A Scalable River Flow Forecast and Basin Optimization System for Hydropower Plants

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***Abstract*—Optimized operation of cascaded hydropower plants (HPPs) is critical, with important environmental and economic outcomes. These outcomes include reduced floods and waste of water, uninterrupted supply of water for drinking, irrigation and industrial use, and maximized energy generation. In this article, we present a large-scale and extensible system for river flow forecast and basin optimization. The system facilitates short-term and long-term river flow forecasts using meteorological and hydrological models, in addition to machine learning, ensemble, and hybrid learning methods. It produces optimization results for the cascaded HPPs using particle swarm optimization, based on the generated river flow forecasts and constraints of the basin. The optimization procedure can be short-term for flood prevention, and long-term for maximized energy generation. The forecast and optimization results produced, together with the automatically collected data from external systems are stored in a central database and are made accessible via a Web-based GUI application. The system is currently operational for a single basin in Turkey, but is extensible to cover other basins as well. The system is significant as it helps reduce floods and wasted water, and increases energy generation in the cascaded HPPs. Additionally, it stands as a large-scale system implementation for the domains of hydrology and hydropower.**

***Index Terms*—Artificial neural networks, Basin optimization, Hydrological models, Hydropower, Particle swarm optimization, River flow forecast, Support vector machines, WRF-Hydro.**

I. Introduction

HYDROPOWER is a ubiquitous renewable energy type with a significant share in global energy generation. Hydroelectric power plants are usually classified as storage (impoundment), run-of-river (diversion), or pumped storage type plants [1]. A storage-type hydropower plant (HPP), which is the relevant type considered in the current paper, has a dam to store water in a reservoir, while a run-of-river type plant usually does not have a dam or reservoir and pumped storage plants are hybrid plants which utilize excess power generated by renewables like wind and solar to store some amount of water in an elevated reservoir [1]. There are mainly four functions of storage-type HPPs: (i) electricity generation, (ii) flood prevention, (iii) supply of drinking water, (iv) supply of irrigation water and water for industrial use, while the only objective of the latter two plant types is electricity generation. In order to fulfill these tasks adequately and efficiently, storage-type HPPs installed on the same river should be operated using a centralized river flow forecast and basin optimization system. The main benefits of such a forecast and optimization system include (i) minimized number of floods, (ii) uninterrupted supply of drinking and irrigation water, and water for industrial use, (iii) minimized waste of water, (iv) maximized generation of electricity, (v) enhanced planning and management of the overall electricity grid, (vi) maximized profit in the energy market.

In this paper, we present an integrated river flow forecast and basin optimization system (RFBOS), which is implemented within the scope of the ATHOM project, aims to attain all of the above-listed benefits, except increased profit in the energy market. The system has the necessary components for: (i) data collection, (ii) river flow forecast, (iii) basin optimization, (iv) visualization and reporting of results (i.e., graphical user interface (GUI)). The system is a fully-automated and operational decision support system implemented for a selected basin (named Seyhan) in Turkey. This particular basin is chosen due to its high-coverage network of hydrological measurement facilities and including both snow and rain types of precipitation. Yet, although it is currently operated for this single basin, the system is designed and implemented as a scalable system with the required underlying infrastructure, so that it can be extended to cover the other basins in the country.

Main contributions of the paper are presented below:

- The implemented system produces long-term and short-term river flow forecasts using lumped and distributed hydrological models in addition to supervised machine learning methods, ensemble and combination models.
- The system performs short-term optimization (for flood-prevention) and long-term optimization (for maximized energy generation) of cascaded storage-type HPPs in the basin, using particle swarm optimization.
- The produced results are presented to the users through the system's Web-based GUI application,

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as time-series graphs, tables, geographical maps, animated display of cascaded plants, and automatically-generated reports.

- The system stands as a significant implementation of a large-scale and integrated river flow forecast and basin optimization system. With its current underlying infrastructure, the system is the first system in Turkey and scalable to cover other basins, as long as the necessary data streams are made available.

The rest of the paper is organized as follows: In Section II, a review of the literature on river flow forecast and optimization approaches/systems for HPPs is presented. Section III provides an overview of the implemented forecast and optimization system while Section IV describes its data collection module. Section V includes the details of the river flow forecast modules while Section VI presents the details of the basin optimization modules of the system. In Section VII, Web-based GUI application of the overall system is presented. Finally, Section VIII includes sample results of the system and Section IX concludes the study with a summary of main points.

