ML-based tool for RPC currents quality monitoring

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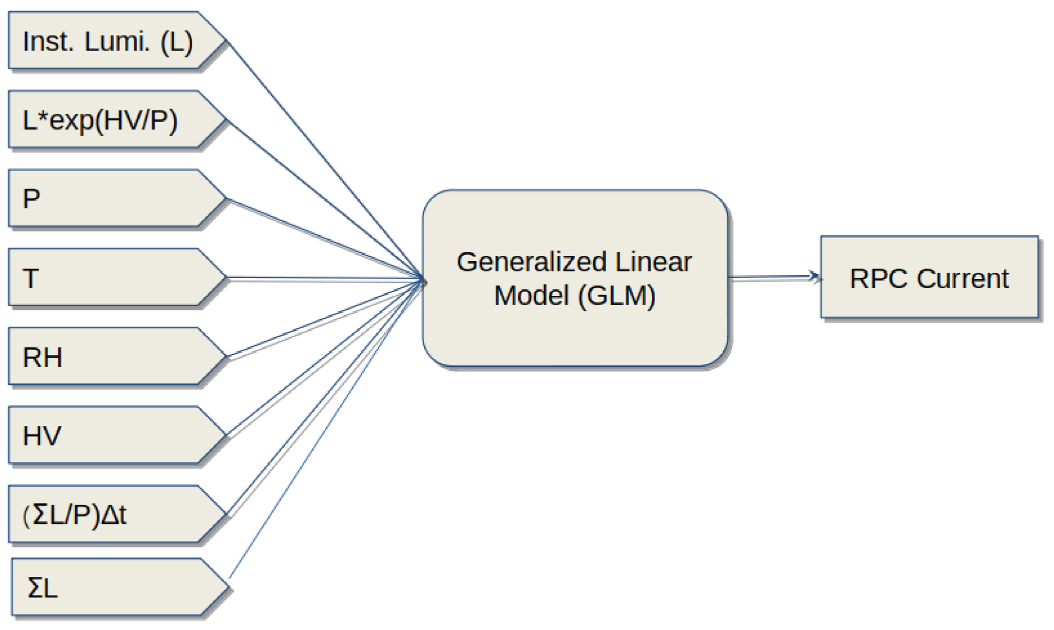
Introduction

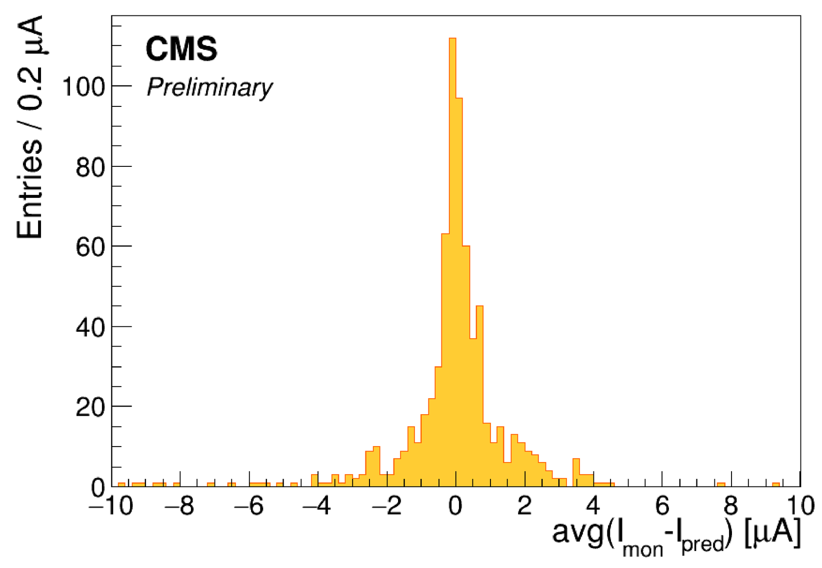
The muon system of the CMS experiment hosts 1056 Resistive Plate Chambers (RPCs). Detector current monitoring is fundamental for controlling and verifying detector operation. An automated monitoring tool to carry out this task has been developed. It models the behavior of chamber currents by using Machine Learning (ML) methods [1]. Two types of ML approaches are used: Generalized Linear Models (GLM) and Autoencoders (AE).

Generalized Linear Model

A set of parameters such as environmental conditions (pressure, temperature, relative humidity), LHC parameters (luminosity) and HV are used to characterize the behavior of the current.

