AI-Based Approaches for Enhanced Flow and Energy Forecasting in the European Hydropower Industry

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Energy Division, CARTIF Technology Centre
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[TECHNOLOGY CENTRE] CARTIF

Our goal

To generate cutting-edge scientific and technological knowledge, enabling innovation and technology transfer to address complex challenges in key factors

247 Staff (40 PhD)

AGRIFOOD AND PROCESSES

INDUSTRIAL AND DIGITAL SYSTEMS

ENERGY

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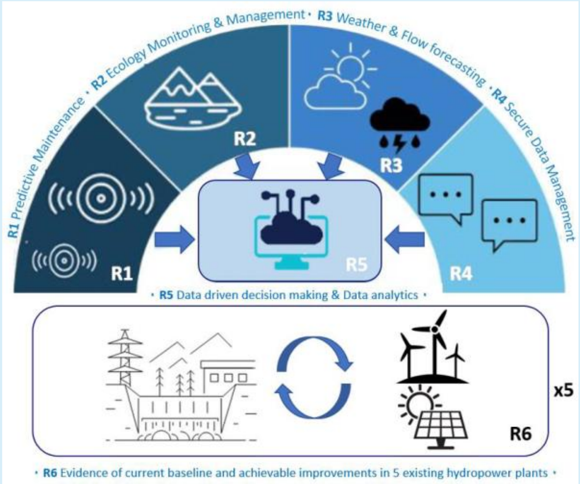
ENERGY

iAMP-Hydro

iAMP-Hydro improves the digital operation of existing Hydro Power plants through iAMP, an intelligent Asset Management Platform with new digital sensors, services, and secure open data-sharing protocols



Horizon Europe Programme

Solutions:

1. Condition monitoring and predictive maintenance
2. Ecological status
3. **Improved flow forecasting**

iAMP-Hydro validation sites

CUERVA sites
Granada, Spain

Bermejales

La Vega

Bérchules

PPC sites
Western Macedonia, Greece

Asomata

Agia Varvara / Makrochori

Ilarion

PPC-R site
Western Macedonia, Greece

iAMP-Hydro validation sites

CUERVA sites
Granada, Spain

Bermejales | La Vega | Bérchules

PPC sites
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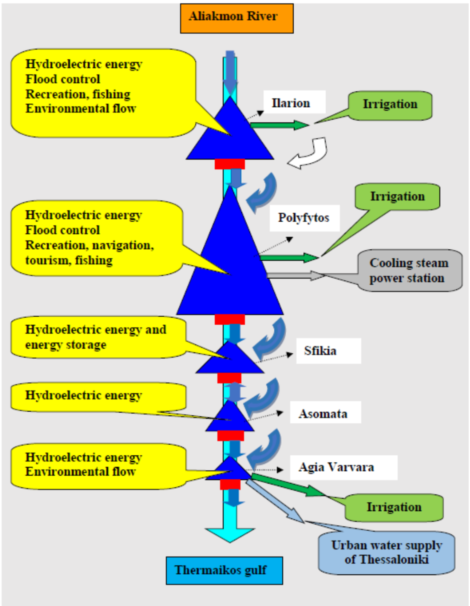
Asomata | Agia Varvara / Makrochori | Ilarion

PPC-R site
Western Macedonia, Greece

Complex cascade system
Aliakmon River



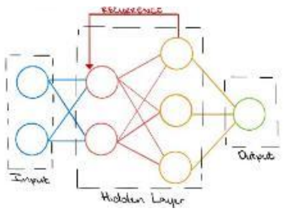
[Panagiotis I. Bakanos, 2020]

Modelling approaches for flow/energy forecasting

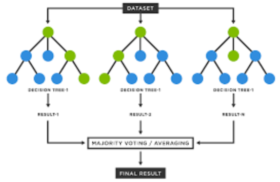
- Increasing trend in AI applications HP forecasting over 20 years. Diverse **countries** and **climates** (China, Brazil, USA, Spain and Italy)
- Type of HP plants: reservoirs, RoR, cascade systems
- Key AI algorithms identified for forecasting: water level, inflow or **extreme events** (floods)

- AI-based:

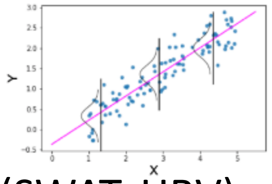
  Deep learning (DL): recurrent neural networks (RNN) →Long Short-Term Memory (LSTM) networks



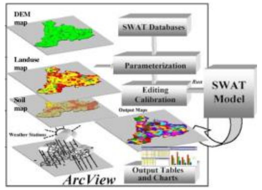
  Machine learning (ML): classification algorithms → Random Forest (RF), Gradient Boosting (GB) or Support Vector Machine (SVM)



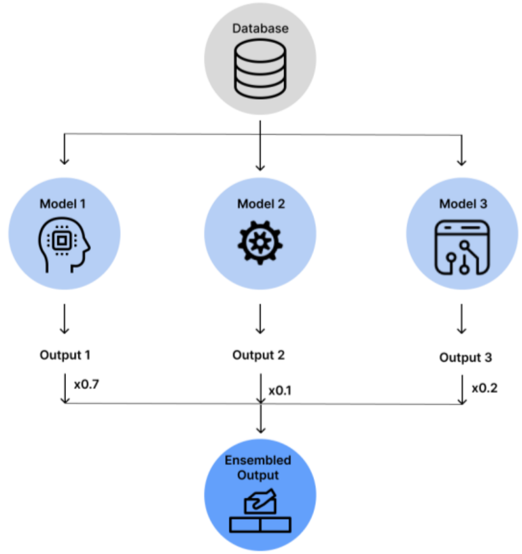
- General **linear** model



- Existing **physical models** (SWAT, HBV)