II. Literature Review

River flow forecast and basin optimization have been studied for decades, particularly due to their impact on short-term and long-term operational decisions for hydroelectric power plants. Especially river flow/streamflow forecasts/simulation approaches are very common in the recent studies [2]–[6]. Artificial neural network (ANN) is a widely-employed and high-performance machine learning approach used for streamflow/inflow forecasting, as reported in several studies [7], [8]. Different ANN architectures are tested for forecasting monthly watershed runoff, using precipitation and temperature forecasts as inputs, in [9]. It is concluded that forecast performance is improved when feedback is included in recurrent neural networks (RNN) [9]. In [10], ANN and regression-based models for inflow forecasting are compared and it is concluded that the use of ANN leads to superior forecast performance. In another related study, short-term daily streamflow forecasting experiments are performed using different ANN models [11]. Another neural network based river flow forecasting approach is presented in [12] where the particular approach used is Extreme Learning Machine (ELM) [13] which is claimed to produce more accurate forecasts within shorter durations. Unorganized machines, ELM and echo state networks (ESN) are used to predict monthly seasonal streamflow series, associated with three important Brazilian hydroelectric plants [14]. A variant of particle swarm optimization (PSO) is also used to determine the filter parameters [12]. Another machine learning approach, namely, Support Vector Machine (SVM) is employed for long-term discharge forecast in [15]. It is argued that SVMs achieve favorable performance when compared to regression models. In [16], the effects of forecast uncertainties of deterministic and probabilistic streamflow forecast products on the operation of a single reservoir are studied. Apart from machine learning approaches like regression, ANN and SVM; hydrological models such as Hydrologiska Byråns Vattenbalansavdelning (HBV) [17] and snowmelt-runoff model (SRM) [18] are commonly utilized for automatic river flow forecasting [19], [20].

Automatically produced river flow forecasts and operational constraints regarding the reservoir/basin under consideration are utilized by the subsequent optimization modules to produce optimal operation schedules for the HPPs.

In [21], the authors target at daily reservoir operation for flood prevention in a multi-reservoir system. They propose a state-space mathematical model for flow forecasting, and an optimization approach based on linear quadratic Gaussian (LQG) control for the operation of the system [21]. In [22], it is reported that using best inflow forecasts to reservoirs as a hydrological state variable can improve reservoir operation optimization, using stochastic dynamic programming (SDP). In [23] state incremental dynamic programming (SIDP) is used to optimize six reservoirs in lower Seyhan basin in Turkey. Similarly, modified forms of SDP are used for reservoir optimization in [24] and [25]. A proprietary statistical approach is presented in [26] for short-term scheduling of large basins. In [27], stochastic dual dynamic integer programming (SDDiP) is applied to the problem of hydropower scheduling. In [28], as an integrated system, which is consisted of streamflow predictions and optimizing reservoir operation with considering floods, water supply and environmental flows, is constructed for maximizing revenue of the electrical energy produced. In [29] a decision support system based on short-term climate forecasts for optimizing reservoir operations in terms of water quality, flood control, reservoir balancing and hydropower revenues. A recent survey of the literature on optimal operation of a network of reservoirs is presented in [30].

III. System Overview

The architecture of the river flow forecast and basin optimization system (henceforth referred to as RFBOS, or *system*) is demonstrated in Fig. 1. RFBOS is implemented to be operated by the national organization called State Hydraulic Works (http://en.dsi.gov.tr/) which is responsible for the operation of storage-type HPPs.

In the RFBOS center, there are a number of dedicated servers which host (i) the system's central database and (ii) the service software of the system. The types of service software include data collection, river flow forecast, basin optimization, and data presentation services (for the GUI application). These services and related modules are overviewed in the rest of this section, and their details are presented in the corresponding sections of the paper. On the lower right corner in Fig. 1, the logo of the project, in the course of which RFBOS is implemented, is depicted. This logo includes the abbreviation of the system in Turkish (as ATHOM).

In order to build the underlying database infrastructure, RFBOS includes software services for the collection of relevant measurement and weather forecast data from the corresponding data sources. Collected data is stored in a central database, to be served to the system users and to be used by the river flow forecast and optimization modules of the system. Details of the data collection module are provided in Section IV.