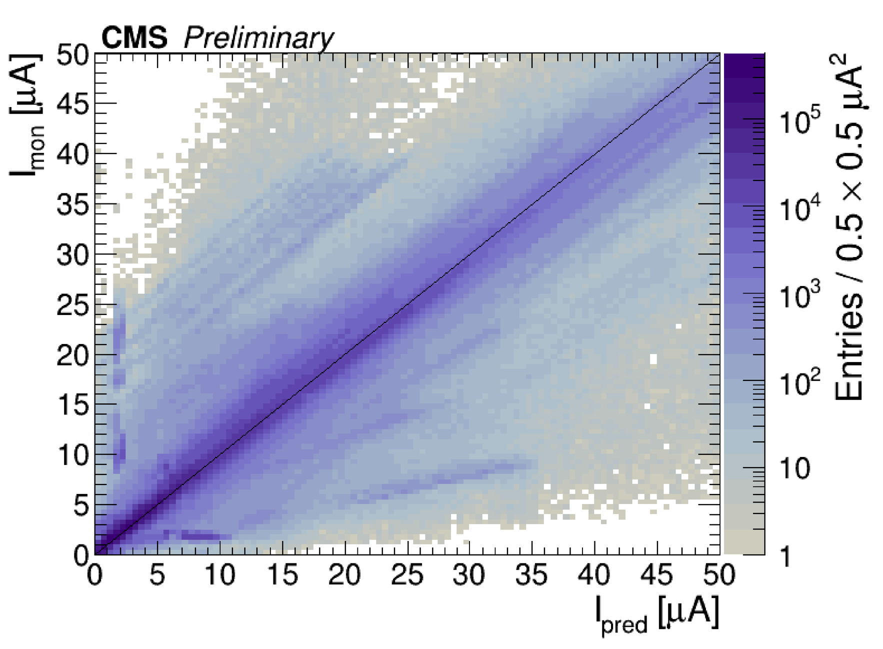


GLM performance - 1D histogram



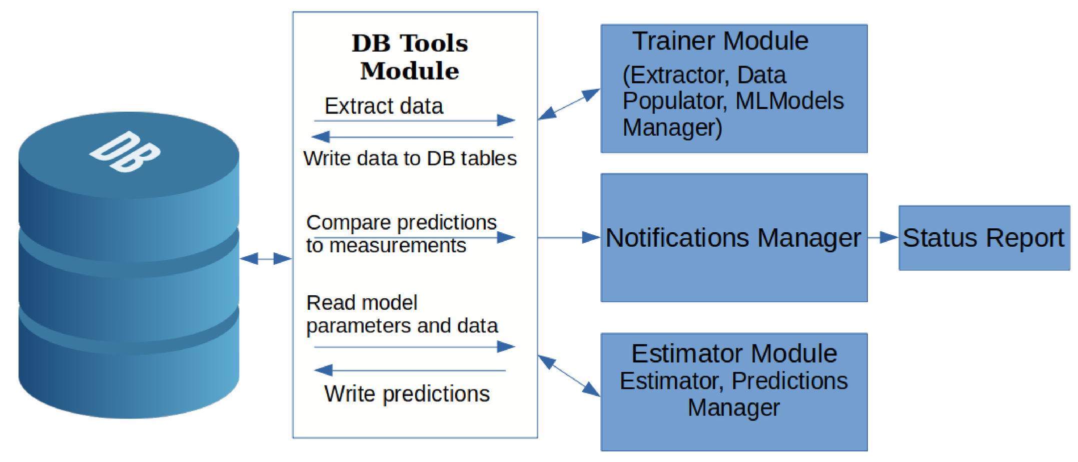
Mean = 0.21 μA; σ = 0.59 μA

GLM performance - 2D histogram



MAE = 0.72 μA; MSE = 3.24 μA^2

Modular software implementation

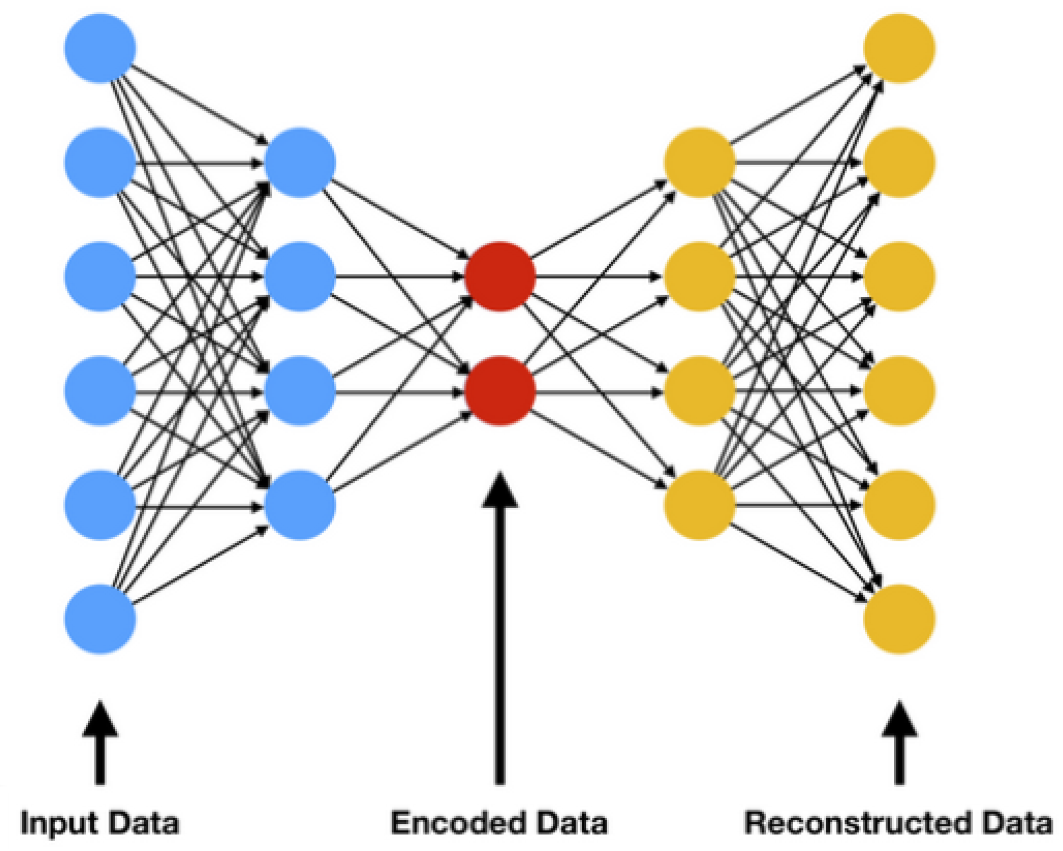


Results and Conclusions

The performance histograms reflect the predictive capabilities of the ML models. There are three training scenarios that were used: short-term (ST) monthly, mid-term (MT) yearly and long-term (LT) two-yearly training. ST is able to spot a rapid increase in the RPC currents, while MT and LG can be used to search for deviations from the overall RPC currents course. All models have Mean Averaged Error of less than 1.5 μA (from 0.49 μA for ST AE to 1.23 μA for ST GLM)

Autoencoder

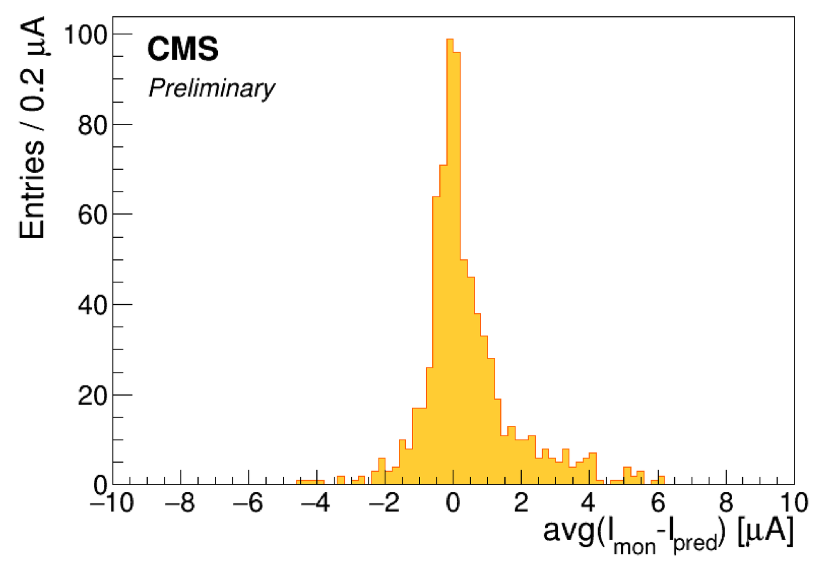
The set of currents for all of the high-voltage channels of the RPC system are used as input and the autoencoder network is trained to reproduce these inputs on the output neurons.



