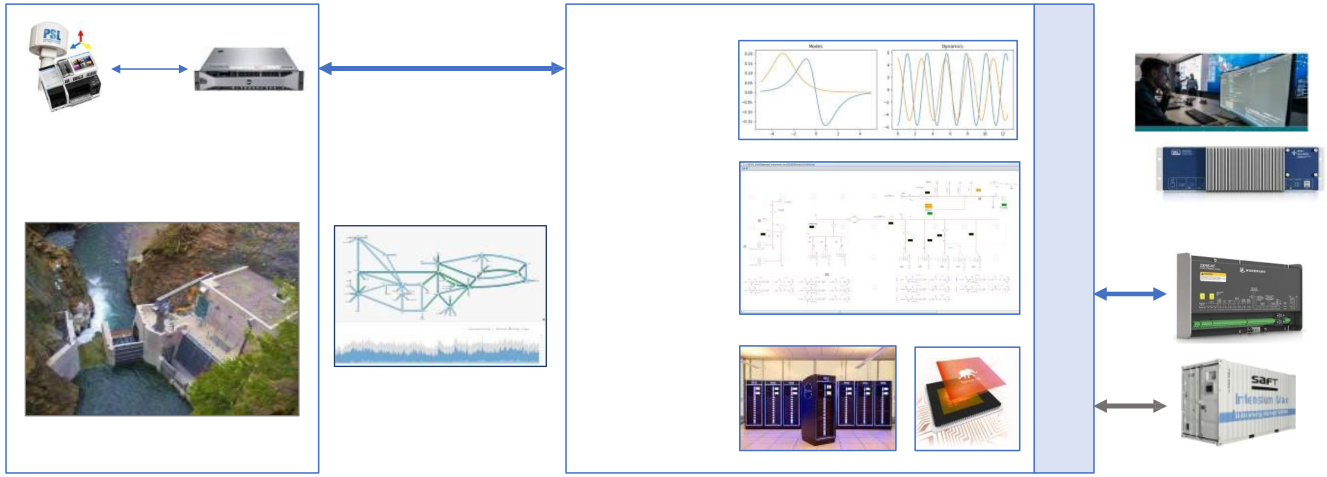
1.2.4.404 – Data-Driven Approach for Hydropower Plant Controller Prototyping Using Remote Hardware in the Loop (DR-HIL)



https://www.energy.gov/eere/water/hydrowires-lab-call-projects

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THURSDAY, JULY 28, 2022

Project Overview

Project Summary
Real-time prototyping of hydropower plant controls can help reduce the cost and risk of field deployment. In this project, we (1) collect design and operational data from actual hydro plants, (2) use a physics-informed machine learning approach for real-time emulation of hydropower plants, including turbine and penstock hydrodynamics. Data-driven models will be interfaced with digital real-time s mu NREL's F r s C mpus f r c r er-hardware-in-the-loop (CHIL) testing of the hydro-governor. This approach will establish connectivity-based remote CHIL capability using real-time data streams from an actual hydro plant.

Intended Outcomes
As a Seedling project, to demonstrate the ability to test digital governors as CHIL, the focus will be on establishing an approach for early-stage hydropower control technologies. The expected outcomes of the R&D in this project are:

- Robust real-time connectivity to stream hydropower plant data from the field.
- Data-driven, physics-informed machine learning representation of hydraulic models for use in real-time simulations.
- Rapid prototyping environment for hydropower controls using CHIL.
- Integrated CHIL and data-driven control prototyping environment.

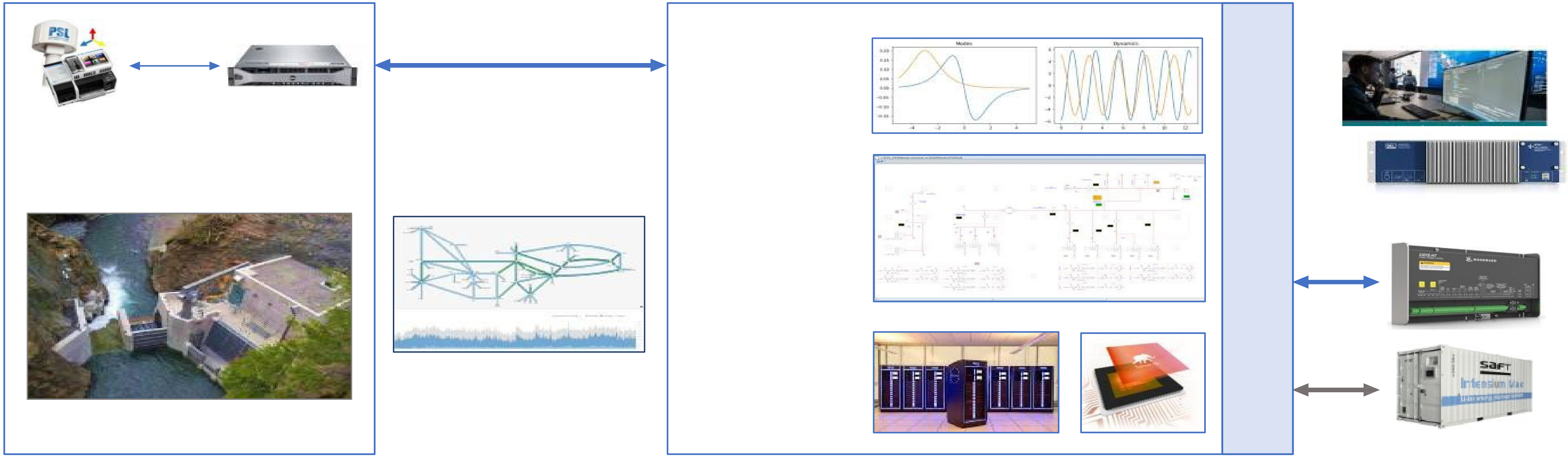
Project Information
Principal Investigator(s)
• Mayank Panwar
Project Partners/Subs
• MIT, Auburn Univ., Cordova Electric Coop. • R. Hovsapian, J. D. Osorio (NREL) • E. Muljadi, J. Kim (Auburn) • C. Chryssostomidis, G. Karniadakis (MIT) • C. Koplin (Cordova Electric Cooperative) • H. Balliet, S. Bockenhauer, P. Soltis (WPTO) • T. Oyvang (USN, Norway)
Project Status
Completed
Project Duration
• Start date: 10/01/2020 • End date: 6/30/2022 (no-cost extension)
Total Costed (FY19–FY21)
$89,949

Project Objectives: Relevance

Relevance to Program Goals:

- This project will establish a high-fidelity hydropower controls testing and prototyping environment using actual hydro plant data for at-scale testing, and eventually could be used for integration with energy storage technologies, renewables, and hybrid energy systems.
- The design modification and prototyping of hydro controls can be costly and introduces unnecessary risk during field deployment and commissioning. This CHIL environment will serve as a platform to risk reduced, cost-effective mechanisms of controls development and testing using remote hardware-in-the-loop.
- This will also facilitate collaborative research between industry/utilities and national laboratories for high-fidelity, data-driven, at-scale testing. A research collaboration with the University of South-Eastern Norway was established under the existing MOU between DOE and the Research Council of Norway.

