MACHINE LEARNING FOR ELECTRICITY PRICE FORECAST IN BRAZIL

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OVERVIEW

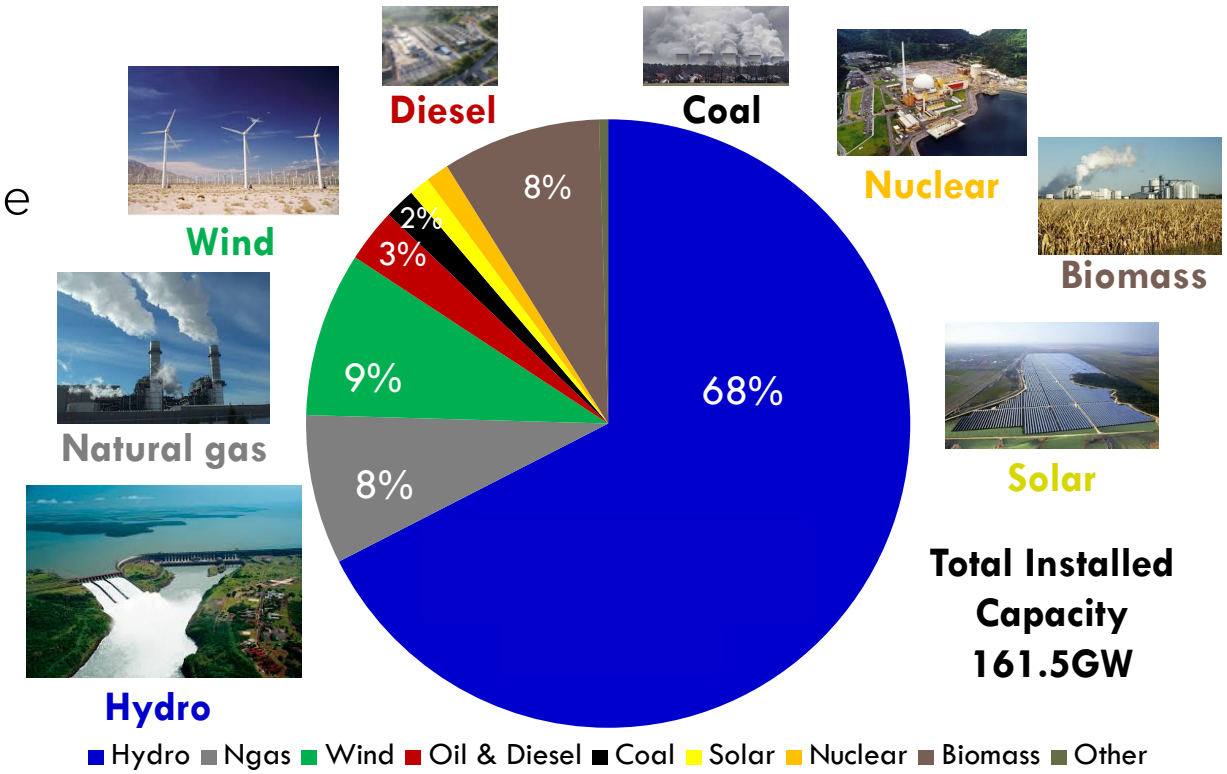
- Introduction
- Coordination of Energy Resources & Horizons
- The Forecasting Problem
- Artificial Neural Networks for Inflow Forecasting
- Case Study
- Conclusions & Final Remarks

INTRODUCTION

- Renewable power sources became a key aspect around the world by disrupting old frontiers
- These energy sources are linked to sustainable development that is one of the main goals of the modern society these days
- The raise of renewable power installed capacity demands new studies about its effects
- Analytics and decision-making techniques are essential for operational and planning actions

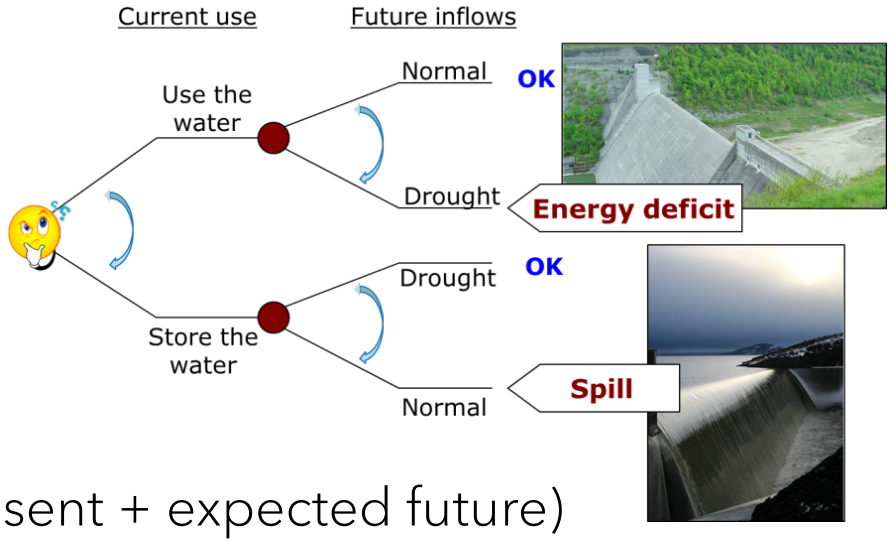
BACKGROUND

- Brazil presents a highly dominant renewable generation matrix (mostly Hydro)
- Wind is a promising renewable source in the country, reaching installed capacity of 14.5 GW
- The main problem with renewable power is its dependence on natural resources (may not be available when necessary)
- Often represented as uncertainty sources for decision-making models in power systems



