NONLINEAR SYSTEM IDENTIFICATION OF SUPERCONDUCTING MAGNETS OF RHIC AT BNL*

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Abstract

The Quench Detection System (QDS) of RHIC detects the Superconducting (SC) magnet quenches by voltage sensing. The real-time voltage across the SC magnet is compared with a predicted voltage from a behavioral model, a deviation from which triggers the quench event and energy extraction. Due to the limitations of the magnet model, many false quench events are generated that affect the RHIC availability. This work is targeted towards remodeling the magnets through nonlinear system identification for the improvement in QDS reliability. The nonlinear electrical behavior of the SC magnets is investigated by statistical data analysis of magnet current and voltage signals. Many data cleaning techniques are employed to reduce the noise in the observed data. Piecewise regression has been used to examine the saturation effects in magnet inductance. The goodness-of-fit of the model is assessed by field testing and comprehensive residual analysis. Finally a new model is suggested for the magnets to be implemented for more accurate results.

INTRODUCTION

The RHIC SuperConducting (SC) magnets store an energy of 70MJ in the form of magnet currents during a full energy run. The SC magnets are susceptible to quenches that lead to the development of tiny resistive zones. An operating current near 5000A (for a dipole magnet) can dissipate this enormous energy at this tiny resistive point causing catastrophic damage.

To safeguard against such failure, Quench Detection System (QDS) is employed. It monitors the SC magnets to detect the developing quenches and sends the magnet power dump signal and beam abort signal to the beam permit system [1]. Voltage sensing is employed for recognizing the developing quenches. The QDS consists of DSPs which store the electrical behavioral model of the SC magnets. The actual magnet output is compared to the model output, and a deviation is sensed as a developing quench, which generates a quench trigger.

The SC magnets exhibit a highly nonlinear behavior due to saturation and hysteresis of steel yoke [2]. Due to mathematically intractable nature of this behavior, the magnet model parameters are manually calibrated, which inhibit the accurate tuning of the model. Also it consumes valuable time when RHIC is running at 4K temperature. Inaccuracies introduce deviation in the model output, which leads to false failures, and resulting in unnecessary machine downtime. Thus to improve QDS reliability, it is necessary that the model truly imitates the SC magnet behavior. The aim of this work is to facilitate automatic generation of accurate magnet models through nonlinear system identification that will improve the reliability and availability of QDS.

Original Magnet Model

The SC magnet circuit's electrical behavior is modeled as a pure inductor with a series resistor. The pure inductor represents the SC magnet and the resistance represents the current leads to the magnet. The model is

$$V_c = L\frac{dI}{dt} + RI$$

Here I is the current through the magnet, L is the nonlinear magnet inductance, R is the lead resistance and V_c is the calculated voltage from the model. This voltage is compared to the observed voltage V_o across the magnet in real time. When a quench develops, additional resistance will appear causing V_o to deviate from V_c. A difference more than 25 mV is triggered as a quench event.

The parameter L is highly nonlinear in nature. It exhibits saturation i.e. its value decreases with increasing current. Also the L *vs.* I curve changes with the change in current ramp waveform. The model stores lookup table for L *vs.* I values, which have to be updated manually every time a new current waveform is introduced. An L *vs.* I lookup table is shown in Fig. 1. This gives us a rough idea of the nonlinear behavior of L.

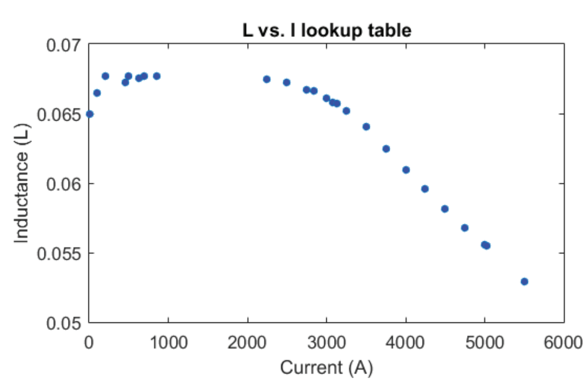

Figure 1: L vs. I lookup table values

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SYSTEM IDENTIFICATION

Our aim is to find an accurate inductance variation with the current change to construct accurate *L vs. I* tables to be used in the DSP model. We analyze the magnet current and voltage data for a magnet tap named B1DSD9_5VT. For this particular voltage tap connected across dipoles, the *R* value is zero, so we are left with the following model

$$V_c = L\frac{dI}{dt} \tag{1}$$

One of the techniques that can be applied to solve for *L* is the linear regression, where the explanatory variable is the first derivative of the current and the response variable is voltage. We mine the voltage and current data from RHIC database using MATLAB® [3], which is found to be quite noisy. Particularly for the derivative of current, noise is highly amplified. Thus we attempt to clean the data first. We analyze the frequency spectra of the current and voltage data, and their variation over time through spectrograms shown in Fig. 2.