Project Objectives: Approach



Data From Hydro Plant

Operational: Electrical – Phasor Measurement Units (PMU), and SCADA; hydraulic and mechanical – SCADA.

Design: Electrical, mechanical, hydraulic, controls, concept of operations.

Real-Time Data Streaming

One-way data stream: Operational data, collected at NREL for emulation. GPS time-stamped data (PMU and SCADA).

Bidirectional: To show feasibility of hydro plant as hardware-in-the-loop (HIL) under channel latencies.

Hydro Plant Emulation

Physics-informed machine learning: Data-driven representation of hydro plant based on available data.

Validation of response against operational data.

Emulation using Digital Real Time Simulation (DRTS) for rapid control prototyping and CHIL.

CHIL and Rapid Control Prototyping

RCP with emulated hydro plant in DRTS at NREL.

Verification of suitability for local and remote HIL under channel latencies.

CHIL using DRTS programmable hardware controller.

Project Objectives: Expected Outputs and Intended Outcomes

Outputs:

- Establishment of an approach for early-stage hydropower control technologies and the ability to test digital governors as CHIL.
- Evaluation of data-driven approaches, including physics-informed machine learning, for hydropower representation in rapid control prototyping.
- Remote data-driven governor CHIL.

Outcomes:

- Real-time connectivity to stream hydropower plant data from the field.
- Data-driven, physics-informed machine learning representation of hydraulic models for use in real-time simulations.
- Rapid prototyping environment for hydropower controls using CHIL.
- Integrated CHIL and data-driven control prototyping environment.

Project Timeline

FY 2020–2021

Task 1: Establish real-time connectivity to stream hydro operational data.

Task 2: Develop physics-informed machine learning hydraulic models.

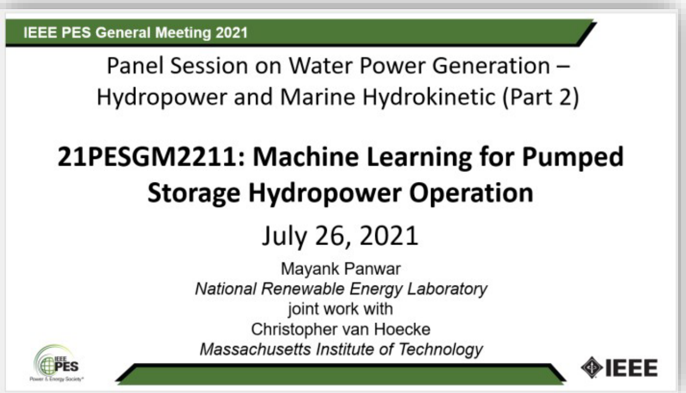
Task 3: Establish Quality of Service of communication link and latency mitigation.

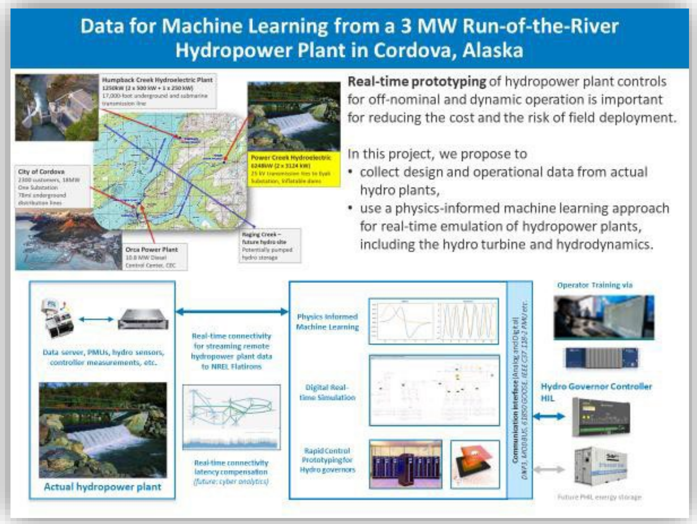
Task 4: Establish preliminary proof-of-concept rapid prototyping environment through integration of data-driven hydro operational model in digital real-time simulation and controller as CHIL.

Task 5: Demonstrate the ability to test digital governors as CHIL.

Task 6: Coordinate research with the Research Council of Norway.

- Presented project progress in Seedling Showcase 2021
- Participated in panel presentation on the application of machine learning to pumped storage hydro at IEEE PES General Meeting 2021.





Project Budget

FY19	FY20	FY21	Total Actual Costs FY19–FY21
Costed	Costed	Costed	Total Costed
$0K	$0K	$90K	$90K

- No-cost time extension through 6/30/22 to spend the remaining $35K.

End-User Engagement and Dissemination

- Stakeholder engagement strategy
  - As part of the Seedling project, one utility partner (Cordova Electric Coop.) was engaged to provide hydropower plant operational data (electrical, mechanical, hydraulic) from SCADA, and high-resolution phasor measurement unit (PMU).
  - The data was used for physics-informed machine-learning-based representation of a hydropower plant.
  - Established an approach for early-stage hydropower control technologies and the ability to test digital governors as CHIL.
- This project was presented in the *DOE WPTO Seedling Showcase 2021,* and as a panel presentation for "Machine Learning in Pumped Storage Hydropower Operation" at the IEEE PES General Meeting 2021 in the *Panel Session on Water Power Generation – Hydropower and Marine Hydrokinetic (Part 2).*
- The outcomes of this Seedling project are directly used in the FY22–24 HydroWIRES Hydro Emulation project at NREL Advanced Research on Integrated Energy Systems (ARIES), where GE, Stantec, Cordova Electric, and Siemens are engaged as part of an Industry Advisory Board.