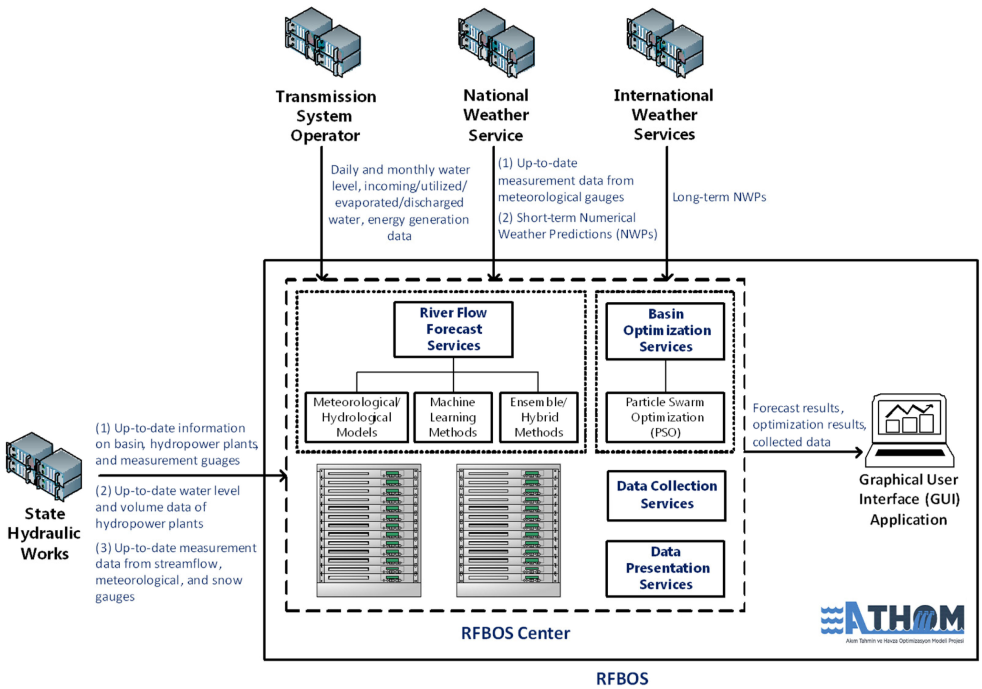

Fig. 1. Architecture of the proposed streamflow forecast and basin optimization system.

The river flow regime and river system display significant nonstationary and stochastic behaviour. Considering the complex nature of river flow and its variability, expert systems like RFBOS and nonlinear statistical and hydrological river forecasting models used in that system, are appropriate models for such a stochastic process. RFBOS produces two main types of river flow forecasts: long-term forecasts to be used by the optimization module for maximized energy generation and short-term forecasts to be used by the optimization module for flood prevention. Each of these forecast types, in turn, utilizes several different methods including hydrological, supervised machine learning, hybrid, and ensemble models. The Numerical Weather Prediction (NWP) models predict weather by using mathematical models of atmosphere and oceans. The NWP is very important for short-term and long-term forecasting of several parameters related to the weather behaviour. NWPs of different meteorological models are utilized by learning-based river flow forecast methods. River flow forecast modules of RFBOS are described in the upcoming Section V.

Similar to its modules for river flow forecast, the optimization modules of RFBOS produce long-term and short-term outputs, for energy maximization and flood prevention purposes, respectively. Both of the optimization methods are based on particle swarm optimization (PSO) and they are described in Section VI of the current paper.

The final significant component of RFBOS is its Web-based GUI application which facilitates data visualization (of both collected data and generated results), automatic report generation, and manual triggering of river flow forecast and optimization models using model inputs and parameters tuned by domain experts. Additional means of data supply to the system users include automatic e-mails of up-to-date river flow forecast and optimization outputs. Details and sample snapshots are provided in Section VII.

RFBOS is a fully-automated system and is currently operational for Seyhan basin of Turkey, after making the data streams for this basin continuously available to the system and studying and modeling the cascaded structure and constraints of the HPPs at this basin. Seyhan is one of the 25 basins in Turkey, and its location on the country map is given in Fig. 2.

The basin is named after its main river, Seyhan, which has its source at Taurus Mountains and discharges to Mediterranean [31]. It has a total length of 560 km and has two main tributaries: Zamanti and Goksu [31]. There are dams and HPPs installed in a cascaded manner on this river basin. RFBOS performs long-term and short-term river flow forecasts and then performs long-term and short-term optimization resulting in water levels for the considered dams, at monthly and daily resolutions.

RFBOS has a modular structure (see Fig. 1) and is a scalable system which can be extended to cover other basins as well, with limited customization and programming effort. The scalability of the system is achieved through (i) ensuring the availability of the corresponding measurement and NWP data streams, (ii) studying and modeling the placement and operational constraints of the dams and plants of the basin, (iii) tuning forecast and optimization parameters for the basin.

IV. Data Collection

RFBOS has a central database created on a relational database management system. Related numeric, textual, and spatial data are all stored in this database.