Validation and tests

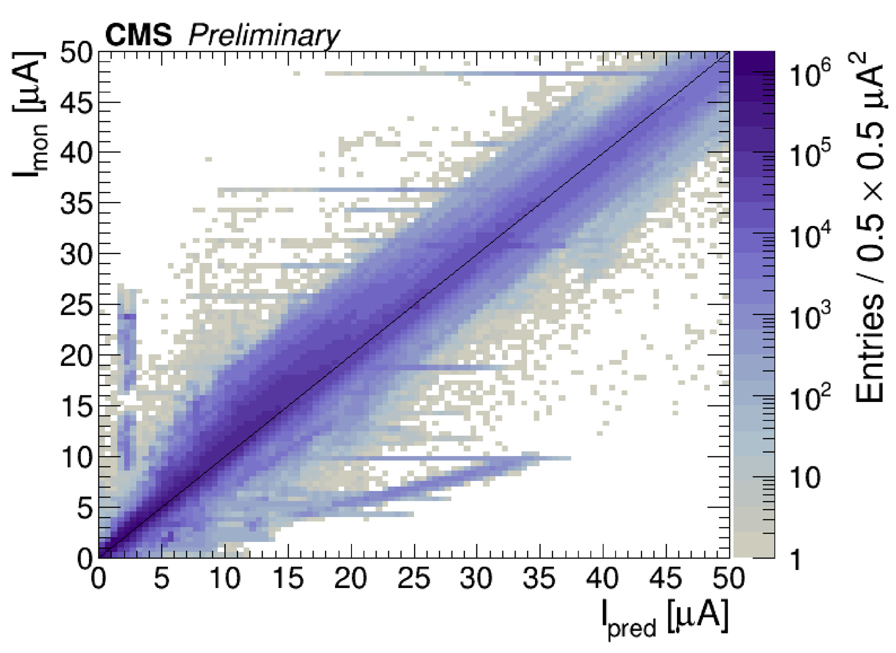
The tool has been tested on all non-event data from Run 2 (2016-2018). The histograms below show the distributions of the averaged differences between the predicted and measured currents. Herein, examples of the best-performing scenarios are shown.

