

Anomaly Detection Using Machine Learning Techniques for Beam Injections from the SPS to the LHC at CERN

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Statement of Originality

I, the undersigned, declare that this is my own work unless where otherwise acknowledged and referenced.

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Signed _____

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Acknowledgements

Abstract

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BLM Beam Loss Monitors	3
BPM Beam Position Monitors	4
CERN European Organization for Nuclear Research	
Gy/s Grays per Second	4
IQC Injection Quality Check	2
LHC Large Hadron Collider	2
LS Logging Service	2
MJ Mega Joule	
mm millimetres	4
PCA Principal Component Analysis	
SPS Super Proton Synchrotron	
TDI Beam Absorber for Injection	3
TL Transfer Line	3

Introduction

Background and Literature Review

2.1 Understanding the Problem Domain

The purpose of the Large Hadron Collider (LHC) at CERN is to accelerate and collide two proton beams [1]. In order to fill the LHC with a beam of the required intensity, twelve injections consisting of a number of electron bunches of around 1 MJ of stored energy each are required [2]. This is a challenging task given the high energy of the beam, the very small apertures and the delivery precision's tight tolerances. Thus, multiple sensors are installed around the CERN particle accelerator complex [3] which gather readings and data that can be used to check the quality of the injected beam.

For this particular study, data generated from the sensors around the injection from the SPS to the LHC will be of particular interest. This data is stored using CERN's Logging Service (LS) [4]. While many studies have been made using this logged data and lots of statistical tests have been done with regards to injection quality checks for the LHC (such as [2] and [5]), no literature was uncovered where researchers used unsupervised machine learning methods to analyse this data. Figure 2.1 highlights the particular area of interest of this study.

The Injection Quality Check (IQC) software currently installed has a set of hard-coded rules for detecting anomalies in the SPS-LHC injection [2], however there are documented cases in the past where situations occurred which were outside the originally foreseen rules and were therefore not caught as anomalies.

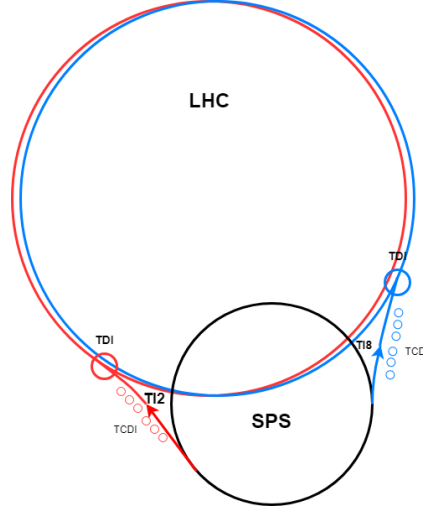


Figure 2.1: Diagram of the particular area of interest of the CERN Particle Accelerator Complex for this study

2.2 The Instruments Used to Gather Data

Throughout this study, different data recorded as the beam leaves the SPS and enters the LHC was used as input parameters to the chosen anomaly detection algorithms. This data was recorded using different sensors located in different parts of the injection life cycle. This section describes the different types of sensors that were used to collect the data, highlighting the particular points which need to be considered when analysing the data.

The Beam Loss Monitors (BLM) are some of the most safety critical modules of the LHC because a loss of a very small fraction of this beam may damage parts of the machine or cause a quench in the superconducting magnets [6]. A high beam loss reading could also indicate over-injection. In fact, an injection of a high intensity beam into the LHC is only allowed if there is a low intensity bunch circulating the LHC in order to avoid settings errors [5]. The BLM module is the mostly used module in the current IQC checks [2]. The BLMs must be reliable; the probability of not detecting a dangerous loss was found to be 5×10^{-6} per channel and they are only expected to generate 20 false dumps per year [6]. The BLMs are extensively logged to a database for offline analysis [6].

For this particular study, the readings logged for the Beam Absorber for Injection (TDI) BLMs and the Transfer Line (TL) BLMs in TI2 and TI8 will be used (refer to Figure

2.1). These readings come in 10 second windows around the injection of a bunch in Grays per Second (Gy/s).

The Beam Position Monitors (BPM) were installed as a system for fast monitoring of the beam's position with respect to its orbit drift [7]. The trajectory offsets recorded by the BLMs in the transfer lines must be minimised in order to reduce losses [2]. In fact, if the change in orbit substantially exceeds its provided boundary values then the beam should be dumped [7] so as to not cause any damage to the equipment. Unlike the TDI BLMs, the BPM system is independent to the collimator system. For this study, the readings from the transfer line BPMs around TI2 and TI8 will be used (refer to Figure 2.1). Raw values for these readings are stored by the LS in millimetres (mm) and are logged every 1 - 5 seconds on average.

2.3 Feature Selection and Reduction Techniques

PCA uses statistical and mathematical techniques to reduce the dimension of large data sets, thus allowing a large data set to be interpreted in less variables called principal components [8]. This non-parametric method can be used as a means of revealing the simplified structures underlying complex datasets with minimal effort. The fact that this technique is non-parametric gives it the advantage that each result is unique and only dependent on the provided data set since no parameter tweaking is required [9] however, this is also a weakness of this technique as there is no way of exploiting prior expert knowledge on the data set.

2.4 Unsupervised Anomaly Detection Techniques

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