Prepared for submission to JINST

XV Workshop on Resistive Plate Chambers and related detectors 10 - 14 Feb 2020, Roma, Italy

A new approach for CMS RPC current monitoring using Machine Learning techniques

A. Samalan[a] ,M. Tytgat[a] ,N. Zaganidis[a] ,G.A. Alves[b] ,F. Marujo[b] ,F. Torres Da Silva De Araujo[c] ,E.M. Da Costa[c] ,D. De Jesus Damiao[c] ,H. Nogima[c] ,A. Santoro[c] ,S. Fonseca De Souza[c] ,A. Aleksandrov[d] ,R. Hadjiiska[d] ,P. Iaydjiev[d] ,M. Rodozov[d] ,M. Shopova[d] ,G. Sultanov[d] ,M. Bonchev[e] ,A. Dimitrov[e] ,L. Litov[e] ,B. Pavlov[e] ,P. Petkov[e,1] ,A. Petrov[e] ,S.J. Qian[f] ,C. Bernal[g] ,A. Cabrera[g] ,J. Fraga[g] ,A. Sarkar[g] ,S. Elsayed[h] ,Y. Assran[hh,hhh] ,M. El Sawy[hh,hhhh] ,M.A. Mahmoud[i] ,Y. Mohammed[i] ,C. Combaret[j] ,M. Gouzevitch[j] ,G. Grenier[j] ,I. Laktineh[j] ,L. Mirabito[j] ,K. Shchablo[j] ,I. Bagaturia[k] ,D. Lomidze[k] ,I. Lomidze[k] ,V. Bhatnagar[l] ,R. Gupta[l] ,P. Kumari[l] ,J. Singh[l] ,V. Amoozegar[m] ,B. Boghrati[m] ,M. Ebraimi[m] ,R. Ghasemi[m] ,M. Mohammadi Najafabadi[m] ,E. Zareian[m] ,M. Abbrescia[n] ,R. Aly[n] ,W. Elmetenawee[n] ,N. Filippis[n] ,A. Gelmi[n] ,G. Iaselli[n] ,S. Leszki[n] ,F. Loddo[n] ,I. Margjeka[n] ,G. Pugliese[n] ,D. Ramos[n] ,L. Benussi[o] ,S. Bianco[o] ,D. Piccolo[o] ,S. Buontempo[p] ,A. Di Crescenzo[p] ,F. Fienga[p] ,G. De Lellis[p] ,L. Lista[p] ,S. Meola[p] ,P. Paolucci[p] ,A. Braghieri[q] ,P. Salvini[q] ,P. Montagna[qq] ,C. Riccardi[qq] ,P. Vitulo[qq] ,B. Francois[r] ,T.J. Kim[r] ,J. Park[r] ,S.Y. Choi[s] ,B. Hong[s] ,K.S. Lee[s] ,J. Goh[t] ,H. Lee[u] ,J. Eysermans[v] ,C. Uribe Estrada[v] ,I. Pedraza[v] ,H. Castilla-Valdez[w] ,A. Sanchez-Hernandez[w] ,C.A. Mondragon Herrera[w] ,D.A. Perez Navarro[w] ,G.A. Ayala Sanchez[w] ,S. Carrillo[x] ,E. Vazquez[x] ,A. Radi[y] ,A. Ahmad[z] ,I. Asghar[z] ,H. Hoorani[z] ,S. Muhammad[z] ,M.A. Shah[z] ,I. Crotty[aa] on behalf of CMS collaboration

[a]*Ghent University, Dept. of Physics and Astronomy, Proeftuinstraat 86, B-9000 Ghent, Belgium*

[b]*Centro Brasileiro Pesquisas Fisicas, R. Dr. Xavier Sigaud, 150 - Urca, Rio de Janeiro - RJ, 22290-180, Brazil*

[c]*Dep. de Fisica Nuclear e Altas Energias, Instituto de Fisica, Universidade do Estado do Rio de Janeiro, Rua Sao Francisco Xavier, 524, BR - Rio de Janeiro 20559-900, RJ, Brazil*

[d]*Bulgarian Academy of Sciences, Inst. for Nucl. Res. and Nucl. Energy, Tzarigradsko shaussee Boulevard 72, BG-1784 Sofia, Bulgaria.*