Autoencoder performance - 1D histogram



Mean = 0.14 μA; σ = 0.83 μA

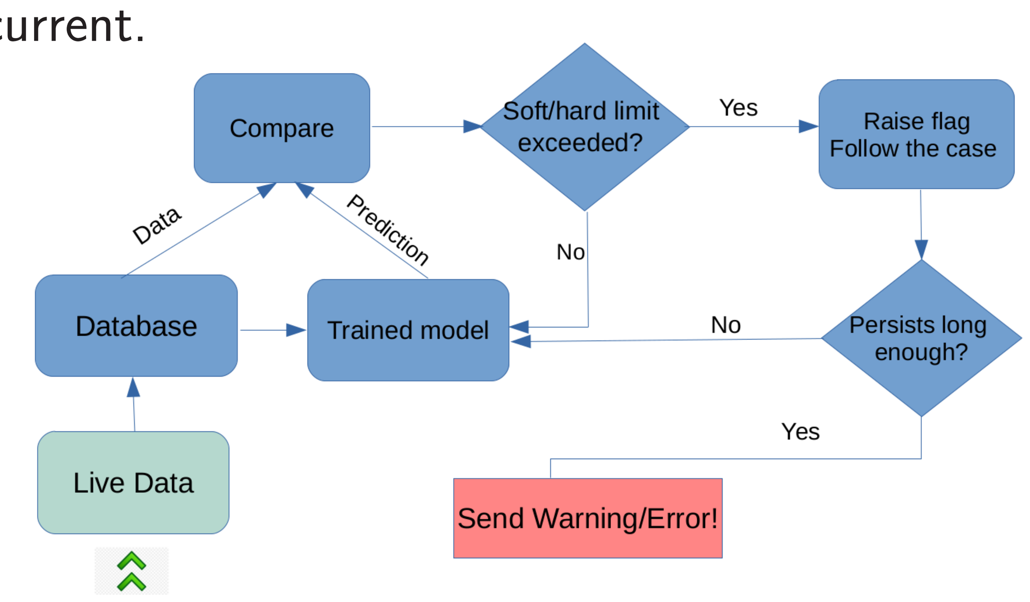
Autoencoder performance - 2D histogram



MAE = 0.49 μA; MSE = 1.39 μA^2

Monitoring tool

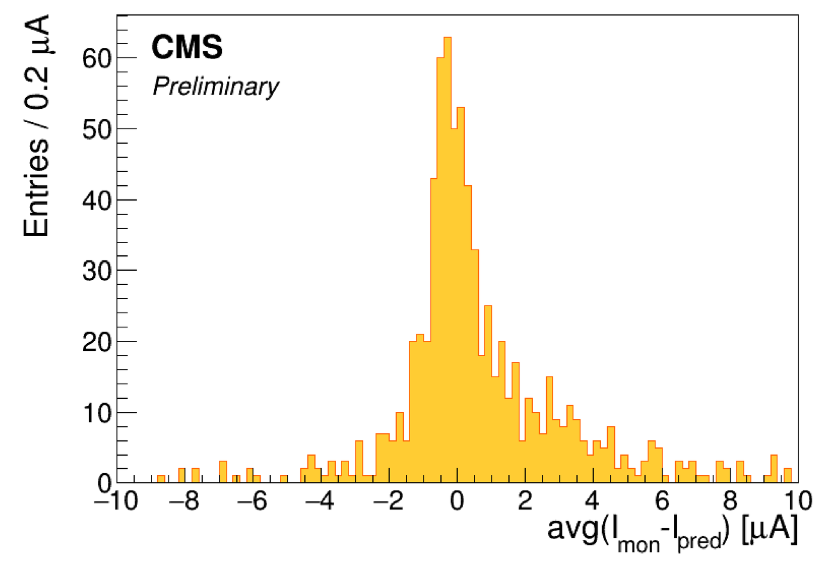
The predictive capabilities of the ML models are integrated in a monitoring tool which follows the evolution of the current and notifies the user in case of discrepancies between the measured and predicted current.



Hybrid network

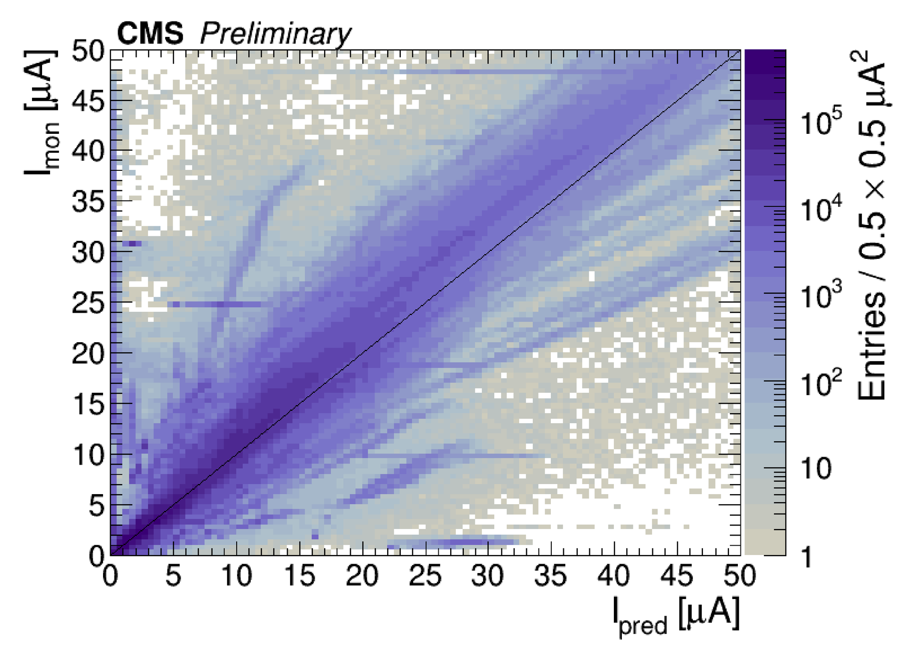
The hybrid network (HN) combines the two previous approaches, utilizing the GLM output as input for the autoencoder network. It shows good predictive capabilities, even better, on average, than the two separate approaches on their own, in the scenario of a distant prediction. In such a scenario, there is a significant distance in time (e.g. 1 year), between the end of the training period and the beginning of the prediction period.

