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MACHINE LEARNING ANALYSIS OF ELECTRON COOLER OPERATION FOR RHIC*

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Abstract

A regression machine learning algorithm was applied to analyze the operation data of RHIC with electron cooler LEReC during the 2020 physics run. After constructing a black-box surrogate model from the XGBoost algorithm and plotting their partial dependency plots for different operation parameters, we can find the effects of an individual parameter on the RHIC luminosity and optimize it accordingly offline.

MOTIVATION

For a circular collider like the RHIC, the luminosity formula for round Gaussian and equal beams at the interaction point (IP), as is the case in RHIC, can be expressed as Eq. (1) which is:

$$L = n_b \frac{f_c N^2}{4\pi\sigma^2} H, \tag{1}$$

where L is the luminosity, n_b is the collision bunch number, f_c is the collision frequency, σ is the transverse rms beam size at the IP, and N is the particle number per bunch. H is a geometric factor that accounts for the hourglass and crossing angle effect.

During the RHIC operation, there are lots of parameters that can affect the integral luminosity. Meanwhile, in the 2020 RHIC physics run, to improve the integrated luminosity and lifetime limited by IBS, the Low Energy RHIC Electron Cooler (LEReC) [1-6] has been operational during the RHIC low energy run. The LEReC also has lots of parameters that can affect the integral luminosity.

All these parameters can affect the luminosity at the same time and their effects are mixed or entangled. Therefore, their effects on the luminosity are difficult to distinguish from each other because they could be changed at the same time. Meanwhile, it is not feasible to optimize these parameters one by one according to the nosiy integrated luminosity.

With the help of a machine learning algorithm, after getting these parameters's operation data, it is possible to find their individual effects on the luminosity via a machine learning method - XGBoost [7, 8].

OPERATION DATA

Data Acquisition

Some RHIC and LEReC operation parameter data is acquired before constructing an XGBoost model. Table 1 lists these parameters.

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Table 1: Parameters and Their Abbreviations

Parameters	Abbreviations
Intensity B	IntenB
Intensity Y	IntenY
Emittance B	SizeB
Emittance Y	SizeY
Tune B H	TuneBH
Tune B V	TuneBV
Tune Y H	TuneYH
Tune Y V	TuneYV
Chrom B H	ChromBH
Chrom B V	ChromBV
Chrom Y H	ChromYH
Chrom Y V	ChromYV
Collimator BH	CollBH
Collimator BV	CollBV
Collimator YH	CollYH
Collimator YV	CollYV
Beta* Squeeze Ramp	Ramp
Luminosity	Lumi
Electron BPM B Cooling	ebpmB
Electron BPM Y Cooling	ebpmY
Ion BPM B	ibpmB
Ion BPM Y	ibpmY
Solenoid 1 B	Bsol1
Solenoid 1 Y	Ysol1
Electron Beam Current	Current
Electron Beam Energy	Energy
B Y Quadrupole Current	BYquad

We excluded some parameters from constructing the XGBoos model. These parameters are the ion beam loss rate (or the ion beam decay) and the electron beam angles. First, they are not the controllable parameters that we can directly tune during our operation. Second, they have fewer effects on the machine learning model, and they have some correlations with other parameters that will affect our analysis.

Correlations

To check the correlation between all input parameters before implementing a machine learning algorithm, we can use the efficiency of correlation to evaluate the degree to which two input parameters are linearly related. When we explain the results of a machine learning black box model, to avoid an inaccurate interpretation, we should pay more attention to the input parameters with a high correlation coefficient between themselves.

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Figure 1 is the matrix with correction coefficient values that shows the correlations between some input parameters. The correction coefficient between the luminosity and other parameters show in the green box at the bottom of the Fig. 2. The IntenY and the IntenB have a positive 0.5 correction coefficient between the luminosity. That means that the luminosity will likely increase if the ion intensity increase. That is consistent with the theory result [Eq. (1)].

The correction coefficient between the luminosity and the SizeY (the rms beam size of ion beam in the Yellow RHIC ring.) is abnormal. It has a positive 0.51 instead of a negative value. Presently, we can explain it by the high correction coefficient of 0.69 between the IntenY and the SizeY.

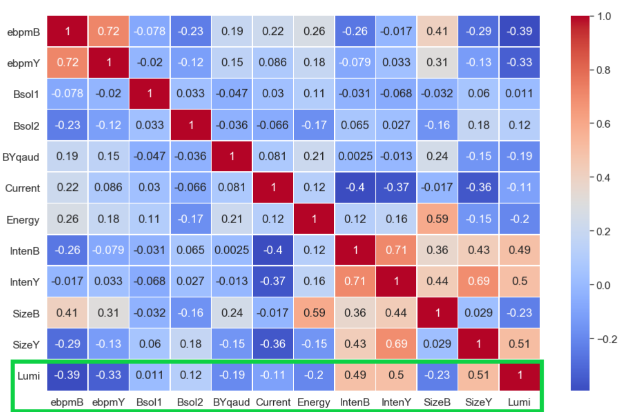

Figure 1: The correlations between some variables.

