Digital technologies emergence in the contemporary hydropower plants operation

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Abstract: Digitalization of hydropower plants gives rise to the implementation of new technologies, such as Artificial Intelligence, Smart Energy Systems, Smart Grid, Digital Twins, Industrial Internet of Things and others. These technologies can enable both a single hydropower plant and the whole fleet to function reliably and efficiently within the electric grid. By obtaining sensor-based data from in-situ and beyond, analyzing them in real time and comparing with historic data, conclusions can be drawn for optimization, generation and maintenance predictions. This paper summarizes and reviews the modern approach of these new technologies and their benefits which can enhance hydropower operation practice.

Key words: hydropower plants, digitalization, contemporary technologies, optimization

1. INTRODUCTION

Hydropower plants play an important role in the electrical power system because of their capability to store energy, thus balancing the production and consumption of the grid. Furthermore, they are a renewable energy source and the increase of their production can contribute to reducing the emission of greenhouse gasses. This is why hydropower plants (HPPs) should be optimized to work reliably and efficiently, and to maximize their production.

There are several approaches in HPP optimization, many of which are presented in [1], such as the reduction of head loss, improvement of mechanical and electrical equipment, the usage of variable speed control and so on. However, optimization can also be achieved by implementing state-of-the-art digital technologies, since they are estimated to provide better utilization of the available hydraulic power, ensure safety, enable larger energy production on an annual level and lower the costs of maintenance. Digitalization will also provide enhanced flexibility and the stability of the electrical system, the prolongation of the lifetime of the hydropower equipment and an increase in the overall efficiency [2]. It is assumed in [1] that digitalization of the existing HPPs would provide around 1% increase in efficiency and around 11% of energy generation achieved by using high quality inflow forecasts.

Digitalization, in its own sense, represents a process of transforming a signal into a digital form that can then be stored and manipulated, meaning that a signal has to be acquired first. This is done using various sensors such as temperature, pressure, vibration sensors and others. It is fortunate that nowadays sensor technology has achieved a relatively high level of development, thus being reliable, precise and widely available. Furthermore, it is best if the sensor data is acquired continuously, i.e. by monitoring.

Sensor data can be stored either in a local database or on a cloud. If the data is stored on a cloud, it could be remotely accessed and cloud services such as cloud computing can be applied. Nevertheless, the already stored data, referred to as historical data, along with the data acquired in real time allow the implementation of various models and algorithms. The data availability and manipulation can be enhanced by implementing a big data platform that systematically organizes and centralizes the gathered data. Along with the Internet of Things (IoT) technologies, it is possible to enable remote access to gather and analyse the obtained data.

Therefore, in order to implement these modern digital technologies, it is required to have a reliable infrastructure that would enable data acquisition, since most of these technologies are data-based. The data can be manipulated using Industrial IoT, Artificial Intelligence, Digital Twin and other contemporary technologies. By incorporating digitalized hydropower with other renewable technologies into the Smart Grid, electricity demand and prices can be estimated to stimulate the end-user and to provide grid stability.

These technologies can enable both a single hydropower plant and the whole fleet to function reliably and efficiently within the electric grid. By obtaining sensor-based data from in-situ and beyond, analyzing them in real time and comparing with historic data, conclusions can be drawn for optimization, generation and maintenance predictions.

This paper summarizes and reviews the modern approach of these new technologies and their benefits which can enhance hydropower operation practice. The paper is organized as follows: Section 2 reviews the Artificial Intelligence approach in reservoir inflow forecasting, Section 3 gives an overview of the contemporary maintenance techniques, while the concept of Digital Twin is presented in Section 4. A brief summary is given in Section 5, along with the drawn conclusion regarding the use of contemporary digital technologies.

2. RESERVOIR INFLOW FORECASTING

The information on future reservoir inflow $\boldsymbol{Q}_{\mathbf{R}}$ aids in decision making and operation scheduling. The generated mechanical power on the turbine shaft can be written as:

$$\boldsymbol{P}_{\mathbf{T}} = \boldsymbol{\rho g Q}_{\mathbf{T}} \boldsymbol{H \eta}_{\mathbf{T}}$$

where $\boldsymbol{\rho}$ is the water density, $\boldsymbol{g}$ the acceleration due to gravity, $\boldsymbol{Q}_{\mathbf{T}}$ the water flow through the turbine, $\boldsymbol{H}$ the net head and $\boldsymbol{\eta}_{\mathbf{T}}$ the turbine efficiency. The net head $\boldsymbol{H}$ depends on the height difference between the free water surface of the headwater reservoir and the tailrace reservoir, and this height difference is dictated by the reservoir inflow, the flow through the turbine, and the losses that are also a function of the flow through the turbine $\boldsymbol{H} = \boldsymbol{H}(\boldsymbol{Q}_{\mathbf{R}}, \boldsymbol{Q}_{\mathbf{T}})$. Since the turbine efficiency is a function of both the flow and the head, it can be written as $\boldsymbol{\eta}_{\mathbf{T}} = \boldsymbol{\eta}_{\mathbf{T}}(\boldsymbol{Q}_{\mathbf{T}}, \boldsymbol{H}(\boldsymbol{Q}_{\mathbf{R}}, \boldsymbol{Q}_{\mathbf{T}}))$.