[e]*Faculty of Physics, University of Sofia,5 James Bourchier Boulevard, BG-1164 Sofia, Bulgaria.*

[f]*School of Physics, Peking University, Beijing 100871, China.*

[g]*Universidad de Los Andes, Apartado Aereo 4976, Carrera 1E, no. 18A 10, CO-Bogota, Colombia.*

[h]*Egyptian Network for High Energy Physics, Academy of Scientific Research and Technology, 101 Kasr El-Einy St. Cairo Egypt.*

[hh]*The British University in Egypt (BUE), Elsherouk City, Suez Desert Road, Cairo 11837- P.O. Box 43,Egypt.*

[hhhh]*Department of Physics, Faculty of Science, Beni-Suef University, Beni-Suef, Egypt*

[1]Corresponding author.

[i]Center for High Energy Physics, Faculty of Science, Fayoum University, 63514 El-Fayoum, Egypt.
[j]Universite de Lyon, Universite Claude Bernard Lyon 1, CNRS-IN2P3, Institut de Physique Nucleaire de Lyon, Villeurbanne, France.
[k]Georgian Technical University, 77 Kostava Str., Tbilisi 0175, Georgia
[l]Department of Physics, Panjab University, Chandigarh 160 014, India
[m]School of Particles and Accelerators, Institute for Research in Fundamental Sciences (IPM), P.O. Box 19395-5531, Tehran, Iran
[n]INFN, Sezione di Bari, Via Orabona 4, IT-70126 Bari, Italy.
[nn]ENEA, Frascati, Frascati (RM), I-00044, Italy
[o]INFN, Laboratori Nazionali di Frascati (LNF), Via Enrico Fermi 40, IT-00044 Frascati, Italy.
[p]INFN, Sezione di Napoli, Complesso Univ. Monte S. Angelo, Via Cintia, IT-80126 Napoli, Italy.
[q]INFN, Sezione di Pavia, Via Bassi 6, IT-Pavia, Italy.
[qq]INFN, Sezione di Pavia and University of Pavia, Via Bassi 6, IT-Pavia, Italy.
[r]Hanyang University, 222 Wangsimni-ro, Sageun-dong, Seongdong-gu, Seoul, Republic of Korea.
[s]Korea University, Department of Physics, 145 Anam-ro, Seongbuk-gu, Seoul 02841, Republic of Korea.
[t]Kyung Hee University, 26 Kyungheedae-ro, Hoegi-dong, Dongdaemun-gu, Seoul, Republic of Korea
[u]Sungkyunkwan University, 2066 Seobu-ro, Jangan-gu, Suwon, Gyeonggi-do 16419, Seoul, Republic of Korea
[v]Benemerita Universidad Autonoma de Puebla, Puebla, Mexico.
[w]Cinvestav, Av. Instituto Politécnico Nacional No. 2508, Colonia San Pedro Zacatenco, CP 07360, Ciudad de Mexico D.F., Mexico.
[x]Universidad Iberoamericana, Mexico City, Mexico.
[y]Sultan Qaboos University, Al Khoudh,Muscat 123, Oman.
[z]National Centre for Physics, Quaid-i-Azam University, Islamabad, Pakistan.
[aa]Dept. of Physics, Wisconsin University, Madison, WI 53706, United States.

E-mail: Peicho.Petkov@cern.ch

Abstract: Monitoring the RPC current stability proves to be challenging in CMS experiment where one needs to deals with more than 1000 individual Resistive Plate Chambers. The current depends from several parameters applied voltage, luminosity, environmental parameters, etc. and it is not obvious if it changes due to variation of the external conditions or if it is chamber malfunctioning. We propose an approach to monitor the RPC currents based on a Machine Learning technique.