Scattering Plots

To investigate the effects of some parameters, we plot the luminosity scattering plot as a function of these parameters. The top two plots in Fig. 2 are the relationships between the luminosity and the ion beam intensity. From these plots, one can find that a higher ion intensity tends to have a higher luminosity, which is predicted by Eq. (1). They are also consistent with the correlation results. But for the relationship between the blue beam size and the luminosity, it is not easy to find a clear trend between them.

XGBOOST

To distinguish the effects on the luminosity from each parameter, it is desirable to have an Eq. (2) which is

$$Lumi = f(x_1, x_2, x_3 \ldots x_n) \tag{2}$$

while $x_1, x_2, x_3 \ldots x_n$ are all ther parameters or variables that can affect the luminosity individual without the effects from other parameters.

To achieve that, a supervised machine learning algorithm Extreme Gradient Boosting (XGBoost) is also used for this kind of data analysis. XGBoost is a powerful decision tree algorithm for either classification or regression via using gradient descent to optimize the loss function [9-11].

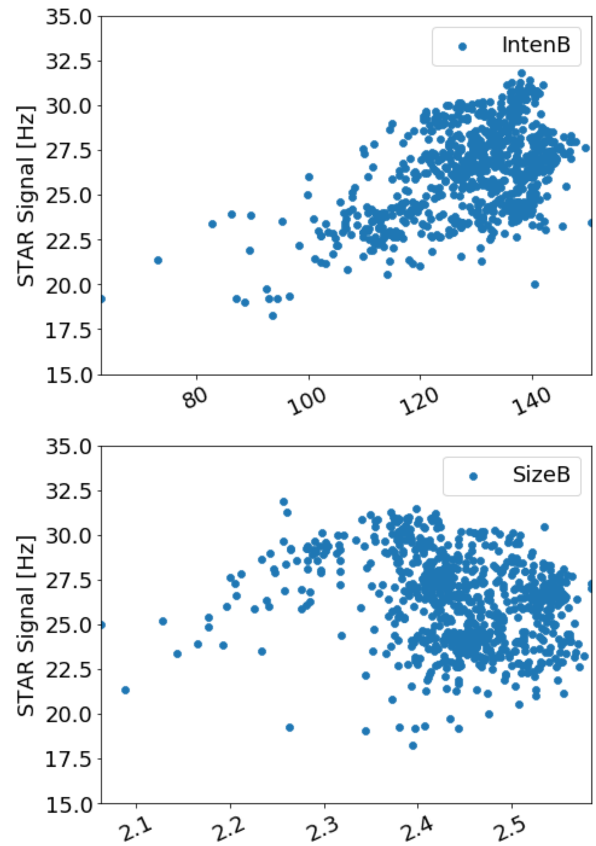

Figure 2: The scattering plot of the luminosity as function of the ion beam intensity and beam size.

After constructing an XGBoost model, a R^2 score function (the coefficient of determination) is used to evaluate the model performance. It is 0.87 for the best XGBoost model. Normally, $R^2 = 1$ means the prediction of a regression model matches the actual value perfectly. The test data points (15%) and their model predictions agree very well and are plotted in Fig. 3.

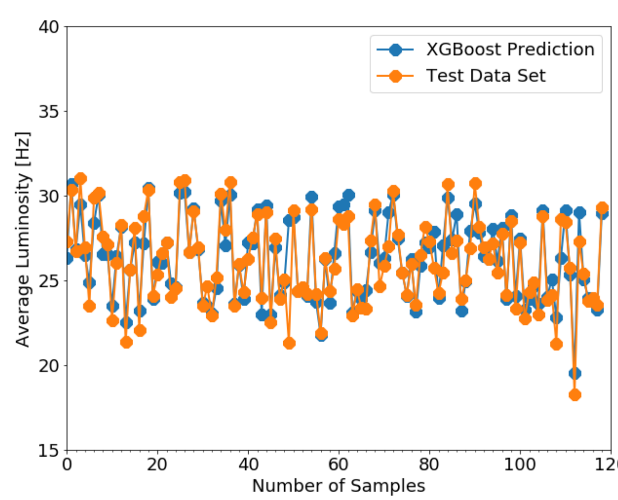

Figure 3: The comparsion plot between the test data points and their prediction from the model.

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PARTIAL DEPENDENCE PLOT

To optimize the luminosity only according to their individual effects, after getting an XGBoost model, some partial dependence plots (PDP) [12-14] were plotted. A PDP can plot the marginal effects of one or two input parameters on the model prediction.

