

OPTIMIZATION OF DCCT MAGNETIC CORE MATCHING USING UNSUPERVISED MACHINE LEARNING TECHNIQUES FOR HIGH-PRECISION BEAM CURRENT MEASUREMENT*

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Abstract

DC Current Transformers (DCCTs) are essential instruments for non-interceptive beam current measurement in particle accelerators. The zero-flux modulation principle demands exceptional symmetry between paired magnetic cores to achieve sub- μA offset stability. Conventional core matching based on static magnetic parameters provides only an engineering approximation, as it neglects the dynamic magnetization behavior under AC modulation. This paper presents a novel approach employing unsupervised machine learning techniques applied to 6 dynamic magnetic parameters (μ_a , δ , B_r , B_m , H_c , H_m) measured at 50 kHz sinusoidal excitation for 19 Fe-based nanocrystalline cores. Principal Component Analysis (PCA) reduces the feature space while preserving 89.64% of total variance. An adaptive multi-objective K-Means strategy successfully isolates anomalous specimens ($K = 2$), while a density-based evaluation framework partitions the remaining operational cores into 5 highly homogeneous sub-groups. This two-tier matching scheme enables a physically rigorous core pairing that accounts for real-world dynamic magnetization and domain wall losses under actual DCCT operating conditions.

INTRODUCTION

Based on the zero-flux principle, Direct Current Current Transformers (DCCTs) are the standard for non-interceptive absolute beam current measurement in accelerators [1, 2]. In a dual-core DCCT, an AC modulation signal drives two identical toroidal cores into deep saturation. Ideally, their symmetric dynamic B - H loops cancel out even harmonics when no beam is present. However, residual magnetic asymmetry between the paired cores generates a parasitic second-harmonic signal, manifesting as zero drift [3]. For high-precision applications like the China Spallation Neutron Source Phase-II (CSNS-II) beam instrumentation, achieving sub- μA stability imposes strict requirements on core matching.

Traditional matching relies on quasi-static DC parameters (remanence B_r , coercivity H_c). However, this approach fails for Fe-based nanocrystalline alloys under dynamic AC modulation, as it ignores frequency-dependent eddy current losses, domain wall dynamics, and amplitude permeability μ_a variations that directly govern waveform symmetry.

To address these limitations, this work proposes an unsupervised machine learning approach to cluster and

pair nanocrystalline cores based on their high-dimensional dynamic magnetic responses. By applying an adaptive K-Means strategy and density-sensitive analysis to a 6-dimensional dynamic feature space, we establish a physically rigorous framework for high-precision core pairing.

EXPERIMENTAL METHODOLOGY

Core Specimens and Measurement

Nineteen toroidal core specimens wound from Fe-based nanocrystalline ribbon (nominal dimensions: OD 260 mm, ID 245 mm, H 8 mm) were fabricated by Guangzhou Jinchina Co. for the CSNS-II DCCT R&D phase. The dynamic magnetic properties of these 19 samples were fully characterized using an automated AC magnetic measurement system (LINKJOIN CX-3110AW) under a 50 kHz sinusoidal excitation condition.

Feature Selection

Based on the zero-flux modulation principle and electrical symmetry demands, 6 dynamic parameters were selected as the high-dimensional feature vector for clustering analysis: Amplitude Permeability μ_a , Loss Angle δ (deg), Remanence B_r (mT), Maximum Induction B_m (mT), Coercivity H_c (A/m) and Maximum Field Strength H_m (A/m). The statistical distributions of these extracted dynamic features across all 19 fabricated nanocrystalline specimens are summarized in Table 1.

As indicated by the data, the maximum induction B_m exhibits an extremely narrow standard deviation (0.06 mT), which confirms that all cores reached a highly consistent, predefined deep saturation level under the 50 kHz sinusoidal voltage control. Conversely, key structural-sensitive parameters such as the amplitude permeability μ_a and dynamic coercivity H_c demonstrate profound operational variance, with the maximum μ_a value exceeding its minimum counterpart by a factor of four. This remarkable intra-batch discrepancy highlights the inadequacy of traditional single-point matching methods and underscores the crucial necessity of implementing a high-dimensional clustering framework to ensure dynamic magnetic symmetry.

