ISBN: 978-3-95450-168-7 doi:10.18429/JACoW-IPAC2015-TUAC3

OPTIMIZATION OF BEAM LOSS MONITOR NETWORK FOR FAULT MODES*

Z. Liu#, D. Liu, S. Lidia, Z. He, Q. Zhao, FRIB, East Lansing, MI 48824, USA

Abstract

Beam Loss Monitoring (BLM) System is an essential part to protect accelerator from machine faults. Compared with the empirical or uniform BLM arrangement in most accelerators, our new optimization approach proposes a "minimum spatial distribution" for BLM network. In this distribution, BLMs shall be placed at a small set of "critical positions" that can detect all failure / FPS trigger-able events of each fault mode. In additional, to implement a more advanced function of fault diagnosis, BLM should also be placed at "discrimination points" for fault-induced loss pattern recognition. With examples of FRIB failure event simulations, the author demonstrates the proof of concept to locate these "critical positions" and "discrimination points" for the minimum spatial distribution of BLMs.

INTRODUCTION

As an essential part of Machine Protection System (MPS) input, the BLM system plays an important role to detect and diagnosis machine faults. This imposes categorized functional requirements for BLM system. For example, the fault detection requires BLM device to have fast response for big losses, while the fault diagnosis requires BLM device sensitive enough to diagnose issues with beam tuning/slow losses and able to differentiate between controlled and uncontrolled losses. These requirements determine the type and structure of BLM system, e.g., FRIB BLM system including fixed position Halo Monitor Ring, BCM and movable radiation detectors. In this paper, we are not going to discuss the structural determination of BLM system, instead, we will focus on the spatial optimization of a pre-assumed BLM system.

Our goal of spatial optimization for fault detection is to minimize the number of BLMs while still be able to detect all Fast Protection System (FPS) trigger-able failure events that generate significant losses. To achieve this, we need to quantify correlations between BLM locations for classes of events, so that at least one BLM at the "critical positions" can trigger FPS when a component-failure event induces significant losses. Section 2 introduces the methodology to find the ensemble of "critical points", with the simulation example of single cavity failures.

Fault diagnosis, or loss pattern recognition, is a more advanced functional requirement for BLM network. It was typically determined empirically at most accelerators. To prepare for loss pattern recognition, we need to put detectors at "discrimination points" that can distinguish patterns. Section 3 shows how to identify discrimination points for a fault mode with the principal component analysis (PCA) [1] method.

*This work is supported by the U.S. Department of Energy Office of Science under cooperative agreement DE-SC0000661.
#liuz@frib.msu.edu

CRITICAL POSITIONS

As the first goal of spatial optimization for BLM network, we are looking for a set of "critical positions", where at least one BLM can trigger FPS when a failure event induces over-threshold losses.

Example Fault Mode Simulation

In order to demonstrate the methodology to find "critical positions", we simulated loss distributions of single cavity quenching events. In the simulation, every accelerator element in the FRIB lattice was considered a loss point. In total there are 572 element/loss points in FRIB lattice. To simulate cavity failure event, we turned off one cavity's voltage and phase completely, did particle tracking and simulated particle loss power with IMPACT [2]. By turning off the 332 accelerating and bunching cavities one by one, we got 241 loss distributions. The other 91 cavities are in the high energy part, where transverse emittance growth from longitudinal mismatch takes longer distance and therefore the failures do not necessarily generate losses.

Using the same terminology in Statistics, the loss positions are "variables" or "dimensions", and the cavity failure are "observations". The loss matrix for single-cavity-failure mode is therefore 572 variables × 241 observations.

Correlation Matrix

As we mentioned in the introduction, the "critical positions" are defined based on quantifying correlations between BLM locations, i.e. loss points, for classes of failure events. If a group of adjacent loss positions are highly correlated with each other in positive direction, they can be considered as a "localized loss area" and only one BLM needs to be placed there.

To quantify the "localized loss area", we need to compute the correlation matrix $R_{n\times n}$ for matrix $X_{m\times n}$, whose element $R(i,j)$ is the correlation coefficient of i^th^ column and j^th^ column:

$$R(i,j) = \frac{Cov(X_i,X_j)}{\sigma(X_i)\cdot\sigma(X_j)}.$$

$cov(X_i,X_j)$ is the covariance of the i^th^ and j^th^ column/loss position, and $\sigma(X_i)$ is the standard deviation of i^th^ column. In our case for beam loss monitoring, we

ISBN: 978-3-95450-168-7 doi:10.18429/JACoW-IPAC2015-TUAC3

consider $R(i,j) > 0.45$ as strong correlation between loss positions.

Figure 1 plots the correlation matrix for single-cavity-fault mode. Since we are looking for critical positions where detector can trigger FPS, we zero out the losses below FPS trip threshold (e.g. 10 W) before calculate the correlation matrix. In addition, for better contrast, all correlations less than 0.45 are excluded from Fig. 2.