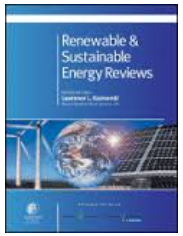
HYDRO-THERMAL COORDINATION

- Find the sequence of hydro releases and thermal plant dispatches for a planning horizon to match system demand
  - Resource management
  - Input variable forecasting
  - Operational aspects
- Basic economic criterion
  - Minimize operational costs (present + expected future)



- Usually modeled and solved using stochastic programming (optimization) techniques

de Queiroz, A.R., (2016) Stochastic Hydro-thermal Scheduling Optimization: An Overview, Renewable and Sustainable Energy Reviews, 62: 382-395



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HTCP MODEL & HORIZONS

$$h_t(x^{t-1}, b_t^\omega) = \min \underbrace{\sum_{\ell \in L} c_\ell^t GT_\ell^t + \sum_{k \in K} u_k^t GD_k^t}_{\text{Present Cost}} + \underbrace{\frac{1}{(1+\beta)} \mathbb{E}_{b_{t+1}|b_1,\ldots,b_t} h_{t+1}(x^t, b_{t+1})}_{\text{Expected Future Cost}}$$

Water Balance

$$\text{s.t. } x_i^t + GH_i^t + S_i^t = x_i^{t-1} + b_{t+1}^\omega + \sum_{j \in M_i} (GH_j^t + S_j^t) \quad \forall i \in I$$

Demand Satisfaction

$$\sum_{i \in I_r} \rho_i GH_i^t + \sum_{\ell \in L} GT_\ell^t + \sum_{k \in K} GD_k^t - \sum_{\substack{r' \in R \\ r' \neq r}} F_{r\,r'}^t + \sum_{\substack{r' \in R \\ r' \neq r}} F_{r\,r'}^t = D_{tr} \quad \forall r \in R$$

Simple Bounds

$$\underline{x_i^t} \leq x_i^t \leq \overline{x_i}^t \quad \forall i \in I$$

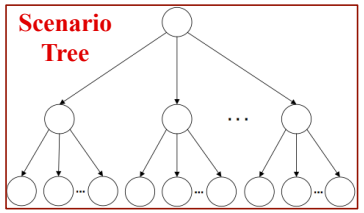
$$0 \leq GH_i^t \leq \overline{GH_i^t} \quad \forall i \in I$$

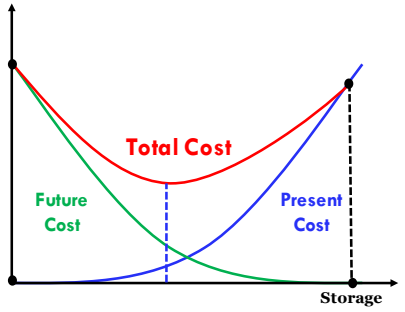
$$0 \leq S_i^t \quad \forall i \in I$$

$$\underline{GT_\ell^t} \leq GT_\ell^t \leq \overline{GT_\ell^t} \quad \forall \ell \in L$$

$$0 \leq GD_k^t \quad \forall k \in K$$

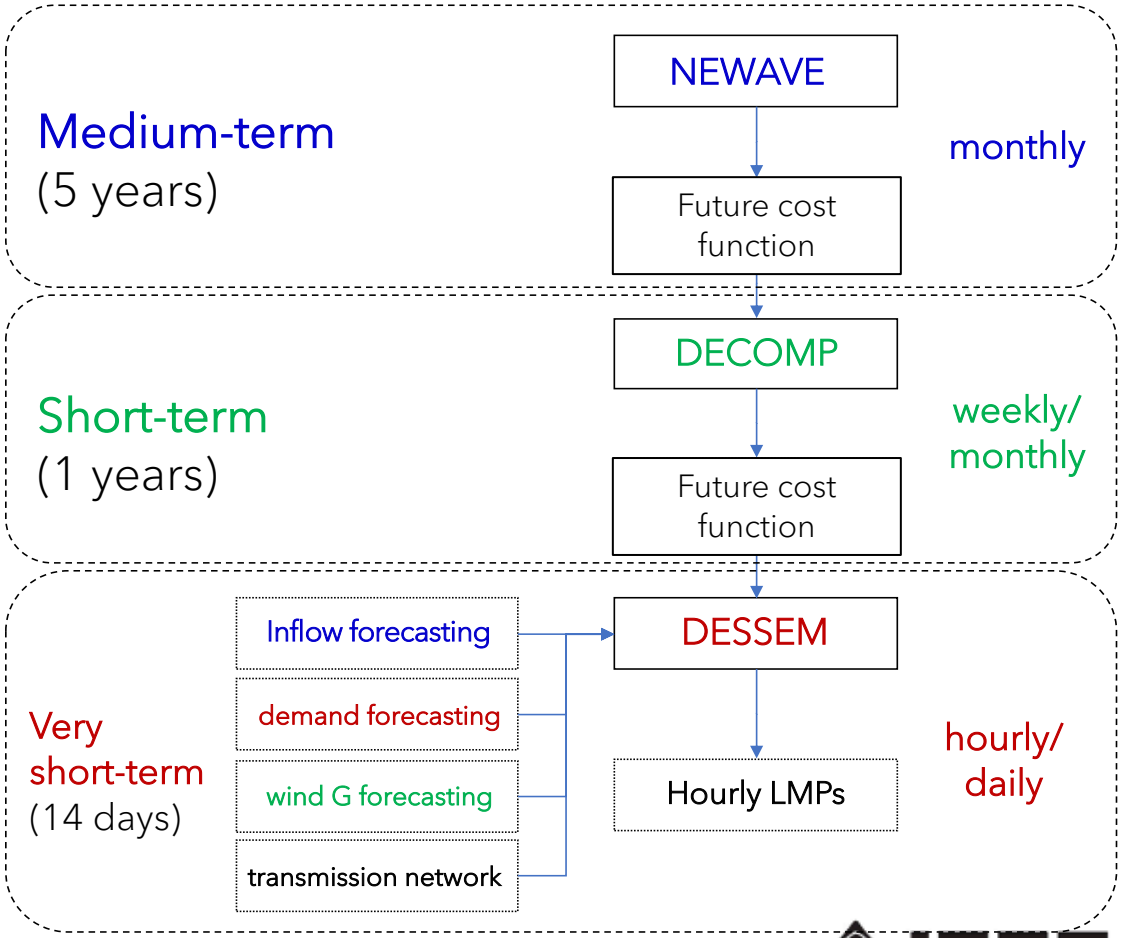
$$0 \leq F_{r\,r'}^t \leq \overline{F_{r\,r'}^t} \quad \forall (r, r') \in R$$