Keywords: Resistive-plate chambers, Generalized Linear Model, Machine Learning, Current monitoring

Contents

1 Introduction

The Compact Muon Solenoid (CMS)[1] experiment at CERN Large Hadron Collider (LHC), uses Resistive Plate Chambers (RPC)[5] in the Muon system[3], together with DT and CSC. RPC is the only muon detector in CMS which present in both Endcaps and Barrel. CMS RPC operate in avalanche mode under severe constantly changing conditions such as high particle flux due to the LHC luminosity, radiation background, variations in atmospheric pressure, and environmental parameters. There are 1056 chambers in the CMS RPC system (480 in the Barrel and 576 in the Endcaps) supplied by 781 high voltage (HV) channels. The most important RPC detector performance parameters, namely efficiency and cluster size, are kept constant during data collection by maintaining unvaried gas gain against environmental change, so-called PT-correction [6]. The PT-correction is applied, by changing supply high voltage to compensate for variations in environmental pressure and temperature. The gas mixture composition and humidity are kept constant.

RPC current quality monitoring is crucial for the RPC detectors longevity. In this paper, we present an ML-based approach for CMS RPC current estimation. The approach is the first step towards online monitoring system development, which will be able to spot abnormal RPC current behavior. Therefore the RPC Current Monitoring System will help the shift crew and the experts with preventing RPC units to operate at immoderate conditions which can cause detectors malfunctioning.

2 RPC current estimator

We assume that the current drawn by an RPC is uniquely determined by the design parameters, applied HV, gas mixture properties, environmental conditions and the particles flux through the gas gaps. We propose the linearized RPC current estimator model assuming that all parameters have small variations:

$$I_{pred} = C_0 + C_1 L_{inst} + C_2 HV + C_3 T + C_4 L_{inst} e^{HV/P} + C_5 RH + C_6 P + C_7 \Delta t, \tag{2.1}$$

where the coefficients C_i are to be determined by performing least squares fit to the historical data, L_{inst} denotes the instantaneous luminosity of the LHC, HV is the applied high voltage to the RPC gaps, P is the atmospheric pressure, T is the temperature, RH is the relative humidity, and Δt is the time interval since the beginning of the data taking in the given year.

The second term in Eqn. 2.1 accounts for the proportionality of the RPC current to the instantaneous luminosity, the third term is proportional to the ohmic current, the fourth and the seventh terms account for the variations in the residual temperature and pressure by the PT-correction, sixth term corrects the current for variations in Bakelite resistivity due to changes of the environmental relative humidity, and the last term represents the tendency of the RPC current to increase in time with respect to the initial conditions for a given year.

3 ML Model

Machine Learning (ML) is widely used in the modern-days scientific researches. It encompasses broad spectrum of algorithms and techniques for finding knowledge hidden in data. Therefore it is possible to construct models which can make predictions based on the knowledge from the data. In the present paper, we use a regression model to predict the RPC current for a given set of conditions. According to Eqn. 2.1 the estimated RPC current I_{pred} depends in a linear way on the model parameters C_i. Considering the latter we choose Generalized Linear Model (GLM) [8] to predict the RPC current for give instantaneous luminosity, allied HV and environmental conditions. The flowchart of the model is depicted in Fig. 1. The *input data* to train and validate the

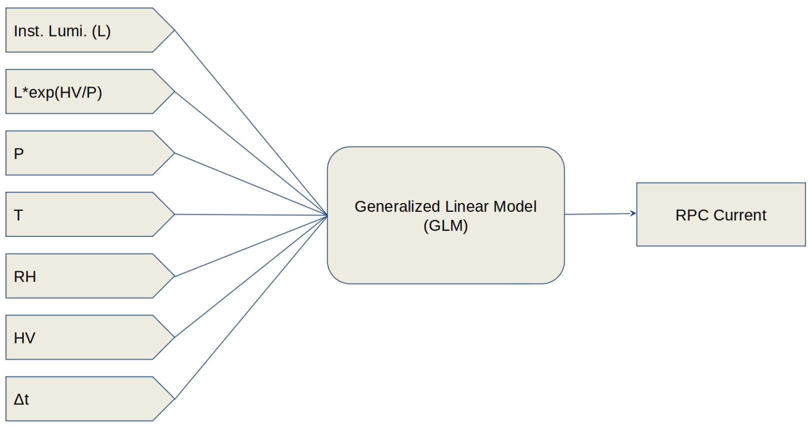


Figure 1: Flowchart of the ML-based RPC current prediction algorithm.

model is taken from the CMS database. To extract information from the database, we use special tool developed by the CMS RPC collaboration called RPC current Automat[7]. It takes the data (RPC current, applied HV, and UXC environmental parameters) from the CMS Online Monitoring Database, synchronizes the data points with the RPC current timestamp and sets an additional flag encoding the LHC state and the HV supply module status. The LHC luminosity data [4] are added to those taken from RPC Current Automat forming the input dataset for training the GLMs.

