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Deep Learning-based Anomaly Detection in Drift Tube Quadrupole Operation for the KOMAC LINAC

The Korea Multi-purpose Accelerator Complex linear accelerator encompasses a Drift Tube LINAC (DTL) structure for high-frequency beam bunches accelerated by a radio frequency quadrupole. The existing anomaly detection system triggers shutdown when anomalies are detected. This study aims to detect anomalies to prevent unnecessary shutdowns through pre-adjustments. Drift-tube quadrupoles (DTQs) focus the beam within the DTL tank, but prolonged usage can degrade performance. To ensure stable beam focusing, the operational status of DTQ power supplies must be monitored. The EPICS input/output controller monitors these operational parameters and triggers alarms when thresholds are exceeded. However, this approach fails to consider changes, such as equipment aging. A machine learning-driven method can assimilate historical data related to the magnet power supply, enabling deriving adaptive thresholds, facilitating anomaly detection. A long short-term memory (LSTM) autoencoder model is employed to detect anomalies in DTQ magnets. Exploratory DTQ magnet operation data analysis was conducted to identify potential failures. The LSTM autoencoder offered a more adaptive and proactive detection model than conventional threshold-based methods. The results show that voltage fault events can be detected range from 30.7 to 286.6 minutes before they may cause a breakdown, enhancing device maintenance and performance through proactive prognostication of impending failures.

Keywords: Deep learning, Anomaly detection, DTQ magnet

1. Introduction

The 100-MeV proton linear accelerator at the Korea Multipurpose Accelerator Complex (KOMAC) has Drift Tube LINAC (DTL) structures for further RF acceleration of 3-MeV proton beam bunches from a radiofrequency quadrupole (RFQ) to a 100-MeV beam. Typically, quadrupole magnets are incorporated in each drift tube to focus the beam. Numerous high-intensity proton accelerator facilities, including SNS, LINAC4, ESS, CPHS, and XiPAF, employ permanent magnet-based quadrupole magnets [1–6]. However, J-PARC and CSNS utilize electromagnets formed by directly shaping a hollow conductor through electroforming technology [7–10], which is complex and expensive. At the KOMAC, the DTL comprises DTL20 sections, which accelerate the proton beam from 3 to 20 MeV, and DTL100 sections, which accelerate the beam from 20 to 100 MeV [11]. The Drift Tube Quadrupoles (DTQs) within the DTL100 sections are constructed using hollow conductors. In contrast, the DTL20 sections, which have a shorter tube length along the beam axis, employ transformer coils with enamel insulation and are immersed in cooling water flowing through a coaxial stem, as illustrated in Fig. 1 (a) [12,13]. Over time, enamel wire corrosion, as depicted in Fig. 1 (b), results in the failure of certain DTQs [14,15]. These failures are a primary cause of beam transmission losses at the corresponding DTQ locations as well as along the downstream acceleration line. Currently, the DTL20 sections comprise of 156 electromagnet-type quadrupoles, each with a distinct size, incurring upfront costs for spare parts. The replacement of DTQs requires substantial human resources and time and involves tasks, such as disconnecting power and cooling lines, removing RF couplers, relocating the tank, realigning components using a laser tracker, and measuring field distribution through bead pulls [16,17]. Moreover, the continuous replacement of drift tubes induces slight changes in the resonant frequency of the tank, requiring adjustments to the slug tuner or altering the operating temperature. Consequently, the field distribution uniformity is adversely affected, which motivates long-term efforts to transition most DTL20 sections to permanent magnets [18,19]. Nevertheless, electromagnetic quadrupoles with adjustable field gradient values are irreplaceable on the low-energy side of DTLs to match the beam with the RFQ.

In current systems, such as The Best Ever Alarm System Toolkit (BEAST) of the Phoebus Control System Studio (CSS), alarms are triggered when the power supply voltages of the DTQ magnets deviate from predefined normal ranges. Typically, deviations of ±0.5% from the normal range generate a minor alarm, notifying operators of a potential future failure. Deviations exceeding ±1% result in a major alarm, urging operators to inspect the hardware at the local installation site due to suspected malfunction. However, these systems are reactive and fail to address the root causes of anomalies, often leading to unnecessary shutdown. A more proactive approach is needed to detect and address issues before they escalate into operational failures. For example, to prevent excessive false alarms caused by large noise exceeding the preset ranges, operators tend to manually widen the normal range. However, this approach not only reduces the false alarm rate but also compromises the system's ability to detect small signal changes, thereby diminishing fault detection accuracy. Thus, a more precise and earlier detection model for DTQ abnormalities is required to reduce the frequency of inaccurate alarms and optimize spare part management and maintenance plans.

