ISBN: 978-3-95450-261-5 ISSN: 2673-7000 doi: 10.18429/JACoW-NAPAC2025-WEYN01

MACHINE LEARNING ENHANCED DETERMINISTIC FEEDBACK CONTROLS IN LASERS AND ACCELERATORS*

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Abstract

Modern laser and accelerator systems require fast, precise, and scalable multi-input multi-output (MIMO) feedback control. As performance demands grow, particularly in high-repetition-rate and nonlinear regimes, traditional strategies face increasing limitations in speed and adaptability. This paper summarizes two application cases of machine learning (ML)-enhanced deterministic feedback control. In both cases, ML models trained on experimental or simulated data provide rapid predictions to support real-time decision-making. Integrated with conventional feedback loops, these models improve response time and robustness across operating conditions. At Lawrence Berkeley National Laboratory, ML feedback enabled the first preemptive pointing stabilization at the BELLA Petawatt beamline, achieving a ~60% reduction in jitter, and reduced response time in a coherent beam combining system by nearly an order of magnitude. These results show that ML can increase speed, stability, and adaptability without compromising determinism, opening new opportunities for intelligent control in next-generation facilities.

INTRODUCTION

High-energy particle accelerators and high-power laser systems are among the most complex scientific instruments in use today, supporting research from fundamental physics to materials science. These systems are challenging to control due to tight tolerance requirements, numerous tunable parameters, environmental disturbances, and nonlinear, cross-coupled responses [1, 2]. Feedback control is widely used to maintain stability and optimize performance [3]. In this work, we present a concise summary of two ML-enhanced deterministic feedback applications, laser pointing stabilization at the BELLA Petawatt beamline [4] and coherent beam combining (CBC) of fiber lasers [5–7], highlighting key methods and results without repeating all details from the original publications.

Feedback control is a foundational technique widely employed in both accelerator and laser systems [3]. As illustrated in Fig. 1, a typical feedback loop consists of sensors that provide measurements of system behavior, a controller that adjusts system variables in response, and a feedback algorithm, effectively the "brain" of the loop, that interprets the sensor data to compute correction signals. The goal is to maintain system stability or optimize performance despite disturbances and drift. Depending on the application, the measured signals can include laser beam pointing [4, 8], spatial diffraction patterns [5–7], magnetic quench indicators, RF waveforms, or accelerator beam trajectories derived from beam-position monitors.

Traditionally, feedback algorithms have relied on two broad approaches: model-based control, where a physics-based reverse model is used to compute corrections [9], and black-box methods such as dither-and-search, which iteratively optimize system performance without explicit models [10, 11]. In this work, we extend these paradigms by integrating data-driven machine learning (ML) models into the feedback loop. These ML-enhanced algorithms maintain deterministic behavior while enabling faster control [12]. We demonstrate this approach in two challenging applications: real-time laser alignment and coherent laser beam combining, showing how ML can improve precision and response time beyond the limits of conventional methods.

ML-ENHANCED REAL-TIME CONTROL IN LASER POINTING STABILIZATION AT BELLA PETAWATT/1Hz BEAMLINE

Requirements and Control Challenges

High-power lasers have enabled major advances in areas such as particle acceleration, advanced imaging, and future energy technologies. Among these, laser-plasma accelerators (LPAs) stand out for their potential to significantly reduce the size and cost of high-energy accelerators. However, LPAs are extremely sensitive to laser pointing stability, micron-scale shifts in the laser axis can cause substantial errors in the electron beam trajectory. For future applications like X-ray free-electron lasers or collider-grade LPAs, pointing stability on the order of microradians is required.

Passive stabilization techniques help mitigate slow drifts but are insufficient on their own, as thermal effects, mechanical vibrations, and other environmental factors can introduce long-term instabilities. Active feedback systems are needed to compensate for these disturbances, but they are fundamentally limited by the repetition rate of the high-power laser system, which is often too low to support rapid corrections.