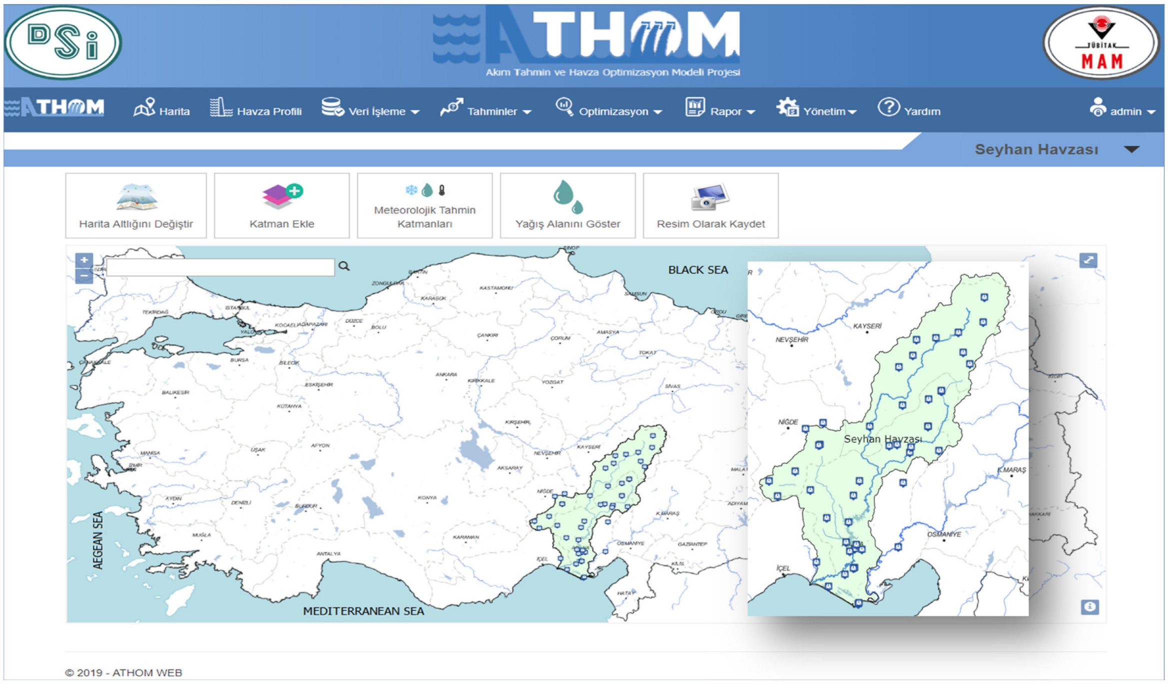

Fig. 2. Locations of Seyhan basin (in green) and real-time streamflow gauges (as squares) are depicted on the opening page of the Web-based GUI of RFBOS.

There are mainly four data sources of RFBOS, as shown in Fig. 1. They are (a) General Directorate of State Hydraulic Works (abbreviated as DSI), (b) the transmission system operator (TSO) in Turkey, namely, Turkish Electricity Transmission Corporation (abbreviated as TEIAS), (c) General Directorate of Meteorology (abbreviated as MGM) which is the national meteorological service, and lastly, (d) European Centre for Medium-Range Weather Forecasts (ECMWF) which is an international weather service.

DSI supplies several different types of data to RFBOS from its information system, through Web services. The types of data collected from DSI through this scheme include:

- Descriptive information about the basins, administrative regions, dams, plants, measurement gauges installed, including their geographical coordinates,
- Daily water level and volume data for plants,
- Hourly water level and river flow rate measurements obtained from river flow gauges installed,
- Daily precipitation and evaporation measurements obtained from meteorological gauges operated by DSI,
- Seasonal measurements obtained from snow gauges, where these measurements include snow depth, snow-water equivalent, and average snow weigh,
- For each dam, daily amounts of water used for energy generation, for drinking, for irrigation, and by industry.

Data obtained from TEIAS through Web services include:

- Daily water levels in 4-hour resolution, at the reservoirs of the power plants.
- Daily amounts of incoming water to the reservoir, water utilized for energy generation, evaporated and discharged water.
- Hourly energy generation at the plants

Data collected from MGM through file sharing include:

- Hourly measurements obtained from automatic meteorological gauges operated by MGM. These measurements include precipitation, snow depth, evaporation, humidity, pressure, temperature, wind speed and direction, and radiation, among others.
- Short-term numerical weather forecast outputs of ALARO and WRF meteorological models. These outputs span a three-day interval in hourly resolution.

Finally, seasonal weather forecasts are obtained from ECMWF, through file sharing. Each data file downloaded once a month spans a 7-month interval in daily resolution. The meteorological parameters include those related to precipitation, snow, temperature, humidity, pressure, and wind.

V. River Flow Forecast

Long-term and short-term river flow forecasts are produced to be fed into long-term and short-term optimization schemes which are performed periodically for energy maximization and flood prevention, respectively. Long-term forecasts span 15 months (required due to operational issues) in monthly/daily resolution while short-term forecast span 3 to 10 days in daily/hourly resolution. The details of these two forecasting schemes are provided in the following subsections.

A. *Long-Term Forecast*

Long-term river flow forecasts are performed using three distinct approaches: ANN, SVM, and HBV where the first two of them are parametric machine learning models and HBV is a semi-distributed hydrological model. These three algorithms are used within an ensemble model in order to produce a fourth combined long-term forecast output. Additionally, probabilistic forecasts are produced for all of the employed models.

Multi-stage ANN model with one hidden layer is used in the forecast model with different neuron numbers and best parameters giving lowest error in the calibration period are selected. The Resilient Backpropagation (Rprop) optimization method is used, to find the global minimum value of error function [32]. Weight values and the step size are determined dynamically as given in (1).

$$w_i{}^{(t)} = w_i{}^{(t-1)} - \eta^{(t-1)} * sgn\left(\frac{\partial \mathrm{E}^{(t-1)}}{\partial w_i{}^{(t-1)}}\right) \quad (1)$$

where *w* is the weight value, *i* is the weight number, *t* is the number of iterations, η is the step size and *E* is the error function. The most successful neuron number is found as a result of the experiments and logarithmic activation function was used here. Predictions such as precipitation, temperature, soil moisture, surface flow and evaporation and measurement data are used as input for ANN lumped type model.