The environmental pressure and relative humidity represent well defined seasonal yearly based behavior. Therefore, we prepared the training and validation dataset so that each dataset should encompass a period of at least one year of data-taking and the RPC chambers should have worked at least at two HV working points. Such conditions ensure proper models training to determine all of the parameters.

The HV is correlated with environmental parameters due to applied PT-correction and the fifth term in Eqn. 2.1 depends on the instantaneous luminosity, HV and pressure. GLM model is known to be robust to the overtraining problem because of small number of parameters of the model.

4 Results

We tested the RPC current predicting models for 446 CMS Barrel RPC. The models were trained using 2017 data and validated on 2018 data. Both datasets satisfy the requirements defined in the previous section. In 2, an example of RPC current prediction is shown which corresponds to the inner layer of the the barrel muon station 3 in sector 3 of wheel +2 (namely W+2_S3_RB2in). It shows a good agreement between the prediction and the measured current value. The prediction follows the data points even though the HV working point was changed by about 200 V.

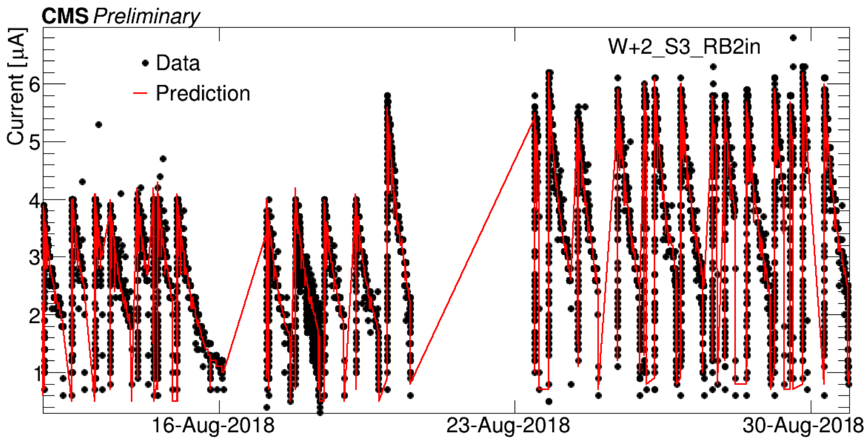
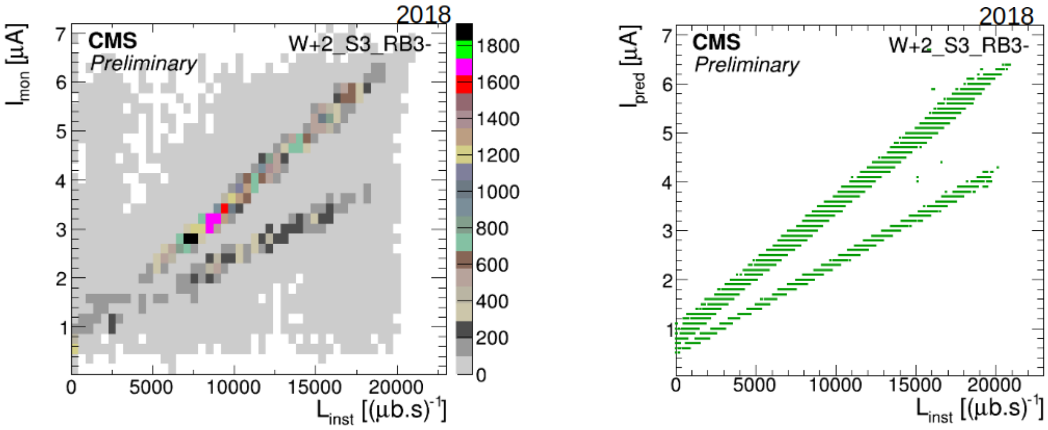


Figure 2: Predicted (red line) and measured (black points) current for RPC W+2_S3_RB2in although HV working point is changed by 200 V on 19 Aug 2018.

