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AI Utilized Dam Optimal Operation System

WATANABE Naoki[*1] TAKAGO Ryuei[*2] SUZUKI Masako[*3] HADAMA Satoru[*4]

Abstract:

JFE Engineering and Hokuriku Electric Power Company jointly developed optimal operation system for dams that integrates artificial intelligence software WinmuSe™ developed by JFE Engineering and dam operation know-how of Hokuriku Electric Power Company, for the purpose of supporting the work of dam managers who are required to increase hydroelectric power generation and strengthen flood control by DX. This paper introduces the latest WinmuSe and functions of optimal operation system for dams.

1. Introduction

In recent years, typhoons and torrential rains caused by linear rainbands have caused flooding damage in many parts of Japan every year, with strong social concern about dam operation as a flood control function in river basins. In particular, after the heavy rains in July 2018, the Cabinet Office of Japan took the lead in encouraging the conclusion of an agreement on flood control with water utilization dam administrators, and there are moves in the direction of requiring a flood control function not only in conventional flood control dams, but also in water utilization dams. On the other hand, because the Japanese government has declared that the country intends to achieve net carbon neutrality by the year 2050, highlighting the importance of hydro power generation as a form of clean energy that does not produce CO_2 emissions in the power generation process, all electric power companies are now working to increase hydro power generation. Under these circumstances, dam operation has become more complicated and complex than in the past, which also tends to increase the workload on dam managers. Since there is no outlook for future population increases in Japan, where a declining birthrate and aging of the population are progressing, improving work efficiency and work automation by digital transformation (DX) are considered indispensable for simultaneously securing a work-life balance and responding to increased workloads.

As DX which supports the work of dam managers, JFE Engineering Corporation and Hokuriku Electric Power Company recently developed an AI-based dam operation support system by integrating the artificial intelligence software WinmuSe™[1)], which was developed in-house by JFE Engineering, and the long years of dam operation know-how possessed by Hokuriku Electric, resulting in the development of the "Dam Optimal Operation System[2)]".

This paper first presents an overview of current WinmuSe, then introduces the dam operation support system, and finally describes the future development of the "Dam Optimal Operation System."

2. Overview of WinmuSe™

WinmuSe is general-purpose AI-based software which is capable of analyzing large volumes of data with high speed and high accuracy by utilizing independently-developed algorithms (**Fig. 1**), and has an extensive record of use, especially in various infrastructure fields that handle time-series data[3–10)].

The core engines that comprise WinmuSe are as follows.

- PAC (Program Auto Creation)

Formulates the causal relationships between data and automatically creates forecasting models.

- RET (Reverse Engineering Technology)

Performs trial-and-error calculations on virtual simulation environments in place of a human agent and

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*1 Group Manager, Digital Solution Dept., Digital Transformation Initiative Center, Digital Transformation Headquarters, JFE Engineering

*2 Civil Engineering Management Team, Renewable Power Dept., Hokuriku Electric Power Company

*3 Digital Solution Dept., Digital Transformation Initiative Center, Digital Transformation Headquarters, JFE Engineering

*4 Group Manager, Digital Solution Dept., Digital Transformation Initiative Center, Digital Transformation Headquarters, JFE Engineering

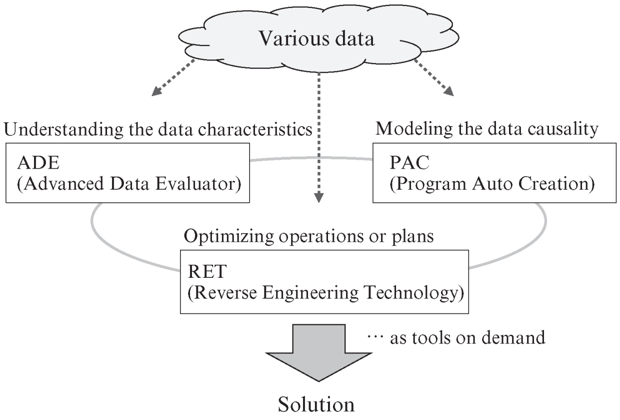

Fig. 1 Overview of WinmuSe™

identifies the optimal plan.