Data Preprocessing and Dimensionality Reduction

To eliminate scaling discrepancies among different physical units, the 6-dimensional feature space was standardized to zero mean and unit variance. Principal Component Anal-

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Table 1: Dynamic Feature Statistics for 19 Fe-based Nanocrystalline Cores at 50 kHz.

Parameter	Mean	Std	Min	Max
μ_a	29502.22	10837.33	9422.10	42827.00
δ (deg)	39.86	5.87	29.54	48.55
B_r (mT)	63.46	7.86	48.77	74.31
B_m (mT)	100.07	0.06	99.94	100.17
H_c (A/m)	2.06	1.03	0.92	4.24
H_m (A/m)	3.34	2.02	1.86	8.45

ysis (PCA) was subsequently executed for dimensionality reduction and structural visualization.

The first two principal components capture 89.64% of the total variance, where PC1 accounts for 54.07% and PC2 accounts for 35.57%. The principal component loading matrix is presented in Table 2.

Table 2: PCA Loading Matrix for the 6 Selected Features

Feature	PC1	PC2
μ_a	-0.517	-0.204
δ (deg)	-0.221	0.613
B_r (mT)	-0.207	0.624
B_m (mT)	0.234	0.417
H_c (A/m)	0.534	0.136
H_m (A/m)	0.549	-0.020

As shown by the loading factors, PC1 represents a contrast between magnetic softness and hardness: it is heavily and positively loaded by H_c (0.534) and H_m (0.549), and strongly negatively loaded by μ_a (-0.517). Conversely, PC2 is dominated by the dynamic phase and hysteresis squareness indicators, showing high positive loadings for δ (0.613) and B_r (0.624).

CLUSTERING ALGORITHMS AND RESULTS

A multi-objective unsupervised learning pipeline was implemented to isolate outliers and extract natural core groupings, leveraging advanced adaptive partition frameworks [4, 5].

Adaptive K-Means Clustering

To find the optimal global partition, an automated scan across $K = 2$ to 10 was performed using four structural indicators: Inertia, Silhouette Score, Calinski–Harabasz (CH) Index, and Davies–Bouldin (DB) Index. The multi-objective tracking metrics as a function of the cluster number K is illustrated in Fig. 1. As the cluster number increases, the evaluation framework metrics show distinct inflection points.

The adaptive algorithm selected $K = 2$ as the optimal global configuration, yielding a maximum Silhouette score of 0.5119 and a minimum DB index of 0.6287. This partition divides the specimens into:

- **Cluster 0** (16 samples): Cores 1, 2, 3, 4, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, and 19. This forms the baseline operational population.

- **Cluster 1** (3 samples): Cores 5, 6, and 7. This group represents a distinct, magnetically harder population.

DBSCAN and High-Precision Sub-Grouping

While global K-Means at $K = 2$ isolates the primary macro-populations, a density-sensitive method is recommended for high-precision DCCT pairing to prevent pairing cores with minor hidden parameter drift. A local within-cluster variation analysis was executed to segment the 19 cores into tighter, highly homogeneous sub-groups. The recommended pairing structure divides the specimens into 5 distinct groups, as outlined in Table 3.

Table 3: Final Core Pairing Groups for DCCT Balancing

Group	Member Cores	Characteristics	Count
0	5, 6, 7	Anomalous; high H_c , low μ_a	3
1	2, 3, 4	High μ_a , low loss phase δ	3
2	8, 9, 10, 12	Moderate μ_a , medium losses	4
3	1, 13, 17, 19	Stable B_r , medium-high δ	4
4	11, 14, 15, 16, 18	Baseline oper. norm	5

The multi-dimensional projection and the established cluster boundaries are visualized in the two-dimensional PCA score space in Fig. 2, displaying clear group separation. Furthermore, the standardized multi-parameter profiles for each specific subgroup are detailed in the radar chart shown in Fig. 3, which graphically defines the unique dynamic magnetic signature of each operational baseline family.

