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Forecasting of Reservoir Inflow by the Combination of Deep Learning and Conventional Machine Learning

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***Abstract*—Recently, forecasting of inflow to a reservoir by employing machine learning techniques is getting attention for maximization of generation of hydroelectricity and prevention of disaster caused by flooding. In this context, forecasting of peak inflow caused by heavy rain or melting of snow is of utmost importance to properly utilize water for hydroelectricity, limit the damage to the reservoir/dam and issue flood advisory. The conventional methods of forecasting, which build a forecasting model by using the reservoir inflow data with observed and/or forecasted weather data by minimizing the overall forecasting errors, fail to predict the peak inflow because the number of peak inflows is very small compared to number of normal inflows. To forecast the peak inflow more accurately, we propose a method called Peak-oriented Forecasting by Model Switching (PForMS) which is a hybrid approach that utilizes the forecasting capabilities of both conventional machine learning and Deep Learning-based methods. To show the effectiveness of the proposed method, we perform experiments with five publicly available dam data sets from Japan and the USA and evaluate the proposed method and existing methods in term of AUC (Area under the ROC Curve) of forecasting peak inflow of various heights. Experimental results suggest that our proposed method is able to forecast the higher peaks of inflow more accurately than the existing methods of conventional machine learning and Deep Learning.**

***Index Terms*—Forecasting, reservoir inflow, water level forecasting, peak inflow, deep learning, dam data**

I. Introduction

Usually, the reservoir (dam) water is used for generation of hydroelectricity, irrigation, or other purposes. Inflow to a reservoir or river is usually caused by the rain and/or snow that falls on the catchment area of the reservoir. Due to heavy rain caused by an approaching typhoon, hurricane, cyclone or other storm, inflow to a reservoir or discharge water from a river becomes very high. If the high inflow is not properly controlled by discharging of water through opening of reservoir gates, it may cause flooding, endangering lives near the reservoir. In case of a hydroelectric dam, due to safety concern during heavy rain, the water is discharged without generating electricity, which result in wasting of water. If the peak inflow or water level (inflow/water level over a threshold) can be forecasted accurately well advance in time, the local administration can issue a flood warning and evacuate people to safe places to prevent disaster; in the case of hydroelectric dam, the electric company or local authority can utilize all the water in the reservoir to generate hydroelectricity and make the dam empty before the heavy rain, thereby maximizing the utilization of the water of the reservoir. Sometimes, the reservoirs are operated remotely, and in case of heavy rain forecast, a patrol person is dispatched to open the gates of the reservoir to prevent flooding of nearby areas. Therefore, forecasting of peak inflow to a reservoir or water level of a river is of utmost importance from both perspectives of maximization of generation of hydroelectricity and disaster prevention.

The inflow to a reservoir or a river depends on the geography, terrains, vegetation cover, and soil characteristic of the catchment area. For this purpose, hydrological modeling tools are widely used [1] [2] [3], which are physical modeling tools requiring detailed data, complex factors, and tuning of a number of parameters. Though these models are expected to forecast inflow accurately if the values of the parameters to the physical models are accurate, it requires professional skills to calibrate the modeling systems and the parameters and requires longer computation time [4]. Without proper tuning of the parameters and unavailability of detailed data, the forecasting errors will be large. Moreover, these tools sometimes cannot predict the dam inflow accurately due to uncertainty and limitations to take into account future trends of temporal and spatial variability [4].

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Recently, instead of hydrological modeling tools, forecasting of inflow to a reservoir or water level of a river by employing various machine learning techniques is getting attention [4]–[8]. For example, the authors in [5] have applied Artificial Neural Network (ANN) to forecast reservoir water inflow of US dams and Genetic Algorithm-based method to optimize the operation of the reservoirs. The authors in [6] have applied ANN and ARMAX to predict one-hour ahead water level fluctuation in a lake and showed that ANN performs better than ARMAX model and hydro-dynamical model. Regression-based methods, such as k-Nearest Neighbor regression, Support Vector Regression (SVR), and multiple linear regression are proposed in [9] to predict five days ahead water level by using available weather data from upstream observation points. The authors in [10] have applied ANN, Random Forests, and SVR to model one-month ahead reservoir inflow using 17 climate phenomenon indices, and current and lagged hydrological information.

The authors in [7] have applied Deep Learning algorithms: Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) to predict outflows for the Xiluodu (XLD) reservoir. The authors in [11] have applied NARX –RNN (Nonlinear Auto Regressive model with Exogenous inputs-type Recurrent Neural Network) for long lead time forecasting of daily flow; in it Fourier transformation is utilized to de-seasonalize the data and then differencing is done to make the series stationary. The study concludes that NARX performs better than ARIMA, but the complexity in determining the hyper parameters in NARX remains a significant challenge.

