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
- Two types of ML approaches are used: Generalized Linear Models (GLM) and Autoencoders (AE)

The CMS experiment

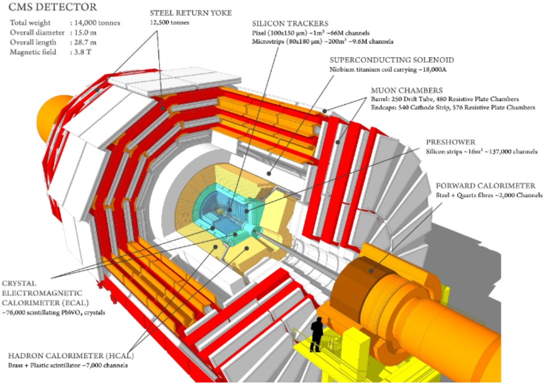
One of the four main experiments on the CERN LHC

CMS is a general purpose detector located at P5 on the LHC

CMS subsystems

Its main subsystems are:

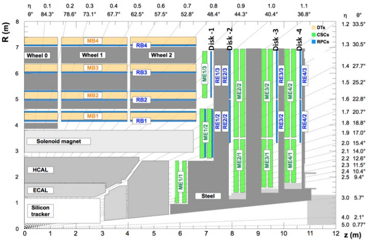
- Silicon trackers
- Electromagnetic calorimeter
- Hadronic calorimeter
- Muon system, consisting of:
  - DT
  - CSC
  - GEM
  - RPC

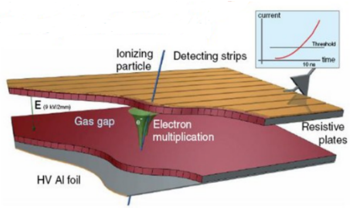


The muon system

The RPC subsystem

The muon system of CMS, along with the CSC, DT and GEM detectors, hosts 1054 RPC chambers, 480 are situated in the barrel and 576 in the endcap regions of the detector. The HV supply of the chambers is provided by over 770 HV channels.





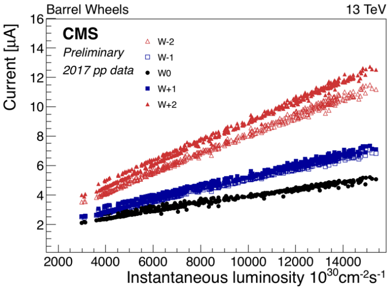
The signal

The passage of a particle through a RPC gap causes an electron avalanche to be developed in the gap, which results in an accumulation of charge on the reading strips and constitutes the RPC signal.

RPC currents

Current vs luminosity

- The detector currents, averaged per wheel, are shown to the right as a function of instantaneous luminosity
- A clear linear tendency is observed, however, there are variations which can be significant on a chamber level
- The variations are not random but are a result of a fluctuations in environmental parameters, working point etc.



Monitoring

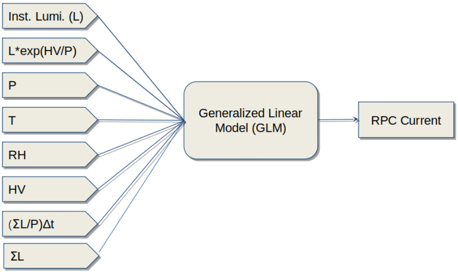
To ensure proper detector operation and be able to intercept problems before they result in a chamber trip, the current that each HV channel draws has to be monitored simultaneously, an impossible task for the shifter.

Generalized Linear Model

Parameters

The Generalized Linear Model takes 8 parameters as inputs:

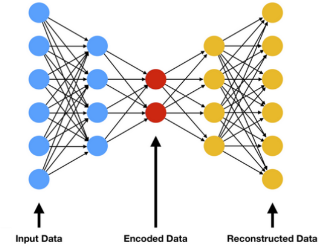
- Environmental parameters: temperature (T), relative humidity (RH) and pressure (P)
- LHC parameters: instantaneous luminosity (L) and integrated luminosity ($\sum$L)
- High-voltage working point (HV)
- Two combined terms: $L \times \exp(HV/V)$ and $(\sum L/P)\Delta t$



Autoencoder

AE network

The set of currents for all of the HV channels of the RPC system are used as input and the AE is trained to reproduce these inputs on the output neurons.