DISCUSSION

Physical Interpretation of Clusters

The unsupervised clustering reveals a significant structural variance within the 19 nanocrystalline rings. As shown in the PCA score space (Fig. 2), Group 0 (comprising cores 5, 6, and 7) exhibits an explicitly isolated position. Physically, these three cores suffer from lower amplitude permeability μ_a and substantially higher dynamic coercivity H_c and maximum field strength H_m . This behavior indicates a higher density of domain wall pinning sites, likely originating from residual internal mechanical stress or local crystallization deviations during industrial vacuum heat treatment.

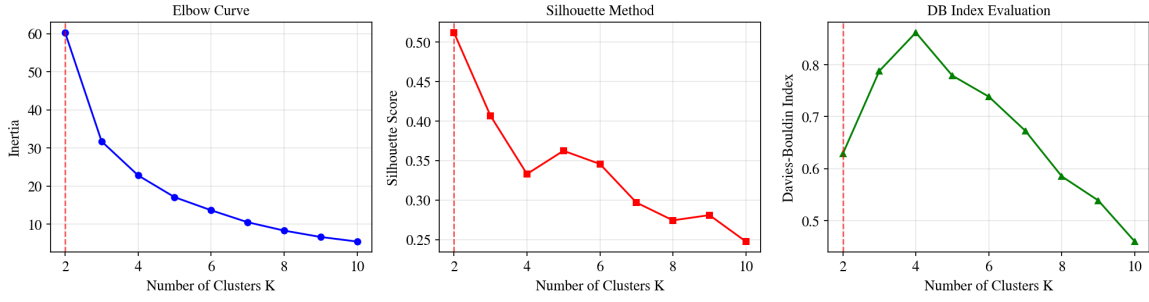


Figure 1: Evaluation of cluster structural metrics (Inertia, Silhouette, CH, DB indices) as a function of cluster number K .

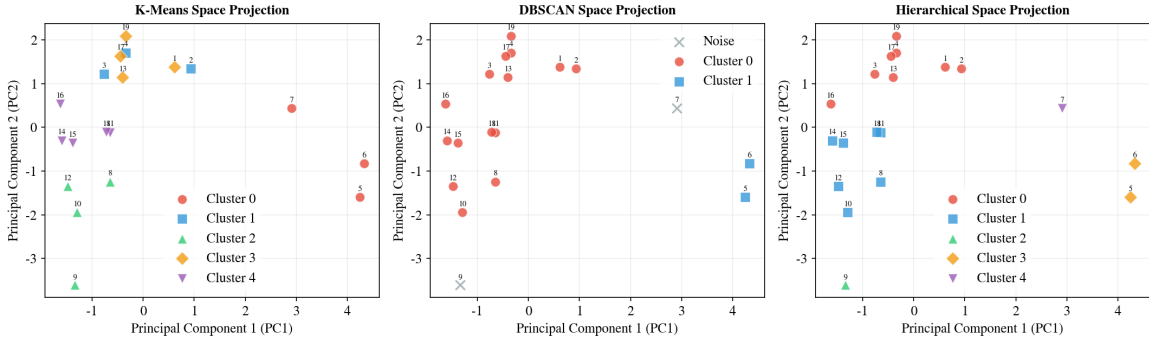


Figure 2: Comparison of sample distributions and cluster boundaries within the 2D PCA score space.

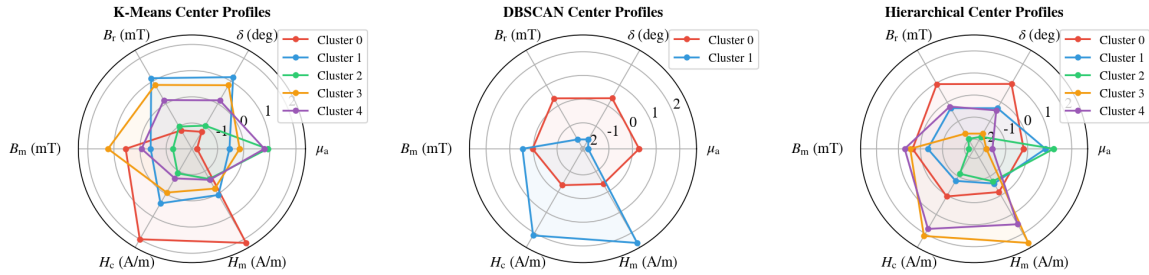


Figure 3: Normalized feature profiles (radar visualization) highlighting the distinct dynamic signatures of each core group.