As it was already mentioned above, the RPC current is proportional to the instantaneous luminosity and the slope depends on the HV working point. The Fig. 3a shows two dimensional histogram of the RPC current versus instantaneous luminosity for 2018 of an RPC in the negative ϕ-part of barrel muon station 3 in sector 3 of wheel +2 (W+2_S3_RB3-). The corresponding GLM reproduces the current for the two HV working points correctly, shown in Fig. 3b. The spread along the y-axis is due to variations in the other conditions.

The distribution of the average difference between measured and predicted RPC current for 2018 data is shown in Fig. 4. RPC current data were written to the database with an accuracy of 0.2 μA. Considering the latter, we can conclude that the distribution is centered around 0 in the range of the RPC current data accuracy. The RMS of the distribution is $\approx 0.96\,\mu A$, which estimates the presented approach accuracy to be of the order of 1 μA.

The RPC chambers with an average difference between monitored and predicted current greater than 2 μA are problematic ones. Most of them are chambers with leaks in the gas system. The



(a) (b)

Figure 3: The monitored (a) and predicted (b) RPC current (I_{mon}) vs. instantaneous luminosity (L_{inst}) of RPC W+2_S3_RB3-. The datapoints are separated in two groups with different slopes due to chamber was operated at two different HV working point in 2018.

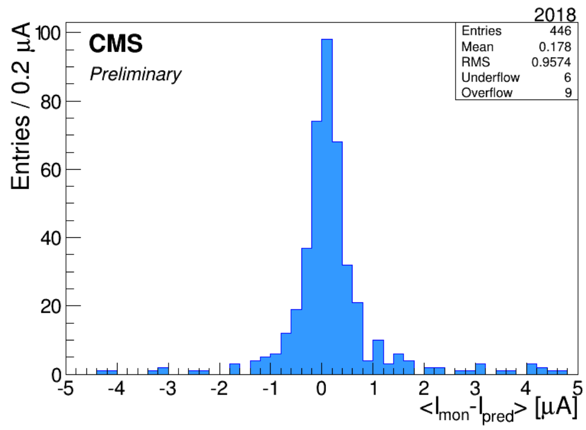
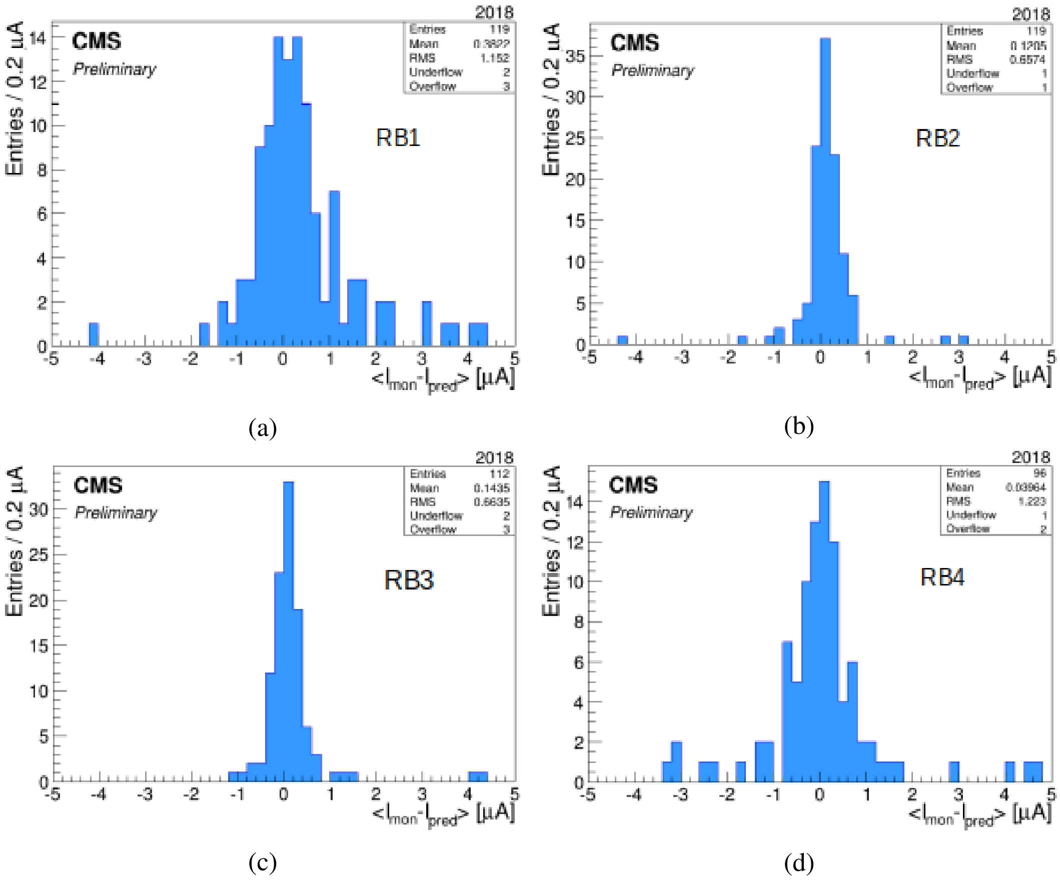


