Machine Learning-Based Injection Quality Assessment and Anomaly Detection for Electron Storage Rings

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Abstract

During the injection process of electron storage rings, bunch parameters undergo drastic changes. Through bunch-by-bunch three-dimensional position measurement technology, this process can be captured and analyzed in real time, yielding multiple beam dynamics parameters related to transverse beta oscillations and longitudinal synchrotron oscillations. How to leverage these measurement results to evaluate and guide the optimization of accelerator operation constitutes an important research problem for synchrotron radiation light source facilities. This paper proposes a machine learning-based approach for injection quality evaluation and anomaly detection in electron storage rings. By selecting the accumulated injection transient process data from the Shanghai Synchrotron Radiation Facility over many years as a sample library, cluster analysis of the dynamics parameters of refilled bunches enables the identification of temporal evolution patterns in the facility' s operational status and the flagging of anomalous data samples that do not belong to the main cluster. A kNN model was trained to predict and validate anomalous data, with experimental results demonstrating that the prediction model achieves a precision exceeding 90%, thereby serving as an effective method for online automatic evaluation of facility operational performance.

Full Text

Preamble

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Quality Assessment and Anomaly Detection for Electronic Storage Ring Injection Based on Machine Learning

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Abstract

[**Background**] During electron storage ring injection, beam parameters change drastically. This process can be captured and analyzed in real time through bunch-by-bunch three-dimensional position measurements to obtain multiple beam dynamics parameters related to transverse betatron oscillations and longitudinal synchrotron oscillations. How to utilize these measurements to evaluate and guide the optimization of accelerator operation is an important issue for synchrotron radiation light source facilities. [**Purpose**] This paper proposes a machine-learning-based method for evaluating injection quality and detecting anomalies in electron storage rings. [**Methods**] Selecting injection transient data accumulated over many years at the Shanghai Synchrotron Radiation Facility (SSRF) as the sample database, cluster analysis of the dynamic parameters of refilled bunches reveals the temporal evolution patterns of facility operation states and identifies anomalous data samples that do not belong to the main cluster. [**Results**] A kNN model was trained to predict and validate anomalous data, with experimental results showing that the prediction accuracy exceeds 90%. [**Conclusions**] This method can serve as an effective approach for online automatic evaluation of facility operation performance.

Keywords: Machine learning, electron storage rings, injection transients, quality evaluation, kNN

Classification: TL99

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1. Introduction

An electron storage ring is a circular accelerator device that stores high-speed electron beams, requiring continuous external injection to maintain stable beam current during operation [1]. A common injection method is the bump injection technique. During normal operation, the storage ring' s equilibrium orbit is far from the septum magnet. When new electron beams are injected, pulsed magnets create a local orbit bump, bringing the beam trajectory close to the septum to inject fresh bunches parallel to the equilibrium orbit in the horizontal plane. After injection, the pulsed magnetic field disappears, and the beam orbit returns to its equilibrium position. Through synchrotron radiation damping, the oscillation amplitude gradually decreases until the beam stabilizes in the storage ring.

The Shanghai Synchrotron Radiation Facility (SSRF) is a third-generation synchrotron light source employing single-turn bump injection [2], as shown in [Figure 1: see original paper]. To ensure beam stability, SSRF has operated in top-up mode since December 2012, with injection intervals of approximately 10 minutes and each injection lasting about 10 seconds [3]. Top-up constant-current operation is a high-performance mode developed for synchrotron light sources in recent years, enabling beam injection while keeping beamlines open without interrupting user experiments, while controlling beam intensity fluctuations within 1%. This operation mode significantly enhances light source stability and experimental efficiency.