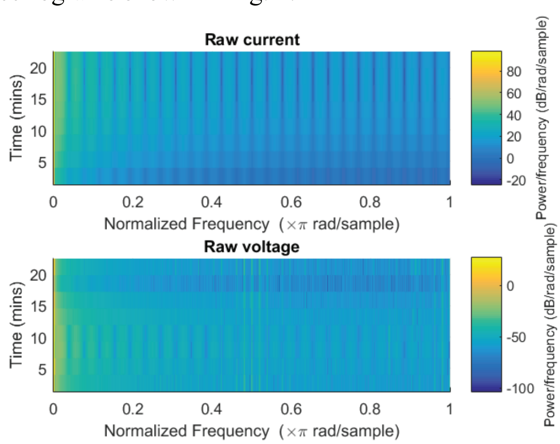

Figure 2: Spectrograms of voltage and current signals

Next we choose to filter the voltage and current data per the frequency characteristics in Fig. 2. The noise in the first derivative of current is now eliminated. Figure 3 shows the filtered (green) and raw (black) signals for the magnet current, first derivative of the current and voltage signals. The periodic noise and spikes in the data are now removed.

Now the data is ready for analysis after the preliminary processing. Consider the *dI/dt* waveform in Fig. 3. There are certain portions of the current where the first derivative of the current is either zero or has very low value. For a good fit of the linear regression model, the explanatory variable should have a substantial magnitude. Thus to apply the regression algorithm using Eq. 1, we eliminate small or zero values of *dI/dt* and corresponding values of *V* from the data. We have written a data classification algorithm to segment and identify the regions in current waveform where the first derivative is non-zero, second derivative is non-zero etc. The segmented portions of the magnet current are shown in Fig. 4.

