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BEAM ENERGY FORECASTING USING MACHINE LEARNING AT THE CLEAR ACCELERATOR

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Abstract

Accurate and stable beam parameters are crucial for the success of particle accelerator-based experiments. Traditional methods for measuring beam parameters, however, often rely on invasive techniques that can disrupt experiments. This paper presents an initial step for obtaining a novel, non-invasive machine learning-based approach for predicting beam energy using parasitic measurements, enabling accurate real-time prediction without interference. The method employs a predictive model optimized for one-step-ahead forecasting and uses time-series data decomposition to handle complex beam energy dynamics, with recursive prediction strategies allowing it to anticipate future variations autonomously. Preliminary results from experiments at the CLEAR accelerator demonstrate the model's ability to capture both slow trends and rapid energy shifts, and adapt to diverse experimental needs. These findings lay the foundation for future studies, emphasizing the potential of machine learning to measure beam energy and provide a real-time, non-destructive alternative to conventional methods. This approach promises significant advancements in accelerator-based applications, especially where destructive techniques are impractical.

INTRODUCTION

Electron accelerators are crucial in fields like medical imaging and materials science [1–4]. Their utility relies on the delivery of a stable and well-characterized electron beam, which is critical for generating high-quality and reproducible data. Achieving such stability involves monitoring various beam and system parameters. Some, such as beam energy, are difficult to measure directly non-destructively and often require invasive methods. Non-invasive signals, such as from RF systems, offer potential for indirect diagnostics. Given the wealth of data available from modern accelerator systems and the complexity of modeling their interdependencies explicitly, Machine Learning (ML) offers a powerful tool for identifying relevant features and enabling robust, real-time diagnostics.

This study explores using ML to predict these hard-to-measure parameters, focusing on leveraging non-invasive signals to estimate beam energy without disrupting operations. Early results show that ML, guided by accelerator physics models, can reveal hidden correlations and enable real-time monitoring. The predictive ability of these models suggests a promising path for improving accelerator diagnostics adding a so-called virtual diagnostics, with the aim to estimate key parameters without intrusive instrumentation [5].

ENERGY MEASUREMENTS AT CLEAR

A precise method for energy measurement in Linear Accelerators (LINACs) uses a magnetic spectrometers to calculate the particle momentum from trajectory curvature in a magnetic field [6, 7]. It is highly reliable, usually invasive and requires a dedicated beamline that can make it unsuitable for continuous or in-situ monitoring. requires At the CLEAR facility, beam energy is typically measured in the VESPER area using a dipole spectrometer with a scintillating screen [8, 9].

In particular, the beam energy is measured from the horizontal beam position observed with an Yttrium Aluminum Garnet (YAG) screen using a 1D Gaussian fit to extract spot centroids.

The accelerator layout, shown in Fig. 1, indicates the location of the reference spectrometer (VESPER) and other experimental areas [10]. This method provides high-resolution energy measurements, but interrupts beam delivery to other experimental test areas, meaning that the energy cannot be monitored continuously during operation. To overcome this,

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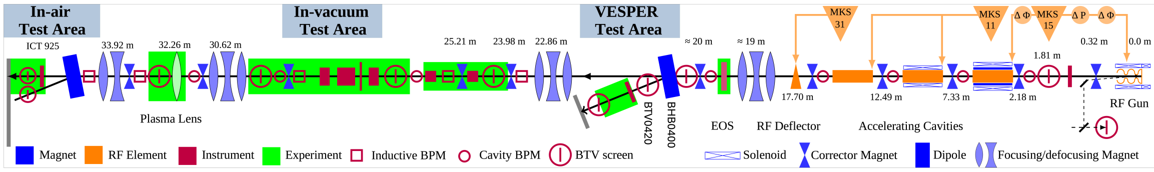

Figure 1: CLEAR beamline layout showing key components and the three main test areas, including VESPER where data were collected. The beam travels right to left, from the RF Gun through magnetic and RF elements to the experimental stations.

we explore a non-invasive ML approach to predict beam energy using parasitic signals during operation. The problem is framed as time series forecasting, with historical beam energy and auxiliary system signals serving as input. A one-step-ahead prediction framework is adopted in this study to ensure simplicity and minimize error.