[Figure 1: see original paper] Layout of SSRF Injection System

During electron storage ring injection, imperfect parameter matching among various components occurs due to the transient nature of the process [4]. Transversely, mismatched pulsed magnet fields and injector-to-ring mismatches induce transverse betatron oscillations in all bunches. Longitudinally, imperfect energy and spatial matching between fresh and stored bunches leads to synchrotron damping oscillations in refilled bunches. While electron storage rings operate very stably under non-injection conditions, certain dynamics parameters can only be measured during injection when refilled charge merges with stored charge, creating disturbances. However, observing this process presents challenges: the refilled charge quantity is extremely small, and the merging time is very brief, making direct observation difficult. Signals from beam position monitor (BPM) probes represent coupled signals from both stored and refilled charges, whose different transient behaviors during injection contain distinct information that must be separated for analysis [5].

Our research group developed the HOTCAP software package [6-8], which enables precise extraction of fresh bunch parameters, making it possible to use fresh bunches as probes for injection process analysis. The software capabilities include bunch-by-bunch 3D position calculation, turn-by-turn 3D position calculation, refilling process analysis, and wakefield analysis.

Extensive research on injection transients has been conducted domestically and internationally. CERN [9] proposed a novel machine learning approach for detecting and classifying collective beam behavior in the Large Hadron Collider (LHC). By training an autoencoder neural network on bunch-by-bunch amplitude data from transverse feedback systems, they used reconstruction errors to separate unstable and anomalous data from normal beams. The autoencoder represented beam signal features as 2D images, enabling clustering of various anomaly types. SSRF [3] employed a digital-oscilloscope-based bunch-by-bunch position measurement system to evaluate injection quality, studying tilt errors, excitation current matching among injection kickers, fresh bunch energy mismatch, and injection repeatability. Brookhaven National Laboratory observed kicker amplitude, trigger timing delays, and waveform mismatches with residual betatron oscillations using a transverse bunch-by-bunch feedback system at NSLS-II [10]. Current domestic and international injection process observations and analyses focus primarily on residual oscillations of stored bunches, with fewer studies targeting fresh injected bunches.

Monitoring and analyzing fresh bunch parameters is more effective for injection quality assessment. During fresh bunch injection, multiple parameters can be extracted, including refilled bunch charge quantity and longitudinal synchrotron damping oscillation parameters such as synchronous oscillation amplitude, frequency, and damping time. In-depth analysis of this non-steady-state process yields numerous beam dynamics parameters that provide scientific basis for evaluating matching between the injector and storage ring, enabling comprehensive assessment of injection system efficiency and precise guidance for system optimization.

The core objective of electron storage ring anomaly detection is to identify potential issues through monitoring and analysis of beam parameters and take appropriate measures. Due to the high complexity of storage ring systems, anomalies may manifest in various forms with potential interconnections, making traditional threshold-based detection and manual analysis inadequate. Additionally, electron storage ring anomaly detection faces numerous challenges, including data noise interference, high real-time requirements, and multi-parameter coupling. With advances in sensor technology and data acquisition systems, the volume of data generated during storage ring operation has increased dramatically, providing rich information for anomaly detection but also imposing higher demands on data processing and analysis. Recent progress in machine learning and big data technologies offers new solutions for electron storage ring anomaly detection. Therefore, this paper proposes a method combining unsupervised learning for storage ring operation state analysis with supervised learning for anomaly detection modeling.

[Figure 2: see original paper] Measured turn-by-turn phase and fitting results of refilled charge

2. Machine Learning Methods

Under normal storage ring operation, longitudinal bunch motion exhibits extremely high stability with negligible longitudinal oscillations. However, in constant-current top-up mode, imperfect parameter matching between the injector and storage ring causes refilled bunches to deviate from the equilibrium center during initial injection stages, manifesting as phase and momentum deviations that induce longitudinal synchrotron damping oscillations [11]. The longitudinal oscillation equation is:

$$z_d = z_m \sin(\sqrt{\Omega^2 - \lambda_s^2} t + \varphi_0) e^{-\lambda_s t}$$

where z_m is the synchronous oscillation amplitude of refilled charge, representing the overall parameter mismatch between refilled charge and ideal particles in the storage ring (including combined contributions from energy mismatch and initial arrival time mismatch). Ω denotes the synchronous oscillation frequency, determined by the accelerating cavity voltage gradient. φ_0 represents the initial oscillation phase of the bunch (i.e., initial arrival time), indicating the particle' s position relative to the equilibrium acceleration phase after injection. The reciprocal of λ_s represents the synchronous damping time τ, a damping term dominated by synchrotron radiation that reflects machine operation stability. The longitudinal tune ν_d describes the collective oscillation frequency of particles, representing the number of oscillation periods per revolution, defined as the normalized value of the longitudinal phase advance per turn relative to 2π.

Under small-amplitude conditions, refilled bunches exhibit standard damped oscillator motion longitudinally from injection into the storage ring, as shown in [Figure 2: see original paper]. However, measured signals still contain many glitches, which are removed using median filtering [12]. The synchronous damping oscillation curve of refilled bunches is fitted using least squares method according to the equation above, shown as the red curve in [Figure 2: see original paper]. Samples with coefficient of determination $R^2 > 0.8$ are selected as successfully fitted data. For the example in [Figure 2: see original paper], multiple important synchronous oscillation parameters are obtained after fitting: longitudinal initial amplitude of 114.54 ps, initial oscillation phase of 0.96 rad, longitudinal damping time constant of 2033 turns $\approx$ 2.94 ms, and longitudinal tune of 0.0070.

Unsupervised learning aims to extract sample features from raw data and discover patterns through the data' s inherent structure, generating pseudo-labels through analysis of internal data patterns. Its advantage lies in requiring no labeled data and enabling discovery of unknown patterns. Anomaly detection aims to identify outliers significantly different from most samples in the dataset, which may result from data errors, rare events, or special behaviors. Machine learning model training can be divided into two stages: unsupervised learning and anomaly detection, as shown in [Figure 3: see original paper]. (1) In the unsupervised learning stage, appropriate algorithms are selected based on sample distribution to discover spatial clustering patterns and analyze machine operation patterns. (2) In the anomaly detection stage, anomalous data are manually labeled based on the previous stage' s analysis results to train models for anomaly prediction.

[Figure 3: see original paper] Framework of proposed model

As a data analysis tool, cluster analysis has gained widespread recognition across various fields [13]. Through cluster analysis, datasets are naturally grouped into clusters, where each cluster is a collection of similar elements. Clustering methods can be categorized into hierarchical, partition-based, graph-based, density-based, and grid-based approaches [14,15]. This paper selects the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm for cluster analysis.

Supervised learning-based anomaly detection utilizes labeled data to train models for identifying anomalous patterns. The core idea involves constructing classifiers or regression models through known normal and anomalous samples to predict anomalies in new data. Supervised learning leverages expert knowledge through precisely labeled data to achieve high-precision anomaly detection in specific domains. Common algorithms include traditional machine learning methods (e.g., kNN, decision trees, naive Bayes, support vector machines) and deep learning methods (e.g., neural networks, RNNs, LSTMs). This paper selects the kNN algorithm for supervised learning, which learns data feature distributions to effectively distinguish between normal and anomalous events.

2.1 Density-Based Spatial Clustering of Applications with Noise Algorithm

The DBSCAN algorithm was proposed by Martin Ester et al. in 1996 [16]. DBSCAN performs density-based partitioning of datasets, dividing them into dense and sparse regions, and connects elements in dense regions to form clusters. DBSCAN focuses on spatial distribution information of dataset elements and can identify clusters with complex shapes. Samples not belonging to any cluster are considered noise or anomalies by DBSCAN, which is highly advantageous for handling datasets with non-linear boundaries. Before describing the specific algorithm, several relevant concepts must be defined [17]:

- **Neighborhood**: The region within radius ϵ of a sample is called its ϵ-neighborhood.
- **Core object**: If a sample' s ϵ-neighborhood contains at least $MinPoints$ samples, it is called a core object.
- **Directly density-reachable**: If sample j is within sample i' s ϵ-neighborhood and sample i is a core object, then sample j is directly density-reachable from sample i.
- **Density-reachable**: For samples i and j, if there exists a sample sequence $p_1, p_2, ..., p_n$ where $p_1 = i$, $p_n = j$, and each adjacent pair is directly density-reachable, then samples i and j are density-reachable.
- **Density-connected**: For samples i and j, if there exists sample k such that both i and j are density-reachable from k, then i and j are density-connected.

The DBSCAN algorithm proceeds as follows:

Algorithm 1: DBSCAN

Input: Neighborhood ϵ; density threshold $MinPoints$; sample set Ω
Output: Density-based sample clusters

1. Traverse sample set Ω to identify all core objects and form set ω.
2. Randomly select a core object from set ω and find all its density-reachable samples to generate cluster C.
3. Remove all core objects in cluster C from set ω.
4. Repeat steps 2-3 with the updated set ω to generate the next cluster until set ω is empty.

2.2 k-Nearest Neighbors Algorithm

The kNN algorithm, or k-Nearest Neighbors, was proposed by Cover and Hart in 1968 [18]. In kNN classification, the process consists of three steps: First, calculate distances between the test object and each sample in the training set. Second, select the k nearest samples from the training set as neighbors. Finally, determine the test object’ s class through majority voting among these k neighbors. This paper employs Euclidean distance as the distance metric.

The kNN algorithm proceeds as follows:

Algorithm 2: kNN

Input: Training set X_t; training labels y_t; test set X_e; number of neighbors k
Output: Test set classes y_e

1. Calculate distances $d = \sqrt{(x_e - x_t)^2}$.
2. Sort distances in ascending order: sort(d).
3. Select the k smallest distance points: $P_x = \min_k(X_t)$.
4. Map points to their corresponding labels: $P_y = y_t[P_x]$.
5. The most frequent category among P_y is the prediction result: $y_t = \text{countmax}(P_y)$.

3.1 Clustering Analysis of Longitudinal Parameters for Fresh Injected Bunches

This study analyzes measured data from SSRF, examining injection data from normal user operation periods between September 13, 2021, and June 24, 2024. The data consists of four-channel measurements with 102.5 million samples per channel at a 10 GHz sampling rate, capturing single refilling events. Parameters include injection time, stored charge 3D positions, refilled charge 3D positions, and refilled charge quantity. Least squares fitting of the refilled bunch synchronous damping oscillation curve yields longitudinal parameters including: longitudinal oscillation amplitude, longitudinal tune, longitudinal initial phase, and synchronous damping time. Since real synchronous oscillation amplitude correlates with refilled charge quantity, reflecting matching between refilled bunches and the storage ring, their ratio α can optimize the injector [19]. The standard deviation of refilled charge quantity $\sigma_{\bar{\alpha}}$ characterizes injection process stability. Statistical analysis of longitudinal parameter means and normalized variances is shown in .

The longitudinal tune ν_d and longitudinal initial phase φ_0 remain relatively stable and align with machine design targets, making them unsuitable for cluster analysis. Therefore, this paper employs DBSCAN clustering on longitudinal oscillation amplitude and synchronous damping time. Based on this clustering, we investigate variations of other characteristic parameters across clusters.

DBSCAN requires determination of neighborhood ϵ and minimum samples $MinPoints$ before execution. This paper uses the k-distance graph method: first selecting a k value, then identifying the inflection point in the k-distance curve to find the neighborhood radius ϵ, yielding multiple candidate parameter sets. The optimal clustering parameters are selected by comparing clustering effects on actual sample data: $\epsilon = 0.07$, $MinPoints = 4$.