de Queiroz, A.R., Morton, D.P., (2013) Sharing Cuts under Aggregated Forecasts when Decomposing Multi-stage Stochastic Programs, Operations Research Lett, 41(3): 311-316

Study horizon | Chain of models | Discretization



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THE FORECASTING PROBLEM

CLIMATE & WEATHER EFFECTS

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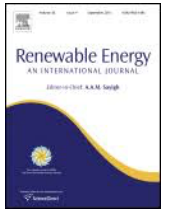
THE FORECASTING PROBLEM

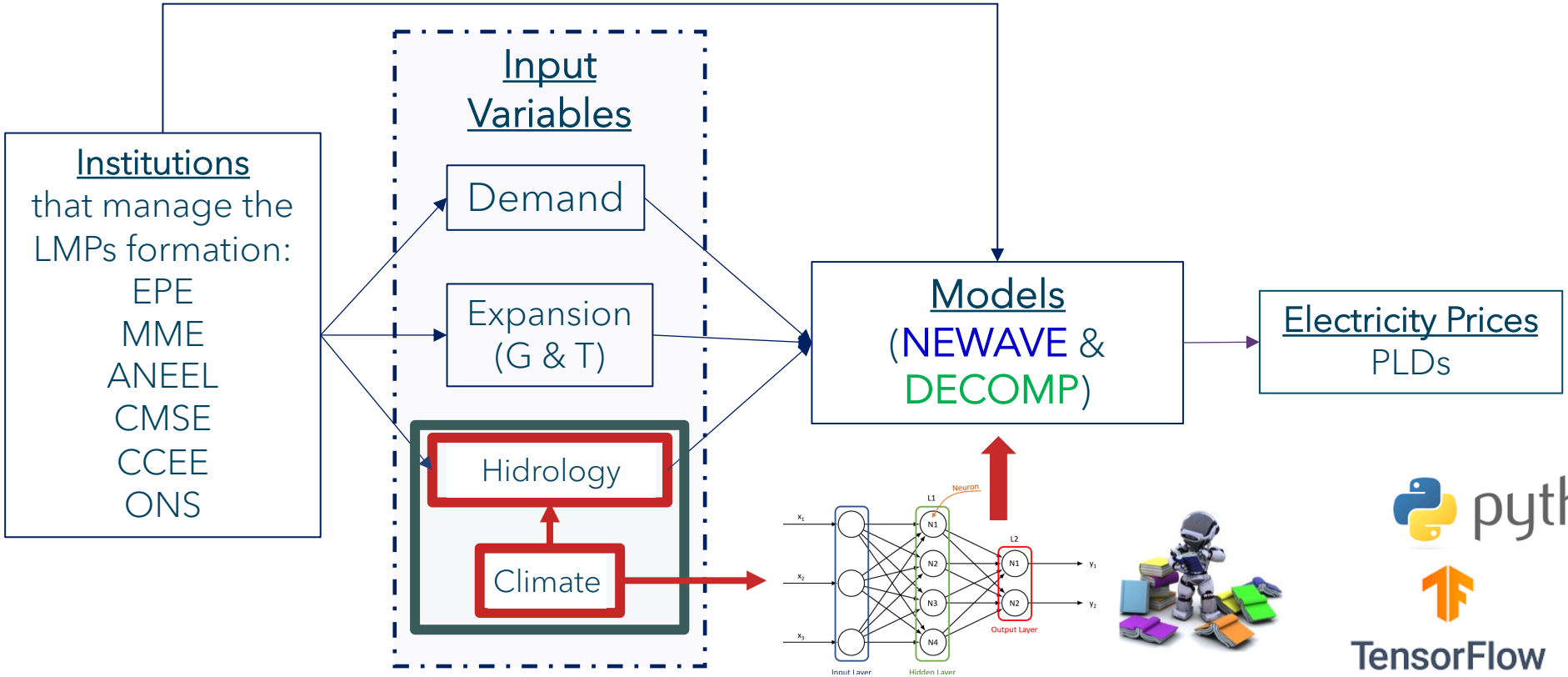
- As a large portion of the generation system is provided by hydro, the LMPs are extremely affected by the water inflows at the hydro plants reservoirs
- Therefore, it is necessary to establish accurate inflow forecasts in order to obtain proper predictions of the LMPs that are the **market clearing prices called PLDs**
- As weather/climate is significantly affecting water inflows & hydropower in the country we consider associated variables as predictors in a potential model

de Queiroz, A. R., Faria, V. A., Lima, L. M., & Lima, J. W. (2019). Hydropower revenues under the threat of climate change in Brazil. Renewable Energy, 133, 873-882



