technological solutions based on advanced control and modelling of the operational parameters of the hydropower plant (HPP) units. A schematic representation is illustrated in Figure 1.

The SPPS consists in two main parts: a database able to provide information about the behaviour of the power plant in the different operating points, and an advanced control, driven by an optimization algorithm, which steers and optimizes the HPP units operation. Its function is to elaborate information coming from database and monitoring measurements, to perform a real time computation of the optimal distribution of set points between the different machines of a HPP. By exploiting the additional knowledge given by the database, the SPPS can make choices oriented not only to respect the general set point given to the HPP, but also to maximise the lifetime of the different HPP components, for instance by minimising the wear and tear on one particular unit.

The optimisation algorithm is fed with analytical functions which model the behaviour of the hydroelectric units. Variables such as: efficiency  $\eta$ , damage index, etc. are indicated in Figure 1 as  $M$  database variables  $y_m$ , as they represent the behaviour of the turbine. The meta models provide analytical formulations of the database variables as a function of state variables  $x_i$  of the system, which represents the operational parameters of the hydroelectric unit, such as discharge  $Q$ , head  $H$  and rotational speed  $n$ . Based on database variables the Health Index  $HI$  can be built. The  $HI$  is the sum of  $M$  health indices  $HI_m$ , functions  $f_{HI,m}$  of the database variables, weighted with the weight  $\omega_m$  which estimates the health of the hydraulic system under different operating conditions. The  $HI$  function is computed by the database and embedded in the optimisation problem objective, so that the latter will not only increase the system flexibility and power production but also maximise the availability of the system by reducing the number of maintenance intervals. Finally, real time measurements are collected by the optimisation problem for monitoring the state of the system and updating the database if needed.



**Figure 1.** SPPS Scheme

## 2.2. Input Data

Digitalization and predictive maintenance based on data-driven methods require an extensive database of examples of the variables to be modelled and forecasted over the full range of operation of the hydroelectric unit. For hydroelectric units, there are several sources capable to provide relevant data for a successful modelling of the unit operation. Within the development of the SPPS, three main activities are carried out to fulfil the database: field tests, reduced scale model tests and numerical simulations. Beside these activities, operational statistics and constraints coming from the HPP owner needs are also leveraged to fulfil the database. Each activity is specific to the case study and HPP characteristics and it has to be carefully selected and performed to have a robust database which is leveraged to model the HPP behaviour.

## 2.3. Meta-Models

To have a comprehensive knowledge of the hydropower plant operation and to be able to leverage this information in the advance control algorithms, it is necessary to build meta-models of the relevant database variables, such as energy, efficiency, cavitation, residual life, pressure fluctuation and wear and tear. These meta-models are fed by the input data, defined in section 2.2, which provide a full database of the relevant variables of the operation over an extended operating range. The meta-models must be read by the control block and, therefore, they have to be analytical functions representing each database variable as a function of the variables of operation.

For this purpose, multivariate regressive models are appropriated techniques to build an analytical function of the database parameters which can feed the optimization algorithm of the advance control block.

For instance, the Multivariate Adaptive Regression Spline (MARS) technique [17] is well suited to build surrogate models for a control-oriented purpose. This technique has the ability to fit the database variables with analytical functions, continuous in their first derivative, which are important characteristics for the optimization frameworks. Furthermore, the MARS modelling allows for evaluating the influence of each independent variable by using only an initial exploration data-set which is convenient to validate the selected independent variables [3, 18].

The MARS modelling technique is formulated as follows. By considering a dependent database variable  $y$  as a function of the independent operating variable  $x$ , the MARS approximation is built as a linear statistical model:

$$y = f(x, \gamma) = \gamma_0 + \sum_{p=1}^P \gamma_p \cdot B_p(x) \quad (1)$$

$P$  is the number of independent basis functions and  $\gamma_p$  the unknown coefficient for the  $p^{\text{th}}$  basis function.  $B_p(x)$  denotes the basis function which is built as a combination of univariate basis functions  $b_p^{\pm}$  in the form of a truncated linear function:

$$\begin{aligned} b_p^+(x, t) &= |x - t|_+ = \max(0, x - t) \\ b_p^-(x, t) &= |t - x|_+ = \max(0, t - x) \end{aligned} \quad (2)$$

