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Adaptive Hybrid 1D Modeling for Digital Twin of Hydropower Systems

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Abstract

This paper presents a progress update on a research project that is being currently funded by the Water-Power Technologies Office of the US Department of Energy per performed and executed by the Oak Ridge National Laboratory (USA) and Pacific Northwest National Laboratory (USA) in collaboration with Norwegian University of Science and Technology or NTNU (Norway). This paper summarizes the dynamic modeling of hydropower systems for the development of digital twin (DT) for hydropower systems. The obtained modeling suite covers the penstock dynamics, turbine and generator dynamics, and linkages to the grid, where linearized models have been developed for various components in the NTNU testing system. In this context, a discretized input and output model for the turbine shaft speed control has been obtained as a starting point to build the adaptively learned models representing the relationship between the guided vane opening, shaft speed, and water head. This allows the establishment of adaptive learning strategy where the data from any reference hydropower generation unit can be used to learn the model parameters. To enhance the robustness of the online learning of model parameters, a modeling error dead-zone based recursive least squares algorithm has been developed. In terms of the synchronous generator, standard d-q axis model has been used. Both the real-time data driven modeling and synchronous generator- simulation have been performed and desired results have been obtained.

Keywords: Hydropower systems; Digital twin; Modeling and simulation; Adaptive learning; Recursive least squares,

1. INTRODUCTION

With the increased penetration of renewables, the operation of power grid needs to deal with large variations in terms of frequency, voltage and power flow regulations and control. This requires hydropower generation to provide fast responding services to the grid. As a result, hydropower generation needs to operate in a large range, even larger than it was before – presenting challenges on solving responsive operational optimization and proactive asset management. To address such challenges, it is imperative to develop a full-scale hydropower digital twin (DT) to provide an effective R&D and operational platform for the hydropower plant operators and utility companies to explore best practices for the process optimization and monitoring (Parrott and Warshaw, 2017; Tao, et al. 2019).

To develop the required digital twin (DT), it is imperative that dynamics of the hydropower generation be modeled well. This requires the modeling of various components of the systems such as penstock, turbine, generator and linkages to the power grid in general. On the other hand, it is also important that digital twin has desired capabilities in terms of user's friendly interface and visualization that can help the users to perform relevant testing on the DT for system operation optimization and fault diagnosis. Once built, it is also expected that the DT can be connected in parallel to the actual hydropower system so that the real-time operation data can be injected into the DT for the updating and tuning of the models. In this perspective, the following problems need to be solved:

1) Adaptive learning of the dynamics of the system needs to be developed so that the models in DT can effectively learn the system dynamics using the real-time data from the operational control system (such as the data from SCADA and DCS systems).

2) Interface and data process tools need to be established that support the adaptive modeling and dialog between the users and the DT.

To solve the first problem, a recursive learning algorithm needs to be developed (Wang, Liu and You, 1991; Goodwin and Sin, 2009; Weldcherkos, et, al, 2021). Since the data from the system contain measurement noises it is important that robust learning algorithm is to be used to realize a reliable learning. In this paper, the dead-zone and normalized recursive least square will be used for the input and output model learning of the hydro-turbine system whilst the standard d-q axis modeling for the synchronous generator will be employed.

In order to address the second problem as stated above, an affordable solution needs to be developed. Indeed, the DT should be affordable to implement and operate. It should be simple enough so that it can be operated by technical workforce that can be easily accessible and can be trained. Regarding data use and integration, DT should have both backward and forward compatibility. In other words, DT should provide a platform that can integrate data from both heterogenous legacy systems and devices and new sensors and equipment using open interoperable protocols and using an open system architecture for creating solutions (Wang, et al, 2021).

To address such requirements, an open platform DT is conceived as the best path forward for providing affordability while offering wide coverage on data integration. In developing the Digital Twin, certain features and functionalities are envisaged as the core elements: 1) capability of accommodating internet of things (IoT) platform; 2) data acquisition, curation, and integration; 3) object modeling that allows easy configuration using user friendly graphical interface; 4) data processing, data modeling and management using Data Orchestration process, and 4) User Interface that shall include a very robust portfolio including simple dashboard, mobile apps, 3D visualization, augmented reality, and virtual reality. The Digital Twin will also have an applications layer for predictive analytics, control, optimization and grid services with an effective user interface. The Digital Twin will be designed to be open access and will serve as an R&D platform for accelerating the pace of developing new technologies for the significant growth and sustainability of the hydropower industry, national labs, and academia.