• ADE (Advanced Data Evaluator)

Data analysis tools that extract the inherent characteristics in datasets, performs data grouping, etc.

2.1 Time Series Data Forecasting Engine (PAC)

Time series data forecasting refers to forecasting of future data by analyzing the inherent causal relationships in time series data. As shown in **Fig. 2**, first, the causal relationship between a target value (objective variable) included in time series data and the boundary condition (explanatory variable) is learned from actual data, and a forecasting model (function consisting of multiple formula groups) is identified. Specifically, an unknown function f which describes the input-output relation shown by Eq. (1) is identified by learning.

$$T_{t+1}=f(T_t, T_{t-1}, T_{t+2} \ldots, B_{t+1}, B_t, B_{t-1}, \ldots) \cdots (1)$$

T : target value

B : boundary condition

t : current time

Next, the boundary condition for the identified function f (= forecasting model) is input, and the forecasted value of the target is output. It is also possible to maintain high forecasting accuracy for the most recent data by timely relearning of the actual data accumulated after the original learning.

An appropriate learning engine is selected from multiple algorithms according to the characteristics of the problem to which it will be applied. However, in any case, a DNN (Deep Neural Network) architecture in the wide sense is selected by an original solution method. The features of the algorithms are shown below.

• PAC 1: General purpose learning type

GMDH (Group Method of Handling Data) network architecture optimized by genetic programming. Implements a unique mathematic system to enable compact handling of large-scale data dimensions. Applicable to all types of time series data.

• PAC 2: Online learning type

Network architecture specialized in high speed learning in real time. Suitable for time series data with a fixed period.

• PAC 3: Physical model learning type

Network architecture based on partial differential equations describing physical phenomena. Suitable for time series data of physical phenomena.

2.2 Time Series Data Optimization Engine (RET)

Time series data optimization means derivation of the manipulated variable (operation value) for achieving the desired state (monitoring value) of a certain system. As shown in **Fig. 3**, time series data optimization is applied to problems in which the optimal operation pattern is determined for each device under various constraints in order to operate the monitoring value (objective function) within a specified target range. Specifically, the operation value x formulated by Eq. (2) is identified by an optimization calculation.

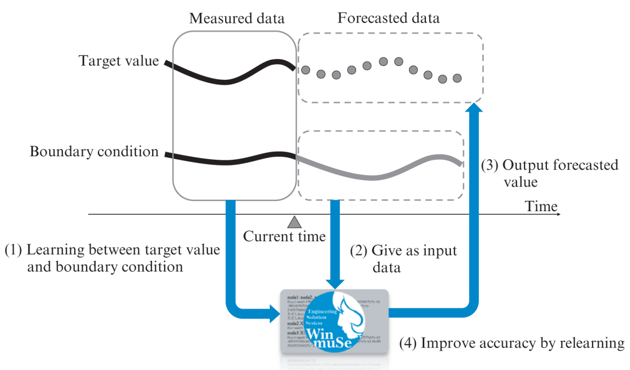

Fig. 2 Overview of time series data forecasting

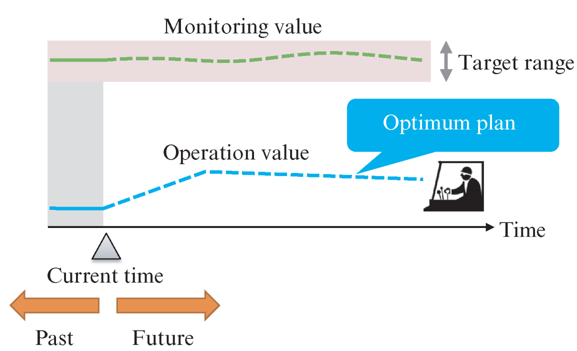

Fig. 3 Overview of time series data optimization

$$\max: \quad f(x) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (2)$$
$$\text{subject to}: g(x) \leq 0$$
$$h(x) = 0$$
$$a \leq x \leq b$$

x : manipulated value (operation pattern)
f : objective function
g : equality constraint function
h : inequality constraint function

As the optimization engine, an appropriate technique is selected considering the characteristics of the problem to which it is to be applied. The characteristics of the algorithms are as follows.