In [12], LSTM is used to forecast daily flow rate for 3 days ahead using dam discharge and precipitation data. In [13], Temporal Neural Network (TNN) is implemented to forecast daily reservoir inflow by using inflow, precipitation, snow melt, maximum, minimum and mean temperature as input variables. The authors conclude that adaptive memory networks like RNN and Time Delayed RNN perform better than Multi-layer perceptron models. In [14], the authors have applied Deep Belief Network (DBN) and Deep Neural Network (DNN) to predict daily reservoir inflow of the Three Gorges reservoir in China. Finally, the authors in [4] have compared the performance of seven machine learning models: Decision Tree, Multilayer Perceptron(MLP), Random Forest Gradient Boosting, LSTM, CNN (Convolutional Neural Network)-LSTM, combined methods of Random Forest-MLP and Gradient Boosting-Perceptron Model for prediction of dam inflow using 40 years of rainfall data from the Soyand River Dam on Hans River basin of South Korea.

Most of these methods focus on minimizing the overall forecasting errors. However, these methods fail to accurately forecast the peak inflows because the number of peak inflows is very small compared to huge number of normal inflows, resulting in burst forecasting errors. To overcome this problem, we propose a new method called Peak-oriented Forecasting by Model Switching (PForMS) that utilizes the pattern recognition capabilities of both conventional machine learning and Deep Learning methods. We show the effectiveness of the proposed method by performing experiments using five publicly available dam data sets from Japan and the USA.

II. Methods

Usually, in forecasting of reservoir inflow with a machine learning technique, past observed inflow and other dam related data, past observed weather data, and weather forecast data are used. Since there might be a time lag in reaching the rain runoff water from an observation point to a reservoir and the past inflow may influence the future inflow, lagged data of the observed weather data as well as the inflow data are used to build a forecasting model. That is, the reservoir inflow model is defined by the following equation:

$$\begin{aligned} Y(t+\Delta t) = f\,(& X_1(t-l_1), \ldots, X_1(t), \\ & X_2(t-l_2), \ldots, X_2(t), \ldots, \\ & Y(t-l), \ldots, Y(t), \\ & X_{f_1}(t+1), \ldots, X_{f_1}(t+\Delta t), \ldots, \\ & X_{f_m}(t+1), \ldots, X_{f_m}(t+\Delta t)) \end{aligned} \tag{1}$$

where t is the current timestamp, Δt is the forecast step and $X_i(t)$, $Y(t)$, and $X_{f_j}(t)$ are respectively the observed weather data, the observed inflow, and the weather forecast data at timestamp t. l_i and l represents the maximum lag steps of variable X_i of the observed weather and other dam operation data, and the observed inflow, respectively. As observed weather data, rainfall (X_1), temperature (X_2), and soil moisture (X_3) are widely used. Rainfall and temperature data can be GPV (Grid Point Value) data or data from multiple observation points. As other observed dam operation data, outflow from upstream dam (X_4) and stream flow (X_5) are widely used. As weather forecast data, rainfall (X_{f_1}) and temperature (X_{f_2}) from multiple grid points or observation points are used. The data of all the input variables in (1) constitue model input data for a forecasting model.

Though the conventional regression-based methods, such as Linear Regression, Ridge Regression or LASSO (Least Absolute Shrinkage and Selection Operator), can capture the patterns of normal inflow perfectly by using a small amount of time-series data, they fail to forecast peak inflows. On the other hand, Deep Learning-based technique, such as LSTM (Long Short Term Memory) can capture the complex patterns of time-series data and improve the forecasting accuracy to some extent; however, they require a huge amount of time-series data to learn a good forecasting model. To overcome their limitations and utilize their pattern matching capabilities, we propose a hybrid approach called PForMS that learns a conventional machine learning method on a small amount of peak inflow data and a Deep Learning-based method on a huge volume of normal inflow data and during forecasting, selects one or more forecasting models depending on the similarity of model input data with the model learning data used during learning of the forecasting model. Then, using those selected models, forecast values are calculated, and the final forecast value is calculated using an ensemble technique.

A. *Peak-oriented Forecasting by Model Switching*

The outline of PForMS is shown in Fig. 1. In PForMS,

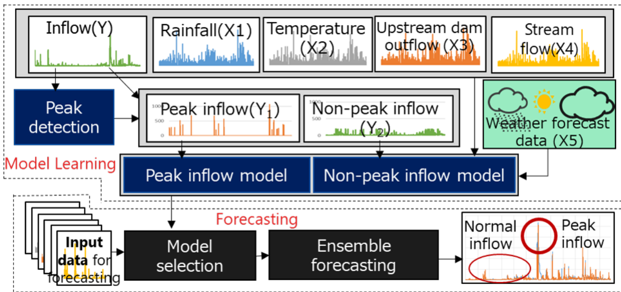


Fig. 1: Outline of PForMS

first, model input data are created taking into account the lag steps of observed variables, forecast steps, and availability of weather forecast data. Then, this model input data is divided into model learning data and evaluation data. Afterward, peak inflows are detected based on a threshold, and model learning data are divided into two groups: peak group (peak inflow group) and non-peak group (normal inflow group) depending on whether the inflow is above the threshold or not. The threshold is calculated using either mean (μ) and standard deviation (σ) of inflow or Kernel Density Estimation (KDE) [15]. In the case of mean and standard deviation, the threshold is set to $\mu + n\sigma$ where n depends on the problem. In case of KDE, the peaks and valleys are used to group inflow data and the last group having sufficient number of samples are selected as peak group and others as non-peak group. Since the number of samples in the peak group will be very small, a forecasting model (called peak inflow model) is learned by using a conventional regression method, such as Ridge Regression, Linear Regression, LASSO or so on, which can learn a model with a relatively small number of samples compared to a Deep Learning-based method.

