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Machine learning for transient test sequences in closed-loop hydraulic turbine rigs: optimization of pump operation for stable head

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Abstract. This study utilizes machine learning methods to alleviate head oscillation and shorten the response time during start-up sequences of a Kaplan turbine in a closed-loop test rig. A large amount of experimental data is collected from the test rig. Artificial neural networks (ANNs) are implemented to describe the non-linear relationship between the head, and other operational parameters, such as pump speeds, guide vane opening, etc., during the transient start-up sequences. Then a proportional-integral-derivate (PID) controller is designed to optimize the pump speed operation under a fixed runner blade angle and predetermined change of guide vane opening during the start-up sequences. With the help of the ANN prediction model and the PID controller, a proper pump speed operation is recommended to alleviate head fluctuations. The numerical results are validated and compared against the experimental data in terms of accuracy and usability. The pros and cons of the proposed method are also discussed.

1. Introduction

With the rise of intermittent renewable electric energy sources, such as wind and solar power, hydropower plants (HPPs) have become an important asset for grid balancing and support [1]. It means that hydroelectric turbines need to frequently change their operating conditions, resulting in transient sequences that can cause more wear and tear on the units [2, 3]. At the design stage and for specific studies, hydro turbines are tested in hydraulic turbine rigs. Such tests are traditionally conducted at stationary operating conditions. However, due to the new role of hydropower, there is a need also to perform studies during transient sequences, and today more test rigs are upgraded and adapted for testing transient turbine sequences [4, 5].

In a closed-loop hydraulic turbine rig system, the model turbine is usually installed between two tanks, i.e. an upstream and a downstream tank, where both tanks communicate with one or several pumps. Transient test sequences pose a challenge, as any change in the turbine settings will influence the entire system. A change in the turbine settings requires a corresponding change in the pump speed settings to keep the head constant. The inertia of the water passing through the turbine and the tanks is typically less than the inertia of the water passing the pump and the tanks, resulting in different response times [6]. Moreover, considering the system dynamics, the differences in water inertia, and the polar moment of inertia of the pump impeller and electrical motor, the change in pump speed settings must start before any changes in turbine settings are made. Therefore, an optimal strategy for operating the test stand and keeping the model test head constant during transient sequences is highly demanded. Since the optimal strategy will vary depending on the individual test rigs' design and dynamics, a general method is needed to determine the optimum operating strategy.

In the present work, we propose an pump operation optimization strategy, based on machine learning models and PID controller, designed to mitigate head oscillations during the start-up sequences of a Kaplan turbine within a closed-loop hydraulic turbine testing rig. Section 2 presents the data acquisition and pre-processing, followed by the methodology in Section 3. The machine learning model and controller's results and discussion are given in Section 4. Conclusions are drawn in Section 5.

2. Experimental Setup

2.1. Test rig description

The experimental setup for this study was conducted at the Vattenfall Research and Development Center in Älvkarleby, Sweden, using a closed-loop Kaplan turbine model test rig. The chosen turbine model, U9-400, is a 1:3.875 scale model of the 10 MW Porjus U9 prototype, which is situated along the Luleå river in Porjus, Sweden. The "400" in the U9-400 model name represents the 400 mm runner diameter, and this down-scaled version was specifically selected for the investigation to facilitate studies of transient operation.

A schematic view of the test rig is presented in Figure 1. It is a closed-loop rig, and therefore the flow rate Q is the same in all parts of the system, except that the two parallel pumps may be operated with different shares of the total flow rate. The water is pumped through the flow meter, the high-pressure tank, the turbine model, the low-pressure tank, and returns to pumps 1 and 2. The turbine rotates at runner speed N_t, and the anticipated head H_M is achieved by a proper pump speed N_p (with two pumps sharing the same speed setting in this study), a guide vane opening α, and turbine blade angle β.