Where  $t$  is a univariate knot. Each  $B_p(x)$  is computed by multiplying an existing basis function by a truncated linear function involving a new variable, as follows:

$$B_p(x) = \prod_{l=1}^{L_p} \max(0, \pm(x_{v(l,p)} - t_{l,p})) \quad (3)$$

Where  $L_m$  indicates the number of truncated linear functions multiplied in the  $p^{\text{th}}$  basis function,  $x_{v(l,p)}$  is the input variable corresponding to the  $l^{\text{th}}$  truncated linear function, and  $t_{l,m}$  is the knot value corresponding to  $x_{v(l,p)}$ . A forward step-wise algorithm, based on linear regression, selects the model basis functions, the corresponding coefficients and the appropriate knots. It is followed by a backward procedure to prune the model terms to eliminate overfitting [17]. The model fitting performances are evaluated by the Mean Square Error (MSE), by the Coefficient of Determination  $R^2$ , and by the Generalized Cross Validation error (GCV) computed as:

$$GCV = \frac{1}{N_{sp}} \frac{\sum_{j=1}^{N_s} (s_y^{(j)}(x) - y^{(j)}(x))^2}{\left(1 - \frac{N_x}{N_s}\right)} \quad (4)$$

Where  $N_x$  is the number of independent variables and  $N_s$  the number of available samples  $s_y$  of the database variable  $y$ .

#### 2.4. Health Index

All analytical functions of the database variables should be considered by the control algorithm of the SPPS to define the best asset for operation. The database variables might have different importance in influencing the choice of the control algorithms and, therefore, each analytical function should be properly weighted before entering the control block.

The formulation of the total health index (HI) as weighted sum of all the specific  $HI_i$ , allows to define the objective of the control algorithm as the maximisation of the health index function  $HI$  of the power plant.

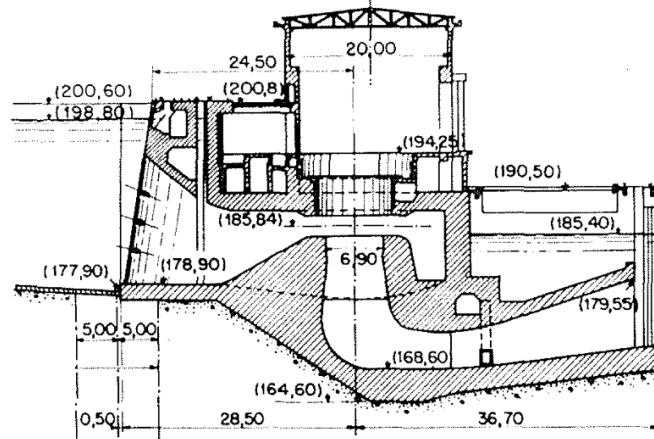
$$HI = \sum_{i=1}^M \omega_i \cdot HI_i(\bar{x}_i) \quad (5)$$

Where  $M$  is the number database variables and  $\omega_i$  are the weights of the different health index function, defined to consider the various needs of the hydropower plants characteristics and targets. This enables the optimisation of operation considering all parameters, instead of looking to a limited number.

### 3. Case study

#### 3.1. Vogelgrun run of river hydropower plant

Built in 1959 on the Grand Canal d'Alsace by the Rhine river in France, the Vogelgrun run of river (RoR) hydropower plant features four low head Kaplan units of 39 MW power capacity each, and 12 m nominal head. A schematic representation of one unit of the Vogelgrun RoR is illustrated in Figure 2. It generates 775 GWh per year which represents among the 10 highest generation schemes in France. This RoR also includes two locks for barge navigation on the Grand Canal d'Alsace used by more than 20 000 boats yearly. The units have long been used for flow and water level control, and today new needs for support the power system frequency balancing are emerging.