The paper is organized as follows: In section 2 the adaptive learning algorithm using dead-zone recursive least squares will be described together with the learning results using the real-time testing data from the pilot hydropower plant in the NTNU Waterpower Laboratory. In section 3, the d-q axis modeling for the synchronous generator will be given. Simulation results of the hydropower system is presented in section 4. This is followed by the description of data engineering process using an open-platform.

2. ADAPTIVE LEARNING OF THE TURBINE DYNAMICS

Figure 1 shows a generic structure of a hydropower generation system, where the shaft speed of the hydro-turbine is controlled by the guide vane opening assuming that the turbine is a Francis type.

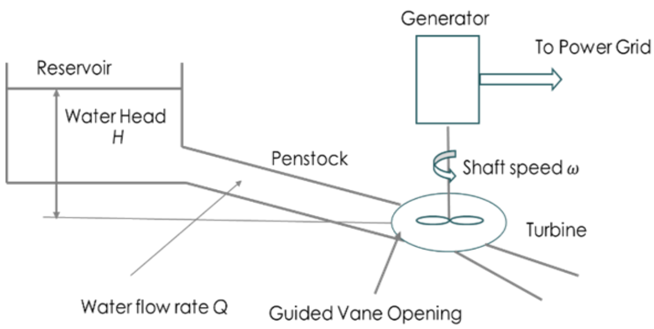

Figure 1. A generic structure of a hydropower generation system.

For such a system, the shaft speed system of a hydro-turbine system can be generally modeled in the following discrete-time input and output form (Wang, Liu and You, 1991; Fang and Shen, 2005):

$$x(k+1) = a_1 x(k) + a_2 x(k-1) + a_3 x(k-2) + b_1 \Delta u(k-1) + b_2 \Delta u(k-2) + c_0 d(k) \quad [1]$$

where $x(k) = x(kT)$ and $\Delta u(k) = \Delta u(kT)$ are the sampled shaft speed and guide vane opening of the turbine in their normalized incremental senses, respectively. $k = 1, 2, ...$ is the sampling index, T is the sampling period for discretization purpose, and $d(k)$ is related to the discretized and normalized incremental value of the load torque with c_0 being a coefficient.

The objective of adaptive modeling and learning is to use the shaft speed and guided vane opening data to estimate the model coefficients in Eq. [1].

To estimate these coefficients in the system, we denote

$$\theta = [a_1, a_2, a_3, b_1, b_2]^T \quad [2]$$

$$\varphi(k) = [x(k), x(k-1), x(k-2), \Delta u(k-1), \Delta u(k-2)]^T \quad [3]$$

Then, when the test runs for the data collection are under a fixed load condition (i.e., $d(k) = 0$), Eq. [1] can be simply expressed by

$$x(k+1) = \theta^T \varphi(k) \quad [4]$$

Assuming that the current sample time is $(k+1)T$ and the data have been available from $k = 1$ up to $k + 1$, the dead-zone normalized least squares algorithm can simply be used to recursively estimate the parameters as shown in the following form.

$$\hat{\theta}(k+1) = \begin{cases} \hat{\theta}(k) + \frac{P(k)\varphi(k)\varepsilon(k)}{m(k)}, & ||\varepsilon(k)|| > \varepsilon_0 \\ \hat{\theta}(k), & otherwise \end{cases} \quad [5]$$

where ε_0 is a pre-specified small threshold that reflects the noise bound in the real-time date and it has been further included that

$$\varepsilon(k) = x(k+1) - \hat{\theta}^T(k)\varphi(k) \quad [6]$$

$$P(k+1) = P(k) - \frac{P(k)\varphi(k)\varphi^T(k)P(k)}{m^2(k)} \quad [7]$$

$$m(k) = \sqrt{(\delta + \varphi^T(k)P(k)\varphi(k)} \quad [8]$$

where δ is a small number typically less than 0.05, and the initial values of $\{\theta(k), P(k)\}$ are pre-specified, respectively, based upon the pre-knowledge of the system parameters and operating conditions.