SVM model is a method which aims to make a certain amount of error in the training set against the principle of giving the best results in ANN training set but to perform better in the test set. Lagrange multipliers and Kernel functions are used for regression type SVM model. Mathematical model of this SVM model is given in (2) as;

$$y = \sum y_i \alpha_j K\left(x_j, x\right) - b \quad (2)$$

where *y* is the output vector, α is the Lagrange multipliers, *K* is the Kernel function that measures the similarity between *x* and x_j and *b* is defined as the shift parameter. The SVM river flow forecast model training phase enables the determination of the parameters that will provide the most successful model performance in accordance with the data set. The SVM model, which is considered as a lumped model, generates flow estimates using the same data used by the ANN model.

Considering the HBV model, it is a semi-distributed model originally proposed for Scandinavia region but is also successfully applied in different regions of the world [17]. It divides basins into sub-basins and into sub-regions wıth respect to the altitude.

The general water balance formula of the model is given in (3). (P: precipitation, E: evapotranspiration, Q: runoff, SP: snow pack, SM: soil moisture, UZ: upper groundwater zone, LZ: lower groundwater zone, VL: lake volume).

$$P - E - Q = \frac{d}{dt}\left[SP + SM + UZ + LZ + VL\right] \quad (3)$$

Since the parameters are crucial for the performance of the model, these parameters should be calibrated. Particle swarm optimization (PSO) is used with the available observations since 2010, in order to calibrate the model parameters. After this calibration phase, aforementioned long-term meteorological forecasts are used as input to the model to obtain the ultimate forecast outputs from the model, as is the case for ANN and SVM-based forecast submodules.

All of the three individual models utilize the long-term meteorological forecast outputs from the Integrated Forecast System (IFS) of ECMWF (as previously mentioned in Section IV) as input. These are daily forecasts span a total of 216 days ($\sim$7 months) for parameters such as total precipitation, temperature, runoff, soil moisture, and evaporation.

The ANN and SVM models are trained on historical forecast and river flow data observed, since 2010. The long-term river flow forecasts are obtained from trained models for $\sim$7 months and by using the pattern between forecasts of these 7 months and the averages observed river flow values in historical data, the forecasts are extended to 15 months.

A hybrid ensemble model is developed based on the aforementioned three forecast models to provide system users with a fourth combined forecast output. This final model produces a weighted average of the outputs of the individual models. The weights are determined and periodically updated automatically with values inversely proportional to historical forecast error rates. This final model is hybrid and ensemble as it combines statistical models with a hydrological model and uses more than one model to achieve improved performance.

B. *Short-Term Forecast*

Short-term river flow forecasts are performed using three distinct approaches: ANN, SVM, and WRF-Hydro where the first two of them are parametric machine learning (similar to long-term models) algorithms and WRF-Hydro is a grid-based fully-distributed hydrological model.

All of the three individual short-term models utilize the 3–10 day meteorological forecast outputs from the WRF model run with ECMWF boundary conditions (as previously mentioned in Section IV) as input. These are hourly forecasts span up to 10 days for parameters such as total precipitation, temperature, soil moisture, surface pressure and snow-water equivalent. Short-term ANN and SVM forecast models are trained with most recent 30-day meteorological forecasts and observed river flow data.

The WRF-Hydro model is a full-distributed model that models the entire basin on a grid-based using the WRF weather forecast model results and can produce point flow forecasts at high resolutions [33]. Here, the WRF model operated with ECMWF boundary conditions to obtain an estimate of 2 km $*$ 2 km resolution is used as input to the WRF-Hydro model. With this hydrological model, 200 m $*$ 200 m resolution grids and high resolution flow estimation results are obtained.

The most important point for the grid-based flow estimates to be produced with the WRF-Hydro model is that the model parameters used are best calibrated values and these parameters are obtained with high accuracy of the 10-day short-term current forecasts obtained. Approximately 1-year data set was used for calibration. When creating the WRF-Hydro zone channel network, one channel is assigned to each channel. If the channel is upstream, the channel order is one. The two upstream assemblies form an arm with two rows of channels. This sequence is performed for all tributaries in the river network and the corresponding Manning channel parameters are determined.

As the arm parameter becomes smaller, the current moves faster and the peaks of the current are observed earlier and larger, and the larger the current moves, the slower the current peaks are later and smaller.

VI. Basin Optimization

The basin optimization module of RFBOS produces long-term energy maximization and short-term flood prevention optimization outputs for each of the reservoirs in the basin. The heuristics-based PSO algorithm is used by the optimization module, due to its favorable characteristics like simplicity and effectiveness [34].

In order to calculate the fitness value of the particles in the algorithm, the constraints are considered as penalty terms and then added to the objective function value. Therefore, the fitness value, *f*, can be calculated as given in (4),

$$f = F + \sum_{i=1}^{I} \mu_i T_i^2 \tag{4}$$

where F is the objective function to be minimized, μ_i is the constraint penalty factor, and T_i is the cumulative penalty term calculated as the difference of the variable and the required limit if the constraint is violated; otherwise, its value is zero. This term is squared because the more the penalty limit is violated, the more its value increases compared to using a linear term. By this way, the algorithm reaches the solution faster with minimal amount of penalties.