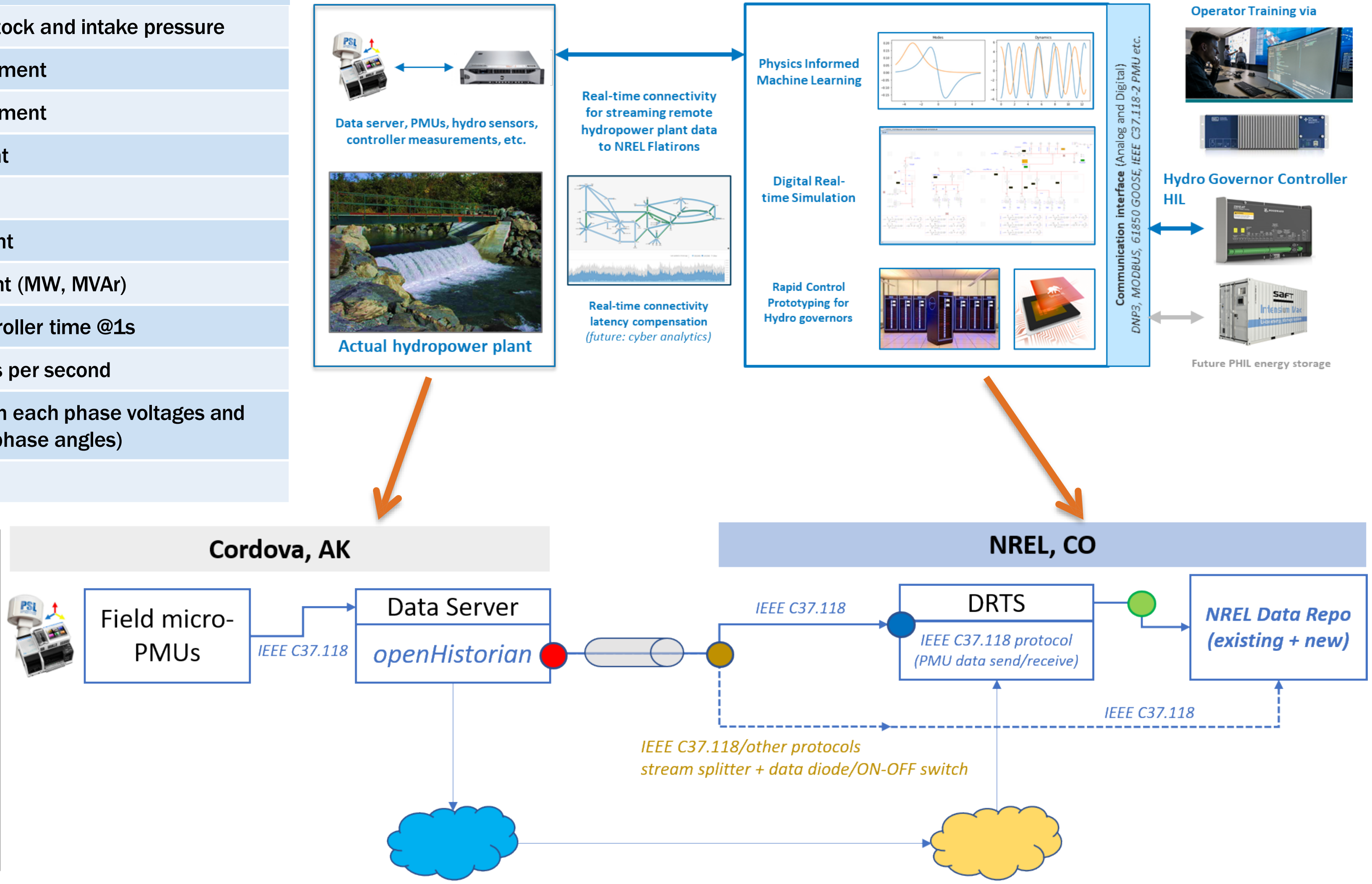
Performance: Key Accomplishments and Progress

- Data-driven representation using physics-informed machine learning (PIML), i.e., multistep neural networks (MNNs) and other data-driven approaches such as reservoir computing and long short-term memory (LSTM), was done for two different hydropower plant configurations.
  - Real-time electromagnetic transient (EMT) model of a 300-MW pumped storage hydro plant.
  - Actual 3-MW run-of-the-river (ROR) hydropower plant in Cordova, AK, with Turgo Impulse turbine.
- Additional EMT models were developed for different Pumped Storage Hydro (PSH) designs and configurations (conventional, adjustable speed).
- Architecture for real-time data streaming was prepared with Cordova Electric and NREL ARIES digital real-time simulation.
- DRTS-based evaluation was set up for digital governor hardware testing as CHIL.
- Successfully engaged with University of South-Eastern Norway (USN) for research collaborations (FY22–24) in support of the existing MOU between DOE WPTO and the Research Council of Norway.

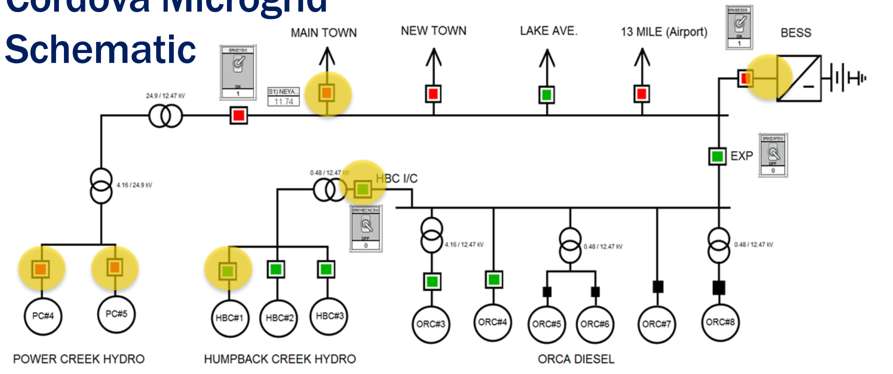
Performance: Accomplishments and Progress (cont.)