Tests were conducted with changes in experiment conditions at the test rig at NTNU in June and July 2022. The system was set up in an open loop control mode initially with guide vane opening as the input and the shaft speed and water head as the outputs.

In this configuration, the guide vane opening (u) was directly changed while keeping other initial conditions fixed; the system load L was fixed at 378 N·m and its normalized incremental value $d(k) = 0$, and the power generated was 14.9 kW. In this experiment, the maximum guide vane opening angle was 14°. To collect the data, it went from 5.60° to 4.60°. These changes reflect the open-loop tests in which the input was the guide vane opening and the outputs were the shaft speed and water head.

Figures 2 – 3 shows the adaptive modeling results when the proposed dead-zone recursive least square algorithm is used, where the speed response and its estimate (red color) is given in the top half of Figure 2 and the water head and its estimated response (red color) are displayed in Figure 3. The bottom diagram of Figure 2 shows the response of the guide vane opening in percentage variations. These responses show that the proposed adaptive learning works well in terms of tracking the system dynamics for the turbine.

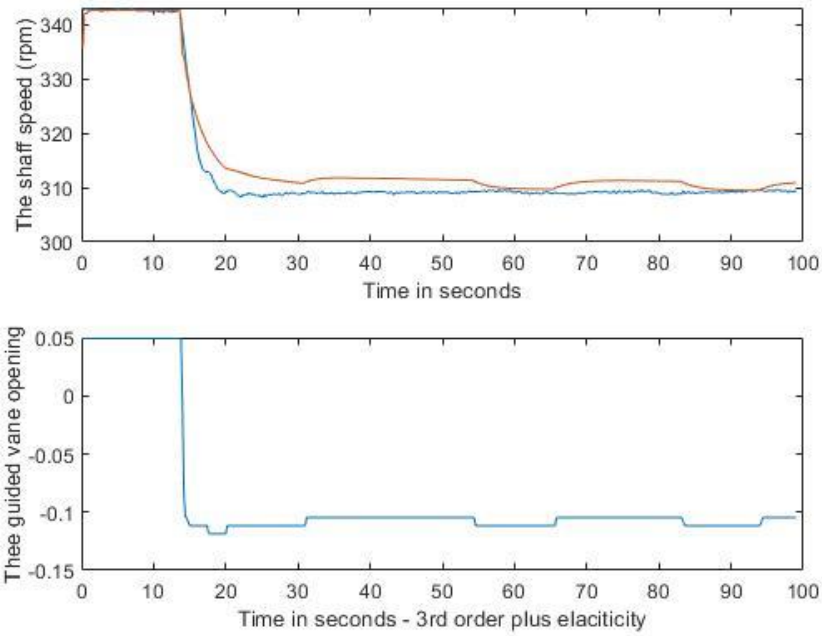

Figure 2. The response of the shaft speed, its estimated response (red color) in their true value ranges and the actual guide vane opening (bottom figure) in its normalized incremental sense.

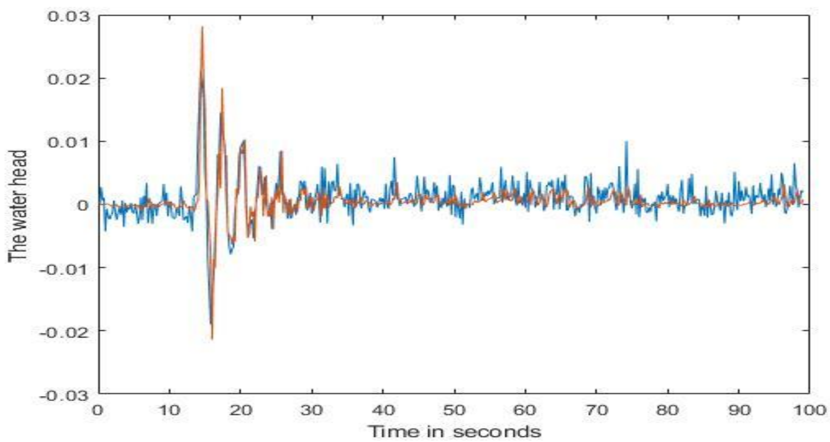

Figure 3. The water head and its estimated response (red color) in percentage variation sense.

