Fusion Engineering and Design 199 (2024) 114126

Contents lists available at ScienceDirect

Fusion Engineering and Design

journal homepage: www.elsevier.com/locate/fusengdes

Efficiency improvement of pulse waveform shaping on high power laser facility using deep learning

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ARTICLE INFO

Keywords:
Pulse waveform shaping
Iterative way
Deep learning
Operation efficiency

ABSTRACT

Laser pulse shaping is one of the key and time-consuming processes for preparing a shot on a high power laser facility. The frequent shifts of laser pulse waveform between shots makes improving laser pulse shaping efficiency an urgency. By combining historical dataset accumulated by iterative way of pulse shaping system and prevailing deep learning method, a U-Net modal is trained and applied on our laser facility. Now the pulse waveform shaping system integrated with this modal is capable of shaping and qualifying most of laser pulse waveforms in less than 5 s. As for part of unqualified outputs, a strategy of first deep learning prediction and then iterative way is able to fix all the rest, which cuts down roughly 80 % percent of time consumption, comparing with the absolutely iterative way.

1. Introduction

Laser-fusion researchers have turned to machine-learning techniques to seek the combinations of laser pulse characteristics and target design to optimize experiments [1–5]. Benefitting from a wealth of data, statistical mapping turns inaccurate code outputs into accurate predictions. This predictive capability led to tripling the fusion yield on OMEGA in just several shot days [6]. The National Ignition Facility (NIF) has a team using machine learning to improve their experimental results and urges applying all promising methods until ignition in hands [7,8]. On December 5th, 2022, NIF performed the first experiment demonstrating controlled fusion ignition in the laboratory. With a 2.05 MJ UV laser drive energy delivered to the target, a neutron yield of 3.15 MJ was released by the fusion reactions in the capsule, providing a net target gain of ~1.5× [9,10]. Employing enormous and historical data to seek optimization in ICF research has become a consensus. Inspired by this, the operation efficiency of laser facility can also seek help from this method to go through some bottlenecks. One of the most critical and time-consuming process in facility operation is laser pulse waveform preparation. NIF has established autonomously iterative pulse-shaping system, which takes 1 hour of execution time to prepare laser pulse waveform [11]. For the largest laser facility in China, due to the limitation of iterative method and singly measuring amongst bundles, also approximately 1 hour is needed to execute pulse-shaping process for all beamlets during only 2.5 hour of shot-to-shot interval, which occupies beamline preparation time and often puts off the whole procedure of next shot. How to speed up pulse-shaping process to satisfy frequent shifts of laser pulse waveform between shots is becoming urgent.

The mechanism of laser pulse shaping is using an electro-optic modulator to vary laser pulse waveform in response to summed electrical impulses [12,13]. Each impulse has a width of 150 ps and a temporal separation of 100 ps. The process of laser pulse shaping is adjusting the amplitude of each electrical impulse and summing them to generate the desired experimental laser pulse waveform. Due to the diversity of multiple components throughout the traveling journey from electrical pulse to feedback point, each beamlet is similar to each other, but also owns its distinctive trait. With adequate consideration of response mechanics and diversity between beamlets, the currently iterative algorithm and process is an optimal method in status quo. It usually takes about 15 rounds of iteration to accomplish mostly arbitrary laser pulse waveform. And for high contrast laser pulse waveform, e.g. higher than 15:1, it is much tardier on low foot part and proceeds more rounds. Even so, it has been a long time, and we have not found any way to enhance operation efficiency. Until now, the booming of deep learning seems to open a new door to explore more possibilities. Laser pulse shaping is a typical scenario of predicting input with a given goal.

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https://doi.org/10.1016/j.fusengdes.2023.114126
Received 29 October 2023; Received in revised form 29 November 2023; Accepted 23 December 2023
Available online 5 January 2024

Now that the reversing transformation from a laser pulse waveform to electrical pulse is technically intricate to implement, we hand over this problem to deep learning.

In this paper, deep learning is applied in pulse-shaping process to enhance operation efficiency on high power laser facility. Combining historical data of electrical pulses and laser pulse waveforms accumulated by iterative way, a deep learning modal of reversing transformation trained by U-Net is proposed and applied.

2. Deep learning model construction

2.1. Pulse waveform shaping process

Fig. 1 depicts iterative method executing pulse-shaping process. With a given goal of laser pulse waveform, the iterative method repeats the procedure of loading, measuring, calculating and calibrating to procure electrical pulse. If a deep learning model has mastered their mapping rule and takes over this process, it will figure out electrical pulse directly in less than 5 s. So we start training a model to learn their mapping rule by feeding historical data of electrical pulse and laser pulse waveforms.