- The amount of data available is significant and we use machine learning techniques, more specifically artificial neural networks (ANNs), in order to obtain data-driven and robust forecasting models for the problem at hand

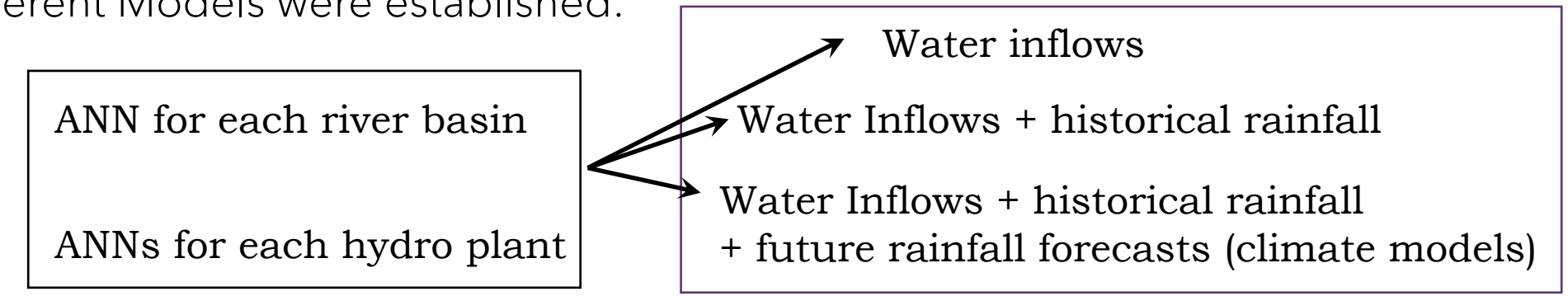
ELECTRICITY SPOT PRICES FORECASTING FRAMEWORK



Multi-Layer Perceptron ANNs

ARTIFICIAL NEURAL NETWORKS

- We were able to create ANNs that use millions of internal parameters using Deep Neural Network training algorithms, concepts and other things:
  - Input variable selection; Filling missing data
  - RELU, Tanh & sigmoid used as activation functions in training; ADAM, RMS prop and gradient descent with momentum (GDM) considered in the optimization process
- Different Models were established:

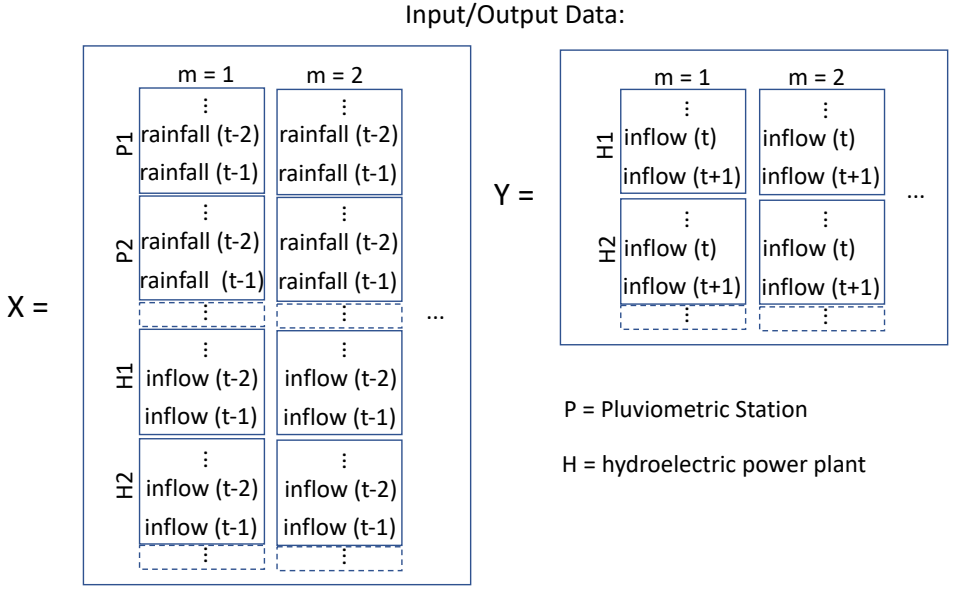


CASE STUDY

DATA AND MODELS

- Historical water inflow data from 2000 to 2019, as well as precipitation forecasts from climate models (GEFS, ETA-40 km) are used to train ANNs
- More than 7000 examples used in the ANNs training process, and we normalize and segment the dataset in: 60% - train, 20% - dev and 20% - test
- Historical water inflows, historical precipitation data from pluviometric stations, calendar data and climate variable forecasts are used
- ANNs using different configurations were tested
- MLPs and results from models used by the Brazilian ISO (hydrological model SMAP and PREVIVAZ) are compared

Input/Output Data:

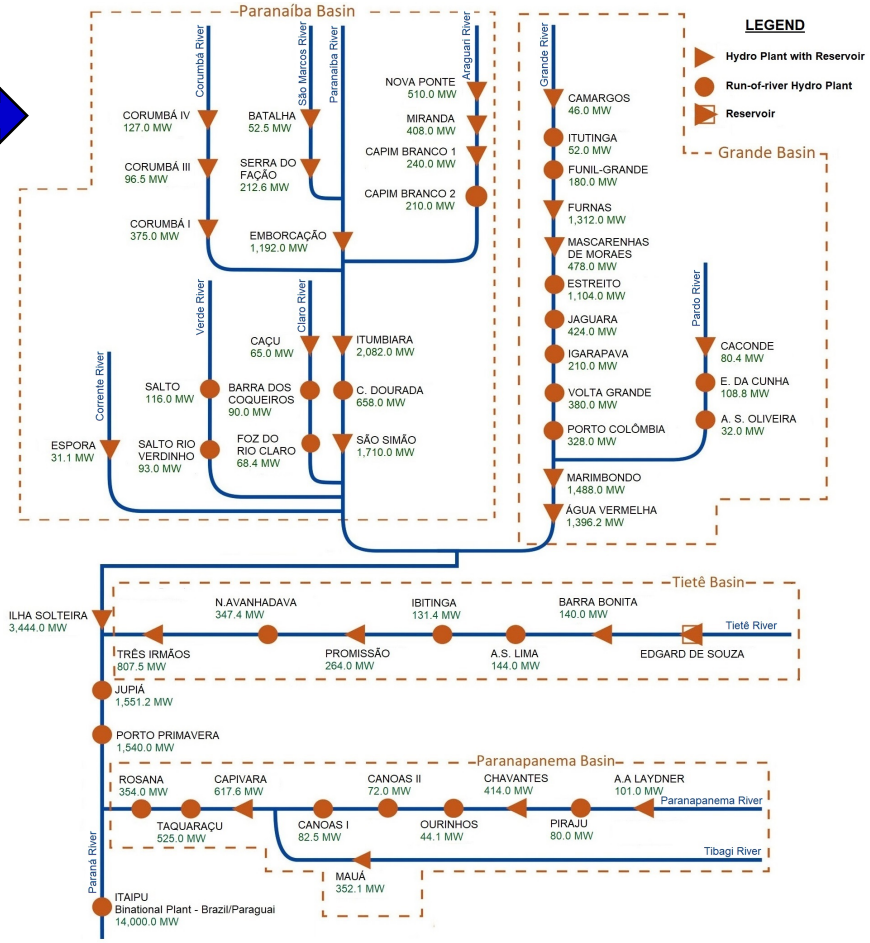


P = Pluviometric Station

H = hydroelectric power plant

CASE STUDY

- ANNs were trained to forecast water inflows 14 days ahead for 55 hydro plants
- Results are compared with the performance of the models currently used by the Brazilian ISO from 2014 up to 2016
- All ANNs trained are fully connected, and the number of neurons in each hidden layer is equal to the number of neurons in the input layer
- Each ANN uses as input 30 days of lag with respect to the water inflow information from the first downstream plant up to the 5th level of upstream hydro plants
- Computational experiments performed using a PC i7-7700k CPU (4 cores, 4.2 GHz), 16 GB RAM, and a GPU NVIDIA GTX 1070 (8 GB). The TensorFlow (TensorFlow, 2019) framework was used with GPU parallelization