3. MODELING OF SYNCHRONOUS GENERATOR

To obtain the power and voltage output from the hydropower, this paper describes the generator dynamics in a classical third-order model (Yang, 2019). Accordingly, the voltage control model for the generator can be expressed as:

$$\frac{dE}{dt} = \aleph\left(E, I, X''_{\mathrm{q}}, X''_{\mathrm{d}}, v\right) \quad [9]$$

which can be further expressed in the following form:

$$\begin{cases} T'_{\mathrm{d0}} \frac{dE'_{\mathrm{q}}}{dt} = v - E'_{\mathrm{q}} - I_{\mathrm{d}}(X_{\mathrm{d}} - X'_{\mathrm{d}}) \\ T''_{\mathrm{d0}} \frac{dE''_{\mathrm{q}}}{dt} = E'_{\mathrm{q}} - E''_{\mathrm{q}} - I_{\mathrm{d}}(X'_{\mathrm{d}} - X''_{\mathrm{d}}) \\ T''_{\mathrm{q0}} \frac{dE''_{\mathrm{d}}}{dt} = -E''_{\mathrm{d}} + I_{\mathrm{q}}\left(X_{\mathrm{q}} - X''_{\mathrm{q}}\right) \end{cases} \quad [10]$$

where v is the excitation control input of the generator. I_d is the direct-axis (d-axis) component current, I_q is the quadrature-axis (q-axis) component current. $\mathbf{E}' = \begin{bmatrix} E'_\mathrm{d} \\ E'_\mathrm{q} \end{bmatrix}$ is the transient internal EMF of the generator with E'_d being the d-axis component and E'_q being the q-axis component. $\mathbf{E}'' = \begin{bmatrix} E''_\mathrm{d} \\ E''_\mathrm{q} \end{bmatrix}$ is the sub-transient internal EMF of the generator with E''_d being the d-axis component and E''_q being the q-axis component. In Eq. [10], $\mathbf{X} = \begin{bmatrix} X_\mathrm{d} \\ X_\mathrm{q} \end{bmatrix}$, which is the synchronous reactance of the generator with X_d being the d-axis component and X_q being the q-axis component. $\mathbf{X}' = \begin{bmatrix} X'_\mathrm{d} \\ X'_\mathrm{q} \end{bmatrix}$ is the transient reactance of the generator with X'_d being the d-axis component and X'_q being the q-axis component. $\mathbf{X}'' = \begin{bmatrix} X''_\mathrm{d} \\ X''_\mathrm{q} \end{bmatrix}$ is the subtransient reactance of the generator with X''_d being the d-axis component and X''_q being the q-axis component. Additionally, $\mathbf{T_0'} = \begin{bmatrix} T'_\mathrm{d0} \\ T'_{q0} \end{bmatrix}$ is the open-circuit transient time constant of the generator; T'_d0 is the d-axis component, and T'_q0 is the q-axis component. $\mathbf{T_0''} = \begin{bmatrix} T''_\mathrm{d0} \\ T''_\mathrm{q0} \end{bmatrix}$ is the open-circuit sub-transient time constant of the generator; where T''_d0 is the d-axis component, and T''_q0 is the q-axis component. The values of these parameters were obtained from the experimental test, as shown in the following Table 1.

The synchronous generator parameters in Table 1 were obtained using an equivalent synchronous generator that has the same power generating capacity as that of the NTNU testing system.