* This work is supported by the Office of Science, Office of High Energy Physics, of the U.S. Department of Energy, and the Laboratory Directed Research and Development Program of Lawrence Berkeley National Laboratory under contract no. DE-AC02-05CH11231.
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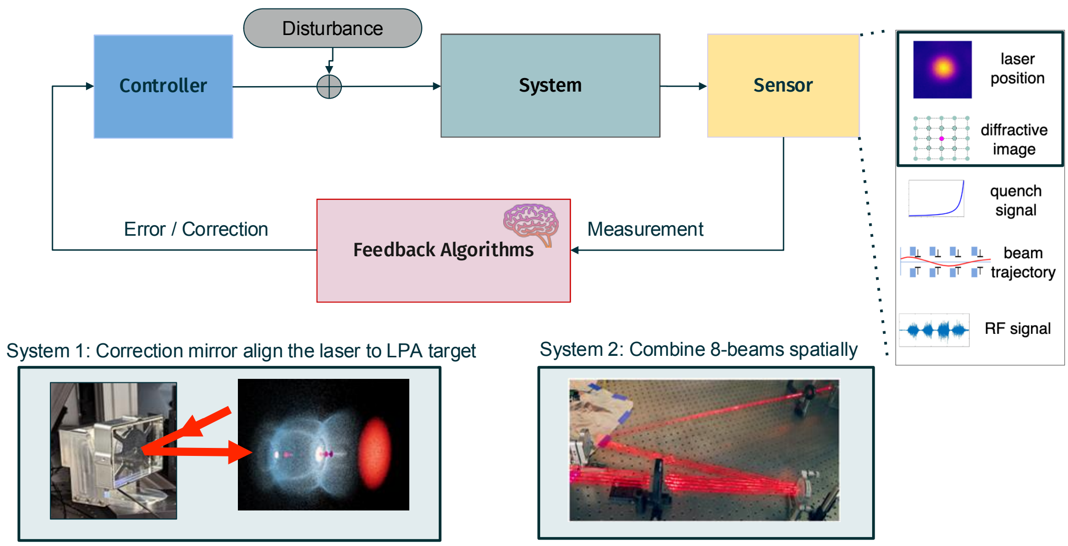

Figure 1: Basic concept of machine learning enhanced feedback control loop, with applications in laser pointing system and the laser combining system.

ML-Based Solution

To overcome the limitations described above, many systems employ a co-aligned, low-power "pilot" beam that operates at a much higher repetition rate than the main high-power beam. This pilot beam enables high-bandwidth monitoring and diagnostics, providing a faster stream of data to inform feedback control. However, the use of large, high-inertia optics, such as beam-steering mirrors, introduces latency, which remains a bottleneck even with fast diagnostic signals.

As shown in Fig. 2, we observed that the pilot beam is strongly correlated with the main petawatt (PW) beam, as both share the same optical path [13,14]. Operating at 1 kHz, the pilot beam captures system perturbations up to 500 Hz, allowing us to resolve fast fluctuations that are invisible in the 1 Hz main beam diagnostics. This high-rate data is crucial for training ML models that require full-spectrum error information; by contrast, 1 Hz signals lack sufficient temporal resolution for meaningful learning or prediction.

Time-series forecasting using machine learning is widely applied across many industries, ranging from stock market prediction to weather and traffic forecasting. Neural networks (NNs), in particular, can model complex, nonlinear mappings from input to output in high-dimensional spaces through trainable weights and biases.

In our application, we train the NN to use recent kHz pilot beam data to predict the future pointing error of the 1 Hz main beam. This enables us to actuate the steering mirror approximately 20 ms ahead of time, just before the main beam arrives, using the predicted correction. As a result, the mirror settles at the optimal position in advance, effectively canceling the main beam pointing error and ensuring alignment with the target reference.