Then, another forecasting model (called non-peak inflow model) is learned by using a Deep Learning-based method such as LSTM or Multi-Input LSTM (MILSTM, described later) with the huge number of samples from non-peak group. The intuition behind this is that since there are a huge number of samples in the non-peak group, a Deep Learning-based method may be able to capture the complex behavior of the data. In this paper, we use both LSTM and MILSTM as a learning method for non-peak group but have found that PForMS with MILSTM returns better results than PForMS with LSTM on most datasets.

During forecasting, the model input data is created in the same way as model learning data (excluding $Y(t + \Delta t)$) taking into account the lag steps of observed variables, forecast steps, and availability of weather forecast data. Then, using the model input data, the matching samples are searched and extracted in the model learning data by employing a similarity search technique, such as k-Nearest Neighbor (kNN), and the learned models corresponding to the matching samples are extracted. Depending on the value of k in the kNN, all the extracted models may be same or may be a combination of peak and non-peak inflow models. After the models of the matching samples are extracted, forecasted values are calculated by inputting the model input data to the extracted models. Finally, the final forecast value is calculated by the ensemble of those forecasted values. As an ensemble technique, the average or the median of the forecasted values can be taken. In this paper, we take the median of the forecasted values. The pseudocode of PForMS is given in Algorithm 1.

B. *Multi-Input LSTM*

Our proposed Multi-Input LSTM (MILSTM) is an extension of LSTM, where the input variables are divided into a number of groups (see Fig. 2). The intuition behind MILSTM is that due to grouping of input variables, the number of model parameters will be much lower than the LSTM, resulting in better learning of the forecasting model for a smaller number of samples. If there are m input variables and h hidden nodes in an LSTM layer, the number of model parameters will be $4(hm + h^2 + h)$. If the m input variables are divided into three groups having m_1, m_2, and m_3 variables, and those variables connect to three LSTM sub-layers having h_1, h_2, and h_3 hidden nodes, the number of model parameters will be $4(h_1m_1 + h_1^2 + h_1) + 4(h_2m_2 + h_2^2 + h_2) + 4(h_3m_3 + h_3^2 + h_3)$ where $m_1 + m_2 + m_3 = m$ and $h_1 + h_2 + h_3 = h$, which will be much smaller than those of LSTM. In this paper, we divide all the variables of the model input data to the forecasting model into two groups: lag group consisting of all the variables of past and present timestamp, and lead group consisting of the weather forecast data.

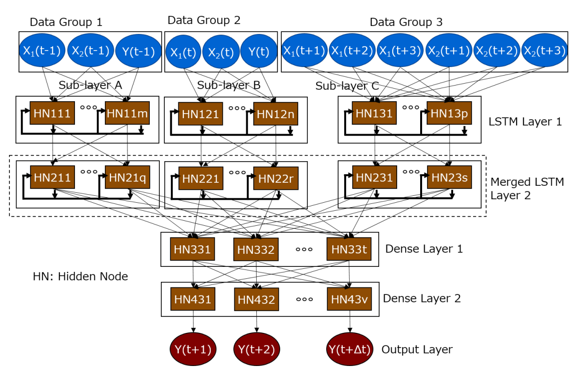


Fig. 2: Example of MILSTM architecture

C. *Evaluation of Forecasting Methods*

In forecasting, forecast errors measured in RMSE (Root Mean Square Error) or MAE (Mean Absolute Error), and the probability as well as the AUC of a forecast value higher than a threshold [16] are used as evaluation metrics. The major problem of RMSE or MAE is that a small shift of the peak inflows will result in very high RMSE or MAE values; whereas for a forecasting method that can predict the majority normal inflows perfectly, the RMSE or MAE

Algorithm 1: Pseudocode of PForMS

Data: Model input data D_l (for learning) and D_f (for forecasting)

Result: Learned models M_{l_r} and $M_{l_{DL}}$, and forecast values corresponding to D_f