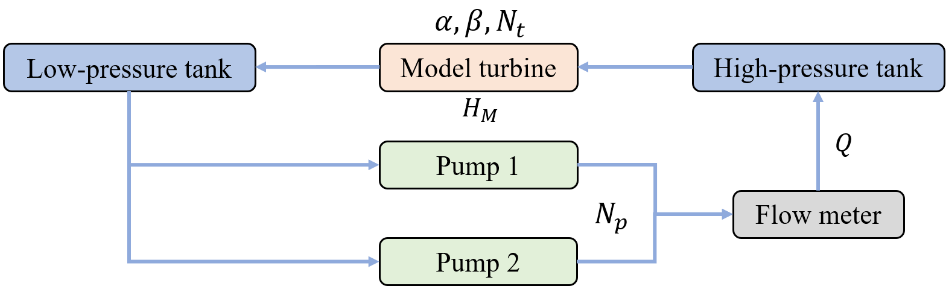

Figure 1. Schematic view of the closed-loop hydraulic turbine test rig.

2.2. Data acquisition

In this study, a total of 55 experimental repetitions of a turbine start-up transient sequences were conducted. The flow rate through the turbine is adjusted by altering the guide vane opening and the runner blade angle. Concurrently, the pump speed is adjusted to maintain a constant test head. The initial head H_M was set at 7 meters, and the runner blade angle β was fixed throughout the experiments. The time variation of the guide vane angle $\frac{d\alpha}{dt}$ was kept consistent across all repetitions. The controlled variable in these experiments was the pump speed N_p, with each test run having a specific ramp-up speed $\frac{dN_p}{dt}$. As a result, unwanted head variations both higher and lower than the target constant value were obtained during the start-up transient sequences.

Figure 2 displays the measurement signals from one experimental run, corresponding to the approximately 40-second start-up sequences. As seen in Figure 2(c), during the start-up sequences, the turbine speed increases from 0 to a stable maximum rotation speed. Concurrently, while adjusting the pump speed and guide vane angle, the head experiences significant unwanted fluctuations. During the measurements, the pump speed was recorded at a frequency of 500 Hz. Other parameters were also recorded at the same frequency but were subsequently downsampled to 200 Hz in the dataset we received.

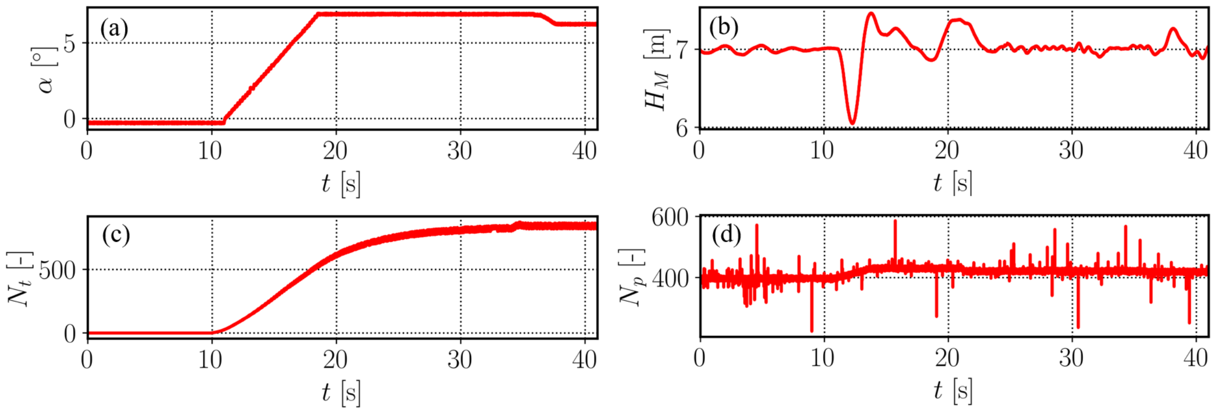

Figure 2. Measurement signals from one experimental run, (a) guide vane angle, (b) head, (c) turbine runner speed, and (d) pump speed.

2.3. Data pre-processing

Given that different variables maintain varying measurement frequencies, the critical step in data pre-processing is the resampling of the data. In this study, each experimental run's data has been down-sampled to 10 Hz.

Figure 2(d) demonstrates that the raw pump speed signal, as initially measured, encompasses considerable spikes and noises. The implemented down-sampling also eliminates those noises and prevents it from introducing significant uncertainty into the establishment of subsequent machine learning models. Figure 3(a) showcases an instance where down-sampling is applied to the pump speed data. In this figure, the red signal signifies the raw data, while the black signal corresponds to the data after down-sampling. As shown, almost all spikes and noises are efficiently filtered out, leaving behind a set of relatively smooth data points.