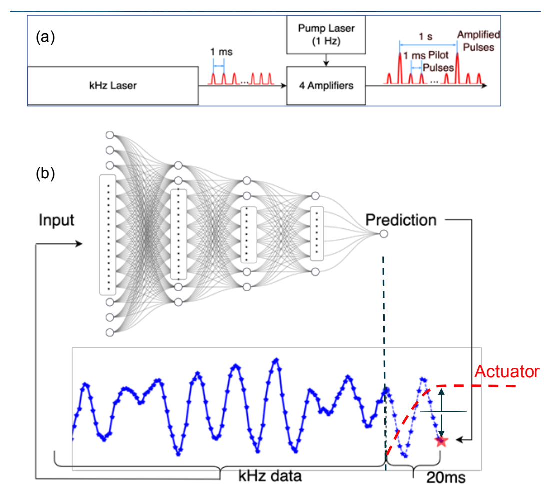

Figure 2: Schematic of the ML-enhanced feedback loop for laser pointing stabilization at the BELLA Petawatt beamline. A high-repetition-rate pilot beam shares the optical path with the main beam and is used to train a neural network (NN) predictor. The NN forecasts the pointing error 20 ms in advance, allowing the system to preemptively adjust the laggy steering mirror and cancel beam jitter in real time.

Neural Network Training and Simulation Results

The neural network (NN) is trained by optimizing its weight and bias parameters to minimize the root mean square (RMS) prediction error, defined as:

$$\mathrm{RMS} = \sqrt{\frac{1}{2}\left[\left(y_{\mathrm{predict}} - y_{\mathrm{real}}\right)^2 + \left(x_{\mathrm{predict}} - x_{\mathrm{real}}\right)^2\right]} \quad (1)$$

As illustrated in Fig. 3(a), the model is trained using labelled data: 600 time steps (corresponding to 0.6 s of history) from the 1 kHz pilot beam are used to predict the main beam's pointing position 20 ms later. As training progresses

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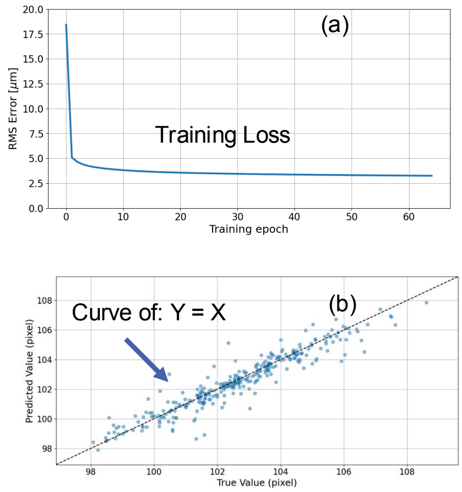

Figure 3: (a) Training loss curve showing the decrease in RMS prediction error with increasing training samples and epochs. (b) Parity plot comparing predicted and ground truth centroid positions on test data. The close agreement along the diagonal line indicates accurate model predictions.

with more samples and epochs, the loss function steadily decreases.

We implemented a multilayer perceptron (MLP) model with 1,200 input neurons, corresponding to 600 × 2 inputs for the X and Y directions, followed by two hidden layers of 600 neurons each. This architecture was selected through hyperparameter optimization using Optuna [15], achieving a balance between model complexity and computational efficiency for real-time feedback deployment.

Once trained, the NN was evaluated on unseen test samples. As shown in Fig. 3(b), the predicted outputs closely match the true values along the diagonal, indicating strong generalization. The residual error represents the inherent limit of the model's predictive accuracy.

To quantify the improvement, we compared the RMS centroid deviations before and after applying ML-based corrections. The relative reduction is defined as the fractional drop in RMS between the free-running (uncorrected) and corrected cases. In simulation, the ML-enhanced control reduced the pointing error by 77.4% in the X direction and 57.5% in the Y direction.

Experimental Results

The experimental setup is shown in Fig. 4(a), which depicts the beamline layout at the BELLA Center. These tests were conducted using a 30 mJ beam under TW-class operation.

As presented in Fig. 4(b), activating the ML-based feedback loop resulted in a significant reduction in beam pointing jitter. The root mean square (RMS) of the centroid distribution was reduced to 4.6 μm in the X direction and 7.9 μmin the Y direction. Compared to the uncorrected (free-running) case, this corresponds to jitter reduction.

ML-ENHANCED REAL-TIME CONTROL IN COHERENT BEAM COMBINING (CBC) SYSTEMS

Control Challenges

Coherent beam combining (CBC) of fiber lasers offers a path to scalable high-power laser systems, but maintaining phase coherence across multiple beams presents significant challenges. The laser phase cannot be directly measured and must be inferred from intensity, which is often ambiguous due to the non-unique mapping from phase to intensity. Additionally, the phase state drifts continuously due to environmental and laser-induced perturbations. As the number of combined beams increases, maintaining high-speed feedback becomes more difficult. While group delay is commonly controlled, other drifting parameters remain uncorrected, complicating system dynamics.