Table 1. Parameters used for the third-order model in Eq. [10]

Parameter	Value
X_d	0.7680
X'_d	0.2490
X''_d	0.1870
X_q	0.5120
X''_q	0.1890
T'_d0	7.8800
T''_d0	0.0490
T''_q0	0.0283

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On the other hand, the generator voltage is controlled through the PID controller, which implements the proportional, the integral, and the derivative terms, as shown in the following.

$$e_v = Voltage\ set\ point - V_\mathrm{g} \quad [11]$$

$$v = K_\mathrm{p,v} e_\mathrm{v} + K_\mathrm{I,v} \int_0^\tau e_\mathrm{v}\, d\tau \quad [12]$$

where e_v is the tracking error of the incremental voltage control for the incremental voltage; V_g is the set-point of the voltage controller, which is the voltage from the generator terminal; v is the output of the voltage controller; for the PI control, $K_{p,v}$ is the coefficient for the proportional gain, and $K_{I,v}$ is the coefficient for the integral gain; and $e_{v,f}$ is the filter error of the incremental voltage control, which can be calculated from the following:

$$T_\mathrm{f} \frac{de_\mathrm{v,f}}{dt} + e_\mathrm{v,f} = e_\mathrm{v} \quad [13]$$

where T_f is the filtering time constant.$e_{v,f}$ is the excitation voltage applied to the excitation circuit of the synchronous generator.

4. SIMULATION RESULTS WHEN CONNECTED TO THE GRID

In the simulation, the focus has been on the performance of the hydro-turbine dynamics when the system is connected to the grid with variable power (load) generation. In this context, the system was regarded as of a one-machine–one load situation. Load torque, denoted as m_L, has the pattern shown in Eq. (14) in percentage variation sense:

$$m_{\mathrm{L}} = \begin{cases} 0, \text{when } t \ \leq 200 \text{ s} \\ 0.1, \text{when } t \ > 200 \text{ s} \end{cases} \qquad [14]$$

This equation indicates that the load was suddenly increased by 10%. Because the speed control system operated in the closed-loop manner this time, the speed was expected to go down initially and then be recovered back to its set point. The simulation results are shown in Figure 4, which shows that the speed (i.e., the frequency) was very well controlled, and the frequency recovered within 9.6 seconds back to 50 Hz.

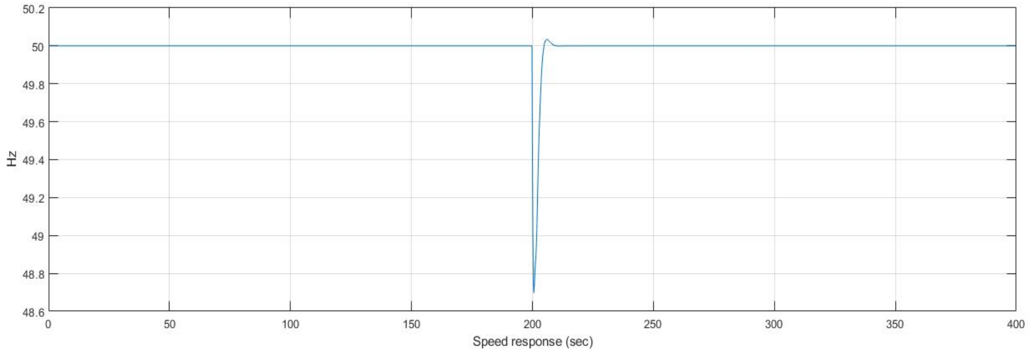

Figure 4. The speed (in frequency) response when the load was suddenly increased by 10% at the time of 200 s.

Figure 5, Figure 6, and Figure 7 show the relevant responses for the water head, water flow rate, and guided vane (inlet gate) opening, respectively, where desired dynamics responses were obtained.