Groups 1 through 4 break down the remaining 16 normal operational cores into localized, highly tight sub-clusters based on subtle variations in their dynamic loss angle δ and remanence B_r . According to the normalized feature profiles in Fig. 3, cores within Group 1, for example, show exceptionally high permeability coupled with minimal phase lag δ , making them premium candidates for ultra-low noise modulator operation.

Two-Tier Core Matching Strategy

To maximize the zero-flux cancellation and lower the DCCT offset drift, we propose a two-tier screening and pairing protocol based on these machine learning findings:

1. **Tier 1: Structural Isolation:** Filter out Group 0 (cores 5, 6, 7) from standard high-precision pairing. Mixing an anomalous core from Group 0 with any normal baseline core would break the modulation waveform symmetry, leaking huge even-harmonic residuals into the sensor output.
2. **Tier 2: Intramural High-Precision Pairing:** Execute final dual-core assembly strictly within each homoge-

neous group. For example, cores (2, 3) from Group 1, (8, 9) and (10, 12) from Group 2, and (1, 13) and (17, 19) from Group 3 can form highly symmetric twin-core channels. The coefficient of variation within these specific sub-groups is minimized, ensuring nearly identical B - H trajectory matching under 50 kHz AC modulation.

CONCLUSION

We have demonstrated that unsupervised machine learning applied to a 6-dimensional dynamic feature space offers a robust, quantitative, and automated framework for DCCT magnetic core selection. For the 19 Fe-based nanocrystalline cores tested at 50 kHz, the multi-objective algorithm successfully isolates manufacturing anomalies (Group 0) and establishes 4 high-homogeneity operational sub-groups to ensure excellent dynamic waveform symmetry under real-world excitation conditions. Future work will focus on tracking the zero-flux offset drift of assembled DCCT prototypes using cores matched via this protocol to experimentally validate the correlation between cluster distance metrics and long-term instrument resolution.

REFERENCES

- [1] K. Unser, "A toroidal DC beam current transformer with high resolution," *IEEE Trans. Nucl. Sci.*, vol. 28, no. 3, pp. 2344–2346, 1981. [doi:10.1109/TNS.1981.4331686](https://doi.org/10.1109/TNS.1981.4331686)
- [2] J.-C. Denard, "Beam current monitors," in *Proc. CERN Accelerator School: Beam Diagnostics*, Dourdan, France, 2009, pp. 141–155. [doi:10.5170/CERN-2009-005.141](https://doi.org/10.5170/CERN-2009-005.141)
- [3] K. Unser, "The parametric current transformer: a beam current monitor developed for LEP," *AIP Conf. Proc.*, vol. 252, pp. 266–275, Apr. 1992. [doi:10.1063/1.42124](https://doi.org/10.1063/1.42124)
- [4] J. Handl and J. Knowles, "Multi-Objective Clustering and Cluster Validation," in *Multi-Objective Machine Learning*, Y Jin, Ed. Berlin, Germany: Springer Berlin Heidelberg, 2006, pp. 21–47. [doi:10.1007/3-540-33019-4_2](https://doi.org/10.1007/3-540-33019-4_2)
- [5] A. Ram, A. Sharma, A.S. Jalal, A. Agrawal, R. Singh, "An Enhanced Density Based Spatial Clustering of Applications with Noise," in *Proc. 2009 IACC*, vol. 04, pp. 1475 - 1478, 2009. [doi:10.1109/IADCC.2009.4809235](https://doi.org/10.1109/IADCC.2009.4809235)