Set the architecture and hyper-parameters of Deep Learning method;
Set k value of kNN;
Build a k-d tree KDT with D_l for searching by kNN;
Initialize a sample-to-model map: $modelmap = \{\}$;
Calculate the threshold I_{th} for grouping of D_l;
// Divide D_l into peak and non-peak groups
$D_{l_{peak}}$={}; $D_{l_{npeak}}$={};
for *each sample S in D_l* **do**
    if $S_{inflow} \geq I_{th}$ **then**
        $D_{l_{peak}} = D_{l_{peak}} \cup S$;
        $modelmap[S] = 1$
    else
        $D_{l_{npeak}} = D_{l_{npeak}} \cup S$;
        $modelmap[S] = 0$
    end
end
Multiply the target inflow S_{inflow} of $D_{l_{peak}}$ by a weight factor $\alpha \geq 1.0$;
Learn a forecasting model M_{l_r} using $D_{l_{peak}}$ with a conventional regression method;
Learn a forecasting model $M_{l_{DL}}$ using $D_{l_{npeak}}$ with a Deep Learning method;
Initialize $forecast\_value$={} ;
for *each sample S_f in D_f* **do**
    Initialize $fval$={};
    Find k nearest samples S_k in D_l using KDT;
    for *each sample $S_{k,i}$ in S_k* **do**
        if $modelmap[S_{k,i}] = 1$ **then**
            // forecast using M_{l_r}
            fv=$M_{l_r}(S_f)$
        else
            // forecast using $M_{l_{DL}}$
            fv=$M_{l_{DL}}(S_f)$
        end
        $fval = fval \cup fv$; // append
    end
    Calculate final value: $fval_f = ensemble(fval)$;
    $forecast\_value = forecast\_value \cup fval_f$;
end
Return M_{l_r}, $M_{l_{DL}}$, and $forecast\_value$;

will be smaller, which can be misleadingly identified as a better method (Algorithm A; see Fig. 3). In forecasting of peak inflows, accurate forecasting of those peaks within a time window in well-advance of time might be valuable to the dam operator who might get reasonable time to make a plan of hydroelectricity generation and issue a flood warning and take necessary steps to prevent disaster. AUC that takes into account the trade-off between false positive rate and true positive rate is a better choice for this task.

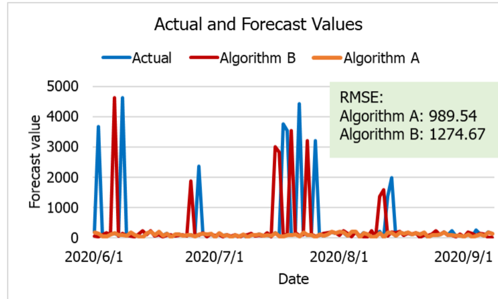


Fig. 3: Illustration of the problem of RMSE

III. Experiments and Results

A. Data

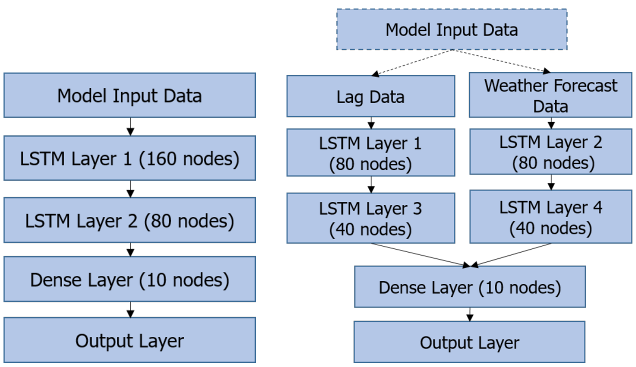
To evaluate the performance of various forecasting methods, we select two dams: Unazuki dam and Miyagase dam from Japan and three dams: Cougar dam, Detroit dam, and Lost Creek dam from the USA. For the two Japanese dams, weather forecast data are unavailable; we use the future values of the observed rainfall as the weather forecast data. Since the forecasting accuracy of a model is influenced by the forecasting accuracy of the weather forecast data, using the future values of observed rainfall will give the best estimate of the performance of the forecasting model of the reservoir inflow. For Japanese dams, the observed rainfalls are available from the rain gauges installed at respectively three and four observation points, maintained by MLIT, Japan, and we add the rainfall data from another observation point (Unazuki) maintained by Japan Meteorological Agency near the dam. The data of Japanese dams can be downloaded from the Water Information System database of MLIT, Japan [17]. For US dams, we downloaded data from https://github.com/shahryaramd/ANN_FlowForecasting, which was used in [5]. For these dams, GFS (Global Forecast System) forecast data of 7-day ahead precipitation, minimum and maximum temperature, and soil moisture are used as weather forecast data. The description of the data is given in Table I.