Recent advances in machine learning techniques, particularly deep learning algorithms, have facilitated their integration into particle accelerator machine protection and data analysis systems. Numerous studies have been conducted on time-series data anomaly detection in particle accelerators, including autoencoders [20] and long short-term memory (LSTM) networks for temperature variables in power supply anomaly detection [21]. This study developed a deep-learning-based LSTM autoencoder to detect even subtle abnormal signals, providing a more adaptive and proactive solution than the conventional threshold-based systems. The LSTM autoencoder gives us two benefits: first, it can predict potential issues earlier, making maintenance scheduling easier; second, it can distinguish voltage false alarms to prevent unnecessary maintenance. It was tested on historical DTQ data stored in accelerator data servers as a feasibility study before its potential implementation in real-time DTQ anomaly detection.

2. Methods

To detect operational anomalies in DTQ magnets accurately, we designed a method employing an LSTM autoencoder [22] to capture temporal dependencies and identify nonlinear patterns in time-series data. These patterns are particularly relevant to DTQ magnet operations, which are characterized by nearly constant resistance values under normal conditions, with minor thermal or electromagnetic noise. In contrast, failures caused by aging magnet coils lead to gradual fluctuations in resistance, eventually culminating in sharp drops due to short circuits.

Existing anomaly detection systems generate alarms when the voltage exceeds the normal range, leading to reactive maintenance. These alarms do not consider the gradual degradation of the equipment or other subtle operational changes. If anomalies due to conditions such as equipment aging or changes in beam operating conditions could be detected proactively, pre-adjustments could be made to prevent shutdowns. This study aims to use six and a half years of historical operational data to develop a proactive anomaly detection system that enables pre-adjustments to prevent shutdowns and improve operational reliability.

Autoencoders are a type of neural network designed to learn efficient representations of input data and capture essential features while reducing redundancy. Autoencoders can reconstruct their inputs through dimensionality reduction and subsequent reconstructions. In the context of autoencoders, the derived equations delineated two primary phases of the operation: encoding and decoding. The encoding phase is summarized by $h = f_1(\omega_i x + b_i)$, where h represents the bottleneck layer— a compressed representation of the input data x shown in Fig. 2. The weight ω_i and bias b_i are parameters that the network learns to optimize the encoding process, and f_1 is the activation function that introduces non-linearity, thus enabling the network to learn complex patterns. The decoding phase is described by $\hat{x} = f_2(\omega_j h + b_j)$, where the goal is to reconstruct the input data from the bottleneck representation h to produce the output $\hat{x}$. Here, ω_j and b_j are the weights and biases for the decoding, and f_2 is the activation function [23]. All parameters $(\omega_i, \omega_j, b_i, b_j)$ are learned during the training process via backpropagation, which iteratively updates these parameters to minimize the reconstruction error. Finally, the Mean Squared Error (MSE), $MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2$, quantifies the performance of the autoencoder by measuring the average of the squared differences between the original data x_i and the reconstructed data $\hat{x}_i$ across all samples. This loss function drives the training process by minimizing the discrepancy between the input and its reconstruction, thereby encouraging the autoencoder to learn a faithful representation of the data. Minimizing this discrepancy forces the model to capture the most essential features of the input while filtering out irrelevant noise. To mitigate the impact of transient fluctuations and noise on the error, which could otherwise lead to false anomaly detection, this study employed a median moving average method with 12 h of data.

LSTM networks can retain information over extended time intervals, making them suitable for modeling the sequential and time-dependent nature of DTQ magnet data, which is critical for effective anomaly detection. This helps the network to decide based on both current and past states of the system, which are crucial for effective anomaly detection.