EXPERIMENTAL SETUP

At the CLEAR facility, a variety of signals were collected to enable accurate machine learning–based beam energy predictions. These signals were selected based on operational experience and physically linked quantities. Although not all signals demonstrated an obvious correlation with beam energy, their inclusion allows the model to uncover non-obvious dependencies.

A training data-set was collected using direct beam energy measurements from VESPER in parallel with multiple non-invasive signals, including RF parameters (input power, reflected power, and phase from klystrons and accelerating structures), laser parameters (UV energy before and after transport from laser-lab to the photocathode), beam charge measured by Integrating Current Transformers (ICT), and magnet currents (solenoid and dipole currents).

Data was collected for 600-shots in continuous acquisition repeated 30 times, with buffer shots to accommodate acquisition system limitations and ensure reliable offline processing. Over 6 h of data were gathered, with a beam repetition rate of 0.833 Hz.

DATASET ANALYSIS

To reduce dimensionality, Pearson correlation analyses [11] were used to assess the relationships between the measured variables and beam energy. Variables with an absolute correlation less than 0.2 were removed, and redundant variables with a mutual correlation greater than 0.9 within the same signal group were filtered out, leaving only the most representative ones.

Figure 2 displays the correlation matrix across all signal categories. After filtering, 20 key parameters were retained for model training (the variables reported in Fig. 2 both bold and underlined). This approach balances comprehensiveness and efficiency, ensuring the ML model is trained on meaningful, non-redundant inputs while preserving the interpretability of the feature space.

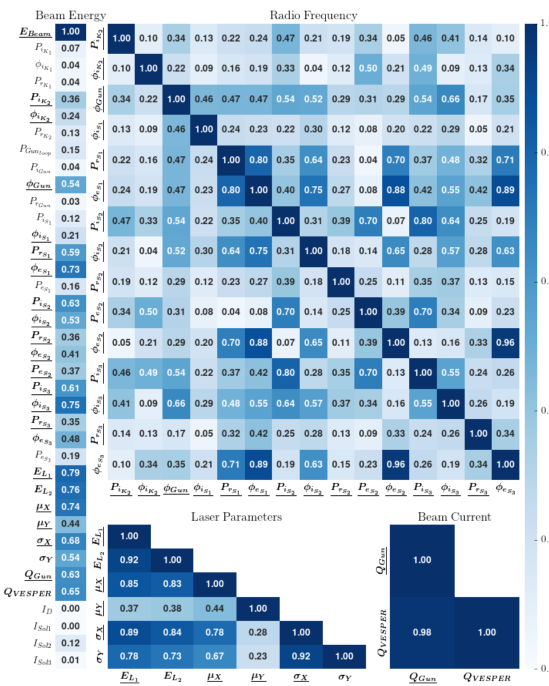

Figure 2: The absolute Pearson correlation matrix, grouped by category, shows correlations between study variables. Beam energy correlations appear on the left; RF signals are in the upper section, while laser parameters and beam current are in the lower-left and lower-right, respectively.

METHODOLOGY

To achieve high accuracy in predicting beam energy, several ML models were tested and optimized using Bayesian Optimization (BO) [12]. Model performance was evaluated using the coefficient of determination, R^2, defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}. \tag{1}$$

here, y_i is the actual value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of the actual values. The numerator represents the Sum of Squared Errors (SSE), while the denominator is the Total Sum of Squares (TSS), representing total variance.

The value of R^2 ranges from $-\infty$ to 1. A value of 1 means perfect predictions, 0 means no better than using the mean as a predictor, and a value less than 0 indicates poor fit or overfitting with the model prediction performing worse than using the mean as a prediction value.