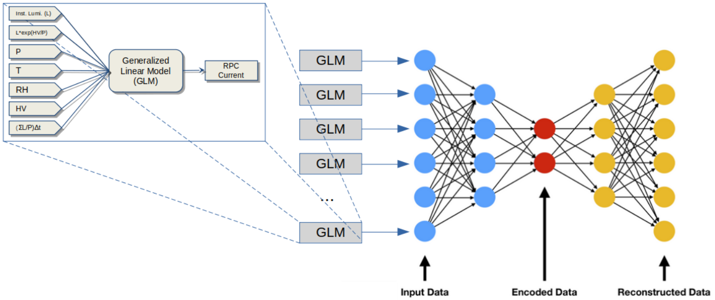
Topology

The input and output layers consist of 774 neurons while the hidden layers consist of 512, 128, 64, 128, 512 neurons, respectively

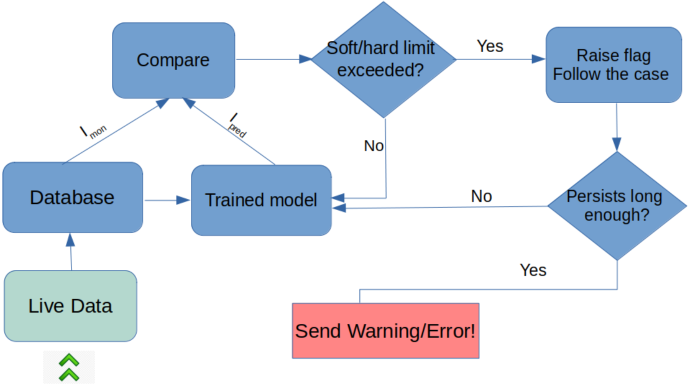
Hybrid network (HN)

Combining two approaches

The HN combines the two previous approaches, utilizing the GLM output as input for the autoencoder network.



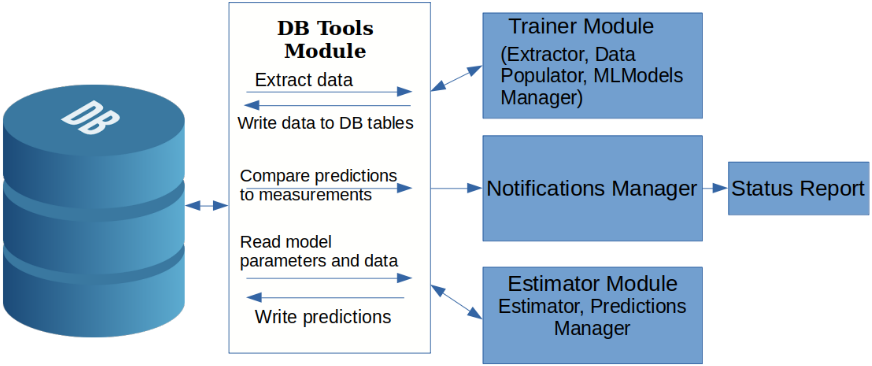
Monitoring tool - block diagram



Conditions for warnings and errors

When the soft limit (currently has a value of 3 μA) is exceeded, a warning is sent, while an error is sent when the hard limit (5 μA) is exceeded

Monitoring tool - software implementation



Current monitoring

The tool will be synchronized with other tools from the RPC automation. It will run every 4 hours, calculating the differences of the predicted and the measured current. Three sets of predicted currents will be used, predictions based on:

- Short-term training. Such models are able to spot a rapid increase in the RPC currents
- Mid-term training. Appropriate for describing the seasonal behavior of the currents
- Long-term training. Appropriate for searching deviations from the overall RPC currents course

ML models performance

The overall performance of the ML models was investigated using all available non-event RPC data for 2016, 2017 and 2018. The following training scenarios were explored:

- ST training, with data of the period from May to September 2018.
- MT training, with data from July 2017 to July 2018.
- LT training, with data from May 2016 to July 2018.

All model predictions were tested against the measured RPC currents from September to the end of October 2018

Definitions

$\text{MAE} = \sum_{i=1}^{N} \frac{|\text{I}^i_{mon} - \text{I}^i_{pred}|}{\text{N}}$; $\text{MSE} = \sum_{i=1}^{N} \frac{(\text{I}^i_{mon} - \text{I}^i_{pred})^2}{\text{N}}$. Expressed in units of μA and $(\mu\text{A})^2$ respectively.