• RET 1: Evolutionary calculation type

The operation pattern is redefined as a genetic sequence, which is then evolved to the optimal genetic sequence (=optimal operation pattern) by repeatedly performing genetic manipulations (selection, crossover, mutation) that simulate biological evolution.

• RET 2: Reinforcement learning type

Compensation conditions that express the desirability of the state of a certain event are set in advance as functions, and the operation pattern suited to that state is learned by using the compensation obtained by trials of operation patterns for various scenario cases by the AI agent on a virtual environment.

3. Dam Optimal Operation Support System Utilizing AI

The following introduces the "Dam Optimal Operation System," which was developed jointly by JFE Engineering and Hokuriku Electric Power Company, as a recent example of simulation utilizing AI using the time series data forecasting/data optimization engines of WinmuSe.

3.1 Overview of Dam Optimal Operation System

In cases where the inflow volume to a dam increases due to concentrated heavy rain, etc. and is expected to exceed the surplus capacity of the reservoir, water must be discharged from the spillway gates (floodgates) of the dam, as shown in **Fig. 4**. Since it is important to accurately forecast the inflow volume, which changes depending on the weather, in order to carry out a proper discharge operation, Hokuriku Electric itself created an observation network and forecasting system, and is actively engaged in their maintenance and improving forecasting accuracy. In addition to the increased frequency of flooding in recent years, higher accuracy in forecasts of the inflow volume is also necessary in response to the decreasing number of successors to dam operation technology accompanying a declining working population and the heightened importance of renewable energy. Therefore, JFE Engineering and Hokuriku Electric decided to develop a dam optimal operation system utilizing AI (hereinafter, dam operation AI).

Dam operation AI forecasts the inflow volume to a dam accurately using the amount of rainfall as an input condition, and proposes the optimal outflow volume (flood discharge) and volume of water to be used in power generation based on that inflow volume. This development was carried out in three stages, that is, dam inflow volume forecasting, optimal operation of single dam, and operation of a series of multiple dams on the same river system (serial dams). The following explains the content of each stage.

3.2 Dam Inflow Volume Forecasting

In Stage 1, an inflow volume forecast model was constructed for the Asaida Dam (Hida City, Gifu Prefecture) of Hokuriku Electric Power Company located in the upper reaches of the Jinzu River system.

The conventional system, as shown in **Fig. 5**, had forecast the inflow volume by using a distributed-type runoff model divided into a detailed mesh. However, this model involved an enormous number of set parameters such as the thickness of the soil layer, gradient of slopes, etc. in the dam basin, and also required labor in parameter tuning to improve forecasting accu-

Fig. 4 Scene of ASAIDA dam discharge

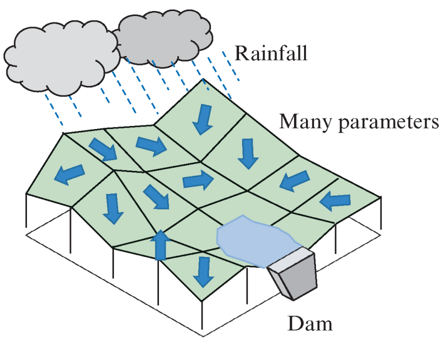

Fig. 5 Conventional inflow forecast

racy. Specifically, accuracy was improved by conducting annual inspections of the company's observation network, which was arranged in the catchment area of the dam and its surrounding area, organizing the data, and tuning the parameters of precipitation amount, inflow volume and flow time for each mesh by engineers so as to coincide with those parameters at the time of the peak flow rate during floods.

In inflow volume forecasts by dam operation AI, the analysis and evaluation of the parameters are performed by AI, as shown in **Fig. 6**, making it possible to construct a relational expression for precipitation, inflow volume and time for the entire period, including the time of the peak flow rate. This enables simplification (including abolition) of the maintenance required by the conventional observation system.