Several methods have been developed to estimate phase errors for feedback control. One approach uses secondary interferometers to measure the phase of each beam relative to a reference, but this significantly increases system complexity and optical components [16]. Iterative phase retrieval methods are typically too slow and sensitive to noise for real-time control [17]. LOCSET, which uses electronic frequency tagging, reduces the number of detectors needed but cannot scale well due to bandwidth constraints on the dither frequencies [18]. The most common method is stochastic parallel gradient descent (SPGD), which optimizes the combined beam power by dithering input phases. While effective in continuous-wave and high-repetition-rate systems, SPGD requires roughly ten feedback steps per beam [19], making it too slow for kHz-level pulse combination with hundreds of channels. Moreover, the dithering process introduces noise and instability.

Machine learning control (MLC) has emerged as a promising alternative for CBC systems. By combining data-driven learning with control-theoretic principles, MLC can address the complexity and dynamic nature of large-scale CBC. Early studies have shown that reinforcement learning (RL) controllers can successfully maintain phase coherence in two-beam systems and scale up in simulation to 128-beam temporal combinations [20, 21]. Experimental demonstrations using spatial light modulators have achieved coherent combination of 100 beams with RL-based control [22]. These results suggest that ML approaches could overcome the limitations of traditional feedback methods, enabling scalable, fast, and noise-tolerant control for high-power laser systems.

Despite this promise, a critical barrier remains: in practical CBC systems, the phase state is not directly observable, and the measurement data is noisy and constantly drifting. As a result, collecting high-quality, labelled training data, i.e., mapping observed interference patterns to known control corrections, is often infeasible. This limits the applicability of standard supervised learning approaches. Without reliable ground truth, training a machine learning model to perform robust real-time feedback becomes a significant

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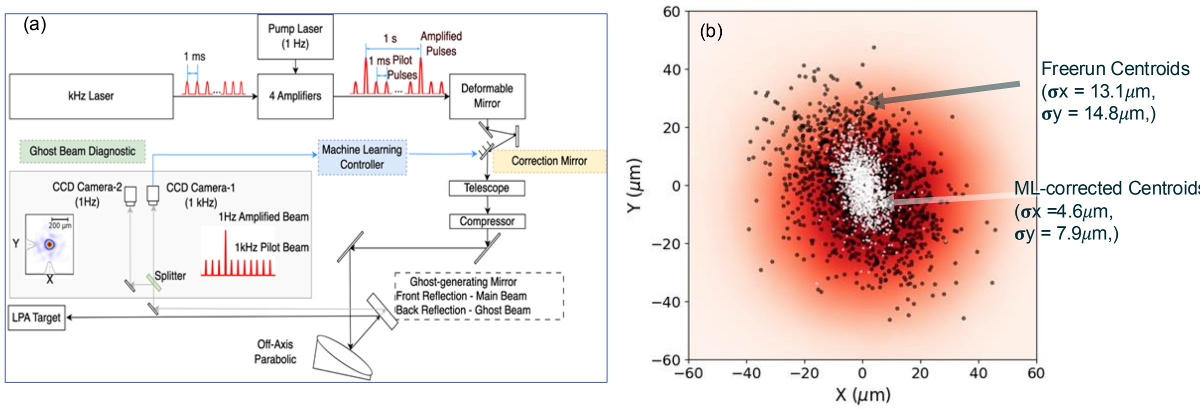

Figure 4: (a) Experimental setup at the BELLA Center showing the beamline configuration used for pointing stabilization tests with a 30 mJ laser beam (TW-class operation). (b) Centroid distribution before and after applying ML-based correction. The ML-enhanced feedback significantly reduced beam jitter in both transverse directions.

challenge. This motivates the development of alternative training strategies that do not require clean labels or steady-state conditions.