Figure 4: Distribution of the average difference between monitored and predicted current for 446 Barrel RPC for 2018.

rest are isolated cases of wrongly predicted current due to change in the RPC operation conditions leading to inconsistent training dataset and stable but relatively high monitored current with respect to the predicted one.

5 Conclusions

We developed a ML-based approach for predicting RPC currents. It was tested on 446 CMS Barrel RPC and the validation showed overall accuracy of about 1 μA. The model was able to find RPC chambers with known hardware problems and some RPC chambers with unusual current trends to be carefully monitored. The tool is used for historical analysis of the CMS RPC currents and can be used for predicting RPC currents behavior in the conditions of new data taking period. The prediction power of the model is expected to be improve by including more input variables.



(a) (b) (c) (d)

Figure 5: Distribution of the average difference between monitored and predicted current for CMS Barrel RPC in muon stations: RB1 (a), RB2 (b), RB3 (c) and RB4 (d).

Acknowledgments

This paper is partially supported by the Bulgarian Ministry of Education and Science (contract D01-205/23.11.2018) under the National Science Program "Information and Communication Technologies for a Single Digital Market in Science, Education and Security (ICTinSES)", approved by DCM#577/17.08.2018. We would like to thank especially to Anton Dimitrov and Osvaldo Miguel Colin who mainly developed the RPC Condition Automate ideology and implementation respectively, and all our colleagues from the CMS RPC group and L1 muon trigger group for their dedicated work to keep the stable performance of the RPC system. We wish to congratulate our colleagues in the CERN accelerator departments for the excellent performance of the LHC machine. We thank the technical and administrative staff at CERN and all CMS institutes.

References

[1] Chatrchyan, S. *et al.*, *The CMS experiment at the CERN LHC*, *JINST* **3** (2008) pg. S08004

[2] Sirunyan, A.M. *et al.*, *Performance of the CMS muon detector and muon reconstruction with proton-proton collisions at* $\sqrt{s}$ = 13 *TeV*, *JINST* **13** (2018) pg. P06015

[3] Layter, J. G. *et al.*, *The CMS muon project: Technical Design Report*, CERN, CMS Collaboration, Technical Design Report CMS, (1997), CERN-LHCC-97-032, https://cds.cern.ch/record/343814

[4] CMS Collaboration, *CMS luminosity measurement for the 2017 data-taking period at* $\sqrt{s}$ = 13 TeV,*CERN Report* **CMS-PAS-LUM-17-004** (2018), https://cds.cern.ch/record/2621960

[5] M.A. Shah, *et al.*, *The CMS RPC detector performance and stability during LHC RUN-2*, *JINST* **14** (2019) pg. C11012

[6] S Colafranceschi, *et al.*, *Performance of the Gas Gain Monitoring system ofthe CMS RPC muon detector and effectiveworking point fine tuning*, *JINST* **7** (2012) pg. P12004

[7] Osvaldo Miguel Colin *et al.*, *CMS RPC Condition Data Automation*, XIV Workshop on Resistive Plate Chambers and Related Detectors (RPC 2018), https://indico.cern.ch/event/644205/contributions/2862294/

[8] McCullagh, P., Nelder, J. A. ,*Generalized Linear Models.*, London: Chapman & Hall / CRC., (1989)