Hydro Plant Operational Data	Source	Comments
Head level (m)	SCADA	Water level at intake structure
Water flow (cfs)	Estimated	Estimated based on penstock and intake pressure
Nozzle valves position (%)	SCADA	Percent opening measurement
Deflector position (%)	SCADA	Percent opening measurement
Temperature (deg F)	SCADA	In-plant RTD measurement
Mechanical speed (rpm)	SCADA	RPM measurement
Electrical frequency (Hz)	SCADA	Power meter measurement
Electrical power (MW, MVAr)	SCADA	Power meter measurement (MW, MVAr)
Time (s)	SCADA	Programmable Logic Controller time @1s
Electrical frequency (Hz)	Micro-PMU	Estimates at 120 samples per second
Electrical voltage, current, power (kV, kA, MW, MVAr)	Micro-PMU	Power calculated based on each phase voltages and current (magnitudes and phase angles)
Time (s)	Micro-PMU	GPS time

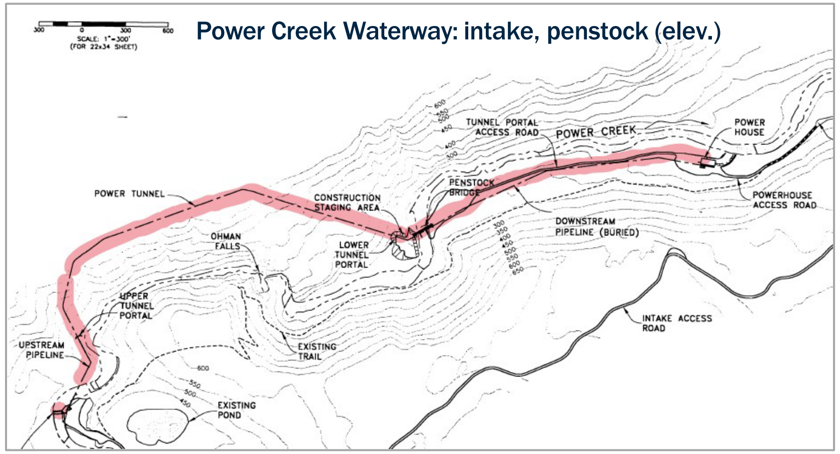
Real-Time Field Sensor Data Streaming Architecture

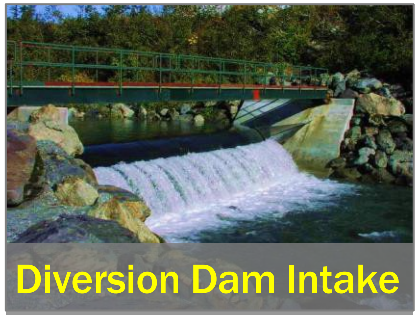


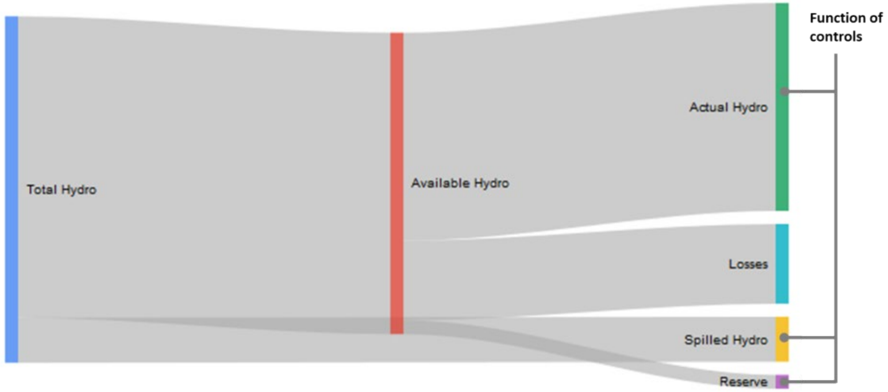
Cordova Microgrid Schematic



Results: Cordova's Hydropower Plant Design and Operational Data







Unit and plant power
Mechanical speed
Nozzle/deflector positions
Indoor and outdoor temperatures

Head level (forebay, rel.)

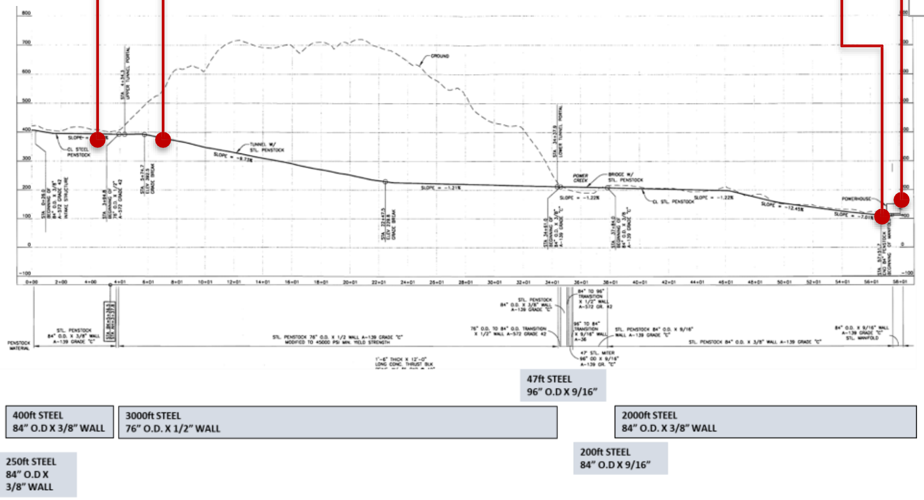
Penstock pressure sensor

Hydro pressure sensor

No direct flow measurement; estimating by correlating sensor outputs (Hydpsi, Headlevel, Penstockpsi) to power (electric)

$$P_{tur} \approx P_e = \eta Q \rho g h$$

η: urb e eff c e cy
Q: c u urb e f w
ρ: w er e s y
g: cce er ue r v y
h: h e he urb e m ss



Normal elevation = 420 ft
Dam height = 420 – 412 = 8 ft

Turbine elev. = 114 ft
Tailrace channel elev. = 102 ft

- No direct water flow measurement.
- Exact location of pressure measurements is not known.
- Flow estimates are obtained by correlating power, pressure measurements, and physical design details.

Flow of water down pipe

Hagen-Poiseuille equation

$$\Delta P = \frac{8\mu L Q}{A^2}$$

$$Q = \frac{A^2 \Delta P}{8\mu L}$$

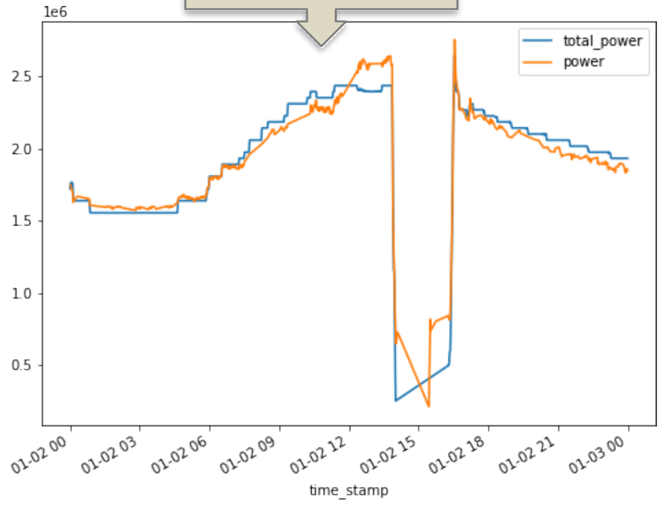
Actual values of Flow

Given power, we can estimate actual values of flow:

$$Power = \eta \rho Q g h$$

$$Q = \frac{Power}{\eta \rho g h}$$

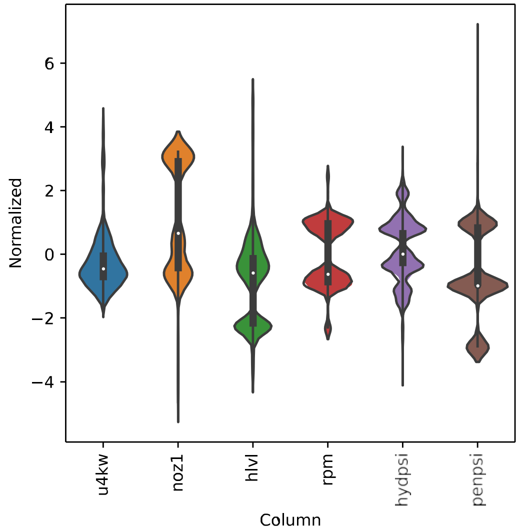
Flow Estimates

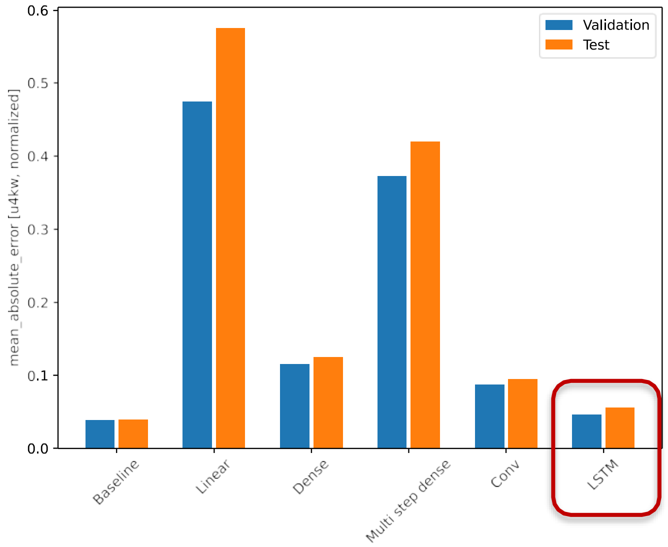


Results: Cordova Hydro Plant Prediction Using LSTM in *Tensorflow*

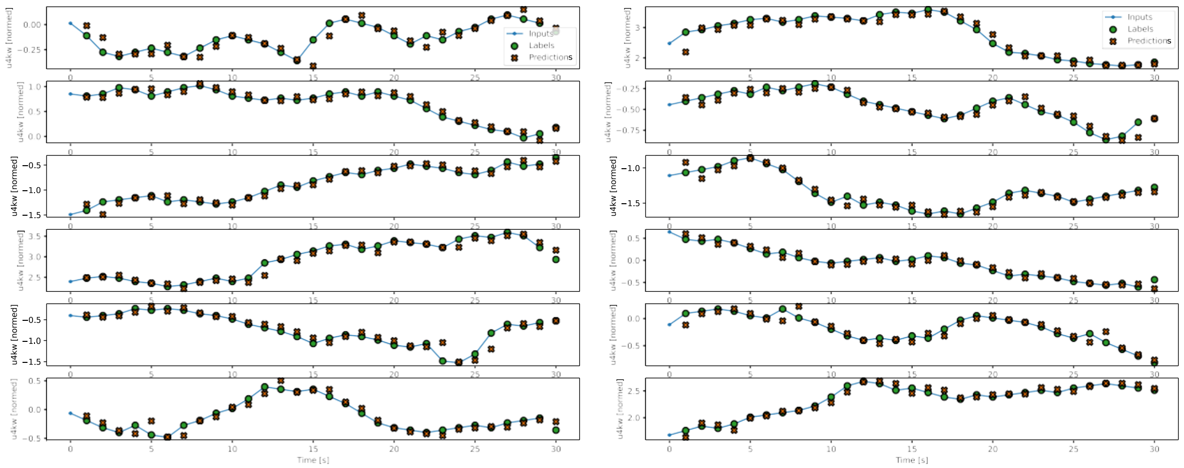
Results: Baseline, linear, dense, multistep dense, conv, LSTM.

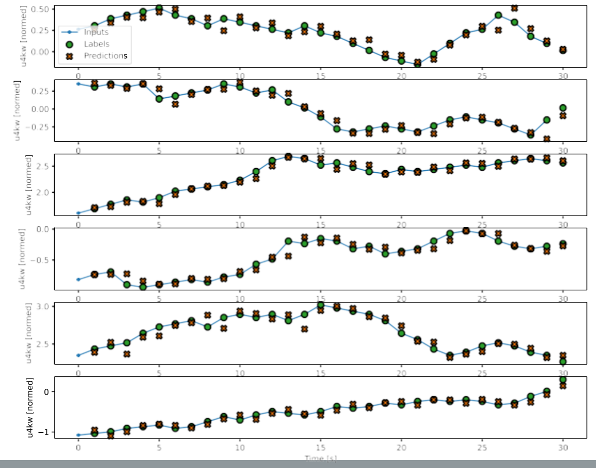
- Data for one day: ~65K pts (clean ~7K). Power output prediction: 1 s ahead with 30 s history.