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Table 1: Combined Table with Hyperparameter Search Space, Configuration, and Results for Selected Algorithms Using BO

Model	Hyperparameters	Search Space	Configuration	R^2_{ND}	R^2_D
Linear Regression	-	-	-	0.08	0.33
Random Forest	n. of estimators	[2, 500], step=1	496	0.05	0.34
	max depth	[2, 100], step=1	67		
SVR	kernel	{RBF, linear}	linear	0.10	0.33
	C	[0.1, 10]	0.017526		
MLP	n. of layers	[1, 4], step=1	2	0.10	0.33
	n. of hidden neurons	$\{ 2^n \}, 1 \le n \le 9$	(64, 256)		
	activation function	{ReLU, Tanh}	Tanh		
	batch size	[32, 64]	32		
	learning rate	[1e−5, 1e−3]	1e−3		
LSTM	n. of layers	[1, 4], step=1	1	0.14	0.02
	n. of hidden neurons	$\{ 2^n \}, 2 \le n \le 6$	4		
	learning rate	[1e−5, 1e−3]	1e−3		
	batch size	[32, 64]	32		
	weight decay	[1e−2, 0]	0.00543		

The core methodology involves training the model on historical data, using the past 10 data points for both beam energy and exogenous variables to predict the next beam energy. A decomposition approach was used to simplify the forecasting problem and improve performance [13], with a sliding window of size 10 applied to the data. Each window was processed using a Fast Fourier Transform (FFT) to decompose the time-series data into frequency components [14,15]. A bandpass filter was used to isolate a specific frequency range, which was then transformed back to the time domain using an inverse FFT (IFFT). The relevant frequency ranges are not fixed; instead, they are analyzed one by one in a loop, to evaluate their individual contribution to the signal. This filtering process was applied separately to each data window, and the results were combined to reconstruct the filtered signal for the entire dataset.

A variety of ML models were tested, including traditional methods like Linear Regression [16], Random Forest [17], and Support Vector Regression (SVR) [18], as well as neural networks such as Multilayer Perceptron (MLP) and recurrent architectures such as Long short-term memory (LSTM) [19].

RESULTS

The FFT frequency resolution depends on the time series length, sampling frequency (0.833 Hz), and number of data points (10). Shorter time series result in coarser resolution, limiting the number of frequency bands. Given 10 data points at the CLEAR sampling frequency, the signal can be decomposed into a maximum of 6 frequency bands due to resolution and Nyquist limits. The results in Table 1 show the hyperparameter, their search spaces, the selected configurations, and corresponding model performance metrics. The performance metrics are presented as R^2_{ND}, which refers to the performance using non-decomposed data, and R^2_D, which indicates performance using decomposed data, with R defined in Eq. (1).

For all models except LSTM, decomposing the data into 6 frequency bands improves performance. This is a significant result, especially considering that decomposition was not factored into the model selection during the BO search. LSTM models are designed to handle temporal dependencies and so the limited past history (only 10 data points) limits its potential. Nonetheless, optimization on decomposed data significantly improved its performance giving comparable results with the respect to other models.

Interestingly, the simple Linear Regression model, using historical data for predicting the next beam shot, performed similarly to more complex models, demonstrating its efficiency.

CONCLUSION AND OUTLOOK

This study introduced a machine learning-based approach for predicting beam energy at the CLEAR accelerator using non-invasive measurements. By combining time-series analysis with signal decomposition, models were trained to forecast beam energy without direct or destructive diagnostics.

A key finding was that Linear Regression, when applied to decomposed signals, performed similarly to more complex models, offering promising prediction accuracy while being fast and explainable. Future work will focus on improving R^2 performance and testing different approaches. While initial results are promising, further refinement is needed. Once one-step-ahead predictions reach satisfactory accuracy, they can be integrated into a closed-loop system for short-term forecasting over multiple pulses.

This method holds potential for fields like medical accelerators, especially in proton therapy, where precise energy control is crucial. Its non-invasive nature may make it ideal for real-time monitoring in environments where direct measurement is impractical [20,21]. The goal is to integrate this system into a real-time feedback loop for stabilizing beam conditions.

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