The data used in learning by the inflow volume forecast model were the Asaida Dam management data (upstream area precipitation, water level, dam inflow volume, etc.) for a 10-year period up to fiscal year 2016 (excluding the flood event in FY 2016). The usefulness of the forecast model was then verified by inputting the rainfall data for the flood event in FY 2016, which was excluded from the learning data, to the forecast model, and comparing the forecasted value of the calculated inflow volume and the actual observed inflow volume at the Asaida Dam. As shown in **Fig. 7**, the forecast accuracy (RMSE: root mean square error) for serious flooding was substantially improved in comparison with the conventional model, confirming the usefulness of dam operation AI. Therefore, the cloud system shown in **Fig. 8** was implemented, and transmission of inflow volume forecasts for actual use was begun.

3.3 Optimal Operation of Single Dam

In Stage 2, dam operation AI including flood discharge gate operation and water utilization for power generation was developed, as shown in **Fig. 9**, for the same Asaida Dam as in Stage 1.

Because the Asaida Dam has a small reservoir capacity, and early discharge from the dam (decrease of dam water level) at the start of flooding, discharge of water without use at the end of flooding (discharge from floodgates without generating power) and delay in recovering the water level required for power generation are directly linked to reduced power output and generated electricity at the power station, the aim of development was sure flood control and water utilization by system support.

Based on a flood in 2017, the inflow volume forecast, dam outflow volume (water level) and water utilization for power generation were proposed by dam operation AI for the period from the start to the end of the flood. The results were then compared the records of actual dam operation, and the possibility of increasing electric power generation by approximately 1 million kWh (1 GWh) during the period from the start to the end of one flood was confirmed. As shown in