LSTM: Example Batch Profiles and Performance

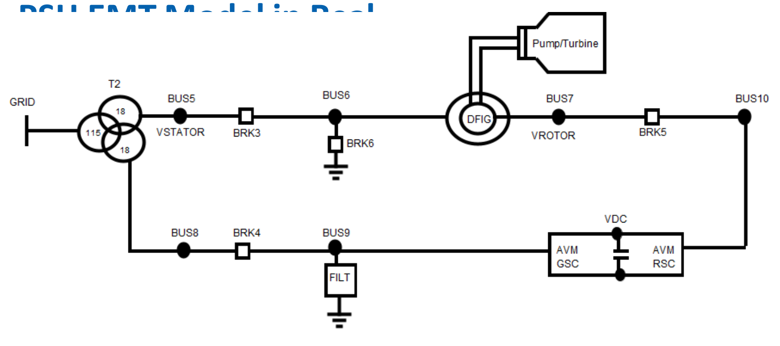


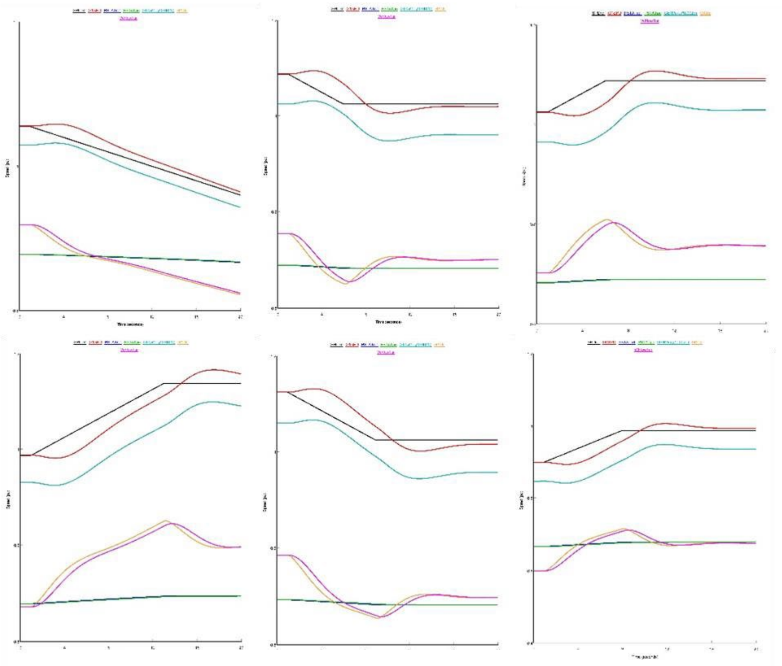


SCADA data points used

	Count	Mean	Std	Min	25%	50%	75%	Max
u4kw	7605.0	1248.594740	44.367676	1177.00	1221.00	1239.00	1265.00	1479.00
noz1	7605.0	48.976953	8.945423	20.10	40.96	46.94	58.83	59.99
hlvl	7605.0	7.672195	0.172342	7.29	7.49	7.70	7.77	8.40
rpm	7605.0	400.168126	0.585754	398.80	399.60	399.80	400.80	401.60
hydpsi	7605.0	1798.378698	2.611716	1788.00	1797.00	1798.00	1800.00	1806.00
penpsi	7605.0	129.143853	0.706048	128.00	129.00	129.00	130.00	133.00

Results: Prediction and Performance Using Reservoir Computing





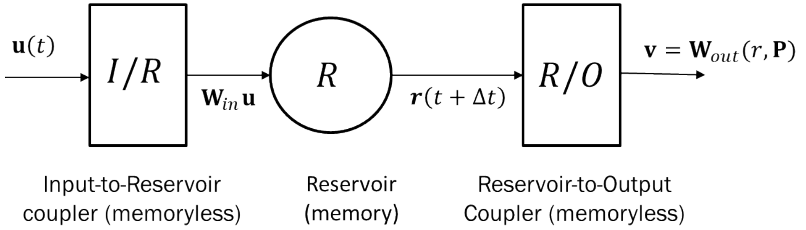
Training data generated using RTDS

Objective: To learn time trajectories using machine learning techniques and predict power, speed, etc. to infer dynamic behavior of PSH.

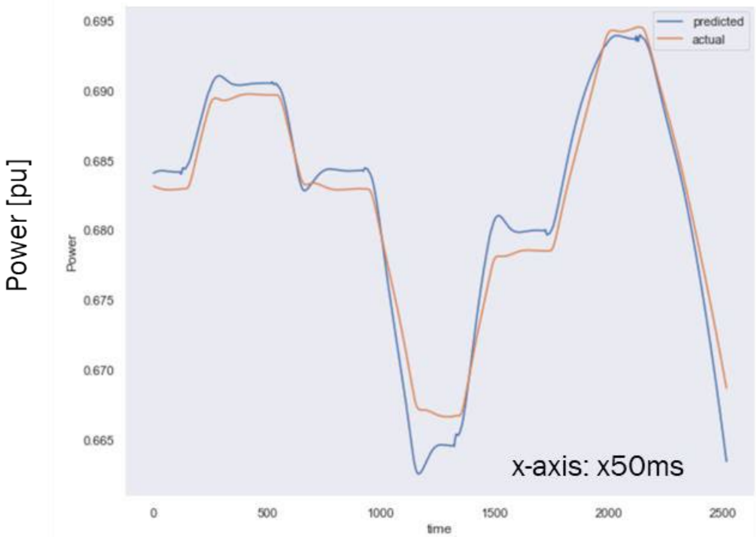
- **Simulation data in turbine mode.**
- **Setpoints varied from 0.8–0.99 pu.**
- **Speed, power, gate, water flow, and control references are captured.**

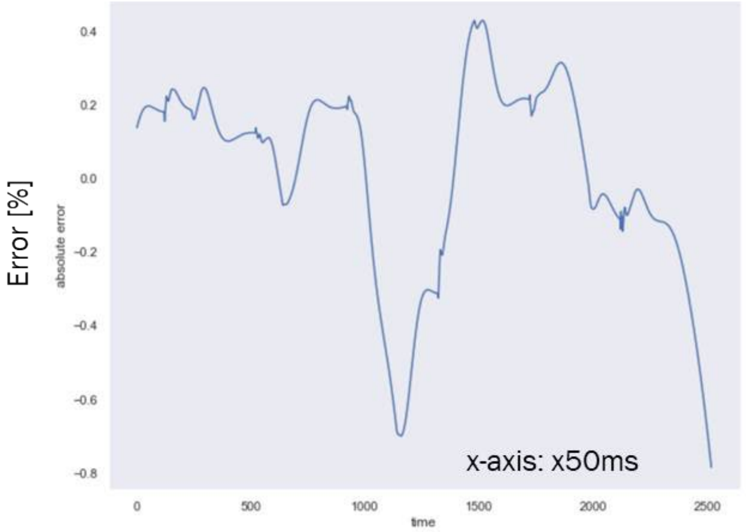
Reservoir Computing using Echo State Networks

$$\mathbf{r}(t+\Delta t) = \tanh[\mathbf{A}\mathbf{r}(t) + \mathbf{W}_{in}\mathbf{u}(t)]$$
$$\mathbf{v}(t+\Delta t) = \mathbf{W}_{out}(r(t+\Delta t), \mathbf{P})$$



Prediction Performance: Power Output Prediction and Actual (Left); Error (Right)