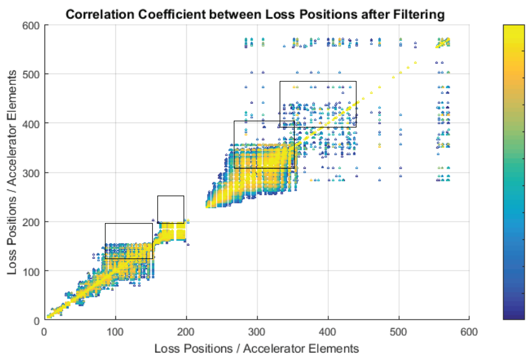


Figure 1: Colour plot of loss positions' correlation matrix for single cavity fault mode. Colours represent the strength of correlation, with the minimum of 0.45.

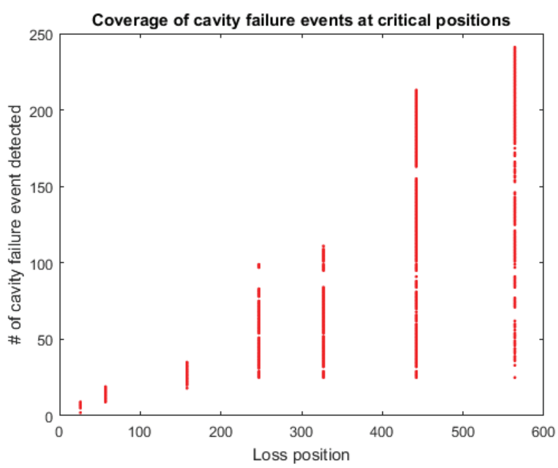


Figure 2: Coverage of single cavity failure events at 7 positions. Every point corresponds to a FPS-triggerable event at this position. >95% failures can be triggered by BLM at these 7 critical positions.

There are at least 4 obvious "localized loss areas" as squared by the black box, i.e., we may only need 4 positions to detect losses in these areas. But the 4 points might not be enough to cover all the single-cavity-failure events. Actually they can only detect a half of 241 failure events.

Ensemble of Critical Positions

To ensure a full coverage of failure detection, we need to re-visit the original loss matrix $X_{572\times241}$, find critical positions outside of these areas that have big losses for the uncovered patterns. An effective way is to sum over each row of $X_{572\times241}$ (i.e. losses of 241 failure event at a position) and sort the loss positions in a descending order of total loss. Starting with the largest total loss, pick only one critical point in each "localized loss area", i.e. [442, 564, …, 247, …, 327, …, 57, …,158, …, 26, …], add more loss positions outside of "localized loss areas" until they cover all failure events. Figure 2 shows that 5-7 critical positions can already detect >95% of single-cavity-failures and trigger FPS.

DISCRIMINATION POINTS

An ideal beam loss monitor network should be able to quantify the following functions:

1) P(error-loss): probability of error sources, given a loss distribution;
2) P(loss-detector): probability of losses to reach a detector;
3) S(detector): detector response function.

While 2) and 3) can be simulated [3] with radiation transport codes, 1) is a more advanced requirement that always be determined empirically. During the machine operation, tons of loss data have been collected but rarely "mined". In this paper, we are trying to pave the way to P(error-loss) knowledge base by first place BLM at "discrimination points" that can distinguish between fault modes and failure events.

Principal Component Analysis

Solving P(error-loss) is essentially a pattern recognition problem. Feature analysis, as a popular theory of pattern recognition, usually has two steps:

1) Recognition of "significant features" rather than reading an exact template, for each fault mode;
2) Contrasts/differentiates between failure events with "distinctive features".

To figure out these features, or discrimination points, Principal Component Analysis (PCA) [1] is usually an effective tool.

Features for Single-Cavity Fault Mode

We applied the PCA transformation to the single-cavity failure induced loss matrix $X_{572\times241}$. Figure 3 plots the histograms of eigenvalues for the first 4 principal components (PC), from which we can see the first PC accounts for 97% of the variance in the data, or 99% with the second PC. This is a dramatic reduction in analysis dimensionality from 572 to 1 or 2, i.e. PC1&PC2 as a linear combination of variables include "significant" and most "distinctive" features / variables.

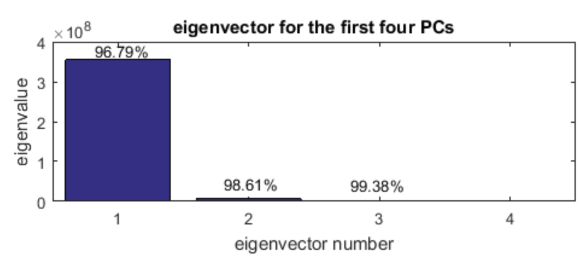


Figure 3: Eigenvalues for the first 4 PCs and the cumulative variations, for the single-cavity-fault-mode.