**Figure 2.** Schematic of the Vogelgrun RoR Kaplan unit

### 3.2. SPPS application

The implementation of the SPPS in the Vogelgrun RoR has the goal to increase the Frequency Containment Reserve (FCR) provision to the power system by respecting the general set point given by the dispatch plan and maximising the efficiency and the lifetime of the different components of the hydroelectric unit, for instance by minimising the wear and tear. As a first step, the development of the SPPS for this purpose requires the modelling of the behaviour of the double regulated turbine in terms of characteristics curve and unit efficiency. The two database variables which are considered for this study are the turbine efficiency  $\eta$  and discharge  $Q$ . For this preliminary study, the wear and tear of the unit is neglected. Kaplan turbines are regulated by two controllable variables: guide vanes opening angle  $\alpha$  and blade opening angle  $\beta$ . The general gate-dominant proportional-integral (PI) control adjusts the position of the blades as a function (called combinator or CAM) of the guide vanes opening angle and the head, to maximise the efficiency for every head and discharge condition.

The turbine efficiency  $\eta$  and discharge  $Q$  can be modelled as nonlinear functions of the net head  $H$ , guide vanes angle  $\alpha$  and blades angle  $\beta$  as follows:

$$\begin{aligned}\eta &= y_1(H, n, \alpha, \beta) \\ Q &= y_2(H, n, \alpha, \beta)\end{aligned}\tag{6}$$

RoR power plants are characterized by the absence of a penstock, or the presence of a very short one. This allows to neglect the dynamic behaviour and consider Equation (6) as representative of the hydraulic system. Therefore, the turbine head can be considered as equal to the net head.

The head losses, given by the presence of a grill at the water intakes to avoid the entrance of floating debris, are still considered by the study.

The rotational speed of the Kaplan unit is constant, starting from equation (6), it is possible to reduce the number of variables by defining the non-dimensional speed factor  $n_{11}$ :

$$n_{11} = \frac{n \cdot D_{ref}}{\sqrt{H}}\tag{7}$$

Therefore, Equation 6 can be rewritten as:

$$\begin{aligned}\eta &= y_1(n_{11}, \alpha, \beta) \\ Q &= y_2(n_{11}, \alpha, \beta)\end{aligned}\quad (8)$$

A method to obtain analytical continuous functions of these database variables has been developed by leveraging the MARS technique as described in Section 2.3.

The meta-models of these two database variables are built by using a training data-set made by 19'400 samples coming from the available characteristic curves of the hydraulic machine and 101'000 samples randomly collected in the available operational statistics. Both models are then validated on the remaining aforementioned operational statistics, corresponding to other 101'000 samples and verified on a testing data-set made by 1-month operational statistics of the successive year. Similarly to [3], the best function degree is selected by performing a preliminary model considering all the parameters and evaluating the coefficient of determination  $R^2$  by changing the maximum function degree between 1 and 5.

For validation, the power generation is computed by running numerical simulation over one month of real time operation of the Vogelgrun power plant.

The power generation of a hydroelectric unit is computed as follows:

$$P = \rho \cdot g \cdot H \cdot Q \cdot \eta \cdot \eta_e \quad (9)$$

Where the density of the water  $\rho$  is considered equal to 1000 kg/m<sup>3</sup> and the gravitation acceleration 9.81 m/s<sup>2</sup>.  $\eta_e$  represents the efficiency of the synchronous generator and it is modelled by a fitting polynomial function at the 5<sup>th</sup> order by using the manufacturer capability curve of the machine. The net head is measured onsite and collected in the operational statistics, while the discharge and the hydraulic machine efficiency are estimated by the meta-models depending on the recorded  $n_{11}$ ,  $\alpha$ ,  $\beta$  which are also available in the collected operational statistics.

In this test case, the health index of the efficiency and discharge metamodels are defined as:

$$\begin{aligned}HI_\eta &= 1 - \eta \\ HI_Q &= (Q - Q_{set})^2\end{aligned}\quad (10)$$

The global health index for this case study is, therefore, defined as follows:

$$HI = \omega_\eta \cdot HI_\eta + \omega_Q \cdot HI_Q = 1 - \eta + (Q - Q_{set})^2 \quad (11)$$

Where the choice of  $\omega_\eta$  and  $\omega_Q$  can be made to prioritize the efficiency of HPP over the discharge tracking, or viceversa.

## 4. Numerical Validation

### 4.1. Efficiency and discharge meta-model

The best performances of the MARS technique for both efficiency and discharge surrogate models are achieved with a sum of piece-wise cubic spline. The fitting performances, defined in Section 2.3, are summarized in Table 1. Both meta-models achieve good performances and accurately fit the samples of the training and validation database.