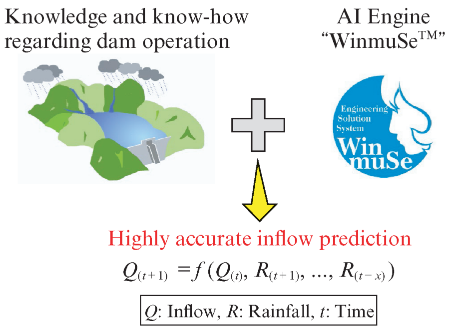

Fig. 6 Relational equation of inflow forecast by utilizing AI

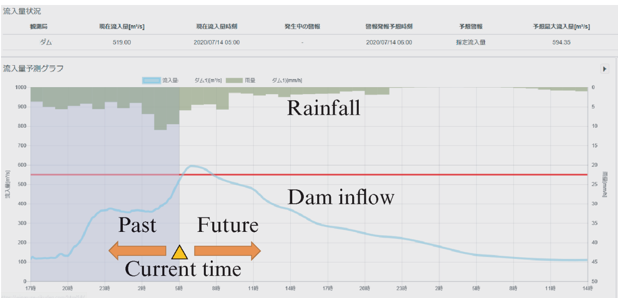

Fig. 8 Web screen of dam inflow forecasting system

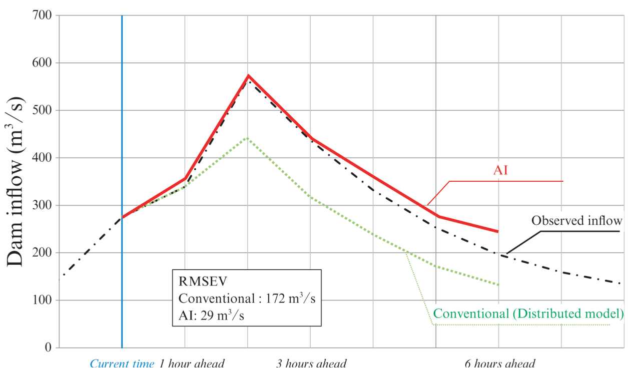

Fig. 7 Inflow forecast by utilizing AI

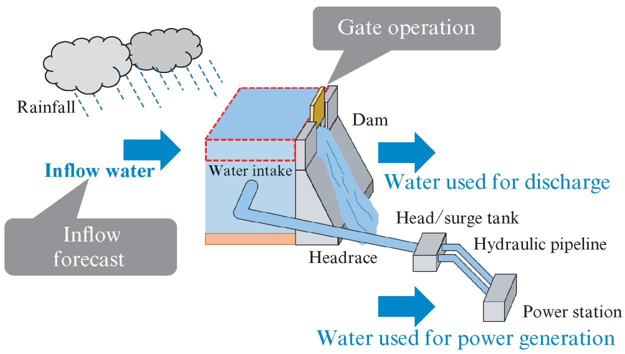

Fig. 9 Operation of hydroelectric dams

Fig. 10, dam operation AI accurately determines the end of flooding, and an increase in power generation is achieved by early recovery of the flow rate required in order to restart power generation. Considering the facts that the frequency of floods is a maximum of 7 floods/year (recent 5-year period) and the effect of proper implementation of flood control and water utilization operation is early recovery of the water level at the end of flooding (at the start of flooding, priority is given to gate discharge from the viewpoint of safety in case of sudden flooding), an increase of approximately 5 million kWh/yr (5 GWh/yr) in electric power generation is expected.

3.4 Optimum Operation of Serial Dams

In Stage 3, application was expanded to a group of dams in the same river system which includes the Asaida Dam (total of 5 dams; from upstream, Asaida Dam, Shin-inotani Dam, and Jinzu River No. 1, No. 2 and No. 3 Dams). **Figure 11** shows the Jinzu River basin system.

Since gate operation and water utilization for power generation at upstream dams affect the inflow volume of downstream dams in a serial dam system, it is necessary to carry out a total optimization for the entire system, which collectively maximizes the total power generation of the 5 dams, based on a river basin system simulation that integrates the inflow volume forecast models of all dams.

Optimal dam operation information is visualized by a graph of the gate discharge rate and water utilization for power generation at each dam by the cloud system, as shown in **Fig. 12**, and it is also possible to display the degree of gate opening for each gate and the detailed operation in 1-minute unit.

Verification is currently in progress by comparing the inflow volume forecasts and proposed values of the dam discharge rate (water level) and water utilization for power generation by dam operation AI and the actual dam operation records for flooding in FY 2021.