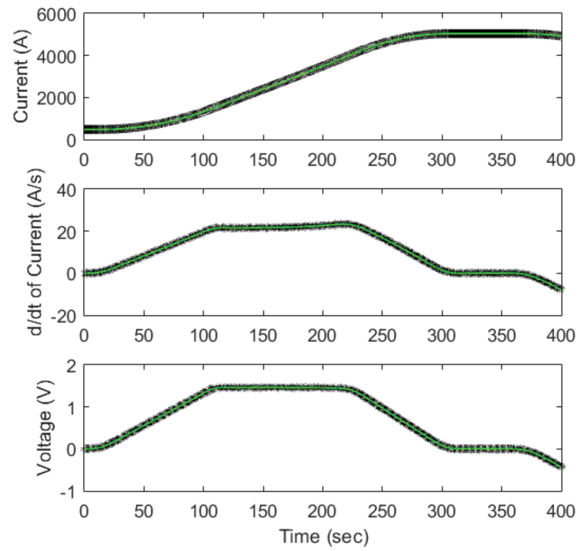

Figure 3: Raw and filtered I, dI/dt and V

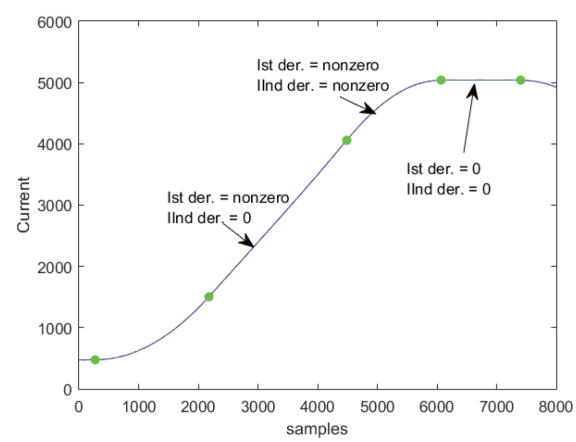

Figure 4: Current segmentation

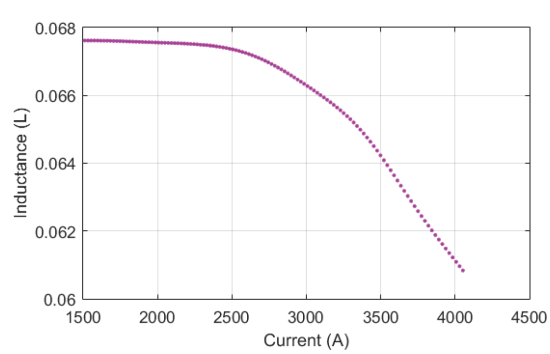

Figure 5: L vs. I curve from piecewise regression

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We use Eq. 1 for regression in region where the first derivative exists. Now we address the nonlinear variation of L with increasing current. One method to deal with this is to use piecewise regression, where the current is divided into very small data sets, and regression is applied to each set for finding L value. The L is assumed constant for this small dataset. Now we plot these values of L with I in Fig. 5 that shows the saturation characteristics of L similar to Fig. 1, but much cleaner.

FIELD TESTING

Before testing the model in the field, we look at the residuals that we obtain from our analysis. The residuals between the filtered voltage and the calculated voltage are shown in Fig. 6. As seen the maximum value of the residuals is about 8mV, which is well below the 25mV limit.

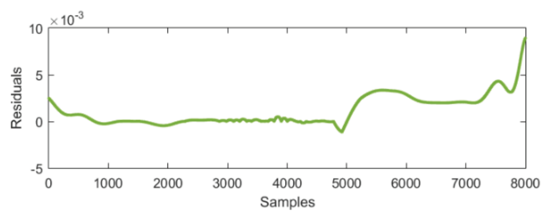

Figure 6: Residuals between the filtered and fitted voltage

The piecewise regression generates a smooth curve of about 200 data points for L *vs.* I curve (Fig. 5). However the DSP model can only store 35 values of L *vs.* I data. It interpolates the L values for in-between I values. We generated L *vs.* I tables for DSP using this data, and a screen shot from the field testing on the same voltage tap is shown in Fig. 7. The difference signal (in blue) is the moving average of 100 values of the actual voltage difference (in grey), which is used for triggering quench event in case it goes beyond 25mV. The maximum value of the trigger signal is found to be 6mV which is quite below the 25mV level.

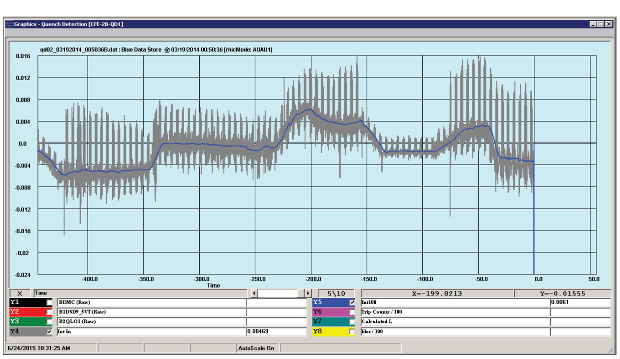

Figure 7: Field testing, quench trigger signal

Residual Diagnostics

The linear regression model validity can be established by residual diagnostics. We use the guidelines discussed in [4] for checking our model.

The true residuals of our model are obtained by the difference between the observed magnet voltage and the predicted voltage from the newly generated DSP table, as this table will actually be used in the field. Similar to the DSP, we find the predicted voltage from Eq. 1, by interpolating the L values for intermediate I values in the table.

We use the following rules for our residual diagnostics as discussed in [4]. It is to be noted that the shape of residuals in Fig. 6 will be visible in these residuals as well. We address this residual pattern later in this paper. First, the explanatory variable should be linearly related to the response variable. This can be observed by plotting the residuals against the explanatory variable. We already linearized our model by piecewise regression so that the residuals will be linear with respect to dI/dt. As seen in Fig 8, the trend is almost linear, with little variability.

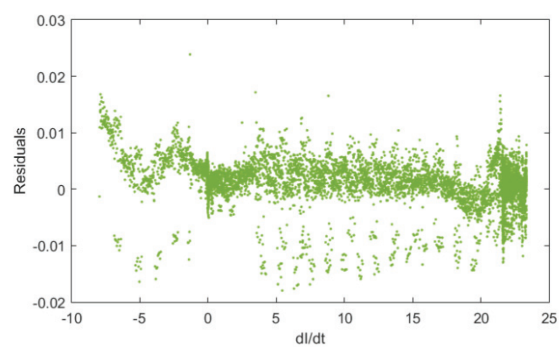

Figure 8: Residuals vs. explanatory variable

Secondly, the residuals should have nearly normal distribution. This can be seen by plotting the histogram and quantile-quantile plot (Fig. 9). From the figure it is seen that the residuals are a little light-tailed but are not skewed, and are nearly normal.