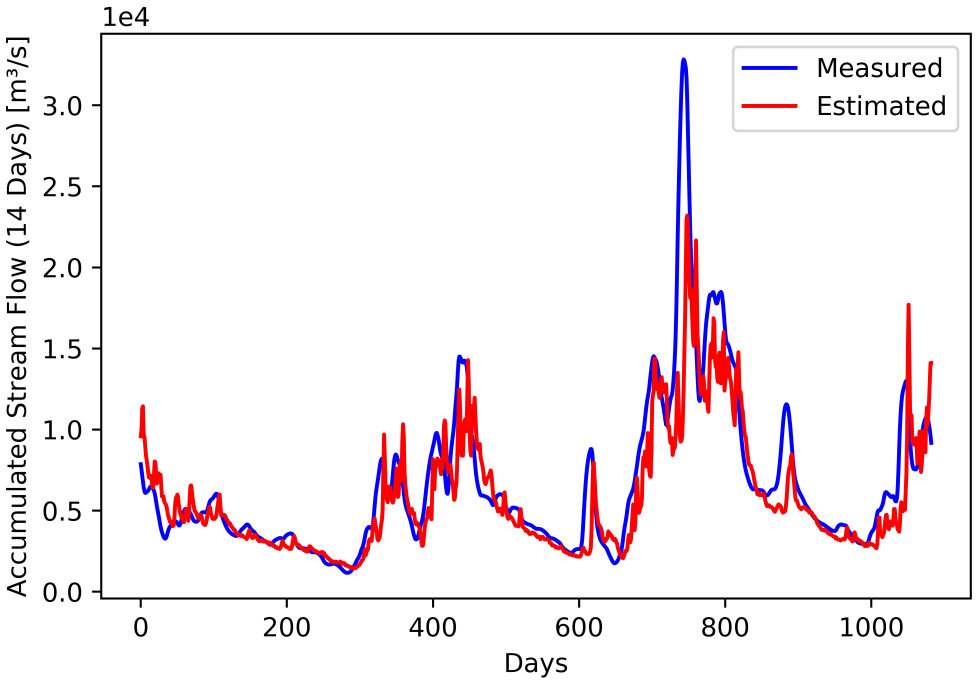
RESULTS AND COMPARISON I

Optimization Algorithm	Activation Function	Error Test Set		Error Dev Set		Avg Epoch	Total Wall Time [h]
		MSE	MAPE	MSE	MAPE		
Adam	ReLU	0.2729	18.71	0.3821	14.92	2598	5.09
	Tanh	0.2574	17.76	0.3762	14.78	1668	4.26
	Sigmoid	0.2577	18.43	0.3883	14.72	1680	4.24
RMSprop	ReLU	0.2668	19.52	0.3700	15.15	2700	5.10
	Tanh	0.2647	18.21	0.3941	15.22	2516	4.67
	Sigmoid	0.2647	20.33	0.3945	15.88	4024	5.35
GDM	ReLU	0.2809	19.37	0.3959	15.50	15862	14.37
	Tanh	0.2605	17.64	0.3785	15.05	19488	16.48
	Sigmoid	0.2749	18.92	0.4011	15.11	15918	13.76

HYDROGRAPHS: ANN ESTIMATE VS MEASURED STREAM FLOW

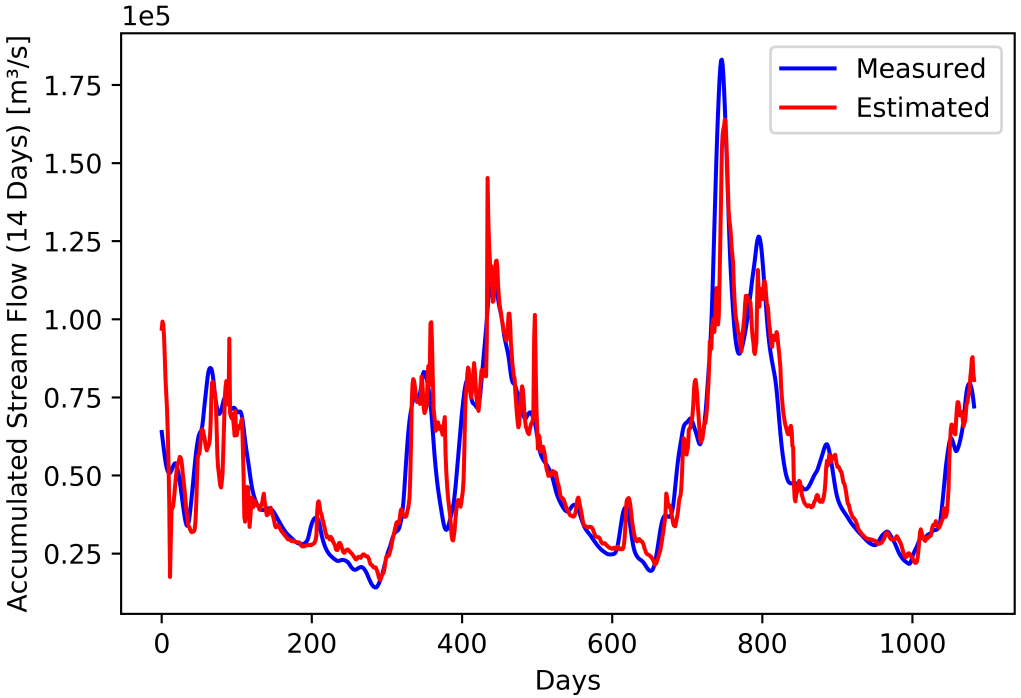
Furnas hydropower plant

Capacity: 1312 [MW]



Ilha Solteira hydropower plant

Capacity: 3444 [MW]