The final resampled data for all 55 test runs are presented in Figures 3(b), (c), and (d) for head, guide vane angle, and pump speed, respectively. Different colors represent data from different test runs. As seen in Figure 3(c), virtually all test runs share a similar guide vane angle adjustment gradient. The pump speed exhibits a variety of ramp-up speeds, covering a broad range. Correspondingly, the head displays considerable variation within this transient sequence. These final pre-processed data are then fed into machine learning modeling.

3. Methodology

The proposed pump operation optimization strategy for mitigating head oscillation during start-up sequences consists of two key components. The first component is a controller that adjusts the pump speed, enabling the head to approach the desired value with minimal oscillation. The

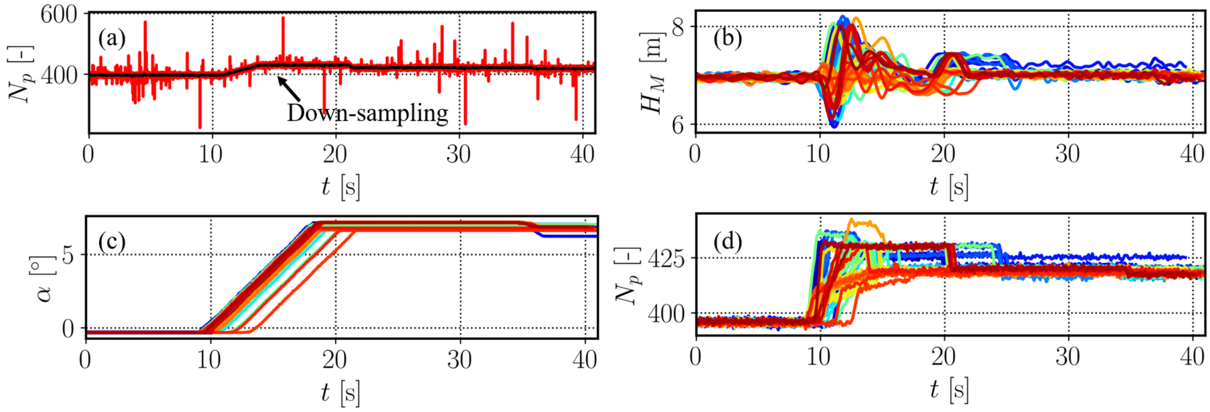

Figure 3. (a) Low-pass filter example for pump speed. Final filtered and resampled data from all 57 test runs, for (b) head, (c) guide vane angle and (d) pump speed.

second component is a predictive model that maps the relationship between pump speed and guide vane opening to the head. This model is critical as it interacts with the controller to produce the predicted head based on different pump settings.

Three methods are commonly employed to predict the head H_M: linear model, internal characteristic model, and non-linear model. Since linear and internal characteristic models are unsuitable for transient processes due to unsteady effects, the non-linear model of ANNs is applied in this study. Furthermore, the PID method is utilized as the primary control technique for regulating the turbine's operational parameters.

3.1. Artificial neural networks

Artificial neural networks are likely the most popular machine learning method for creating complex data-driven (black-box) models. Within a neural network, each neuron is connected to numerous other neurons, enabling signals to traverse the network from the input layer to the output layer in one direction. This includes passing through any number of hidden layers in between. For the turbine rig experiments in this study, since the runner blade angle β is fixed, the head H_M is determined solely by the guide vane opening α and the pump speed N_p. Thus, for a dataset with m samples, the expression for the ANN static model can be written as

$$\hat{H_{M(i)}} = F_{static}(N_{p(i)}, \alpha_{(i)}), \quad i = 1, \ldots, m, \tag{1}$$

where $\hat{H_{M(i)}}$ is the predicted head. An additional dynamic prediction model using ANNs that incorporates the instantaneous slope of the guide vane opening and pump speed is also constructed to account for the acceleration effect during the start-up sequences. This model is expressed as

$$\hat{H_{M(i)}} = F_{dynamic}(N_{p(i)}, \alpha_{(i)}, \frac{dN_{p(i)}}{dt}, \frac{d\alpha_{(i)}}{dt}), \quad i = 1, \ldots, m. \tag{2}$$

The Square Error loss is introduced as the neural networks regression objective function, with a L_2 regularization term $\gamma\|\boldsymbol{w}\|^2$ as

$$Obj = \frac{1}{2}\sum_{i=1}^{m}\left(H_{M(i)} - \hat{H_{M(i)}}\right)^2 + \frac{\gamma}{2}\|\boldsymbol{w}\|^2. \tag{3}$$

Adam, a stochastic gradient-based optimizer is applied to update weights $\boldsymbol{w}$ and minimize the loss [7].