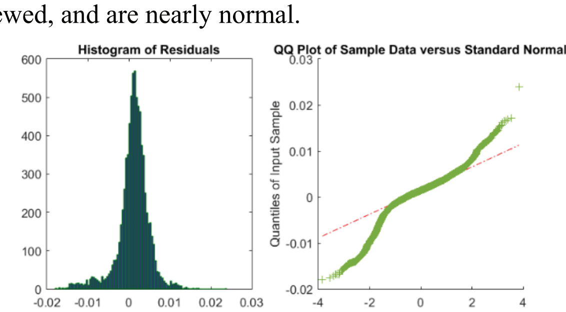

Figure 9: Histogram and QQ plot

Thirdly, the residuals should have constant variability. This can be checked by plotting the residuals against the response variable where the residuals should be randomly

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scattered around the zero value. This rule is satisfied as seen in the Fig. 10.

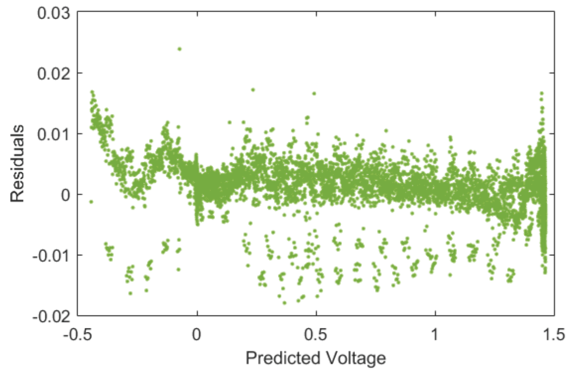

Figure 10: Residuals vs. response variable

Lastly the residual values should be independent of each other. This can be checked by the scatter plot of residuals (Fig. 11). In all the residual plots we see a periodic structure, which is due to the Booster main magnet pulses disturbing the power line [5, 6]. Other than this, the pattern looks random.

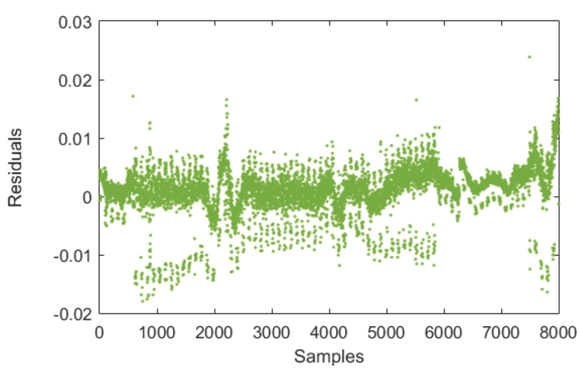

Figure 11: Scatter plot of residuals

DISCUSSION

To further improve the model, the remaining variability in the residuals has to be analyzed. As seen in Fig. 7, we see a pattern in the residuals. This variation depicts a dependence on the second derivative of current, which is shown in Fig 12.

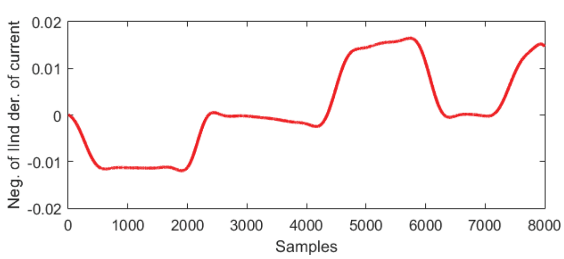

Figure 12: Negative of IInd derivative of current

To accommodate this variance, we can modify the magnet model as the following equation.

$$V_c = L\frac{dI}{dt} + X\frac{d^2I}{dt^2}$$

Here X is a coefficient of second derivative of current, which can be a constant throughout the data, and might not need piecewise regression. This X parameter can then be modeled as an eddy current component and/or parasitic capacitance in the circuit. More accurate analysis can be done by performing the frequency response analysis.

CONCLUSION

We utilize the statistical analysis concepts to reveal the underlying saturation characteristics of the magnet, and validate our model using field testing and residual analysis. This will facilitate the automatic generation of the DSP tables without any manual intervention. This helps to save the valuable resources when the RHIC is running at 4K temperature. Going further, we have also developed an analytical memory model that quantifies the saturation and hysteresis behavior of RHIC superconducting magnets [7]. This will help forecast the *L vs. I* curve for particular current waveform, accounting for nonlinearities due to saturation and hysteresis.

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