TABLE I: Dam datasets used for various experiments

Dam Name	Location	Sampling Rate	Model Learning Data	Evaluation Data
Unazuki	Japan	Hourly	2015-2016	2017-2018
Miyagase	Japan	Hourly	2016-2018	2019-2020
Cougar	USA	Daily	2007-2013	2014-2017
Detroit	USA	Daily	2007-2013	2014-2017
Lost Creek	USA	Daily	2007-2013	2014-2017

B. Experimental Setup

For Japanese dams, we build forecasting models for one-hour to 96-hour ahead inflow forecasting while for US dams, we build forecasting models for 1-day to 7-day ahead inflow forecasting in one pass. To create the model input data, we use 96-step and 7-step lagged data of observed weather data and inflow for Japanese and US dams, respectively, which are merged with the weather forecast data. In PForMS, the forecasting model for peak group is learned with Ridge Regression and that for the non-peak group is learned with either LSTM or MILSTM; we denote this by PForMS (Ridge, LSTM) and PForMS (Ridge, MILSTM), respectively. We set k of kNN to 4; however, for other values of $k(\leq 5)$, the results do not change much. The architectures of Deep Learning methods are shown in Fig. 4. We use TensorFlow and Keras libraries to build the Deep Learning models. The values of other hyper parameters are shown in Table II. The weight factor α of peak values was set to 1.0, 1.15, 1.1, 1.1, 1.1 for Unazuki dam, Miyagase dam, Cougar dam, Detroit dam, and Lost Creek dam. To divide the inflow into peak and non-peak groups, we set the threshold to $\mu + 3\sigma$ for Japanese dams, and $\mu + 2\sigma$ for US dams.



(a) LSTM (b) MILSTM

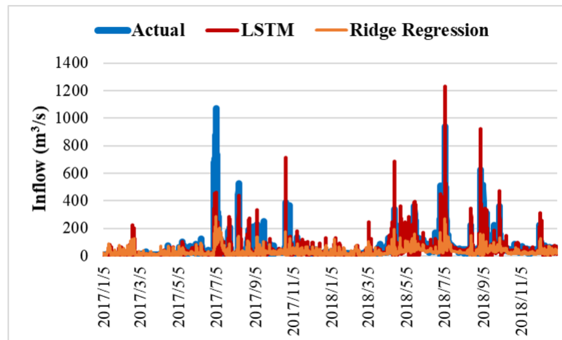
Fig. 4: Architecture of Deep Learning methods

TABLE II: Settings of Hyper-parameters

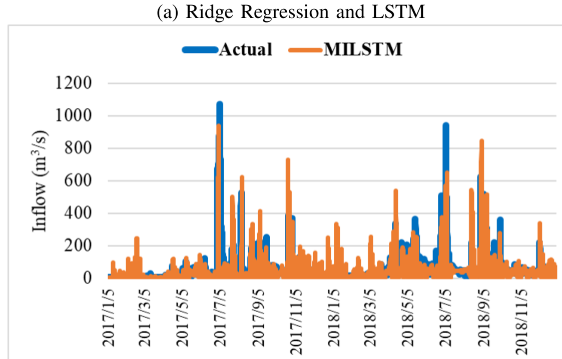
Parameter	Value
Activation method	relu
Epochs	1000
Validation_split (validation size)	0.2
Optimizer	adam
Loss	mean_squared_error
Steps_per_epoch	1

C. Experimental Results

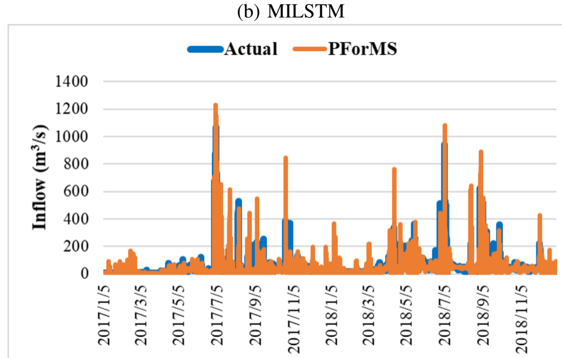
1) Visualization of Forecasted Values: We, first, show the forecasted values of various forecasting methods in Figs 5-8. Due to space limitations and clarity of the graphs, we have omitted the graphs of Linear Regression and PForMS (Ridge, LSTM) because their performances on the datasets are almost the same as the Ridge Regression and LSTM, respectively; similarly, we have omitted the graphs of MILSTM except on Unazuki dam and Cougar dam datasets. In the figures, inflow at each timestamp is forecasted 96 hours (Unazuki dam and Miyagase dam) or 7 days (Cougar dam, Detroit dam, and Lost Creek dam) in advance. In case of Unazuki dam, conventional Ridge Regression cannot forecast peaks higher than 284 m^3/s. LSTM fails to predict the first biggest peak of 1070 m^3/s near 2017/7/4 but is able to forecast the second biggest peak of 938.97 m^3/s near 2018/7/5 with some over-estimation (about 290 m^3/s). MILSTM forecast the biggest peak better than LSTM but fails to forecast the second biggest peak. PForMS (Ridge, MILSTM) is the best forecasting model as it can forecast both the big peaks and other smaller peaks more accurately.