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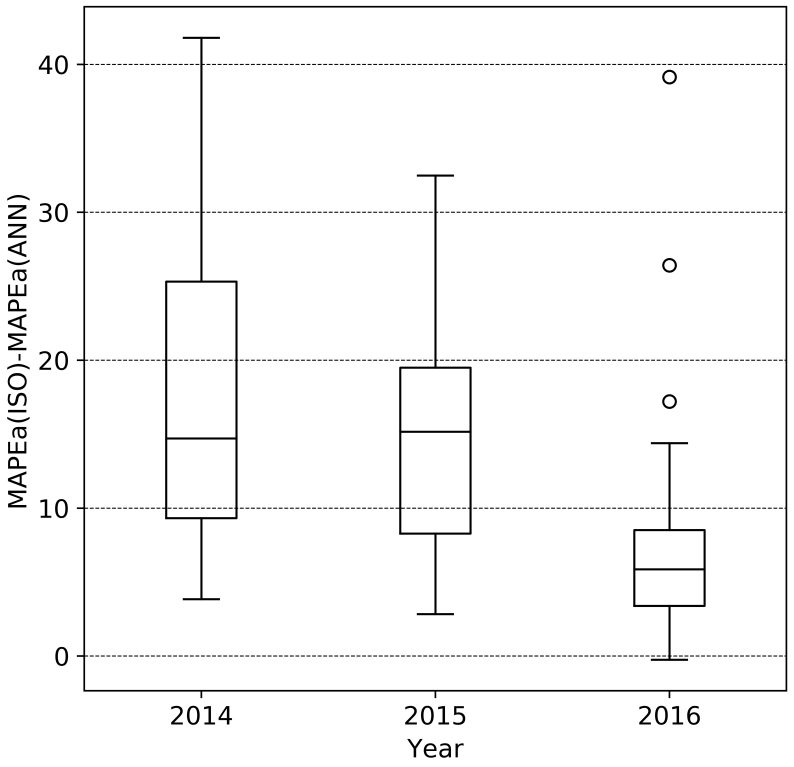
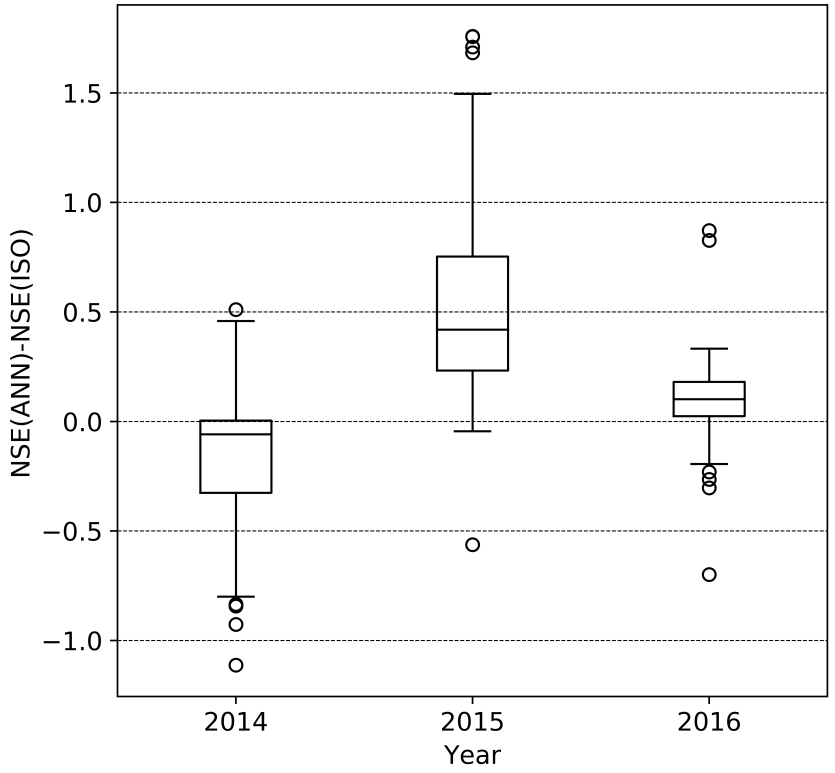
RESULTS AND COMPARISON II

Mean Absolute Percent Error



Nash–Sutcliffe



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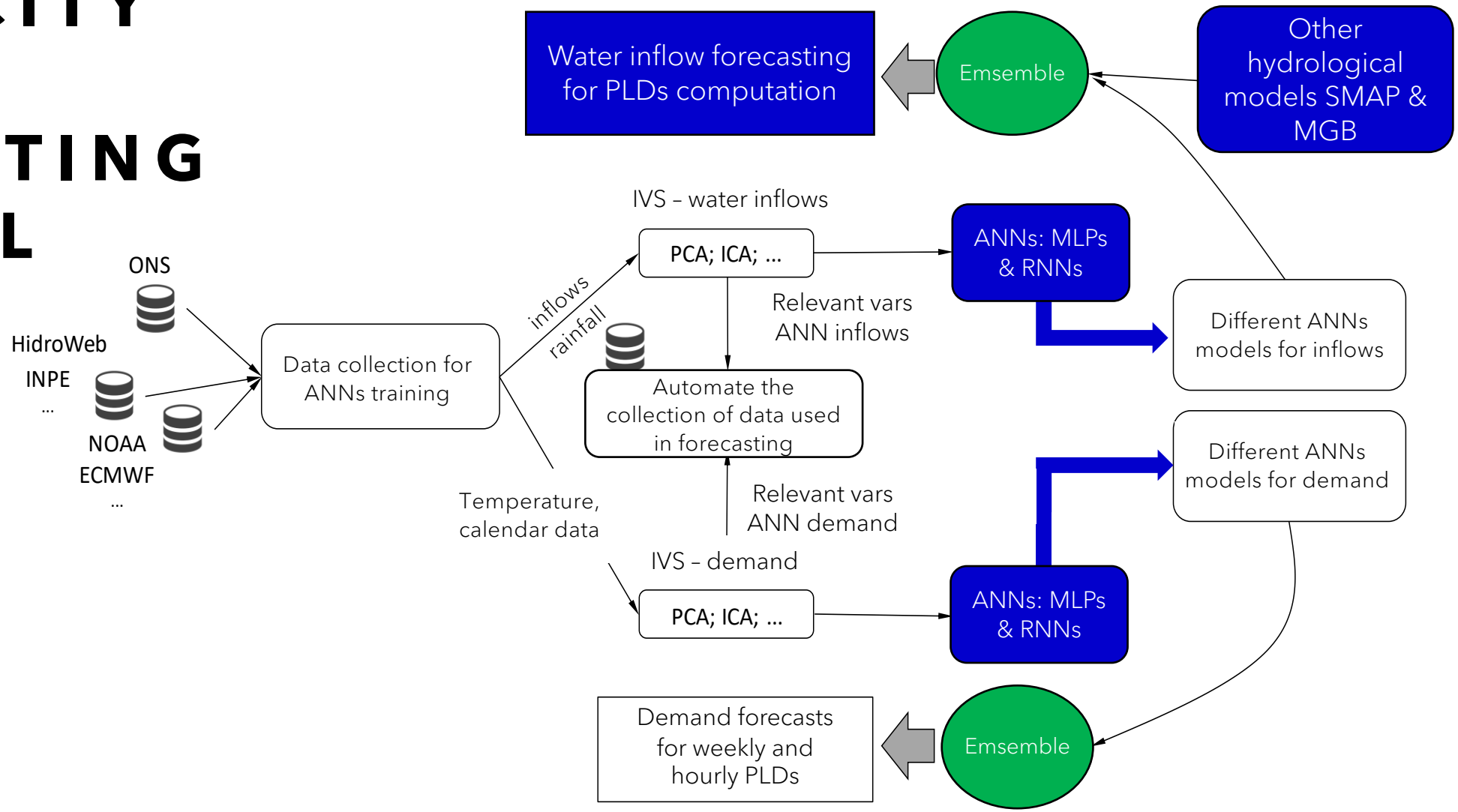
ELECTRICITY PRICES FORECASTING IN BRAZIL