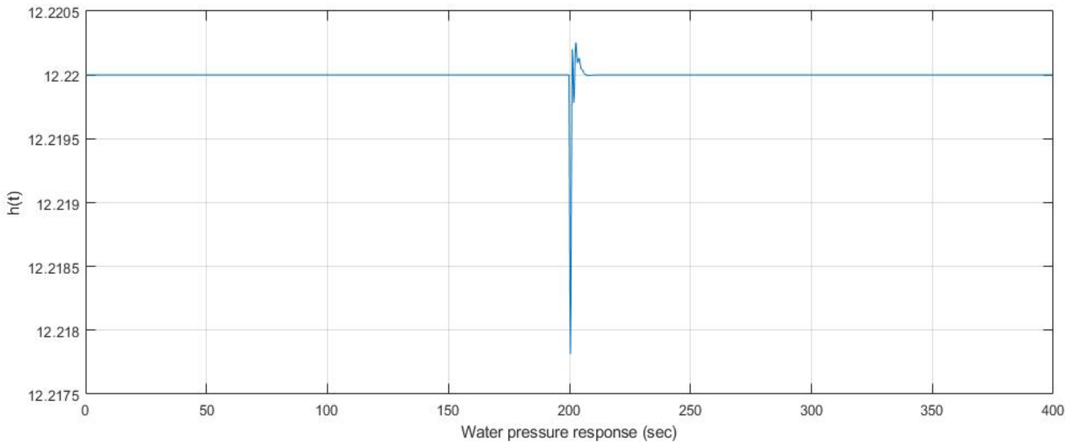

Figure 5. The water head response in meters when the load was suddenly increased by 10% at the time of 200 s.

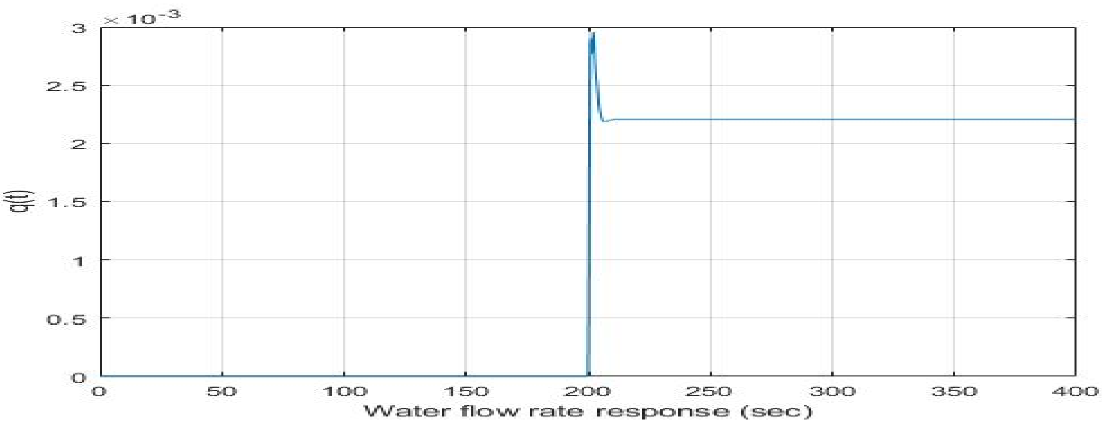

Figure 6. The water flow rate response in percentage variation sense when the load was suddenly increased by 10% at the time of 200 s.

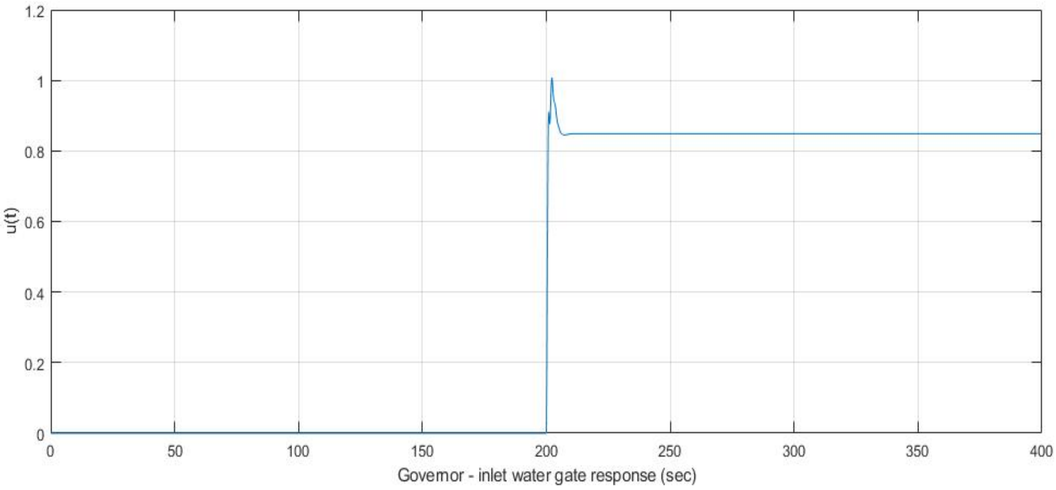

Figure 7. The guided vane opening in percentage variation sense when the load was *L* increased by 10% at the time of 200s.