Our LSTM Autoencoder model was structured to detect anomalies when operating a DTQ magnet by learning to reconstruct the normal operational data, as shown in Fig. 2. The resistance data of the DTQ magnets existed in a time series manner. The time series were segmented into periods defined by the instances when the quadrupole magnet power supply (QMP) power was switched OFF or ON, typically spanning one week, corresponding to the full running time of the DTQ system. This segmentation was flexible and adapted to varying durations of the actual operational cycles.

The divided periods were utilized as training, validation, and test datasets to develop a robust model capable of distinguishing between normal and anomalous operational behaviors. We used data from periods that were previously operated normally as our training and validation sets as well as data from subsequent periods as the test set. To ensure learning stability, only normal data that persisted for more than three days were selected for the training dataset. The validation set was 10% of the training data, and the training was conducted at 10 min intervals with the number of epochs set to 100. The autoencoder layers of 128, 32, 32, and 128 units were selected by reducing the model's sensitivity to random noise. A higher threshold risked missing anomalies, whereas a lower threshold increased the chance of normal data being classified as anomalous. Thus, an MSE loss threshold of 0.125 was selected as an optimal balance to maximize accuracy and minimize false alarms. The Adam optimizer was employed in the optimization process.

Our dataset contained operational data from 24 QMPs used in DTQ magnets, with each QMP providing separate current and voltage measurements. This time-series dataset had sampling interval of 10 s from March 2017 to October 2023. The overall dataset consisted of a two-dimensional array of (3758450, 48), where columns are times and rows are voltage and current values of each QMP channel. To normalize the effects of operational adjustments by workers, which often involve changes in voltage and current levels, the resistance value was computed by dividing the voltage by the current for each QMP dataset. This derived resistance value provided a stable reference point considering that resistance changes were less frequent and more indicative of system anomalies than the raw current and voltage readings. We further refined the dataset by removing instances where the system was off. This ensured that only the data representing active operations were included in the analysis.

To evaluate the overall performance of our anomaly detection model, we employ the standard definition of accuracy from binary classification. Specifically, we define TP (True Positive) as the number of actual anomaly cases correctly identified as anomaly, TN (True Negative) as the number of actual normal cases correctly identified as normal, FP (False Positive) as the number of normal cases incorrectly identified as anomaly, and FN (False Negative) as the number of anomaly cases incorrectly identified as normal. Then, we compute accuracy as (TP+TN)/(TP+TN+FP+FN). This metric reflects the proportion of all correctly classified anomaly and normal samples among the total number of samples.

3. Results and Discussion

The primary goal of this study was to enhance anomaly detection methods for operational data, enabling the early identification of potential issues, reducing false alarms, and minimizing downtime during beam operations. The dataset was divided into two main categories: normal operational data and data with voltage fault events, which were selected based on the operation records that indicated voltage fault events.

Figure 3 illustrates the range of normal operating conditions, providing a benchmark for effectively identifying and comparing unusual events. This figure represents the total operational data divided by periods of the six and a half years of operation. We analyzed the data in reverse chronological order from the most recent cases to earlier instances, which helped us understand the timing and progression of anomalies relative to fault events. To balance the sensitivity for detecting true anomalies while avoiding false alarms, we set the MSE loss threshold to 0.125. We examined 76 distinct periods of operation and identified only two incorrect anomalies in the six-and-a-half-year dataset.

Figure 4 presents an analysis of ten voltage anomaly cases identified during the study period that encompasses the six-and-a-half-year dataset, during which DTQ failures and repair activities were logged. The ten voltage anomaly cases were selected as clean data with minimal contamination. The figure shows the anomaly scores when voltage fault events occur in the DTQ magnets. Five of the ten error cases identified during the study period were confirmed as true anomalies. Compared to the normal data anomaly detection rate of 2.6% shown in Fig. 3, our method can detect 50% of the anomaly cases when a voltage error occurs, as shown in Fig. 4.

The model achieved an accuracy of 92%, based on the proportion of correctly identified anomalies relative to the total number of cases, thereby confirming the reliability of our detection approach. Table 1 indicates that the anomaly cases exceed the thresholds described in Fig. 4. The early detection time is obtained by measuring the time difference between the threshold-crossing moment and the signal-off time triggered by the voltage error. The results show that our model can detect anomalous behavior range from 30.7 to 286.6 minutes before the occurrence of errors.