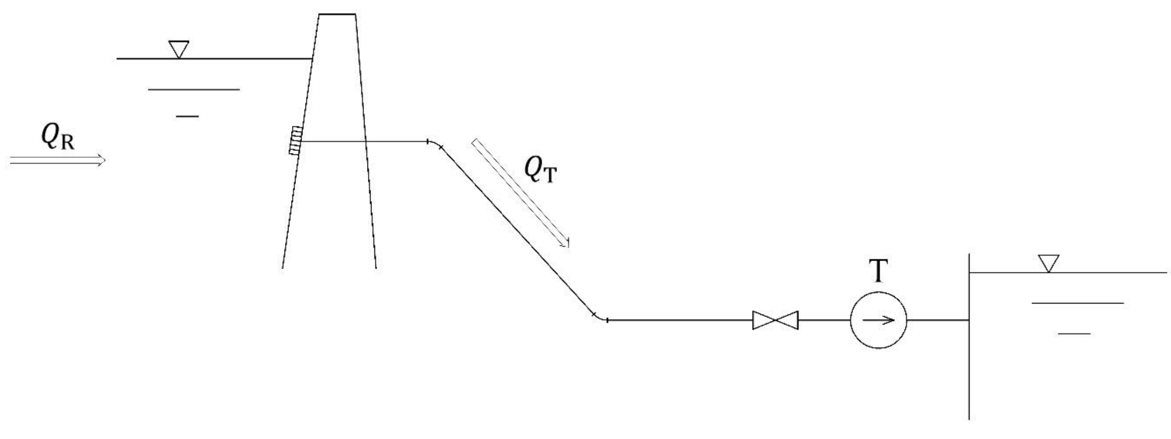

Figure 1 – Schematic of a hydropower plant

The flow of water through the turbine depends on the current energy demand, but also on the reservoir inflow. To ensure safe and rational exploitation, it is essential to minimize the release of water through the spillway. Overall, since the generated power also depends on the reservoir inflow, in order to manage the hydropower production, it is of interest to have a sense of the upcoming inflow.

The reservoir inflow is a complex function of the incoming streams, precipitation, evaporation, soil characteristics, and other parameters. Nevertheless, it is possible to provide an estimation of the upcoming inflow by acquiring various input data such as precipitation and temperatures. Artificial Intelligent methods are employed to analyse the data and find the mapping function which relates the measured values to the output.

A systematic review of the application of Artificial Intelligence methods (Artificial Neural Networks and Support Vector Machine) for making predictions in renewable energy systems (hydro, solar, wind) is given in [3]. The paper also includes case studies and validation of the obtained results.

A detailed overview of Machine Learning algorithms for inflow and streamflow forecastings, such as Artificial Neural Networks (ANNs), Support Vector Machines and Adaptive Neuro-Fuzzy Inference Systems are given in [4]. These methods are compared and evaluated for short-term scheduling (1-7 days), mid-term scheduling (1-52 weeks), and long-term scheduling (1-5 years).

In [5], an ANN approach is used for forecasting the inflow over the upcoming 7 days. The concept is validated over 23 dams in the U.S. with unregulated flow and with different hydrological characteristics and climate regimes. The ANN inputs consist of the numerical weather prediction forecasts of precipitation, temperature and wind speed, antecedent precipitation over the basin, antecedent streamflow into the reservoir and antecedent baseflow. The optimized operation of the HPP, in comparison with the benchmark control rules-based HPP, gained an additional generation of around 5.2% of HPP production (47,253 MWh) over the period of two years.

The above approach is especially purposeful when optimizing the operation of cascade hydropower plants with very complex asymmetric energy characteristics. Combining the optimization methods and ANN, the possibility for additional generation is proved for a system of four hydropower plants in a cascade [6]. The conducted analyses only for intra-station regimes optimization indicate that additional production can be in the range of 1 ÷ 2.5% of annual production (depending on the annual weather and hydrometeorological conditions).

3. MAINTENANCE

In order to optimize the exploitation of machinery and systems, it is essential to maintain them. The goal of maintenance is to increase reliability, safety, prevent failures if possible and minimize the costs. There are different maintenance strategies such as reactive, preventive, condition-based, prognostic (predictive) and prescriptive maintenance. Digitalization gives rise to the implementation of the latter three strategies.