ISBN: 978-3-95450-168-7 doi:10.18429/JACoW-IPAC2015-TUAC3

To extract "significant features", Figure 4 shows the weight/loading of each variable in PC1 and PC2. The variables that have more weight/loading account for major difference between cavity failure induced loss distributions, and therefore are considered "significant features" for the single-cavity fault mode. As shown in Fig. 4, the 11th and 14th multipole magnets, as well as the 13th dipole magnet in the FRIB lattice are obviously "significant features".

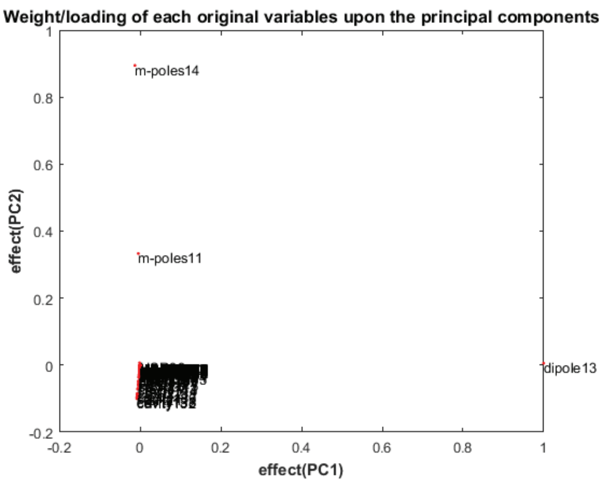


Figure 4: Influence/loading of each original variable upon principal component 1 & 2.

Figure 5 shows the 241 cavity failure events in the significant feature space, or at the three discrimination points. The more distance between points, the easier to distinguish them with only "significant features. About half of the patterns are visually distinguishable. For the points collapse together, we need to exclude significant features and re-do PCA for the rest variables to further locate "distinctive features" between patterns. If there is a sample loss measurement dominated by a certain cavity failure, it will be presented as a point in the feature space and the adjacent points in the space can be considered as potential error sources. In another word, if the observed loss patterns were in conformance with knowledge base, then the projections in the feature space will provide a probability for dominated error source.

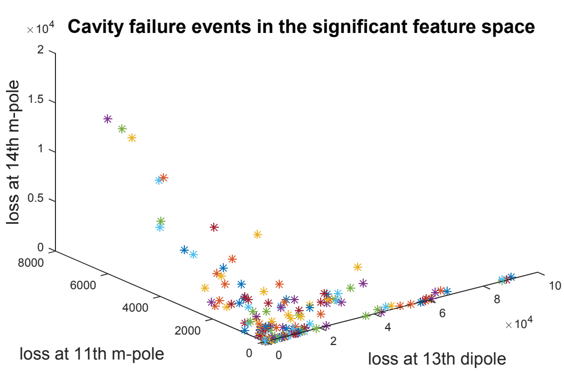
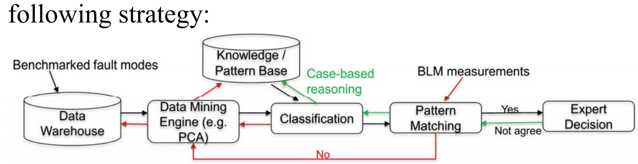


Figure 5: Significant feature space and cavity failure events projected in the space.

CONCLUSION

We have defined two goals of spatial optimization for BLM network: place detectors at "critical positions" for critical machine protection, and "discrimination points" preparing for loss pattern recognition. By computing and grouping the correlation coefficients of loss positions, we demonstrate the proof of principle of "critical positions" for the single cavity failure mode. To complete the optimization, we need not only more simulations on machine faults induced losses, but also experimental benchmark with real loss detectors.

As a preparation for fault diagnosis, i.e. loss pattern recognition, we want to place the detector at the "discrimination points" that can maximize the variance between patterns. We use PCA to demonstrate the feature analysis for single cavity failure mode as a proof of concept. The path forward can be generalized as following strategy:



The core of this strategy is to build a "pattern base", which starts with simulated patterns that were benchmarked by experiments, but is continuously feed with new patterns measured and can also be corrected by case-based reasoning with expert decision. To make this strategy feasible, we may need some pre-requisite such as one or two dominated error sources and effective classification between patterns.

ACKNOWLEDGMENT

The authors want to thank Rebecca Shane for the proof-reading and editing suggestions. The authors also want to thank Dylan Constan-Wahl and Xiaoying Pang for the fruitful discussions.

REFERENCES

[1] http://en.wikipedia.org/wiki/Principal_component_analysis
[2] J. Qiang et al, "An object-Oriented Parallel Particle-in-Cell Code for Beam Dynamics Simulation in Linear Accelerators", J. of Comp. Physics 163, 434-451 (2000).
[3] GEANT4: http://geant4.cern.ch/