**Table 1.** MARS meta-model performances

Parameter	Efficiency meta-model	Discharge meta-model
$R^2$	0.9984	0.9992
MSE	0.0006	5.2865
GCV	0.0006	5.1799

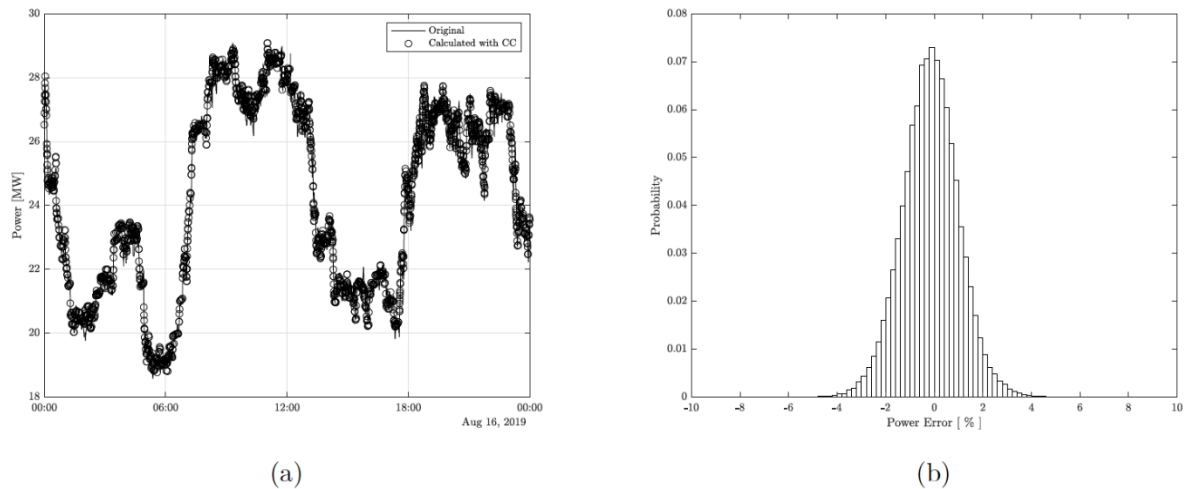


#### 4.2. Production forecast

To check and validate the two meta-models, a comparison with the measured active power generated at the Vogelgrun RoR has been performed over a one-month dataset of operational statistics. The power generated by the unit during one day of operation and the corresponding measured value of the active power is presented in Figure 3 (a). For every second of the day the figure shows the value of active power calculated by using  $Q$  and  $\eta$  as functions of  $\alpha$ ,  $\beta$  and  $n_{11}$ .

The error between simulated power and measured value, for the month-long simulation, is shown in Figure 3 (b). The surrogate model provides an estimation of the produced active power with good approximation, since the error is contained between  $\pm 4\%$ .

This proves the accuracy of the analytical functions and supports the choice of representing the power production by only considering three variables as described in Equation (8).



**Figure 3.** Meta model: (2a) Comparison between measured active power and numerical simulation results for the day of 16th Aug 2019 at Vogelgrün RoR, (2b) Error distribution for a secondly sample one-month dataset.

## 5. Conclusions

In this paper, a control-oriented modelling methodology is proposed within the development of the Smart Power Plant Supervisor, a digital tool targeting the optimization of the operation and maintenance of hydroelectric units to improve ancillary services provision to the power system.

In particular, the structure of the SPPS is presented as a database based on meta-models and the advanced control steered by an optimization algorithm. The modelling technique, focus of the paper, is detailed as well as its numerical validation applied to the Vogelgrun run of river power plant.

The results show that the proposed modelling methodology provide a robust forecast of the power generation of the power plant which can be further leveraged by the control block of the SPPS to find the optimal asset for operation.

In future works the wear and tear will be modelled and included in the health index function to also consider the minimization of the damage function in the choice of the set-points given by the optimization algorithm.

It is expected that, thanks to the presented modelling technique, the operational parameters characteristics of the hydroelectric unit operation can be successfully integrated into an advanced control based and leveraged by an optimization algorithm to define the best operating set-point of the unit. This digital tool has the potential to add several degrees of freedom to the flexibility of the power plant operation and optimise the maintenance interval in respect of the residual lifetime.

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