Hybrid ensemble flow forecasting models

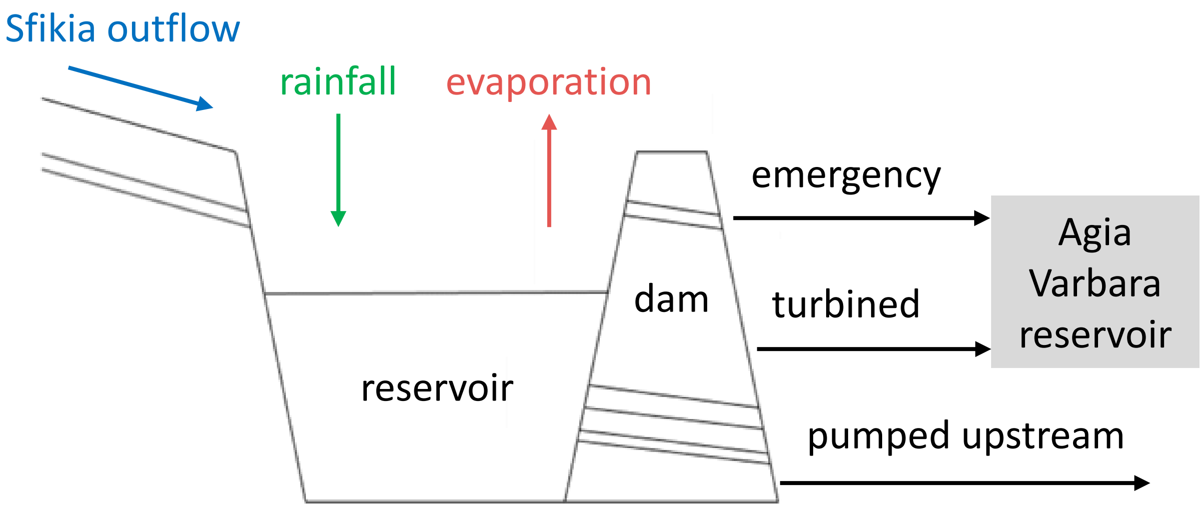


Asomata: Reservoir and dam toe HPP

General Data	
Site operator	PPC
Location	Central Macedonia, Imathia prefecture
Climate	Mediterranean
Water source	Sfikia HPP, and rainfall
Principal use	Power production, irrigation, human consumption, regulation for Sfikia HPP
Type	Reservoir: 53 hm^3 (total), 10 hm^3 (useful)
HPP Technical Data	
Installed capacity (MW)	108 (2 x 54)
Net head (m)	42
Type of turbine	2 x Francis
Speed (rpm)	125
Max. turbine flow (m^3/s)	177

Asomata: System overview

- It is the **4th reservoir** in a cascade on the Aliakmonas River
- Acts as the **lower reservoir** for the Sfikia Pumped Storage Plant
- Inflow **mainly** from Sfikia outflow, **highly regulated** by upstream reservoirs
- **Discharges** to the Agia Varvara reservoir downstream
- Regulating reservoir for Sfikia, **water pumped** upstream



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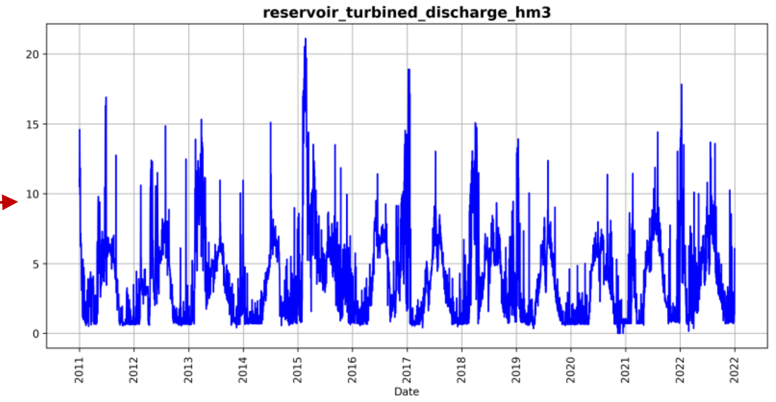

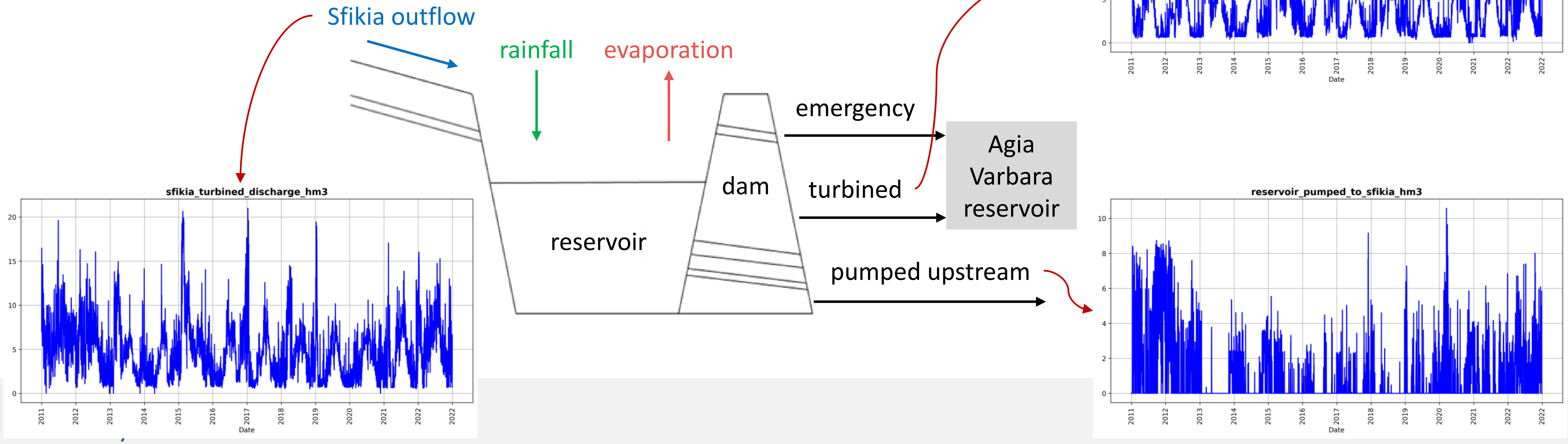

Asomata: Forecasting approach

Medium-term strategy for accurate forecasting of the daily **water volume** used for energy generation, **system efficiency**, and **available power** over a **seven-day** forecasting horizon, using the **latest historical** measurements of the system operational variables and meteorological information.