An integrated framework



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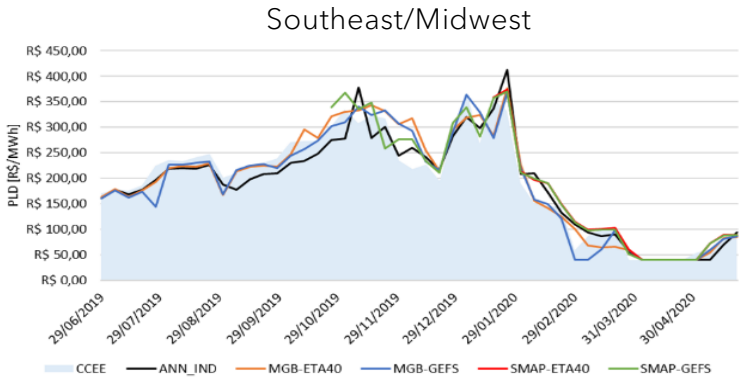

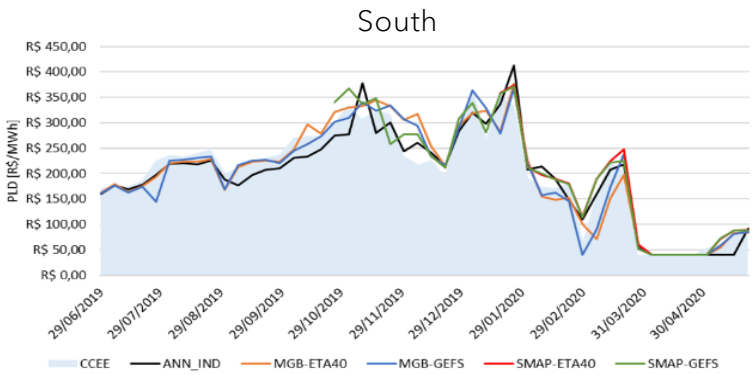

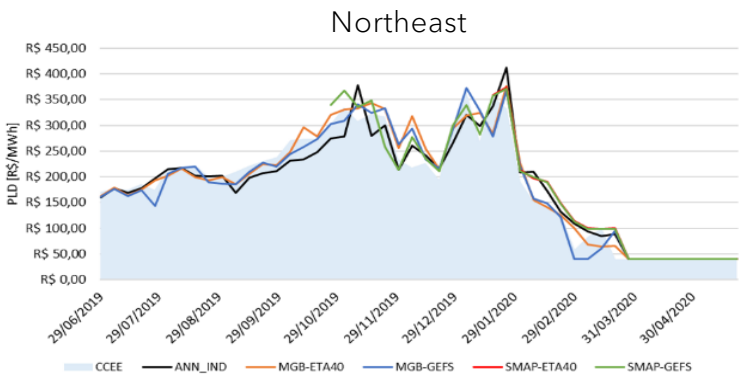

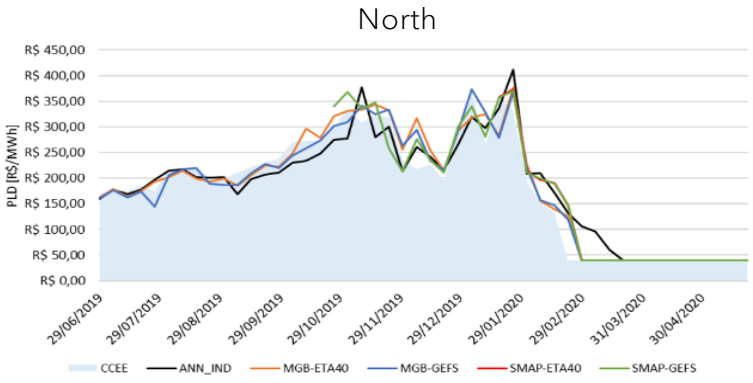

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CONCLUSIONS & FINAL REMARKS

CONCLUSIONS & REMARKS

- We introduced the process of the **electricity prices formation in the Brazilian spot** market and pointed out to the importance of water inflows for the process
- We have presented the use of ANN for water inflows forecasting using state-of-the art techniques used to train deep neural networks
- We presented comparison results of the proposed approach with the Brazilian ISO as well as some results of the integrated framework developed for PLDs forecasts
- **Future works** should evaluate the performance of other ANN techniques such as **convolutional and recurrent when compared to the MLP models** in the forecasting of streamflow and electricity demand for large interconnected hydro systems

THANK YOU!

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