A. Long-Term Optimization

Long-term optimization is performed for energy maximization for a range of 15 months for all of the reservoirs located in a cascaded structure in the basin. The output comprises the optimized monthly water levels for the whole range.

First of all, the particle swarms are created for the water levels in the reservoirs between maximum and minimum values. Next, the flow equation, given in (5), is solved using constraints such as amounts of water needed/reserved/expected for drinking, irrigation, natural life, and evaporation.

$$S(t+1, i) = S(t, i) + I(t, i) - R(t, i) - O(t, i) \tag{5}$$

where *S* is the storage volume of the reservoir, *I* is the inflow water, *R* is the reserved water, and *O* is the outflow water.

The obtained flows are checked against the minimum and maximum flow constraints using penalties. Applicable penalty terms are added to the objective function, given in (6), and the fitness values are computed as in (4). Using these values, PSO solves the problem to produce the optimal water levels for energy maximization. The negation in the objective function is done to turn the maximization problem into minimization so that the generic PSO algorithm can be used.

$$F = -\sum_{i=1}^{I} \sum_{t=1}^{T} \left[O_{tur}(t, i) \left(H_{avg}(t, i) - H_{tail}(i) \, \gamma \eta(i) \right] /3600 \tag{6}$$

where F is the cumulative energy output of the basin (GWh), O_{tur} is the water flowing through turbines in (hm^3), H_{avg} is the average water level throughout the month (m), H_{tail} is the tail water level (m), γ is the specific weight of the water (9.81 kN/m^3), η is the efficiency of the turbine.

The optimization module is run periodically and the outputs are served to the system users through the Web-based GUI interface. Thereby, the long-term operational decisions of the HPPs are performed based on these outputs.

B. Short-Term Optimization

Short-term optimization of the reservoirs in the basin is performed for flood prevention in shorter periods. It is linked to the long-term optimization in a way that the end water levels of the reservoirs are taken as inputs from the long-term optimization in an automatic decision mechanism so that the results of the short-term optimization do not contradict the results of the long-term optimization.

Similar to long-term optimization, PSO is used as the optimization algorithm, but constraints related with energy optimization are not used. Instead, the characteristics of spillways and sluiceways, routing equations, water travel durations, and downstream capacities are used as the constraints. In this optimization scheme, particle swarms are created for flow rates which are used within flow equations as in (5) to calculate the water levels. The conformance of the resulting water levels to the maximum and minimum values and the outflow water amount to the cumulative discharge limit of the turbine, spillway, and sluiceway are controlled via penalties. The objective function is the amount of flood at the downstream of the reservoir, as calculated in (7) and (8), if the downstream capacity is exceeded; otherwise, it is zero. The fitness function is generated as described in (4).

$$flood(t, i) = \max(0, O(t, i) - O_{cap}(i)) \tag{7}$$

$$F = \sum_{i=1}^{I} \sum_{t=1}^{T} flood(t, i)^2 \tag{8}$$

where *flood* is the amount of flood, *O* is the outflow of the reservoir and O_{cap} is the downstream capacity. The flood term is squared in order to produce solutions with more evenly distributed flood amounts among several days rather than those with the same total amount of flood in just few days. For routing of the water in the downstream, the basin is divided into sections, and Muskingum equations are utilized to transform the amount of flow rate at the beginning of the section into that at the end of the section with the required time delay [35].

VII. Web-Based Graphical User Interface

The Web-based GUI application of RFBOS facilitates automatic retrieval, visualization, and reporting of meteorological and river flow forecast and optimization results produced within RFBOS, in addition to collected measurement and meteorological data from external stakeholders.

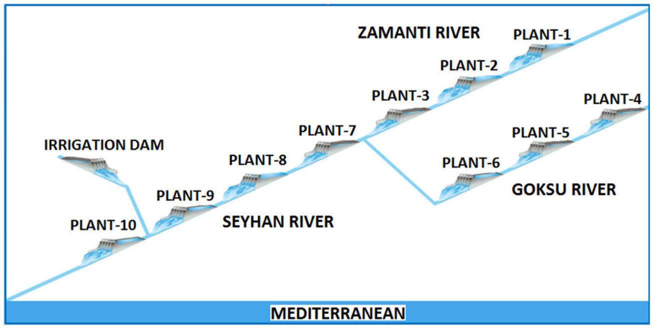

Fig. 3. Storage-type HPPs in Seyhan basin shown in a cascaded structure. The water levels are shown as animations on figure.

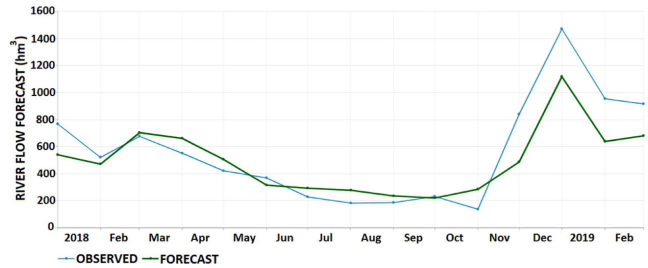

Fig. 4. Long-term river flow forecast of a selected HPP.