GLM performance - LT training

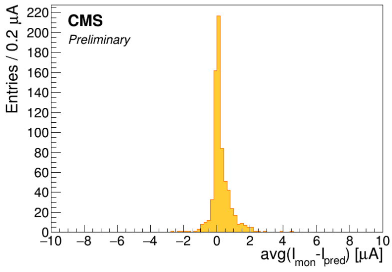


Figure: Mean $= 0.21\ \mu$A; $\sigma = 0.59\ \mu$A

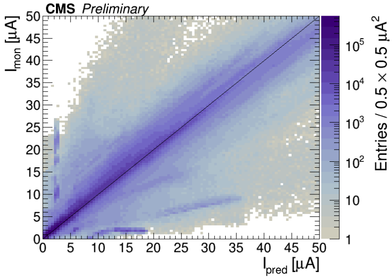


Figure: MAE $= 0.72\ \mu$A; MSE $= 3.24 \mu$A^2

AE performance - ST training

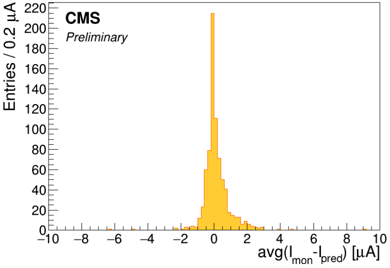


Figure: Mean $= 0.14\ \mu$A; $\sigma = 0.83\ \mu$A

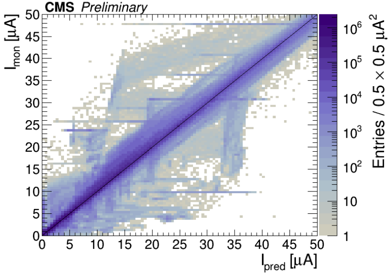


Figure: MAE $= 0.49\ \mu$A; MSE $= 1.39 \mu A^2$

Hybrid network performance

Distant prediction scenario

In this scenario, there is a significant difference in time (~ 1 year) between the end of the training period and the beginning of the prediction period

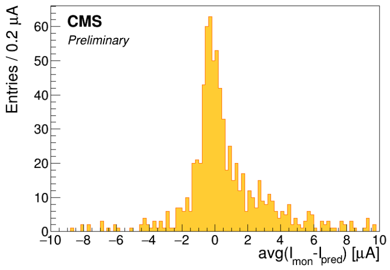


Figure: Mean $= 0.60\ \mu$A; $\sigma = 2.49\ \mu$A

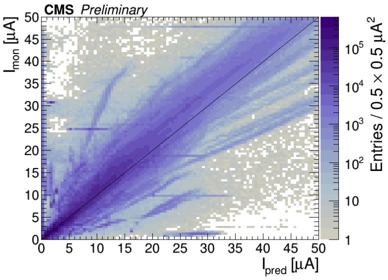
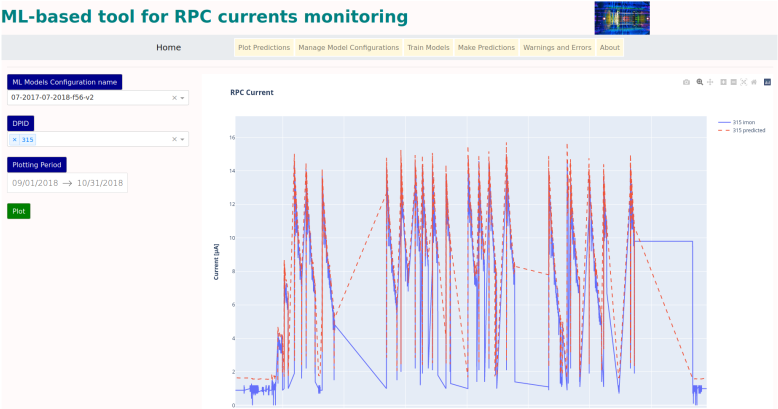


Figure: MAE $= 2.09\ \mu$A; MSE $= 23.19 \mu A^2$

Web User Interface

Deployment

Currently the app is being prepared for deployment on the CERN PaaS platform



Conclusions

- Both the GLM and AE approach were shown to give satisfying results in the modelling of RPC currents
- The monitoring tool makes decisions based on the predictions of the models and their differences with the measured currents
- A WUI has been developed that acts as an interface between the end user and the implemented tools
- The end product of the tool comes in the form of warnings and errors notifying the user (usually the DOC shifter) on any potential issues
- The database will also serve as an archive of historical issues that can assist in the troubleshooting of new ones

Thank You for Your Attention!