3.2. PID controller

The PID controller is a widely adopted and well-established control method, which combines the proportional (P), integral (I), and derivative (D) components to provide optimal control over various dynamic systems. Taking into account that the control objective in this study is to maintain a less fluctuating desired head H_M^*, the PID controller can be expressed as

$$N_p(t) = K_p e(t) + K_i \int_0^t e(t)dt + K_d \frac{de(t)}{dt}. \tag{4}$$

In this representation, $N_p(t)$ denotes the control signal, i.e., the pump speed at time t, in order to achieve the desired head. K_p is the proportional gain, which proportionally adjusts the control signal based on the magnitude of the error. K_i is the integral gain that accounts for the accumulation of past errors over time, enabling the controller to eliminate steady-state errors. K_d is the derivative gain, and it anticipates future errors by considering the rate of change of the error, thus enhancing the system's response to sudden changes. The error $e(t)$ is defined as the difference between the desired head H_M^* and the ANNs predicted head $\hat{H_M}$ at time t, as

$$e(t) = H_M^*(t) - \hat{H_M}(t). \tag{5}$$

The PID controller is tuned to achieve the desired performance by adjusting the gains of each component (K_p, K_i, and K_d).

4. Results

4.1. ANN models for head prediction

For the head prediction machine learning model establishment, out of the 55 experimental test runs in the dataset, the first 53 runs are used to train and tune the hyperparameters of the ANN models F_{static} and $F_{dynamic}$. The 54th and 55th test runs serve as unseen data to validate the predictive capabilities of the models. Figure 4(a) and (c) present the predictive outcomes of both the static and dynamic models for the two validation scenarios, along with the corresponding pump speed N_p and guide vane opening α settings in Figure 4(b) and (d).

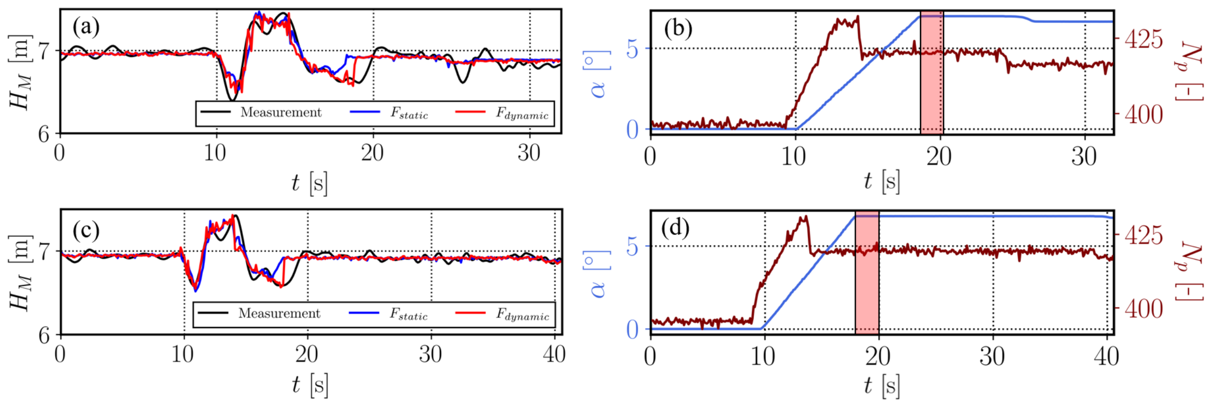

Figure 4. Comparison of head measurements from experimental data and model predictions for (a) the 54th run and (c) the 55th run. Additionally, corresponding guide vane opening α represented by the blue signal aligned with the left y-axis, and pump speed N_p setting indicated by the brown signal aligned with the right y-axis, are displayed for (b) the 54th run and (d) the 55th run.