Based on DBSCAN clustering, samples are color-coded by injection date and refilled charge quantity, as shown in [Figure 4: see original paper] and [Figure 5: see original paper]. The figures reveal clear clustering patterns, with inverted triangles, triangles, squares, and diamonds representing different cluster samples, and stars indicating cluster centers. In [Figure 4: see original paper], dark blue represents 2021 samples, blue represents 2022, green represents 2023, and yellow represents 2024. In [Figure 5: see original paper], color transitions from dark blue to yellow indicate refilled charge variation from 10 pC to 90 pC. Cluster 1 (inverted triangles) primarily contains SSRF injection data from 2021-2023; Cluster 2 (triangles) mainly includes data from 2023-2024; Cluster 3 (squares) represents some injection data from March 2022; Cluster 4 (diamonds) corresponds to injection data from November 2022 to January 2023. Statistical analysis of average longitudinal oscillation amplitude, average longitudinal damping time, average ratio α, and their standard deviations for each cluster is presented in .

Besides outliers identified by DBSCAN, special anomalies occur during clustering. For example, injection samples from January 8, 2024, which should belong to Cluster 2, appear in Cluster 1. This paper categorizes causes for such occurrences: SSRF third-harmonic cavity test operation with storage ring model changes; machine studies with storage ring model changes (at 135 mA current); and machine studies for injection parameter optimization. Cluster 3 emergence is attributed to third-harmonic cavity testing during injection periods. Cluster 4 emergence is caused by unstable SSRF conditions during injection periods, with higher susceptibility to transverse coupled-bunch instabilities.

Analysis of shows that Clusters 1, 3, and 4 exhibit significantly higher refilled charge longitudinal oscillation amplitude and damping time than Cluster 2. This indicates that since 2021, SSRF has achieved substantial improvement in energy matching between the storage ring and injector, with significantly enhanced operational stability. Meanwhile, Cluster 2 refilled charges follow a normal distribution. Compared with other clusters, Cluster 2 has lower average refilled charge quantity and smaller standard deviation, demonstrating high matching between SSRF refilled bunches and the storage ring, good injector optimization, and gradually improving injection stability.

3.2 Machine Anomaly State Prediction Based on kNN Algorithm

Clustering analysis reveals storage ring operation patterns, though injection anomalies may arise from various causes. In anomaly detection, this paper adopts the perspective of determining whether injection states belong to normal categories, treating all non-normal samples as anomalies. During anomaly detection, we preserve the "center" of each normal category from different time periods—normal categories should cluster near these centers while anomalous categories should deviate from them. Samples deviating from cluster centers or falling outside their temporal intervals are considered anomalous. Label "0" is assigned as positive class (normal samples) and label "1"as negative class (anomalous samples), relabeling the storage ring injection data accordingly. Since normal injection data far outnumber anomalous data during storage ring operation, confusion matrices [20] are used to evaluate model accuracy.

A confusion matrix is a two-dimensional table structure with "actual" and "predicted" dimensions, each containing class labels. Columns represent true classes while rows represent predicted classes, as shown in .

** Confusion Matrix**

In : - **True Positive (TP):** Actual positive class correctly predicted as positive
- **False Negative (FN):** Actual positive class incorrectly predicted as negative
- **False Positive (FP):** Actual negative class incorrectly predicted as positive
- **True Negative (TN):** Actual negative class correctly predicted as negative

Initial experiments compare algorithm performance across different k values. With 587 positive (normal) samples and only 50 negative (anomalous) samples, the data exhibits severe class imbalance. Traditional accuracy metrics become ineffective (e.g., predicting all samples as positive yields ~92.15% accuracy). Therefore, metrics focusing on minority class (anomalous samples) performance are selected: - **Precision** $P = \frac{TP}{TP+FP}$: Measures proportion of correctly predicted positive samples among all positive predictions - **Recall** $R = \frac{TP}{TP+FN}$: Measures ability to correctly identify actual positive samples - **F1 Score** $F1 = \frac{2PR}{P+R}$: Harmonic mean of precision and recall for comprehensive performance evaluation

Additionally, **PR-AUC** (Area Under the Precision-Recall Curve) [21] is introduced. By plotting precision against recall at various classification thresholds, the PR curve is generated, with PR-AUC calculating the area under this curve (range 0-1). Higher values indicate better balance between precision and recall, helping select optimal classification thresholds.