In reactive maintenance, a failure of the equipment is solved after it occurs (e.g. a light bulb is replaced when it fails). This strategy does not require almost any activities prior to the failure, thus it is considered simple and affordable but only if the failure does not impact the production or safety. Preventive maintenance includes scheduled activities in defined time intervals when the equipment is checked and maintained. This can sometimes lead to unnecessary stoppage of the production and can cause over-maintaining, which indirectly increases the cost. However, time, personnel and activities required for maintenance can be optimized by further analyses, such as risk assessment analysis given in [7], thus increasing reliability and reducing costs.

The strategy where service of the equipment is based on its condition, i.e. its wear and deterioration, is called condition-based maintenance. This type of maintenance requires the evaluation of the current state of the equipment which may be done by constantly monitoring it using sensors. This maintenance strategy is more costly and thus used on equipment that is valuable, whose failure may cause safety concerns and the stoppage of production. However, this strategy offers optimal utilization of the equipment and better maintenance scheduling, thus reducing the costs associated with them.

In prognostic maintenance, an algorithm is used to predict the wear and failure of the equipment based on real-time and historical data acquired by monitoring. Usually, Artificial Intelligence (AI) methods, such as ANN, are employed to estimate the equipment’s operating life. This requires constant monitoring, a database of acquired sensor data and some computing power which can be solved by

using IoT and cloud technologies. Finally, prescriptive maintenance allows for optimization of the maintenance activities according to the obtained predictions, i.e. scheduling those activities in advance.
Many AI approaches require certain data for training the algorithm to be able to learn how to map the given inputs to outputs. This can be used to forecast a possible failure and the need for the replacement of deteriorated equipment.
A general review of vibration machine diagnostics using AI methods is provided in [8]. This includes methods such as Artificial Neural Networks, Random Forest, Support Vector Machine, Principal Component Analysis and Deep Learning. Condition monitoring and fault diagnostics for hydropower plants using the method Support Vector Machines for fault diagnostics are given in [9]. The employed system enables fault detection and evaluation of the components degradation, including system condition assessment during transients and identification of sudden events. The information is useful for establishing condition-based maintenance for service providers to optimize the maintenance schedule. A novel Key Performance Indicator (KPI) based on a trained Self-Organizing Map for condition monitoring of hydropower plant equipment was proposed in [10]. Case studies were also carried out and in one of the cases an anomaly of a temperature sensor was detected, showing higher values than those which were actually present. The anomaly detection of the sensor prevented the stopping of the unit and is estimated to have saved between 25 k€ and 100 k€. In another case, the proposed condition monitoring strategy detected anomaly symptoms in advance (in comparison with the previously used method), thus it represents a bridge towards fully automated predictive maintenance.
Practical application of maintenance and fault detection of hydropower systems are given in [11]. The paper presents maintenance solutions within the MonitorX jointed industry project, including cases of rotor faults in hydropower generators, monitoring the condition of drainage pumps and monitoring the condition of the hydraulic system of Kaplan turbines. The project's focus was on data analysis models and algorithms for condition monitoring and fault diagnosis that relies on Machine Learning and AI. Several plant operators that participated in the project used a central data collection and storage solution (big data platform) to allow better access to the data (including via handheld devices) and effective maintenance monitoring.

4. DIGITAL TWIN

Lately, a new approach related to simulation and maintenance has been used – creating a virtual model in the virtual space that communicates with the physical model in real space. The communication toward the virtual model is achieved by using sensor data and it allows the virtual model to update itself to resemble a credible copy or mirror of the physical model. Furthermore, the communication is not only towards the virtual model, but also from the virtual model to the physical one. This concept of creating a virtual model and establishing communication in both directions between the virtual and physical model is referred to as making a Digital Twin (DT).