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5. DATA ENGINEERING PROCESS USING OPEN PLATFORM

An overview of Data Engineering Process Using Open Platform is illustrated in Figure 8. In this illustration, it is assumed that a Digital Twin of a Turbine is built. Focusing on the process section, where it can be seen that the data engineering and open platform can address the second problem in section 1 effectively in terms of obtaining interface and data process tools that support the adaptive modeling in sections 2 – 4 and dialog between the users and the DT.

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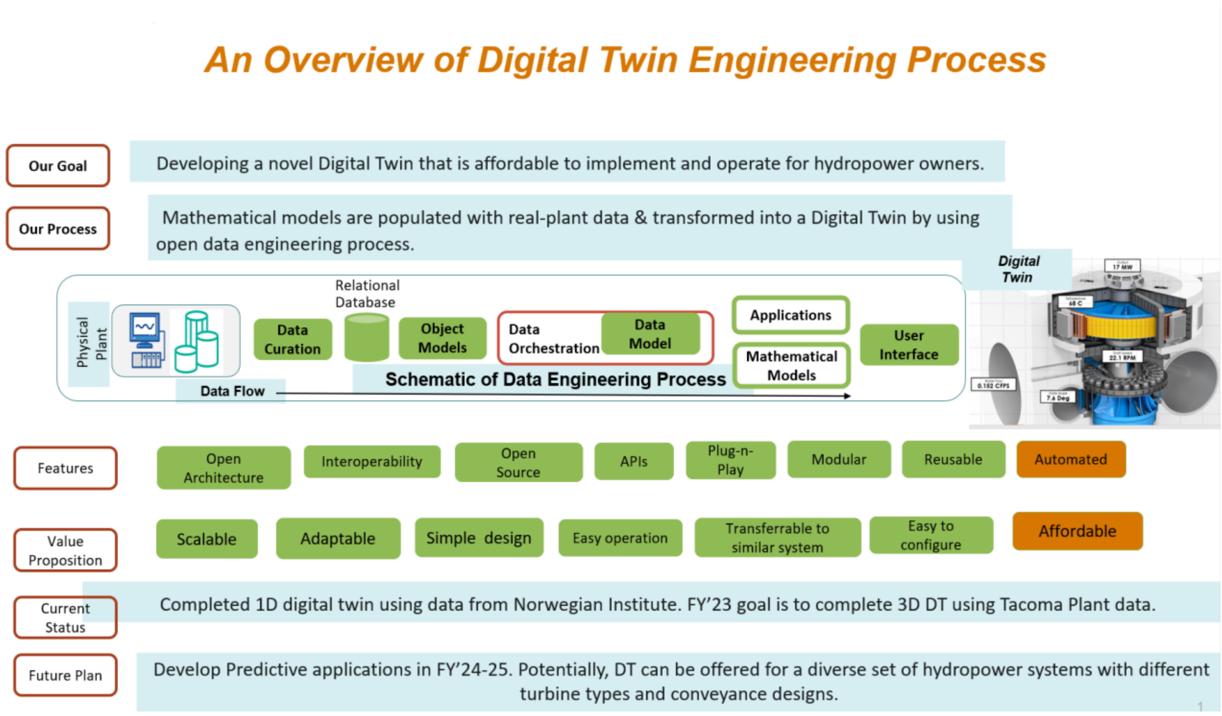

Figure 8. An overview of Open Platform Data Engineering process.

6. CONCLUSIONS

As a powerful tool in realizing the digitalization, digital twin requires both adaptive learned models and effective data process with effective user's interface. This paper has addressed these two issues, where a novel modeling method for the hydro-generation unit has been developed together with data engineering processing and potential interface. In terms of modeling, a dead-zone based robust least square algorithm has been proposed to learn the system dynamics and a desired performance has been achieved when using the testing data from a pilot hydropower system in NTNU (Norway). This is then followed by the overview of a data process and open platform engineering process.

7. ACKNOWLEDGEMENTS

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