As demonstrated in Figure 4, both the F_{static} and $F_{dynamic}$ models can capture the overarching trends of the head changes, albeit with certain non-negligible errors. Specifically, neither model

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accurately represents the gradual return of the head to a stable state when $t \approx 20$ s. And a deeper analysis of Figure 4 reveals interesting insights. In both validation cases, as highlighted by the red frames in Figure 4(b) and (d), there exists a phase where both the pump speed and guide vane opening remain constant, immediately after the termination of guide vane adjustments. This phase corresponds to the gradual increase of the head, as depicted in Figure 4(a) and (c). This suggests a delayed response in the pressure recovery within the test rig system, potentially due to the fluid's imperfect incompressibility and possible structural flexibility. This delay, notably when the guide vanes cease their adjustments, could account for the models' inaccuracies in predicting this specific phase.

However, when considered in its entirety, the $F_{dynamic}$ model, which incorporates the gradients $\frac{dN_p}{dt}$ and $\frac{d\alpha}{dt}$, typically provides a closer match to the actual measurements compared to the F_{static} model. As a result, the $F_{dynamic}$ model will be used in conjunction with the PID controller, serving as the basis for the forthcoming pump operation optimization case study.

4.2. Pump speed optimization

In this section, the $F_{dynamic}$ model is employed in conjunction with the PID controller as the optimization strategy to mitigate head oscillation through the optimization of pump speed. The desired set point for the head H_M^* is set at 7 meters, and the 55th test run is utilized as a representative case study.

Figure 5 presents the results of the pump operation optimization. As seen in Figure 5(a), the implemented strategy facilitates a quick return of the head to a stable phase shortly after the pump starts. While there are brief moments of non-negligible oscillation at the outset of the pump operation, the ensuing head readings are largely stable, lacking the large peaks and range of fluctuations observed in the experimental measurements. Compared to the experimentally set pump speed in Figure 5(b), the optimized pump speed increases when the head is about to decrease, thereby elevating the system pressure to maintain the head near its stable value. Conversely, when the system pressure rises and the head is about to increase, the pump speed is reduced to lower the pressure.

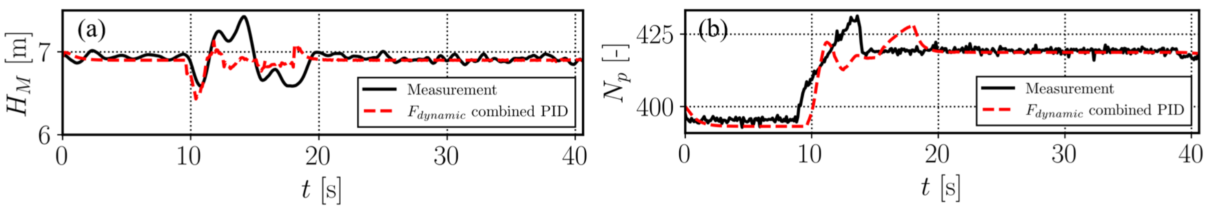

Figure 5. The optimized (a) head and (b) corresponding pump speed setting, for the 57th runs, by model G and the PID controller.

Furthermore, the initial peak (when $t \approx 20$ s) after optimization results from changes in pump speed at steady state that cause variations in flow, leading to substantial pressure changes and, consequently, head fluctuations. This suggests that although head fluctuation cannot be completely eradicated during substantial changes in flow conditions, appropriate adjustments to pump speed, based on the $F_{dynamic}$ model and the PID controller, can effectively minimize the amplitude of head fluctuation and stabilize the head more swiftly.

5. Conclusion

This study demonstrates the potential of using ANN prediction models and PID controllers to optimize pump operation in turbine test rigs, ultimately alleviating head fluctuation in studies of turbine start-up sequences. The main conclusions can be drawn as follows:

- The turbine head in transient sequences predicted by the ANN model that considers the time gradient of the independent variables is more robust than the one without considering the gradient.
- However, the machine learning algorithm currently in use is unable to capture and predict the delayed response in pressure recovery inherent within the test rig system.
- Although head fluctuation cannot be eliminated when there is a significant change in flow conditions, the current optimization strategy effectively reduces the head fluctuation and its duration. It enables the head to achieve the target value in a short time.

In the next stage, more experiments will be conducted using the pump speeds recommended by the optimization strategy to validate the correctness and effectiveness of the proposed method. Since all experimental data in this study are based on the same head and runner blade angle, more experiments with variable changes will be considered in future work to obtain models and optimization strategies closer to actual operation. Moreover, time-dependent machine learning algorithms and more advanced control methods will be applied and compared to further enhance the system's performance.

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