These results highlight the effectiveness of the LSTM Autoencoder in detecting the early signs of voltage irregularities, facilitating smooth operations, and improving system reliability by enabling timely preventive actions.

4. Conclusion

This study employed an LSTM Autoencoder to detect anomalies in DTQ magnets at the KOMAC LINAC. By analyzing voltage and current data, the LSTM Autoencoder demonstrated its ability to identify subtle anomalies frequently overlooked by human operators. The model detected voltage anomalies range from 30.7 to 286.6 minutes before potential breakdowns, achieving an accuracy of 92%. This predictive capability represents a major advancement in maintenance planning, enabling the avoidance of unexpected shutdown. By facilitating early detection, this approach supports smoother operations, more efficient resource management, and lower costs. Overall, the results demonstrate that the LSTM autoencoder can enhance the operational stability and reduce unnecessary shutdowns through proactive anomaly detection.

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Declaration of Interest Statement

The authors report there are no competing interests to declare.

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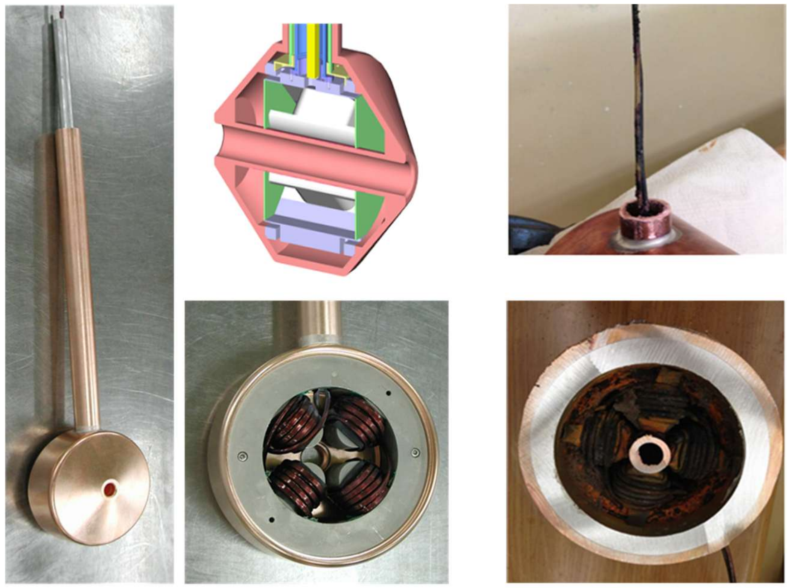
Tables

Table 1. Early detection period when an error occurs.

Detected anomaly cases	**Early detection time**
# 1	151.4 min
# 2	30.7 min
# 3	112.7 min
# 4	250.4 min
# 5	286.6 min
Mean	166.4 min

Figures



(a) (b)

Fig. 1. Drift tube for the 20-MeV DTL in KOMAC: (a) cross-sectional view of drawings and pictures of fresh DTQ before welding the tube and (b) photographs of old DTQ after failing and being cut.