Forecasted variables:
1. Water discharge for energy generation
2. System efficiency
3. Available power

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For the **hydro operator**:
- ✓ Optimizes energy generation and system efficiency
- ✓ Improves daily water management and pumped-storage decisions

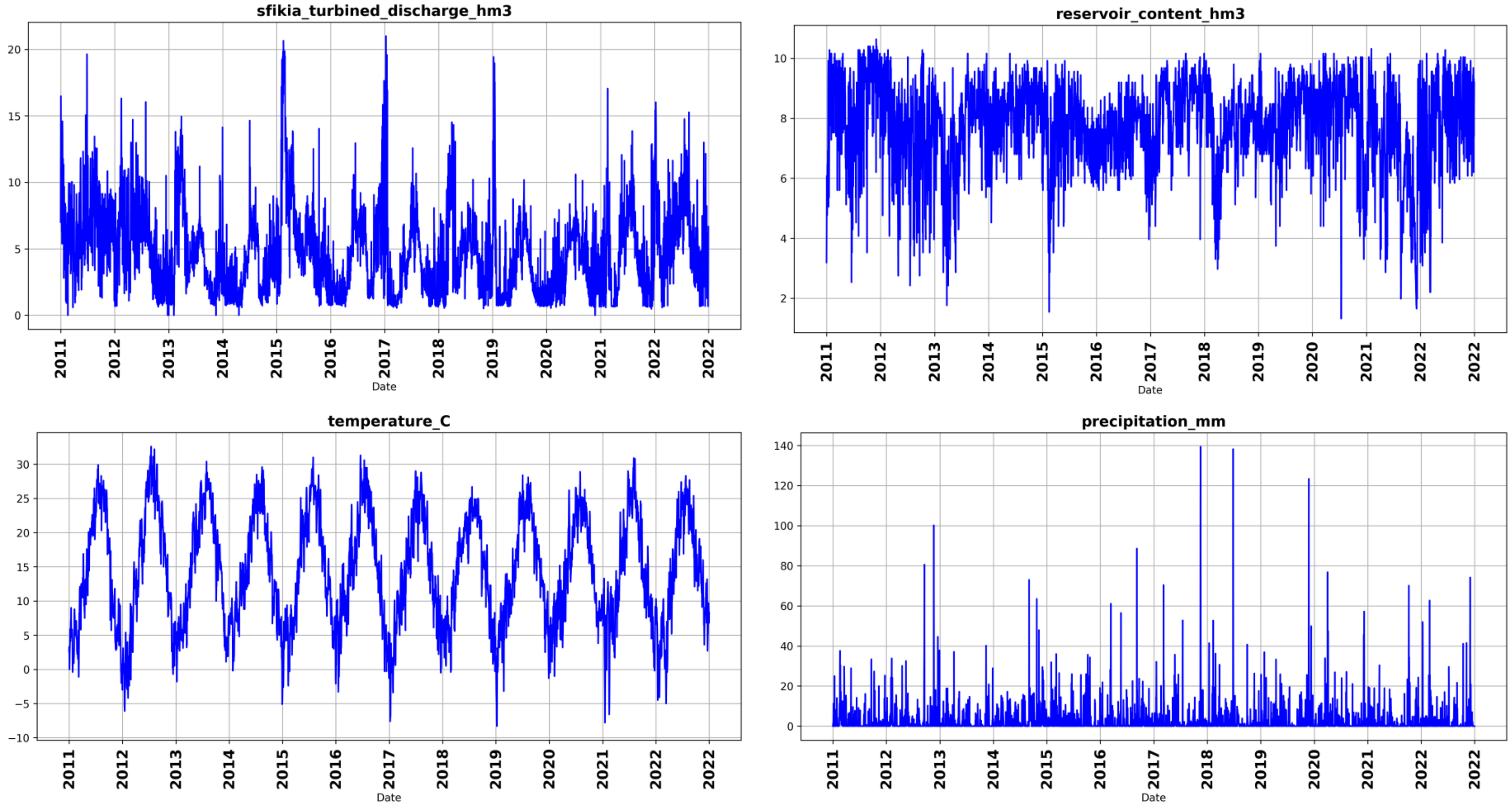
For **Agia Varvara reservoir**:
- ✓ Better control of water coming from Asomata
- ✓ Ensures reliable water supply downstream for irrigation and consumption

Asomata: Available datasets

Historical data **provided** by PPC and Open-Meteo:

Period: 01 Jan 2011 – 31 Dec 2022
Frequency: Daily

Variable	Units
Reservoir level	m
Reservoir content	hm^3
Delta reservoir content	hm^3
Reservoir turbined discharge	hm^3
Reservoir pumped to Sfikia	hm^3
Sfikia turbined discharge	hm^3
Natural inflow	hm^3
Losses	hm^3
Temperature	°C
Precipitation	mm