(a) Ridge Regression and LSTM



(b) MILSTM

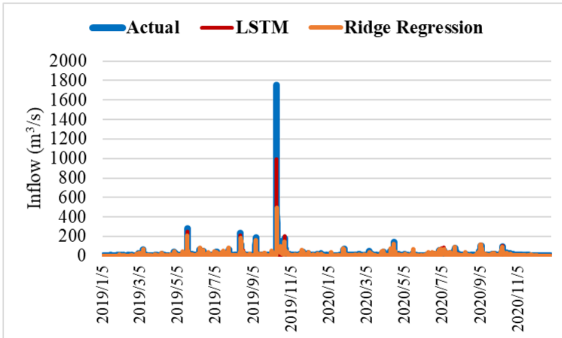


(c) PForMS

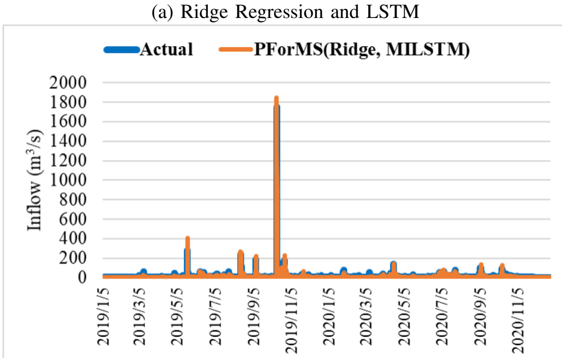
Fig. 5: 96-hour ahead forecasting for Unazuki dam dataset

In case of Miyagase dam, there is the biggest peak of about 1749 m^3/s at 2019/10/12. Only PForMS (Ridge, MILSTM) is able to forecast the peak accurately; other forecasting methods fail to forecast it. It is also able to predict other smaller peaks.

In case of Cougar dam, Ridge Regression, LSTM, and

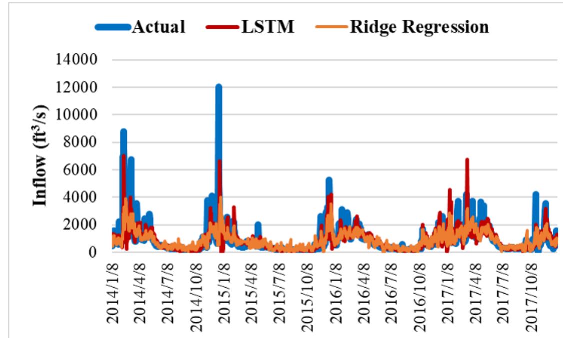


(a) Ridge Regression and LSTM

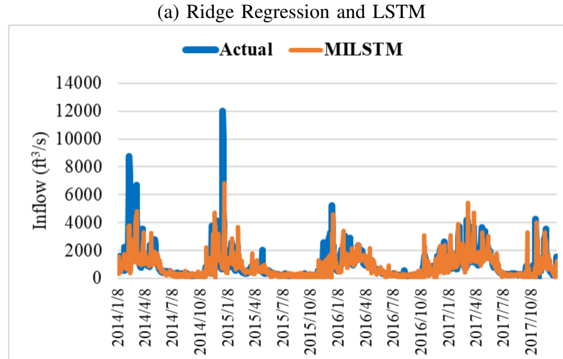


(b) PForMS

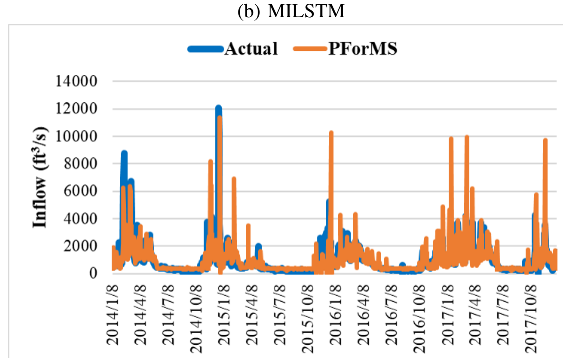
Fig. 6: 96-hour ahead forecasting for Miyagase dam dataset



(a) Ridge Regression and LSTM



(b) MILSTM



(c) PForMS

Fig. 7: 7-day ahead forecasting for Cougar dam dataset

MILSTM fail to predict the biggest peak near 2015/1/8 as well as other bigger peaks. Contrary to this, PForMS (Ridge, MILSTM) can predict the highest peaks as well as other bigger peaks but for some bigger peaks, over-estimation occurs. Similar performance of the forecasting methods is observed on the Detroit dam data.

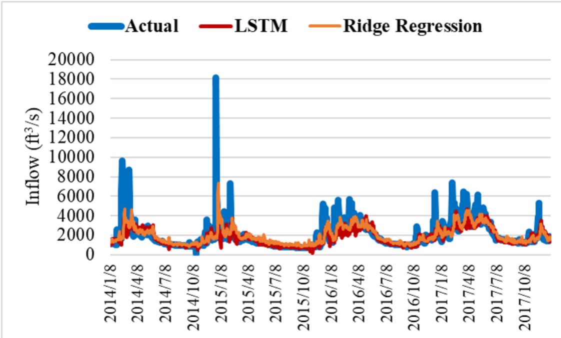
Lost Creek dam dataset is the most difficult one to predict the peaks. All the methods fail to predict the biggest peak. Only PForMS (Ridge, MILSTM) is able to predict the bigger peaks but with some over estimation.