HN performance - 1D histogram



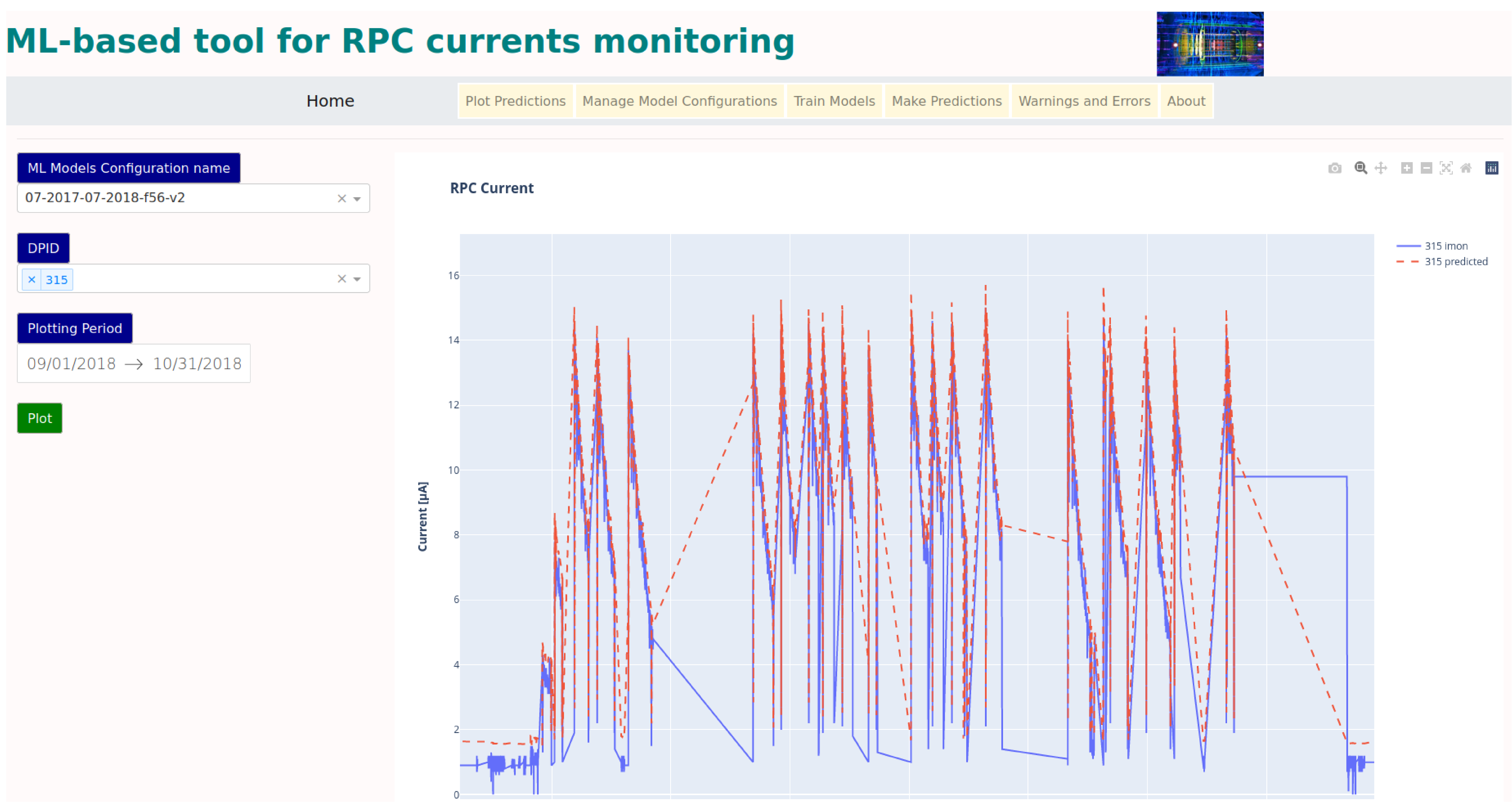
Mean = 0.60 μA; σ = 2.49 μA

HN performance - 2D histogram



MAE = 2.09 μA; MSE = 23.19 μA^2

Web UI (http://rpccurml:8050 from inside CERN network)



References

[1] A. Samalan et al, A new approach for CMS RPC current monitoring using Machine Learning techniques, 2020 JINST 15 C10009