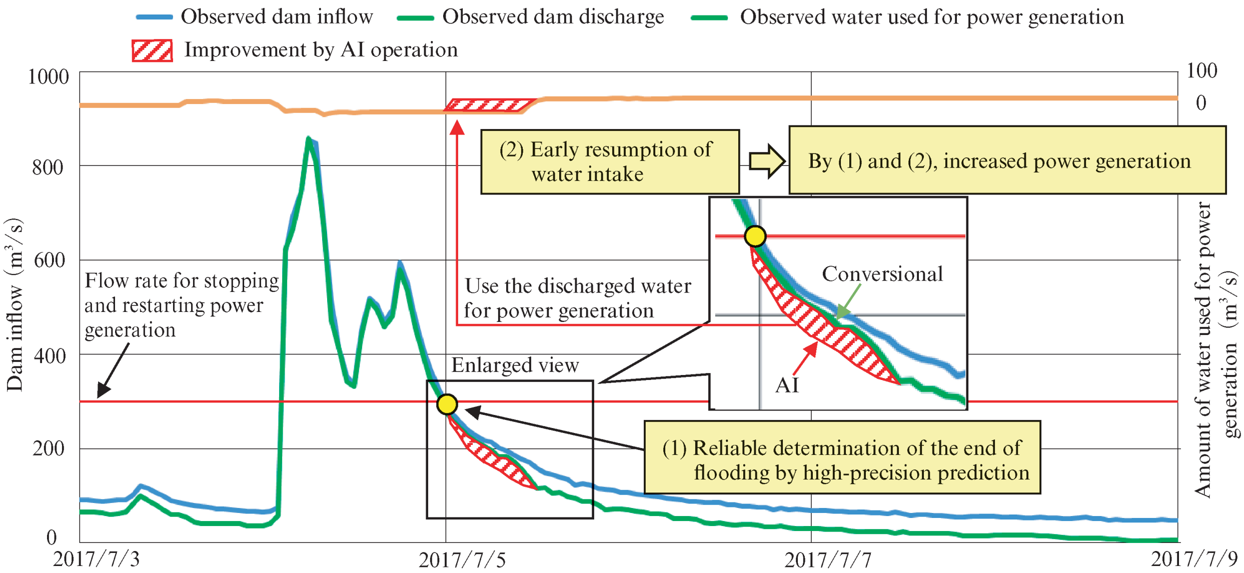

Fig. 10 Increase in power generation by AI operation

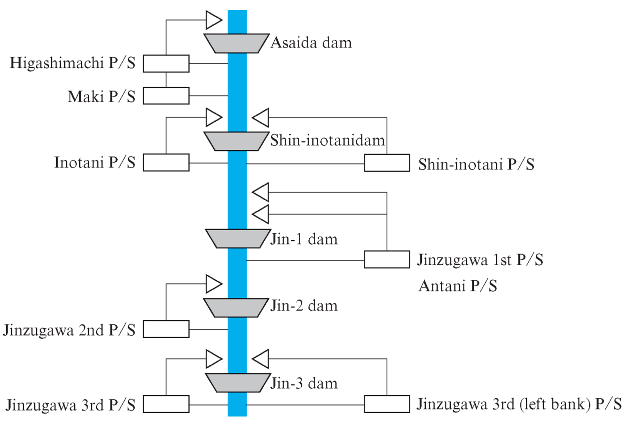

Fig. 11 Jinzu River basin system

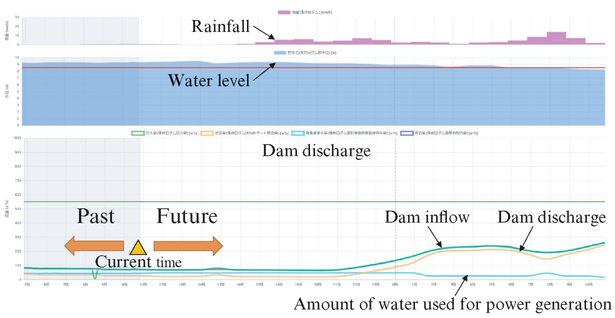

Fig. 12 Web screen of dam operation AI system

A certain increase in the amount of power generation could be confirmed for the main flood season.

4. Future Development

4.1 General-Purpose Version of Dam Operation AI System

JFE Engineering and Hokuriku Electric Power Company intend to expand the object dams for application of the dam operation AI system, and will also develop a general-purpose version of dam operation AI that can be applied to various types of dams for other dam operators.

In addition, we will also constantly develop more advanced and evolved versions of this system while incorporating state-of-the-art AI technologies, and will work continuously to achieve a substantial increase in energy generated by CO_2-free hydro power generation.

4.2 Digital Twin/Digital Parallel

The dam operation AI system introduced here is positioned as a type of digital twin, as it is linked to actual data in real time, quickly and accurately forecasts the condition of dams from the present to the future, and proposes the optimal operational measures.

Moreover, since this is a high speed system which is capable of instantaneous calculation of one scenario case, it is also possible to calculate multiple scenario cases by multiple parallel processing. For example, it is possible to support safer and more optimal operation by simultaneously calculating multiple assumed scenarios such as the effects of sudden increases or decreases in rainfall, the effects of differences in dam operating procedures and the like.

As shown in **Fig. 13**, in contrast to the "digital twin" concept of one-to-one linkage between real space and virtual space, the concept of "digital parallel" is newly defined based on the fact that real space and virtual space are linked in a one-to-many relationship. We also plan to develop this as a next-generation solution.

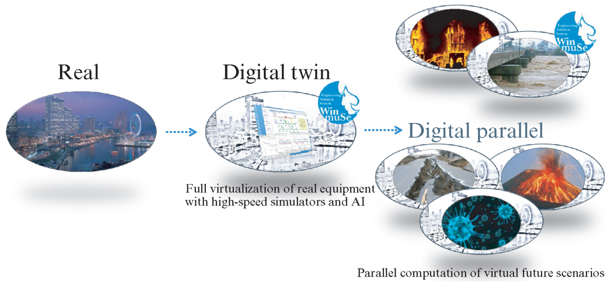

Fig. 13 Concept of digital parallel

5. Conclusion

Against the background of damage caused by heavy rains and progress of CO_2-free hydro power generation in recent years, this paper has introduced a dam operation AI system which was developed jointly by JFE Engineering and Hokuriku Electric Power Company, together with the outlook for the future.

In the future, we will continue to develop more advanced and highly evolved simulation techniques and operation support systems in order to provide the optimum solutions for the challenges confronting dam operators and others.

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