Algorithm evaluation results for different k values are shown in . Results demonstrate that precision, recall, F1 score, and PR-AUC initially increase then decrease with growing k. At $k = 4$, prediction performance peaks at 0.90 precision, with highest F1 score (0.74) and PR-AUC (0.84). Recall at $k = 4$ is slightly lower than at $k = 5$. Overall, $k = 4$ yields the optimal model.

Furthermore, this paper compares kNN ($k = 4$) with Support Vector Machine (SVM), Decision Tree, Random Forest, Logistic Regression, and Naive Bayes for anomaly detection performance. Using precision, recall, F1 score, and PR-AUC as evaluation metrics, results are presented in [Figure 6: see original paper].

Comprehensive metrics show kNN performs best, particularly in precision and PR-AUC, indicating low false positive rates and high accuracy in anomaly identification. SVM achieves high precision with potentially higher computational efficiency, though slightly inferior to kNN, suggesting possible model fusion. Random Forest outperforms Decision Tree, demonstrating ensemble learning’ s anti-overfitting capability. Decision Tree may overfit, causing more false alarms. Logistic Regression’ s linear assumptions may limit capture of complex anomaly patterns. Naive Bayes performs worst across all metrics, likely due to feature independence assumptions deviating significantly from actual data.

4. Conclusion

Analysis of SSRF storage ring historical data shows that longitudinal tune and fresh bunch longitudinal initial phase remain relatively stable, consistent with machine design targets. However, longitudinal oscillation amplitude and synchronous damping time exhibit significant variations across injection events, serving as valuable data sources for accelerator operation state analysis and evaluation. The combination of unsupervised and supervised learning methods enables effective detection and early warning of injection anomalies.

In the unsupervised learning stage, DBSCAN clustering performs metric learning to analyze data spatial distribution, identifying and defining stable operation modes while labeling anomalous events. Results show some refilling events exhibit large synchronous oscillation amplitudes, indicating suboptimal matching between fresh bunch parameters and storage ring optics during those periods. Based on these findings, equipment parameters from the injector and storage ring during those timeframes can be reviewed to prevent recurrence. Among multiple operation modes identified through statistical analysis, groups with superior injection quality emerge, whose corresponding equipment parameters can serve as baseline parameters for optimized operation. In the supervised learning stage, kNN algorithm is selected through comparison to classify anomalous events, successfully identifying unstable refilling events. Analysis results demonstrate this method effectively detects anomalous injection events with 90% precision.

The anomaly prediction model developed in this study enables SSRF to optimize injection processes in several ways: When the model generates consecutive anomaly warnings, the facility has likely deviated from stable operation. Although no explicit faults such as beam loss or lifetime reduction have occurred, operators can intervene proactively to adjust relevant parameters, returning the facility to stable operation and preventing performance degradation into explicit failures.

Future research can further optimize data processing algorithms to improve real-time performance and robustness of anomaly detection. While the model accurately predicts anomalies, it cannot directly identify root causes, requiring case-by-case analysis. Additionally, deep learning methods can be introduced to enhance data analysis accuracy and generalization capability. The approach can also be extended to other accelerator facilities such as free-electron lasers and high-energy synchrotron light sources to further validate its applicability and effectiveness.

Author Contributions: Fang Zikun led model algorithm design and optimization, data processing and analysis, and manuscript drafting and revision. Jiang Tianyu contributed to algorithm implementation and manuscript writing. Zhou Yimei was responsible for experimental data collection and organization. Leng Yongbin provided research guidance, critical manuscript review, and final version approval.

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