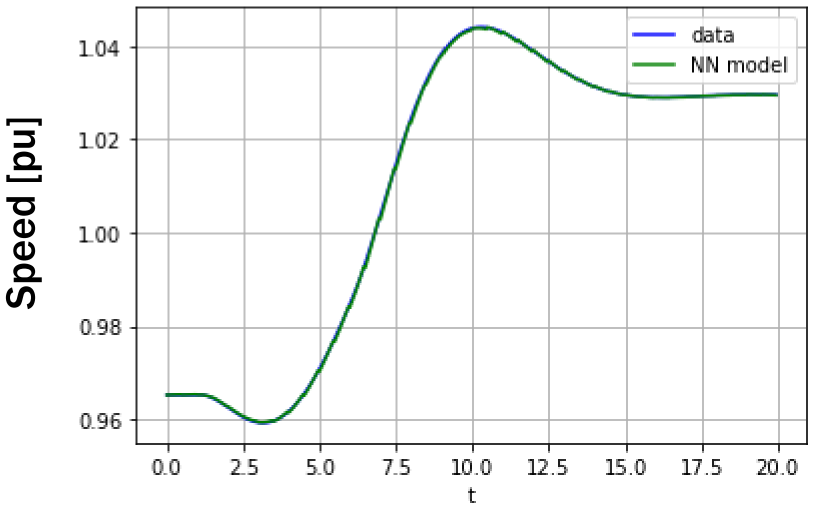


PSH output power based on input features: speed, power, gate, water flow, and control references.

Results: Prediction Using Multistep Neural Network

- A multistep neural network (MNN)* is a *numerics*-informed approach in which the underlying physics is learned from data, and then a numerical integration scheme is used for solving the dynamical representation as ODEs.
- PSH simulation data is employed for training, and prediction is performed for 10 timesteps (each timestep $\Delta t = 50\ ms$); recomputed at 10 Hz.

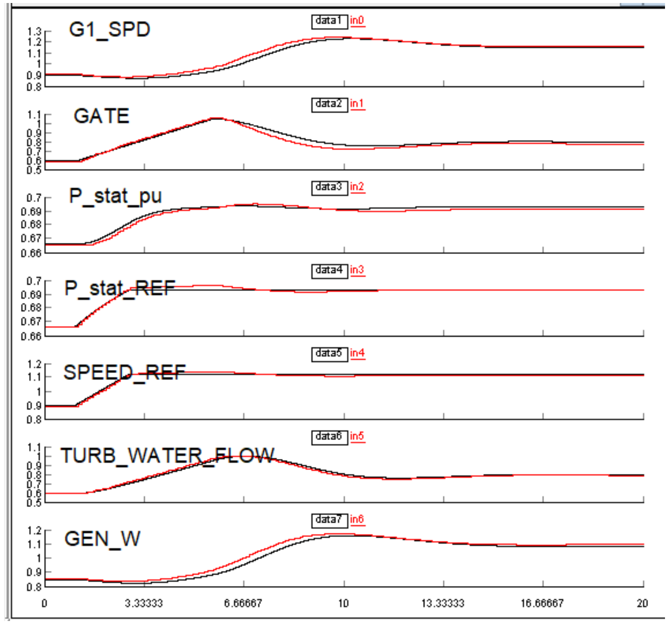
Predicted Output (Test: Offline)



Real-time prediction (red) using MNN;
Actual data (black) update rate: 10 Hz.

Prediction for generator and turbine shaft speeds, gate position, water flow, speed and power references, and electrical power output.

Real-Time Simulation Test Plots

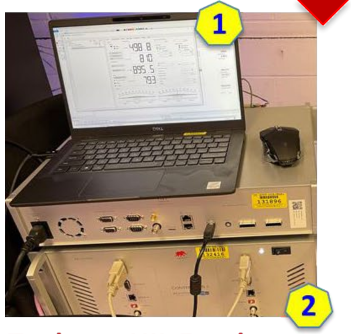


*Raissi, Maziar, Paris Perdikaris, and George Em Karniadakis. 2018. "Multistep neural networks for data-driven discovery of nonlinear dynamical systems." *arXiv preprint arXiv:1801.01236*.

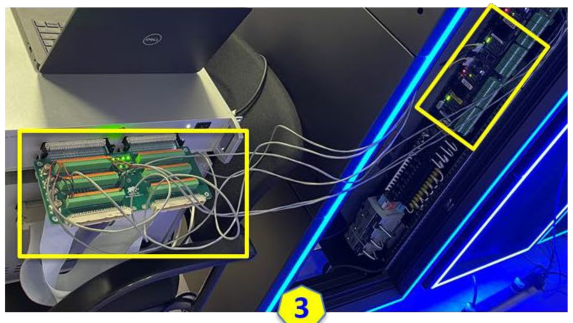
Performance: Accomplishments and Progress – Hydro-Governor CHIL

- Large cluster of digital real-time simulation for regional-level power system dynamics
  - Nine chassis RTDS and four Typhoon HIL emulators

Low-voltage V & I amplifiers for hydro-governor controller HIL



Typhoon HIL Emulator + EPC Connect



Typhoon HIL Interface Board

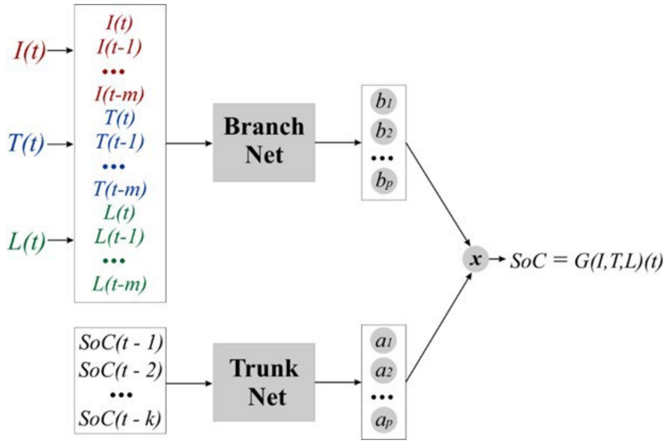
RTDS GTAO & GTAI

RTDS RSCAD

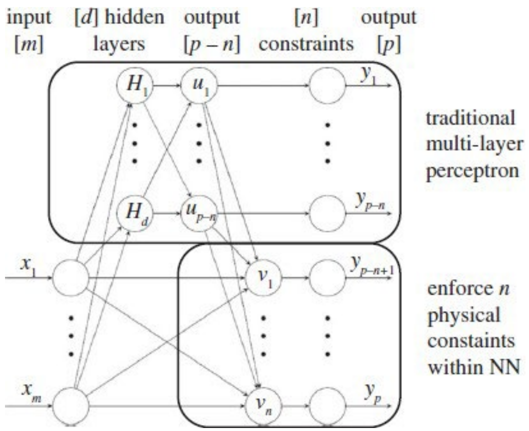
Typhoon HILConnect with EPC Power Corp. Controllers interfaced to RTDS for CHIL

Performance: Accomplishments and Progress – PIML

- **Multiple approaches to include physics in the machine learning**
  - **Joint loss minimization of data-driven and physics governing equations is a popular approach.**



Julian D. Osorio, Zhicheng Wang, George E. Karniadakis, Shengze Cai, Chrys Chryssostomidis, Mayank Panwar, and Rob Hovsapian. "Forecasting solar-thermal systems performance under transient operation using a data-driven machine learning approach based on the DeepONet architecture." *Submitted to Energy Conversion and Management.*



K. Kashinath et al. 2021. "Physics-informed machine learning: case studies for weather and climate modelling." *Phil. Trans. R. Soc. A* 379: 20200093. https://doi.org/10.1098/rsta.2020.0093.