Figure 4 shows the PDP plots of the ion beam intensity and the beam size. The light blue area is the deviation of the model predictions. The predicted luminosity has a clear trend for both the blue and the yellow intensity. It also has a clear trend for both the blue and yellow beam size. The PDP plots of the beam size also agree with the theory [Eq. (1)] qualitatively. While from their scattering plots in Fig. 2, it is not clear for the SizeB. It even doesn't agree with the theory for the SizeY. This PDP plot demonstrated that the constructed XGBoost model and their PDP plots could distinguish the effects of one parameter from other parameters and predict the luminosity correctly.

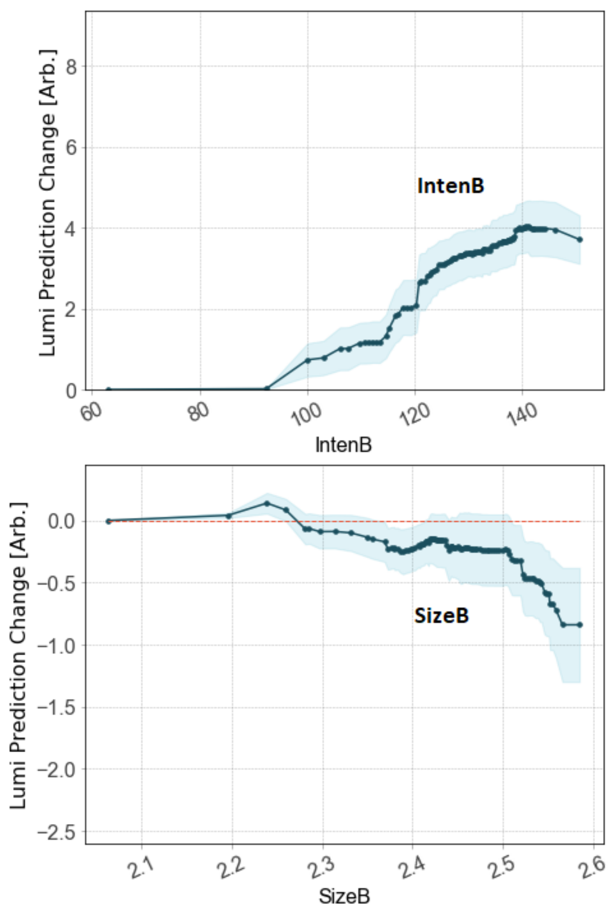

Figure 4: The PDP plot of the ion beam intensity and beam size.

Figure 5 shows the PDP plots of the electron beam and the ion beam position. From these plots, we can find that a better alignment between the electron and ion beam results in a higher luminosity.

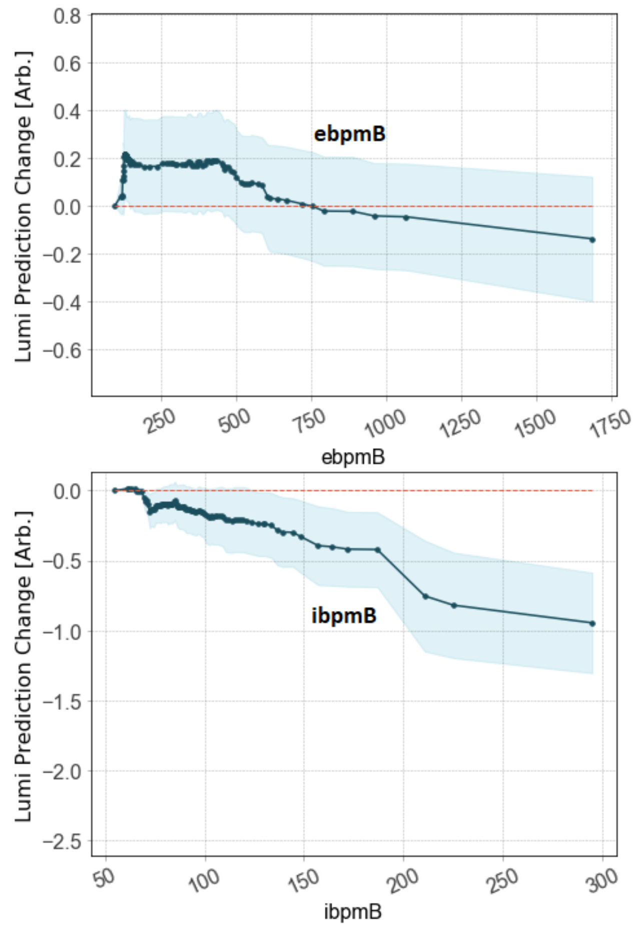

Figure 5: The PDP plot of the electron (top graph) and ion beam position (bottom graph).

CONCLUSION

To find a clear local optimum value or trend for a higher luminosity, XGBoost and PDP plot could be used for the RHIC operation analysis. They can be used as an offline feedback or monitoring tool via checking the results of new operating parameters. By analyzing the history collision data, they can be used to optimize the future RHIC operation parameters.

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