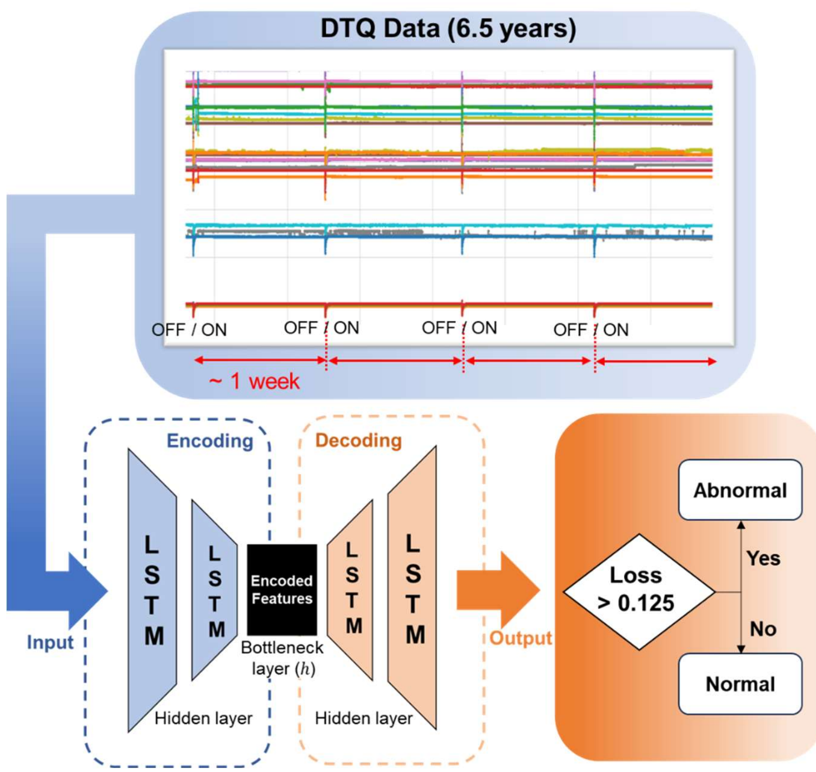


Fig. 2. LSTM autoencoder method for anomaly detection of DTQ magnets

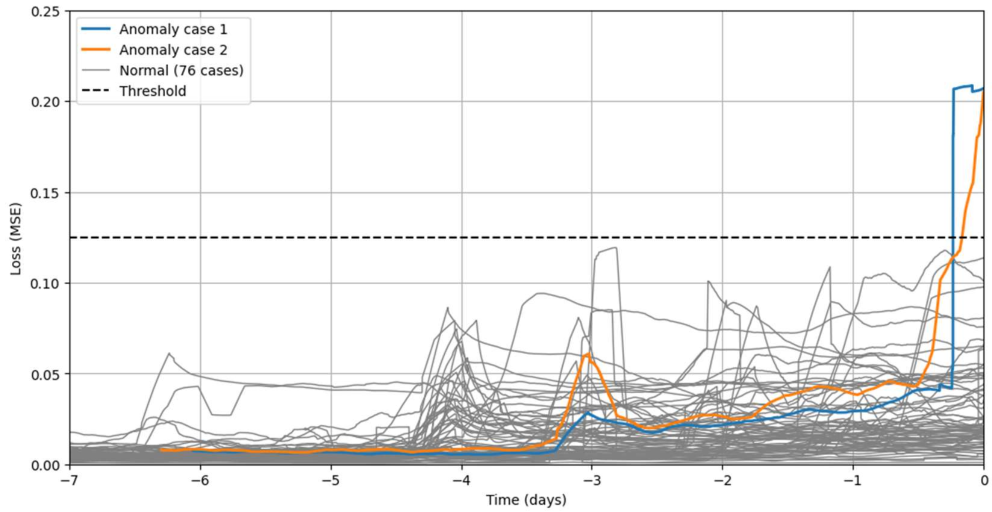


Fig. 3. Anomaly score according to time on 78 normal cases

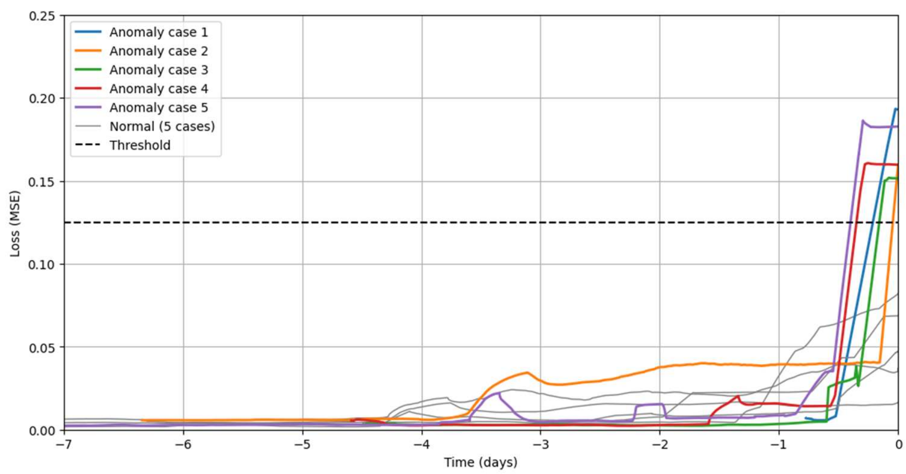


Fig. 4. Anomaly score according to time on 10 anomaly cases