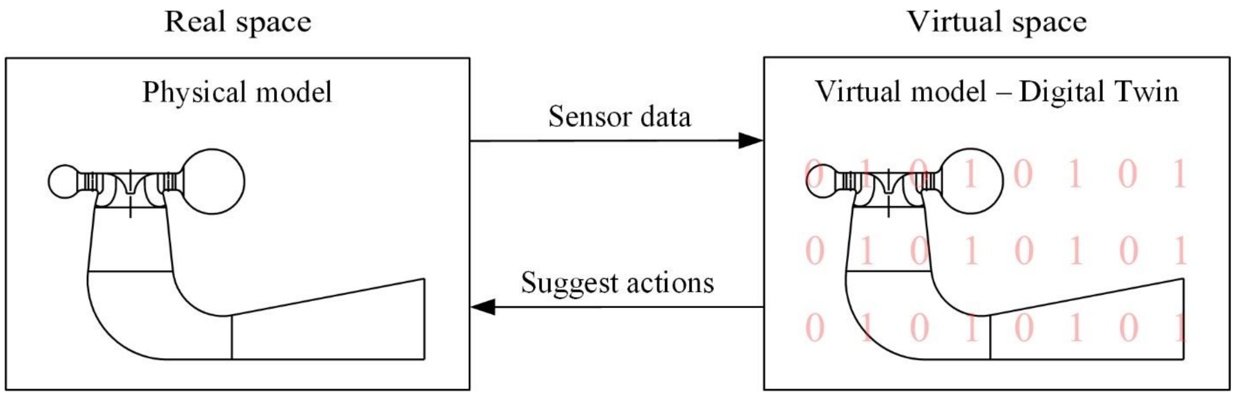

Figure 2 – The Digital Twin concept

The concept of DT was first introduced in 2003 by Michael Grieves in a product lifecycle management course [12], while the first definition of the DT appeared in 2010 [13]. There are many definitions of the DT, mostly depending on the field where it is used, but one of them is that: "DT makes full use of data such as physical models, sensor updates and operation history, and integrates multi-disciplinary, multi-physical, multi-scale, and multi-probability simulation processes to real-time reproduce the dynamics of a physical system in the virtual space" [14]. It is important to reliably model the DT so that it gives a good representation of the physical HPP and its systems. By using historical and real-time monitoring data, an algorithm is developed to simulate different scenarios, describe the behavior of the model, make predictions and then do or suggest actions.

The DT concept has evolved greatly with the growth of IoT, AI and Cloud computing. This can be especially observed in the field of maintenance, where fault prognostics are applied. The concept is being implemented mainly in the fields of manufacturing, energy industry, aerospace, construction, and others [15]. DTs can be involved in the entire life-cycle of a product, from its design and production to its operation and maintenance.

In the DT application in hydropower, there is a wide range of possibilities of running simulations in order to predict HPP performance under various conditions which arise during its exploitation. It can allow the HPP to perform more reliably with higher efficiency and to increase its generation. The changes that are considered in the physical space are simulated in the virtual space, so that the obtained results can be used for development and optimization.

The data, that can be collected to optimize HPP operation, consist of operation-related data which relate to efficiency and monitoring ones – flows, pressures, temperatures, vibrations, stresses and the other. Data from various sources, such as upstream and downstream parameters, weather data and grid data, can also be taken into account for optimization.

Oak Ridge National Laboratory along with Pacific Northwest National laboratory launched a project in 2020 to develop a DT for Hydropower Systems [16]. The goal was to optimize the plant operation for managing electric power demand, to perform fault diagnostics, condition and health monitoring and management of hydropower systems operation. The DT will be constantly updated by real-time sensor data so that it resembles a credible mirror of the physical HPP.

For a pumped storage station in Ireland, the Turlough Hill Power Station, a DT was formed for fatigue assessment and predictive maintenance in order to provide the plant's life extension [17]. The DT makes it possible to assess and identify the risk of structural failure and simulate future events. The benefits of using the DT are the reduction of the total number of outages, improving risk management, focusing inspections on high-stress areas and life extension [18]. This is important as the plant may need to operate in more than one cycle a day because of the dynamics introduced by other renewable energy sources.

In [19] a DT called the Hydro-Clone is implemented for monitoring and fatigue assessment of the penstock of the 200 MW La Bâtiaz hydropower plant. The Hydro-Clone replicates all the pressure variations, that arise in real time during frequent start/stop sequences of the machines. It then converts the pressure to stress using FEM and Barlow's law and assesses the health status of the penstock. This is done by using the number of fatigue cycles obtained from historical data and calculating the damage index profile.

It is worth mentioning that, until 2017, there were not many papers published on the topic of DT, as shown in [12] and [15], however, the interest in publishing such papers has grown lately. Still, there are almost no published papers on the use of DT in the field of hydropower. Perhaps it is also due to the challenges that the DT carries including modernizing the HPPs, implementing sensors, improving maintenance and reliability, increasing flexibility, reducing operational cost and managing cyber-security.

5. CONCLUSION

The implementation of contemporary digital technologies provides benefits such as enhanced flexibility, better safety, larger energy production and lower costs of maintenance. This is achieved through reservoir inflow forecasting, incorporation of prognostic maintenance and simulation of HPP operation. The employed technologies used to gain such benefits include Artificial Intelligence, Big Data platforms, Internet of Things, Digital Twin and others.

Generally, digital technologies enable better management and scheduling (e.g. fewer start/stops of the turbines, the yield towards optimal working parameters, etc.), thus better utilization of the available hydraulic power and safer operation during floods. The applied prognostic maintenance also ensures the safety and reduces the costs by optimizing the working lifetime of the HPP's systems and components. Finally, the simulations employed by the DT are used to optimize HPP operation, predict HPP performance under various conditions and provide the plant's life extension.

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