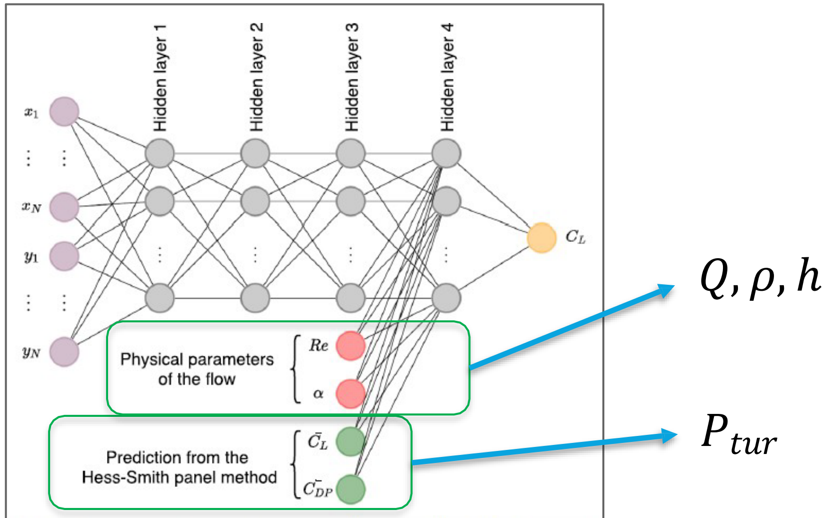


FIG. 2. The representative neural network architecture of the PGML framework used in this study for the aerodynamic force prediction task. The latent variables at the third hidden layers are augmented with the physical parameters of the flow (i.e., the Reynolds number and angle of attack) and the prediction from the Hess–Smith panel method (i.e., lift coefficient and pressure drag coefficient denoted as $\tilde{C}_L$ and $\tilde{C}_{DP}$, respectively).

Suraj Pawar, Omer San, Burak Aksoylu, Adil Rasheed, and Trond Kvamsdal. 2021. "Physics guided machine learning using simplified theories." *Physics of Fluids* 33, 011701 https://doi.org/10.1063/5.0038929.

Performance: Accomplishments and Progress (cont.)

Procedure to include plant physics in machine learning

- Physics equations (algebraic, differential) in the machine learning can be included in a neural network directly at the training stage by augmenting the training data inputs with independent variables from the governing equation at a chosen hidden layer of the network.
- During training, a joint loss function of the complete neural network, including the governing equation, is minimized.

Steady-state

$$P_{tur} \approx P_e = \eta Q \rho g h$$

η: turbine efficiency
Q: actual turbine flow
ρ: water density
g: acceleration due to gravity
h: head at the turbine admission

Penstock dynamics PDEs/ODEs (future)	Detailed turbine PDEs/ODEs (future)

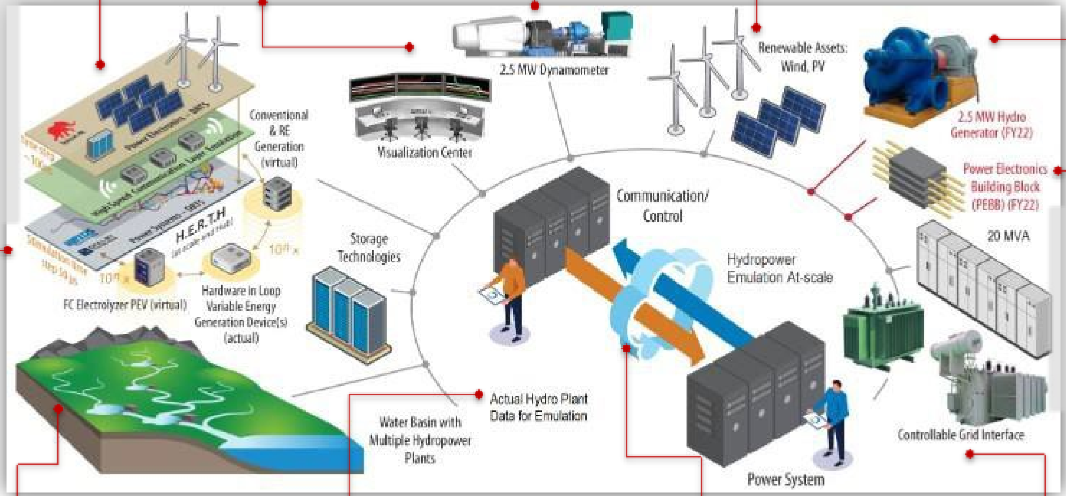
Next steps

- Application of physics-informed machine learning for penstock and turbine dynamics.
  - Non-desirable phenomena such as water hammer, cavitation, etc.
  - Off-nominal dynamic and transient operation.
- Scaling nonlinear behavior for different hydro plant sizes and configurations.
- Rapid prototyping and deployment of real-time predictive controls.

Future Work

Application of Physics-Informed Machine Learning to other hydropower designs and configurations will be evaluated. This Seedling project proof of concept will be developed further in a HydroWIRES project for Hydro Emulation at NREL ARIES (FY22–24). The project objectives are:

1. Establish a controlled real-world hydropower environment at NREL by leveraging ARIES infrastructure.
- Large cluster of DRTS, controllable grid interface (CGI), variable speed hydro-generator, and renewable assets: wind, solar PV, storage technologies (battery, hydrogen).
2. Develop next-generation hydro controls hardware for the grid of the future.
- Utility data-driven and machine learning for scalability analysis. Reduce the cost of integration, increase technology adoption, reduce the risk of field deployment.
3. Develop power electronics building blocks (PEBB) for the hydropower plant as a grid interface.
- The PEBB concept is a modular, standardized hardware and control interface for existing and new hydropower configurations, including other grid technologies such as storage and microgrid connectivity.



NREL

Q&A