2) Evaluation in Term of AUC: Next, we compare the performance of various methods quantitatively. The AUCs of various methods are shown in Figs. 9-13. Since the peaks may be forecasted earlier or later than the actual timestamp of a peak, we set a time window of predicting a peak. For Japanese dams, we set time windows to one hour (one step) and 24 hours (24 steps), and for US dams, we set time windows to one day (one step) and 4 days (4 steps). Since the forecasting models are built for 96-hours ahead and 7-day ahead forecasting tasks, 24 steps and 4 steps time window will give the dam operator reasonable time to make a plan of hydroelectricity generation and issue a flood warning and take necessary steps to prevent disaster.

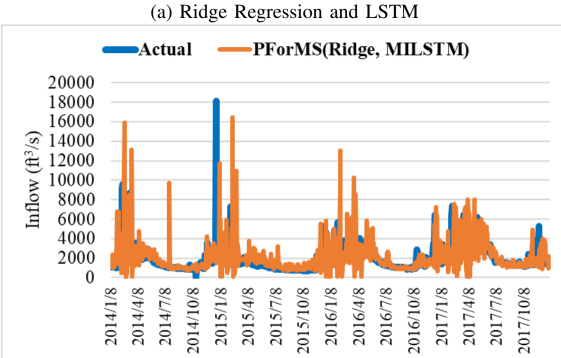
For Unazuki dam, the forecasting power of PForMS (Ridge, MILSTM) is very high, especially when time-window is set to 24 hours; that means it will forecast all the peaks with 80% accuracy within the next day. Interesting observation here is that while forecasting power of other methods decreases as the peaks become higher, PForMS (Ridge, MILSTM) becomes better because in it, the peaks higher than a threshold are learned through a different forecasting model by employing Ridge Regression. The performance of PForMS (Ridge, LSTM) is next to PForMS (Ridge, MILSTM) while Ridge Regression fails to predict most peaks higher than 284 m^3/s as its AUC is about 0.5.

For Miyagase dam dataset, we see that though all the methods can predict peaks lower than 600 m^3/s with sufficient accuracy, only PForMS (Ridge, MILSTM) can predict peaks higher than 1,200 m^3/s. Due to higher weight assigned to peaks and learning those peaks through Ridge Regression gives better AUC at higher peaks.