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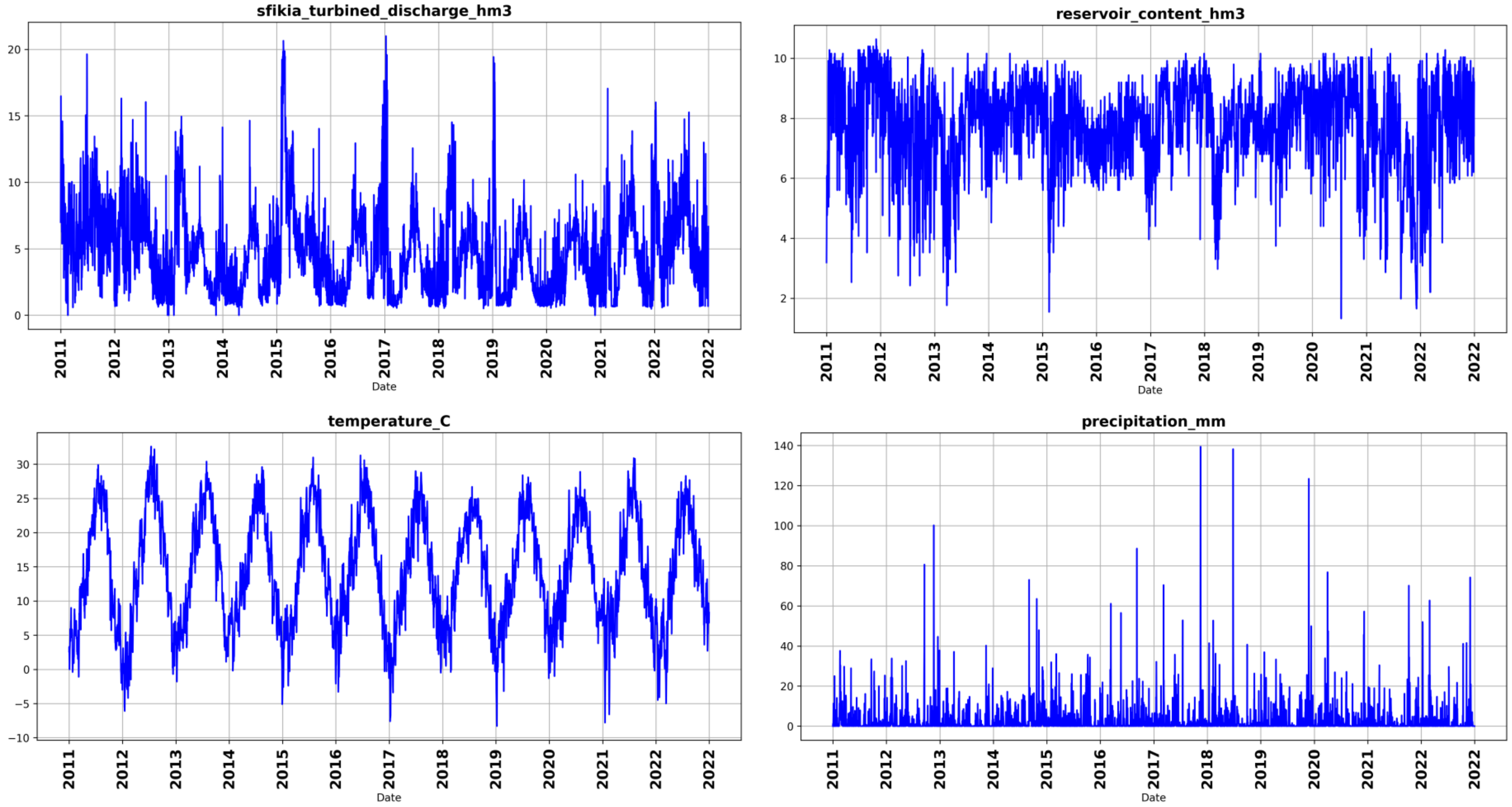

- **Data cleaning (corrections and outlier management)**
- **Data scaling**

Asomata: Data Analysis and variable selection

Assessment of the **impact** of remaining variables on **Reservoir turbined discharge** feature **selection**:

Variable	Correlation	Ensemble Learning	Hypothesis-based
Reservoir level	16.34%	2.68%	True
Reservoir content	16.35%	3.50%	True
Delta reservoir content	5.88%	6.71%	True
Reservoir pumped to Sfikia	24.69%	16.39%	True
Sfikia turbined discharge	74.93%	60.72%	True
Natural inflow	7.32%	1.26%	False
Losses	13.72%	2.14%	False
Temperature	32.79%	5.30%	True
Precipitation	2.47%	1.24%	True

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Variables with **correlation > 50%**

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Top 95% contribution variables

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Selected model inputs

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Asomata: Forecasting models & data splits

- Target variable: **Reservoir turbined discharge**
- Forecasting horizon: **7 days** (steps)
- Input horizon: **7 days** (steps)
- Forecasting models:
  - **ANN model** — Conv1D + LSTM + Dense layers
  - **XGB model** — Extreme Gradient Boosting (XGBoost)
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- Lags: 4</td><td>Lags: 7</td><td>Lags: 7</td></tr>
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Cyclical encoding to model **seasonality**

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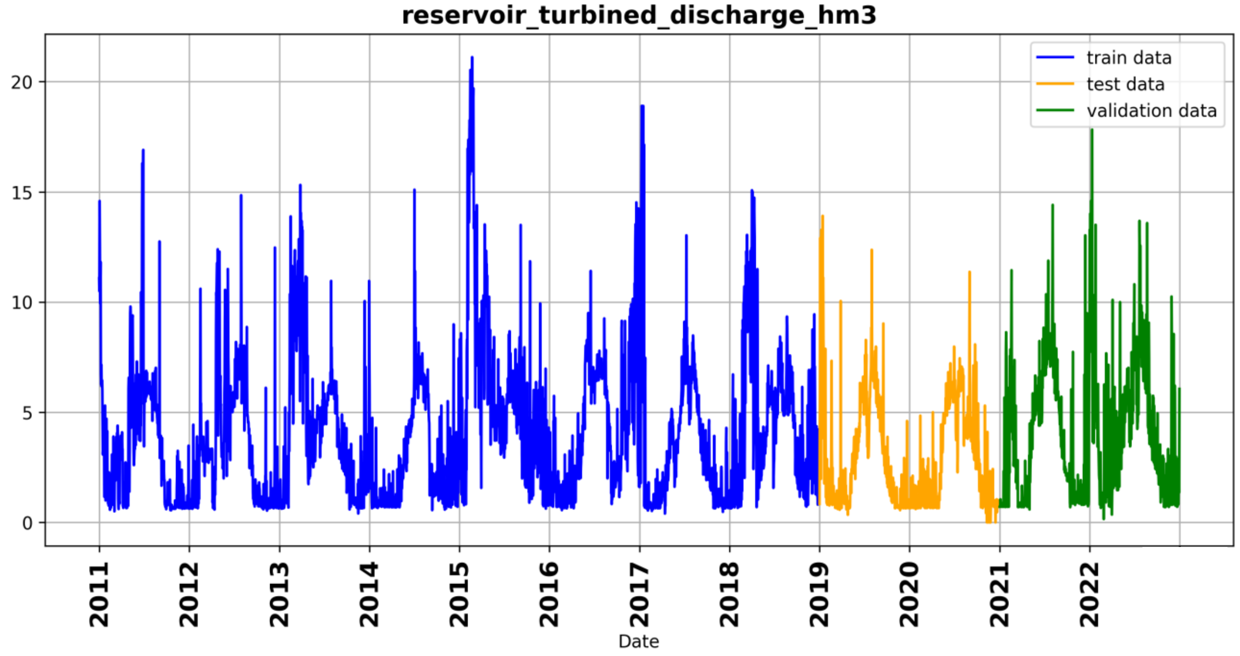
Dataset split:



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Temperature			
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Day of the year			

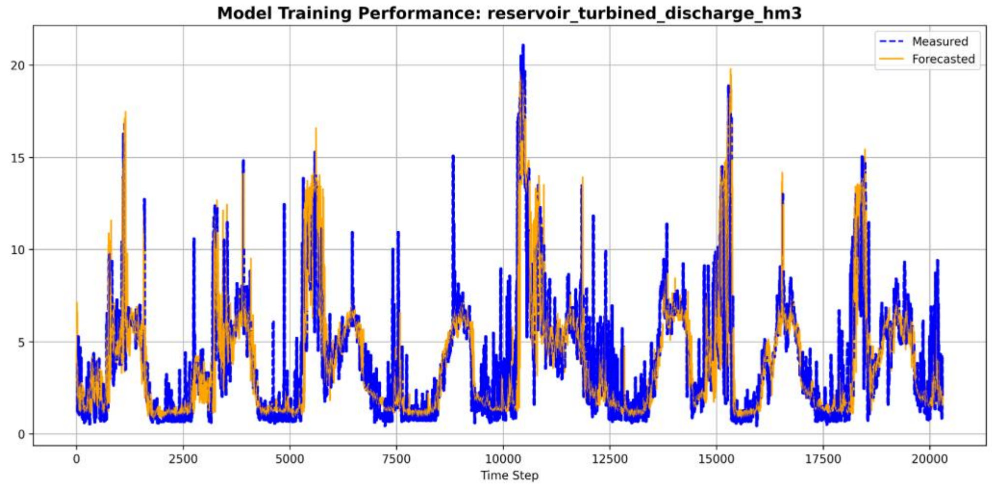
Cyclical encoding to model **seasonality**

Asomata: Forecasting models training and test results

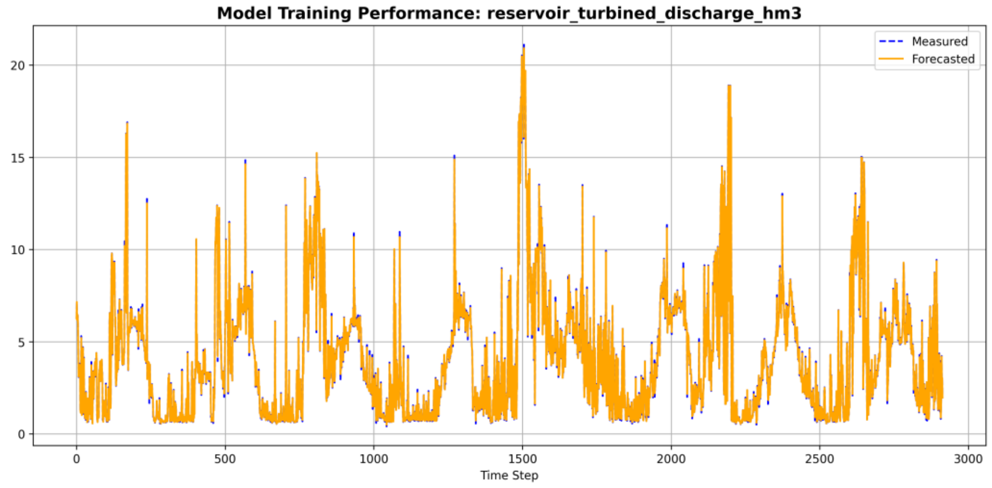
Training and **testing** performance of the forecasting models for **reservoir turbined discharge**

Training results:

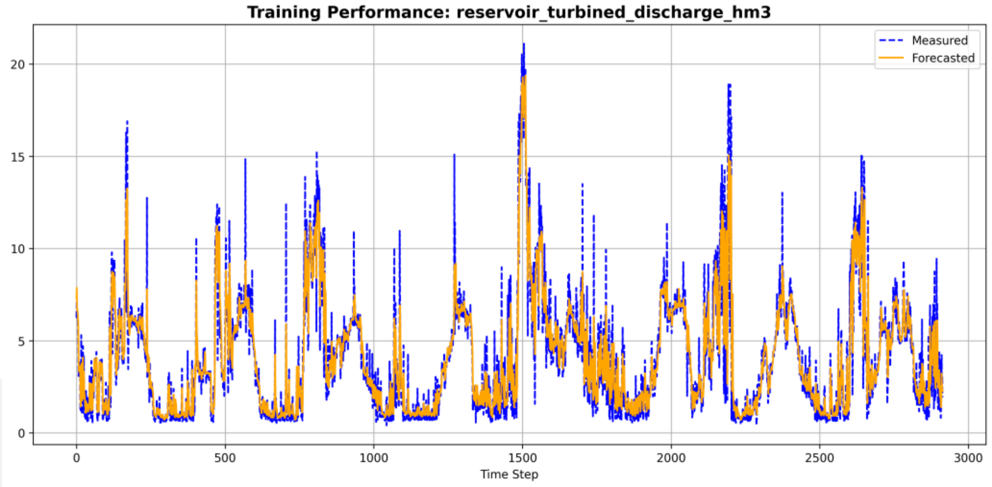
ANN



XGB



RF



Models performance metrics:

Model	MAE hm^3	MSE $(hm^3)^2$	R^2
ANN	1.1780	4.1336	0.6155
XGB	0.0356	0.0029	0.9997
RF	0.5970	0.8545	0.9006

iAMP-Hydro

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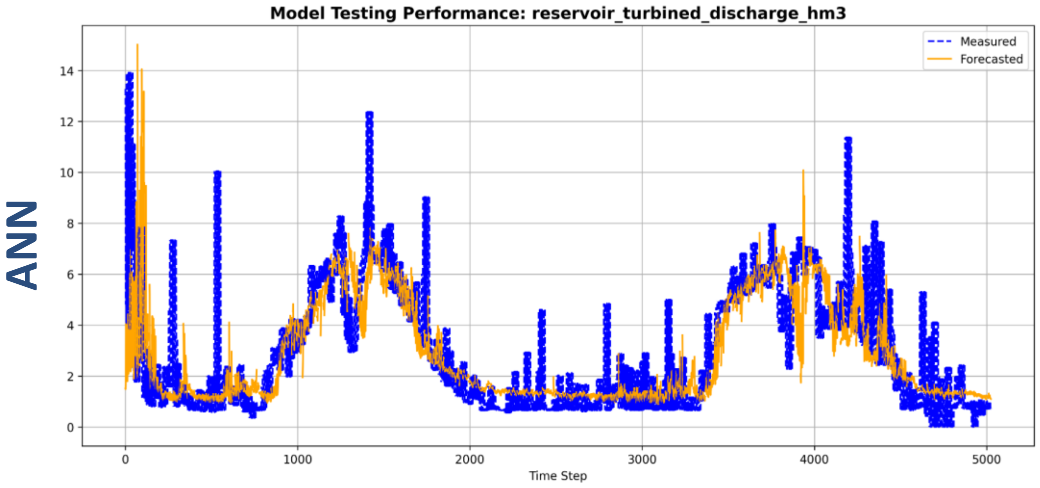
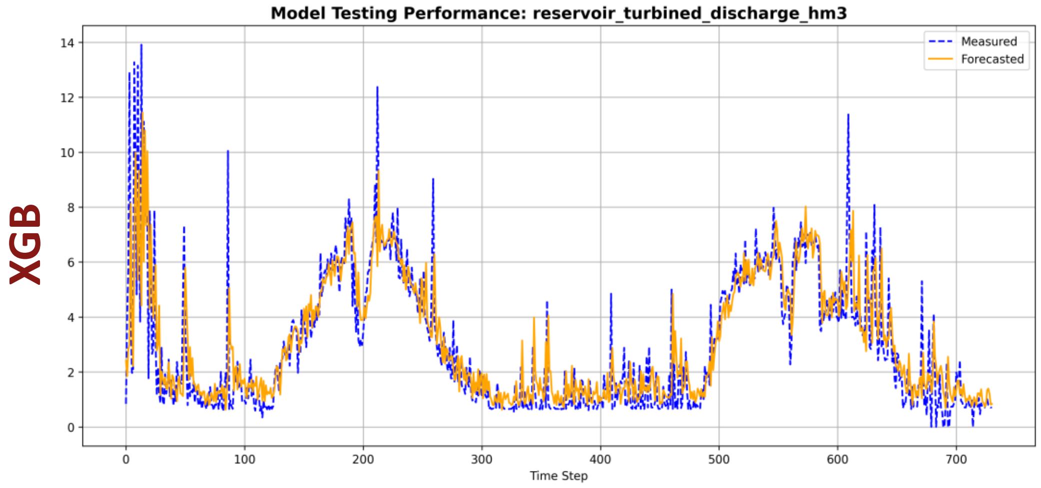
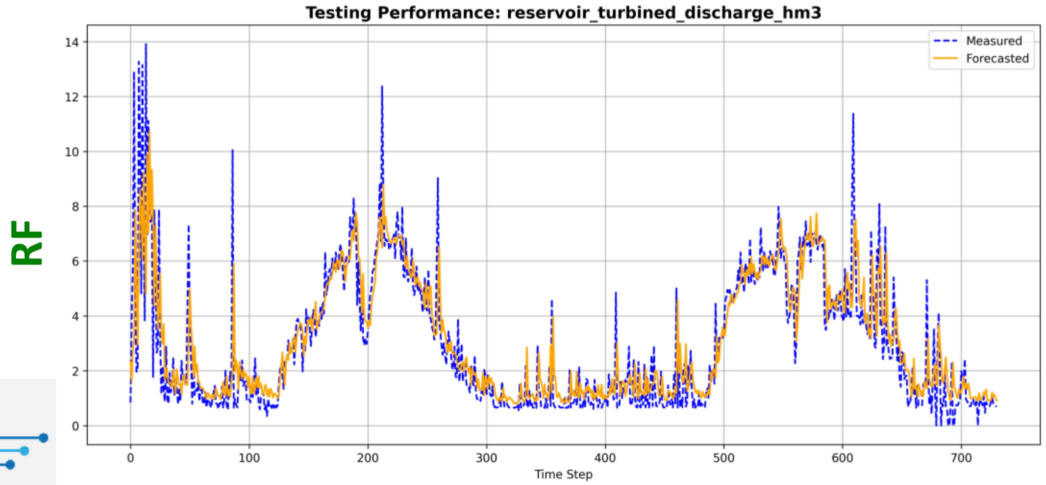
Training and **testing** performance of the forecasting models for **reservoir turbined discharge**

Testing results:







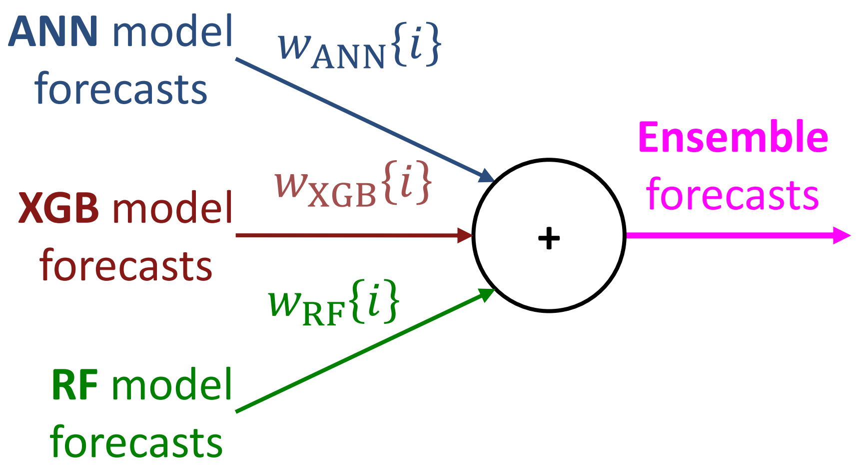
Models performance metrics:

Model	MAE hm^3	MSE $(hm^3)^2$	R^2
ANN	0.9174	2.1805	0.6077
XGB	0.8416	1.8767	0.5818
RF	0.8052	1.7279	0.6123

iAMP-Hydro

Asomata: Ensemble forecasting model

The daily **turbined discharge volume** of the reservoir is forecasted for the **next seven days** using an **ensemble** of **three** models whose individual predictions are combined through a **weighted** summation:



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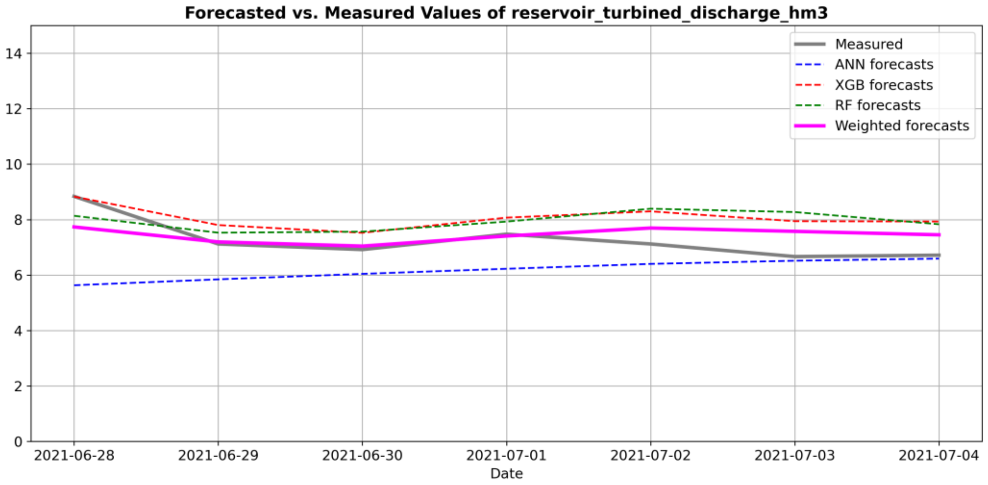
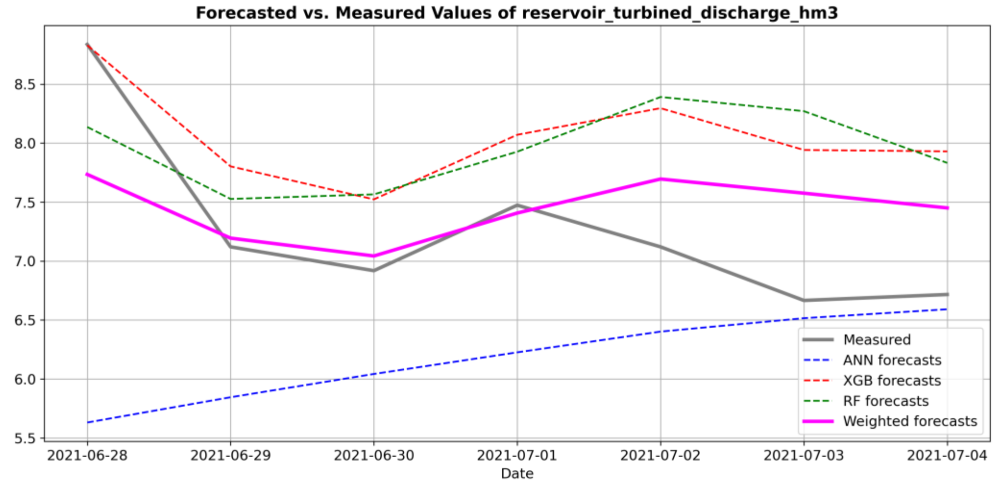
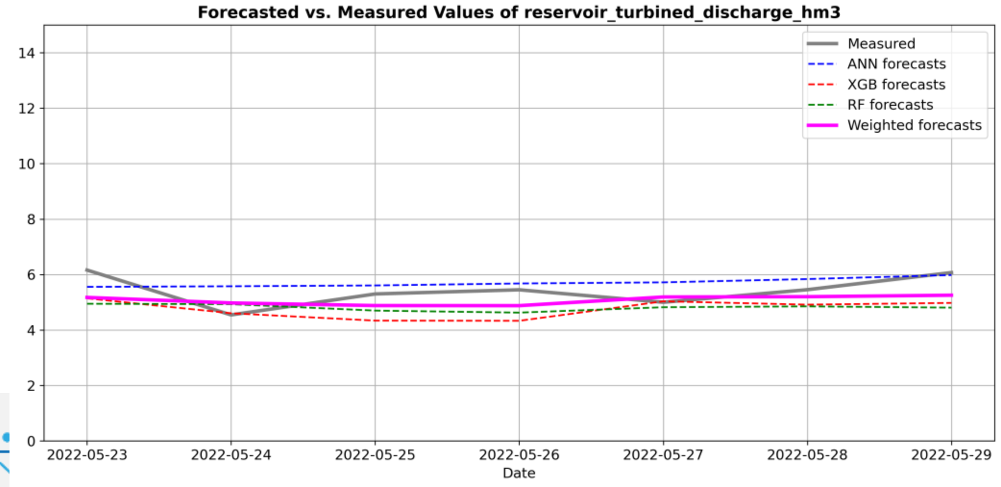
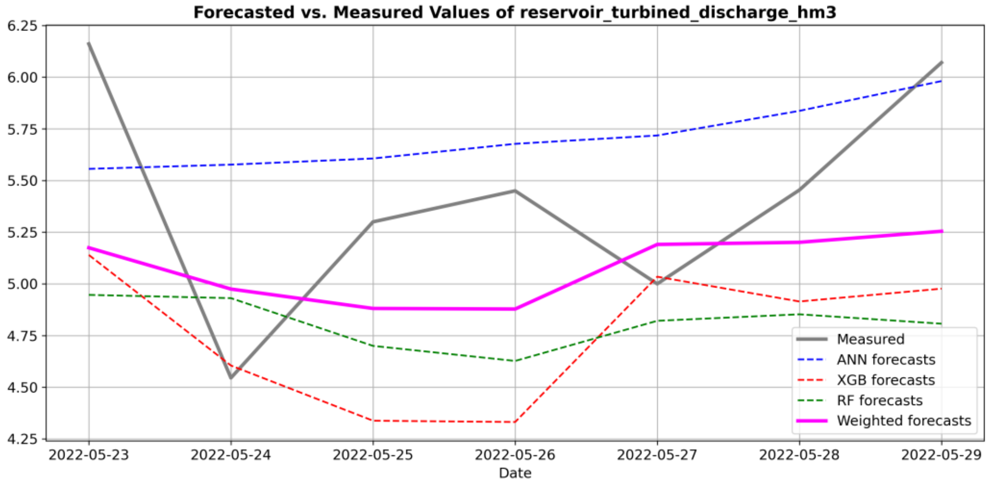
Validation results:

Model	MAE hm^3
ANN	2.1125
XGB	0.8104
RF	0.959
Ensemble	0.4197









Model	MAE hm^3
ANN	0.3208
XGB	0.6730
RF	0.6643
Ensemble	0.3466

Asomata: Energy forecasting

step i	S	H [m]	Q [m³/s]	P [W]
1	S_1	Hgr_1	Q_1	P_1
2	S_2	Hgr_2	Q_2	P_2
…	…	…	…	…
n	S_n	Hgr_n	Q_n	P_n

Dual-turbine operation mode — Head — Flow — Power

Historical monitored data →

Plant efficiency equation

$$\eta_i = \frac{P_i}{g \cdot \rho \cdot Hgr_i \cdot Q_i}$$

$g = 9.81\,\mathrm{m/s^2}$ $\rho = 1000\,\mathrm{kg/m^3}$

Computed turbine efficiency →

η
η_1
η_2
…
η_n

Asomata: Energy forecasting

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Dual-turbine operation mode (S)

Head (H)

Flow (Q)

Power (P)

Historical monitored data →

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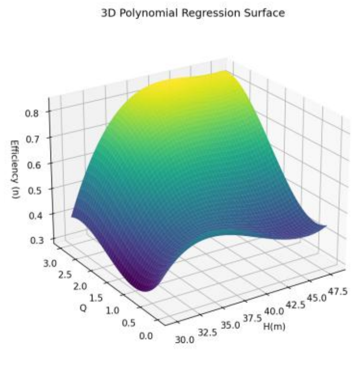
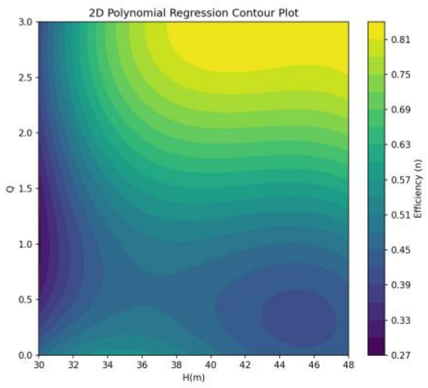
From computed efficiency to a **efficiency surface** $\boldsymbol{\eta}(H, Q, S)$ through a 3rd-degree polynomial regression:





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Dual-turbine operation mode

Head

Flow

Power

Historical monitored data

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Computed turbine efficiency

$\boldsymbol{\eta}$
η_1
η_2
…
η_n

Forecasted power production $\boldsymbol{P}$[W]:

$$P_{t+i} = g \cdot \rho \cdot Hgr_{t+i} \cdot Q_{t+i} \cdot \boldsymbol{\eta}(Hgr_{t+i}, Q_{t+i}, S_{t+i}) \quad i = 1, 2, \dots, 7$$

- Based on **recent** historical data
- **Mean** of historical values for forecasting period

Ensemble model forecasts

Operator-**defined** scenarios based on flow forecasts

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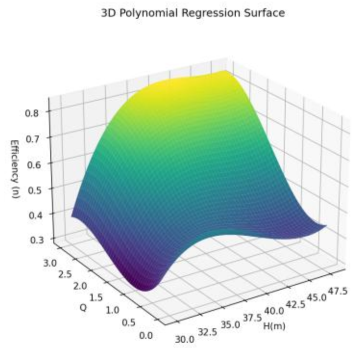

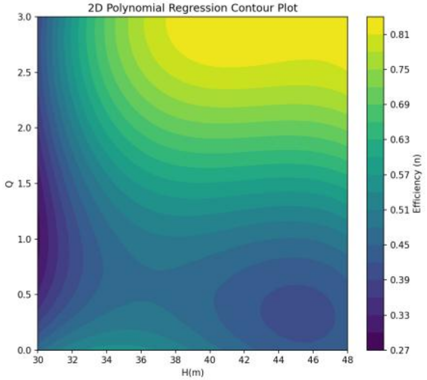

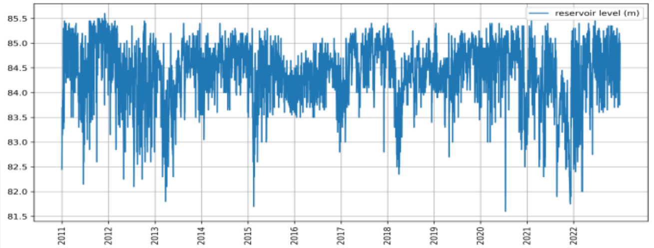

$$E[\mathrm{Wh}] = 24 \sum_{i=1}^{7\ \text{days}} P_{t+i}$$

Asomata: Conclusions

- AI-based models have shown **strong potential** for medium-term flow and energy forecasting in complex hydropower systems such as the Asomata Reservoir.

- The ensemble approach **provide** reliable and stable forecasts across **changing** hydrological and operational conditions.

- This methodology **contributes** to optimized water resource management and enhanced operational efficiency in pumped-storage and cascade hydropower systems, helping to **improve** scheduling, energy performance, and ecological regulation.

- This AI solution can be beneficial for hydropower operators and power companies, as it **improves** forecasting and decision-making, and for water management authorities by enabling more efficient resource allocation and irrigation planning.

Thank you!

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iAMP-Hydro Project

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