Differential Learning Solution: Deterministic Differential Remapping (DDRM)

Our novel machine learning approach, called the Deterministic Differential Remapping Method (DDRM) [6, 7, 23], as shown in Fig. 5, is designed to address the challenges of phase drift and labeling ambiguity in pattern-based feedback control. Instead of learning absolute mappings between observed interference patterns and control actions, DDRM trains the ML model to learn differential relationships between states.

The core idea is to inject a known dither into the system and record the resulting pattern before and after the perturbation. The network then learns to associate this pattern change with the corresponding phase space shift. During feedback operation, the controller receives the current pattern and compares it with a target (typically the highest-efficiency pattern). The ML model infers the control adjustment,i.e., the phase correction vector, needed to transform the system from the current to the target state.

In other words, the neural network is trained to correlate changes in observed patterns with changes in control variables, effectively learning the system's local Jacobian. This makes the method robust to long-term drift and eliminates the need for explicitly labelled data. The system can be retrained in real time during operation, enabling continuous adaptation.

Conceptually, DDRM mirrors human intuition: we learn to manipulate a system by observing how it reacts to controlled inputs. As long as the dither signals are applied faster than the system drifts, DDRM allows the network to learn and operate reliably, even in nonstationary, unstable environments.

Experimental Results on 8-Beam Spatial Combining

We implemented the differential learning scheme on an 8-beam spatial combiner. Training completed in under 40 seconds, with phase drift during training limited to less than 1.4°. Once deployed, the system maintained stable beam combining performance within 0.4% variation for over 30 minutes [7].

Figure 6 presents the experimental comparison between the conventional SPGD algorithm and our neural network-based feedback. Starting from random phase states, both methods require multiple correction steps to reach optimal combining. However, the ML controller achieves convergence in approximately 0.3 seconds, an order of magnitude faster than the 3 seconds required by SPGD, demonstrating its significant advantage in convergence speed.

Scalability of ML-Enhanced Feedback Control

Our differential learning method is well-suited for addressing scalability challenges in coherent beam combining. The network requires only local training, i.e., small perturbations around the operating point, yet generalizes effectively across a wide range of starting states, including complete loss of lock. This reduces model complexity, minimizes data requirements, and supports rapid retraining during operation.

We have demonstrated scalability through simulations of a 9×9 (81-channel) beam combiner [23]. As shown in Fig. 7, our ML-based control scales much better than the traditional SPGD algorithms.

CONCLUSION AND SUMMARY

We demonstrated that machine learning-enhanced deterministic feedback enables fast and scalable control in laser and accelerator systems. At the BELLA Petawatt beamline, an ML model trained on high-rate pilot beam data enabled preemptive pointing stabilization, outperforming conventional feedback limited by low repetition rates and actuator lag. For coherent beam combining, we developed

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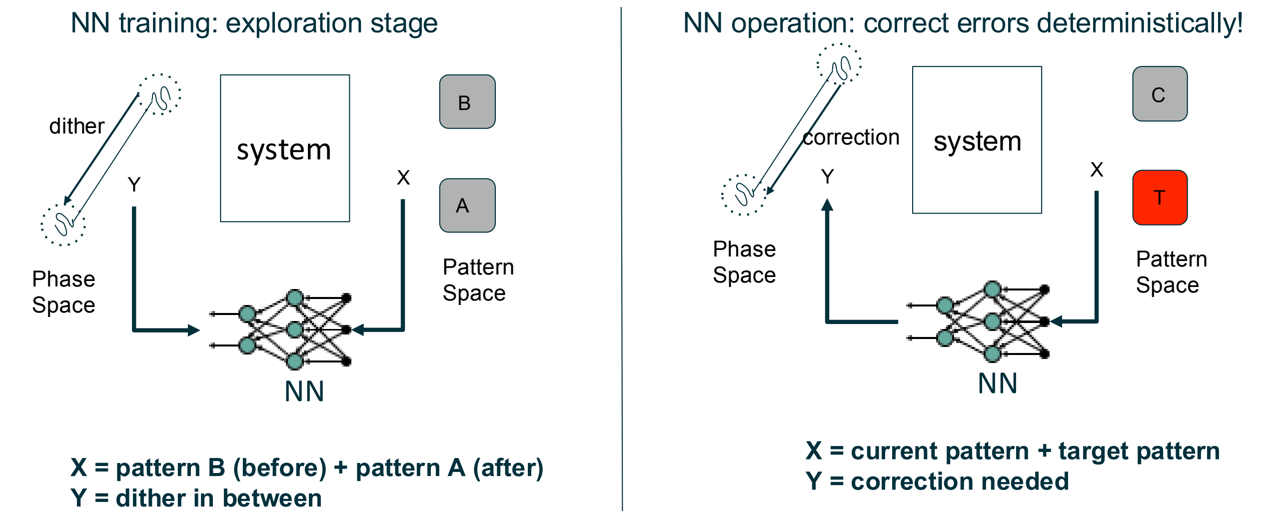