TABLE I
LONG-TERM FORECAST RESULTS

Plant Number	NSE	Volume Accuracy (%)
Plant 1	0.70	99.97
Plant 2	0.47	94.47
Plant 3	0.50	85.25
Plant 4	0.88	92.87
Plant 5	0.91	97.83
Plant 6	0.89	98.82
Plant 7	0.82	99.81
Plant 8	0.86	93.70
Plant 9	0.86	96.12
Plant 10	0.74	87.97

The opening page of the application[1] shows the country map where Seyhan basin (for which the system is currently operated) is zoomed in and its boundaries are highlighted. This opening page with measurement gauges shown as scattered on the basin is depicted in Fig. 2. By clicking on any part of a reservoir on the map, water level trend of the reservoir, long-term river flow forecasts and optimization results can be displayed as a time-series chart.

The main capabilities of the GUI application, available through the corresponding pages and page groups (i.e., modules) that can be accessed using the relevant menu items include:

- As the map of the application's opening page, different maps such as a proprietary map of State Hydraulic Works or freely-available alternatives can be selected to be used, by the system users.
- All of the produced and collected data can be queried and retrieved in the forms of charts and tables. For some data types like daily water levels, the data can also be demonstrated as animations on the cascaded structure of the basin given in Fig. 3.
- The river flow forecast results of different models can be queried and retrieved on a single multi-series chart. Additionally, performance evaluation results of past forecast results with respect to realized flow rates are also provided to the users together with these charts.
- The users can schedule the execution of river flow forecast and optimization modules, in addition to automatically triggered periodical executions. Furthermore, they can tune and change the parameters of the optimization module before scheduling.
- The users can create and retrieve automatic reports of the river flow forecast and optimization results, spanning a time interval and plant that they specify.

VIII. SAMPLE RESULTS

RFBOS system is a real-time system that continuously operates on daily and monthly basis. In this section continuously generated sample results of long-term and short-term river flow forecasts and optimizations are presented.

A. Long-Term Forecast Results

The system generates long-term river flow forecasts with daily and monthly resolution once a month. The sample results of a selected HPP with respect to volume accuracy for 15-months period are given in Fig. 4. A sample case test period January 2018 to March 2019 (15 Months) for long-term river flow forecast is selected and the results of 10 HPPs in the system are given in Table I. The volume accuracy for river flow forecasting is the crucial performance index. Another one is Nash-Sutcliffe Efficiency coefficient (NSE) [36] index which is sensitive to peak changes.

The sample long-term river flow forecasts show that the NSE index changes between 0.47 and 0.91 values which means a powerful peak forecast performance for the forecast model. Similarly, the range of volume accuracy between 85.25% and 99.97% proves the model's long-term forecast reliability.

B. Short-Term Forecast Results

Every day the system runs and generates 10-day ahead river flow forecasts with hourly resolution and this original hourly resolution is converted to daily resolution. The sample short-term river flow forecast results of a selected HPP are given in Fig. 5. For a test period between 01/01/2019 and 10/04/2019 short-term river flow forecast results of 10 HPPs in the system are given in Table II.

The sample short-term river flow forecasts show that the NSE index changes between 0.33 and 0.66 values which means a good peak forecast performance. But when compared with the

[1]The interface language of the application is Turkish. But we do not expect this to prevent interested readers from comprehending the related capabilities of the application, as its snapshots given in the article are accompanied with explanations in text.

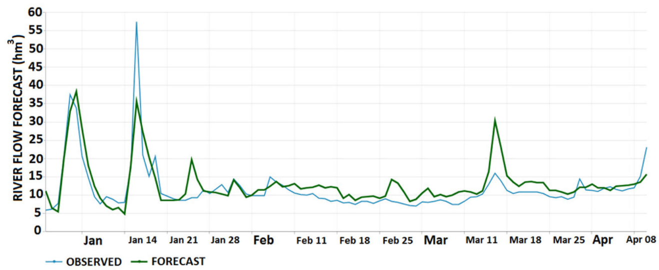

Fig. 5. Short-term river flow forecast of a selected HPP.