For Cougar dam dataset, we find that prediction of peaks

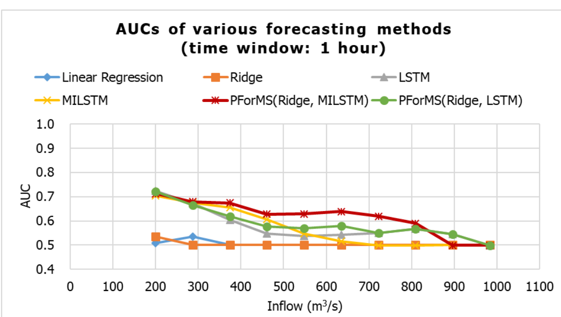


(a) Ridge Regression and LSTM

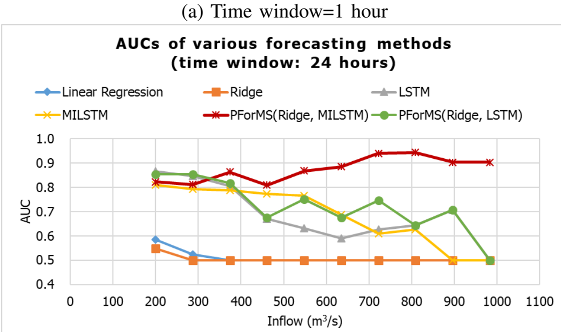


(b) PForMS

Fig. 8: 7-day ahead forecasting for Lost Creek dam dataset

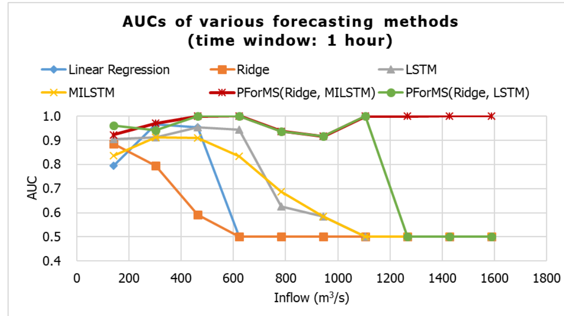


(a) Time window=1 hour

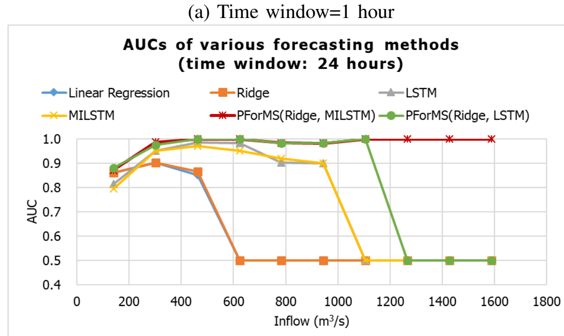


(b) Time window=24 hours

Fig. 9: AUC on Unazuki dam dataset

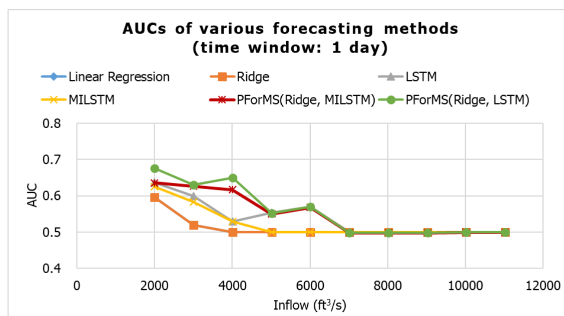


(a) Time window=1 hour

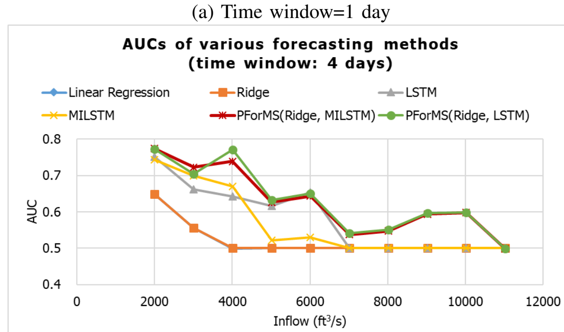


(b) Time window=24 hours

Fig. 10: AUC on Miyagase dam dataset



(a) Time window=1 day



(b) Time window=4 days

Fig. 11: AUC on Cougar dam dataset

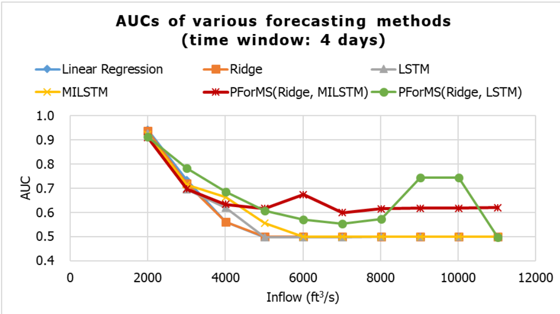


Fig. 12: AUC on Detroit dam dataset

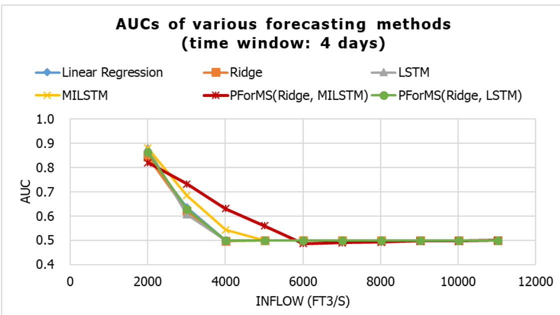


Fig. 13: AUC on Lost Creek dam dataset

higher than 6,000 ft^3/s with sufficient accuracy within the next day is very difficult for all the forecasting methods. However, PForMS (Ridge, LSTM) and PForMS (Ridge, MILSTM) can predict peaks up to 10,000 ft^3/s with accuracy over 0.55 within the next 4 days. Due to the low quality of weather forecast data, the forecasted peaks become shifted. For Detroit dam dataset, almost similar performance is observed. For Lost Creek dam dataset, prediction of peaks higher than 5,000 ft^3/s with sufficient accuracy is very difficult for all the methods.

From the experimental results we observe that the AUCs on Japanese dam datasets using future values of observed weather as weather forecast data is much higher than those on the US dam datasets using GFS weather forecast data. If the quality of weather forecast data is high, the proposed method will be able to predict all peaks with very high accuracy.

IV. Conclusion

In this paper, we have proposed PForMS consisting of a combination of conventional machine learning and Deep Learning-based methods for forecasting of reservoir inflow. The proposed method learns a regression-based forecasting model for the peak inflow group and a Deep Learning based forecasting model for the non-peak inflow group, and during forecasting, selects several forecasting models depending on the similarity of the input data, calculates forecasted values by using the selected models and creates the final forecasted value by the ensemble of the forecasted values. By performing experiments with five dam data sets from Japan and the USA and evaluating in term of AUC, we have found that PForMS with Ridge Regression and MILSTM outperforms other methods in predicting the higher peaks of reservoir inflow. We have found that when weather forecast data are used, the forecasting accuracy of all forecasting methods falls sharply, which suggests that we need a good quality weather forecast data to get more accurate forecasting of reservoir inflow.

However, there remains a number of issues, such as selection of the good hyper-parameters automatically by dividing the model learning data into training data and validation data, and the problem of peak shift occurring due to weather forecast data, that we want to address in our future work.

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