Figure 5: Conceptual diagram of the Deterministic Differential Remapping Method (DDRM). Known dither signals are applied to the system, and the resulting pattern differences are used to train a neural network to predict differential control actions. During feedback operation, the ML model compares the current pattern to a reference target and generates the required phase correction vector to achieve coherent beam combining.

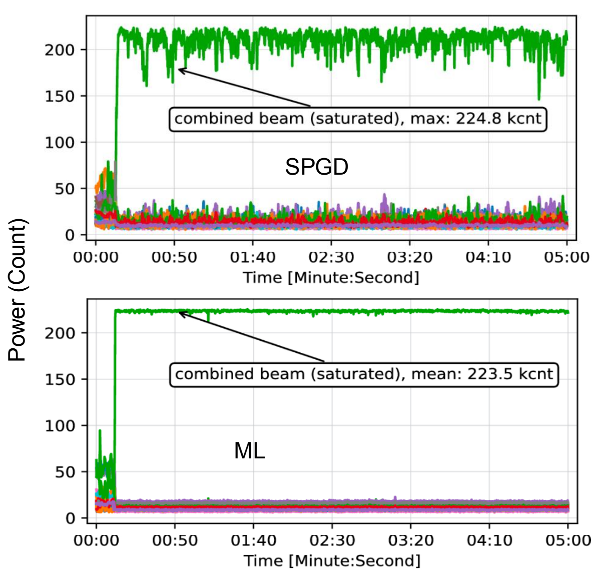

Figure 6: Experimental comparison between SPGD and ML-based feedback on an 8-beam spatial combiner. The neural network controller converges to the optimal phase state faster than SPGD with more stable performance.

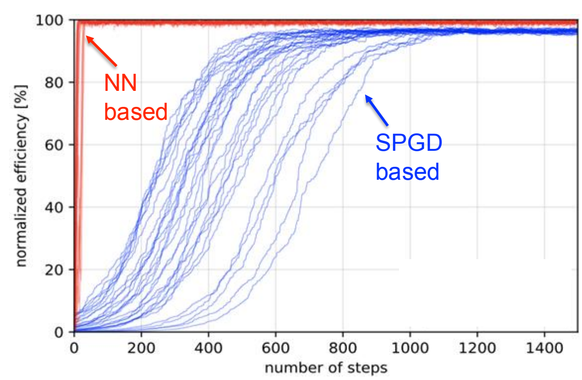

Figure 7: Scalability study of ML-based control for CBC systems with 9 × 9 input beams. The neural network controller outperforms the traditional SPGD algorithm in both convergence speed and final performance.

the Deterministic Differential Remapping Method (DDRM), allowing robust, label-free training under drifting conditions. Experimental results on an 8-beam combiner showed over 10× faster convergence than SPGD, while simulations with 81 beams confirmed the approach's scalability. These results highlight ML's potential to improve precision control across a broad range of advanced photonic and accelerator applications.

ACKNOWLEDGMENT

We want to thank all the collaborators in LBNL: Larry Doolittle, Carlos Serrano, Vamsi Vylta, Remi Lehe, Daniele Filippetto, Gang Huang, Yilun Xu. Collaborators from University of Michigan: Almantas Galvanauskas, Mathew Whittlesey, Alexander Rainville, Lauren Cooper, Hanzhang Pei, et al. And thanks to all the collaborators from SLAC: Zhe Zhang, Xiaobiao Huang.

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