TABLE II
SHORT-TERM FORECAST RESULTS

Plant Number	NSE	Volume Accuracy (%)
Plant 1	0.62	92.34
Plant 2	0.64	98.12
Plant 3	0.33	98.15
Plant 4	0.45	99.62
Plant 5	0.66	93.65
Plant 6	0.64	89.35
Plant 7	0.65	98.68
Plant 8	0.45	98.92
Plant 9	0.61	95.66
Plant 10	0.55	98.09

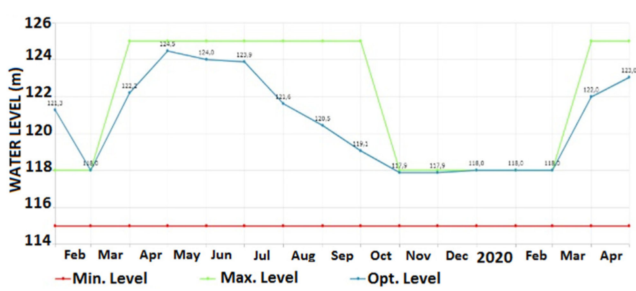

Fig. 6. Maximum, minimum and optimal water levels for the reservoirs of a selected HPP (long-term optimization).

long-term model it can be concluded that day-to-day variation of the river flow is higher and leads to a lower NSE index. On the other hand, the range of volume accuracy between 89.35% and 99.62% of the short-term model proves that the model's short-term forecast performance is higher for that test period.

C. Long-Term Optimization Results

After the model generates long-term river flow forecasts, the long-term optimization model uses them and generates 15-months optimization results for energy maximization considering all HPPs. Sample graph for one sample reservoir, taken from the output of the long-term optimization module is shown in Fig. 6.

D. Short-Term Optimization Results

The RFBOS generates short-term river flow forecast up to 10-days ahead for running short-term optimization model and generates optimum reservoir levels for each dam. Sample outputs of the short-term optimization module of the system, for two of the reservoirs in the cascaded structure in the basin are given in Fig. 7. The results of short-term optimization up to 10-days ahead will allow taking the necessary precautions before a flood to prevent or minimize the damage.

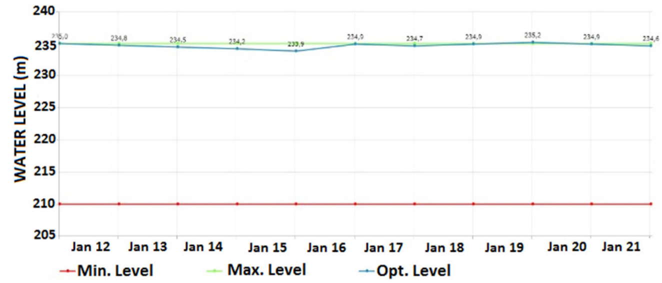

Fig. 7. Maximum, minimum and optimal water levels for the reservoirs of a selected HPP (short-term optimization).

The highly accurate forecast results give confidence to the system operator to follow the suggested reservoir levels. The cascaded structure of the selected basin complicates the management of the whole basin system. Therefore, an expert forecast and optimization system such as RFBOS gives the system operator the opportunity of optimizing the water usage, considering the relevant basin and user requirements.

IX. CONCLUSION

In this paper, a scalable and integrated river flow forecast and basin optimization system for HPPs which is implemented within the scope of the ATHOM project is proposed. The details of the main modules of the system are provided, including a data collection module with a central database, a river flow forecast module, a basin optimization module, and a Web-based GUI application. Sample outputs of the forecast and optimization modules are included in the paper, together with performance evaluation rates for the applicable outputs. These two core modules are based on a number of meteorological and hydrological models in addition to high-performance machine learning and optimization algorithms. The GUI application to facilitate data retrieval and visualization is described with its sample snapshots. RFBOS is the first integrated system in Turkey in terms of water level optimization for cascaded HPPs based on meteorological and stream flow forecasts' results with maximization of energy and preventing floods. The system is currently operational for a single basin in Turkey and future work includes scaling the system to cover all of the other basins in the country. It should be noted that scaling the system to other basins poses a number of challenges, including but not limited to: (1) continuous and high-resolution flow of measurement and NWP data for the new basins should be made available to the system, which will require larger and faster storage capabilities, (2) the forecasting and optimization modules of the system will need more efficient and preferably parallel processing capabilities to produce their outputs for all basins in a timely manner, where employing state-of-the-art and improved computing facilities such as GPUs can be a reasonable decision, (3) especially forecasting river flow for different basins may require the utilization of other hydrological and learning models that are more applicable considering the characteristics and constraints of the new basins included in the overall system, after in-depth analysis of these characteristics and constraints. Employing other forecast and optimization methods, such as those based on deep neural networks, constitutes another significant direction of future work.

Sample results validate the satisfactory performance of the RFBOS system. Especially, the volume accuracy performance of the long-term forecast model is above 85.25%. This high accuracy enables better long-term management of the cascaded HPP system with maximized energy generation from the water resource. Likewise, notable performance of the short-term river flow forecasts (above 89.35%) for the basin will hopefully help prevent floods.

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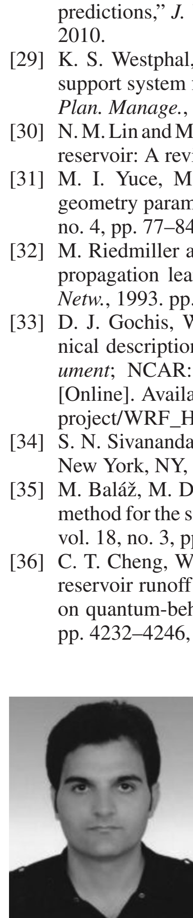

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