2.2. Data preparation

Sufficient data is the primary ingredient to drive a modal training [14,15]. But for current database on each beamlet, only 20 to 40 pairs of electrical pulse and measured laser pulse waveforms are eligible for training. Then here is a dilemma, that it is necessary to build a model for each beamlet with its own data pairs for their individual diversity, while the amount of data is not able to support this idea. So the thought of one modal for one beamlet by its own data has to be discarded. As ref [13] introduced, the response mechanics is similar among all beamlets. Meanwhile, the disparity on each beamlet exists due to integration of each nuanced components. An idea of a generalized modal for all beamlets is proposed, with beam name tags of data pairs in data preparation process. By this way, data pairs are enriched for similarity among beams, and meanwhile beam name plays a feature role for disparity between each other. A further measure of coping with data insufficiency is data augmentation, which is embedded in deep learning process. Fig. 2 illustrates the operation of data augmentation, moving electrical pulse and laser pulse waveform along time-axis randomly. With the consideration of involving all lengths of experimental pulses and augmented data, each pairs of data is extended to 160 points via adding zeros and each point represents one electrical impulse . With these two solutions, training set for this generalized modal is ready.

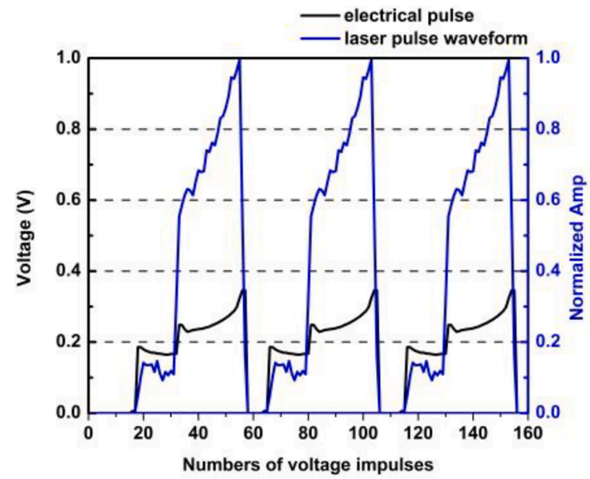

Fig. 2. Data augmentation by moving data paris along time-axis.

2.3. Network construction

With all above ideas about algorithm and data preparation for deep learning, a neural network of U-Net tested effective in pulse waveform scenario [16,17] is employed in this situation. It consists of 11 convolution layers (Conv1D), 4 upper sampling layers (UpSampling1D), 4 maximum pool layers (MaxPooling1D), and 2 Concatenate layers. The U-Net is approximately symmetrical U shape, whose left side is about contraction and the other side is expansion. The role of these convolution layers, which is activated by ReLU function, is to extract waveform features. But with an excess of layers, side effect starts emerging, e.g., features learnt from the front layer may be lost in the backward transmission. Therefore, cross-layer stitching is requisite to preserve data features intact. Throughout these design and consideration, the integrated network architecture is defined in Fig. 3.

Loss function and optimizer are the keys to configuring the learning process [14]. The loss function compares the predictions to the historical

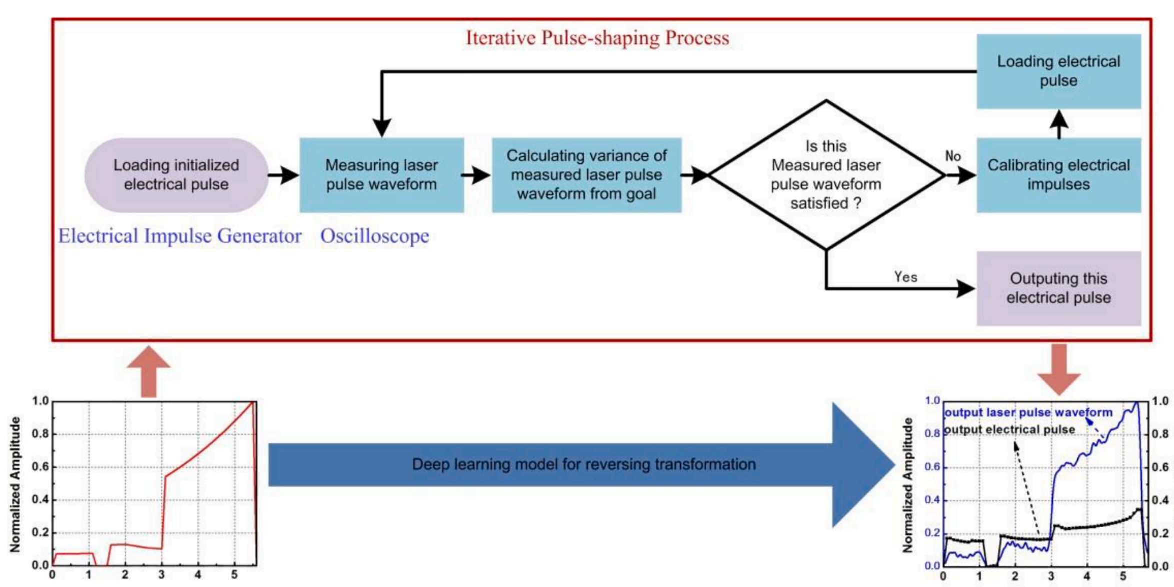

Fig. 1. Procedure of iterative method compared with schematic of directly prediction by deep learning.

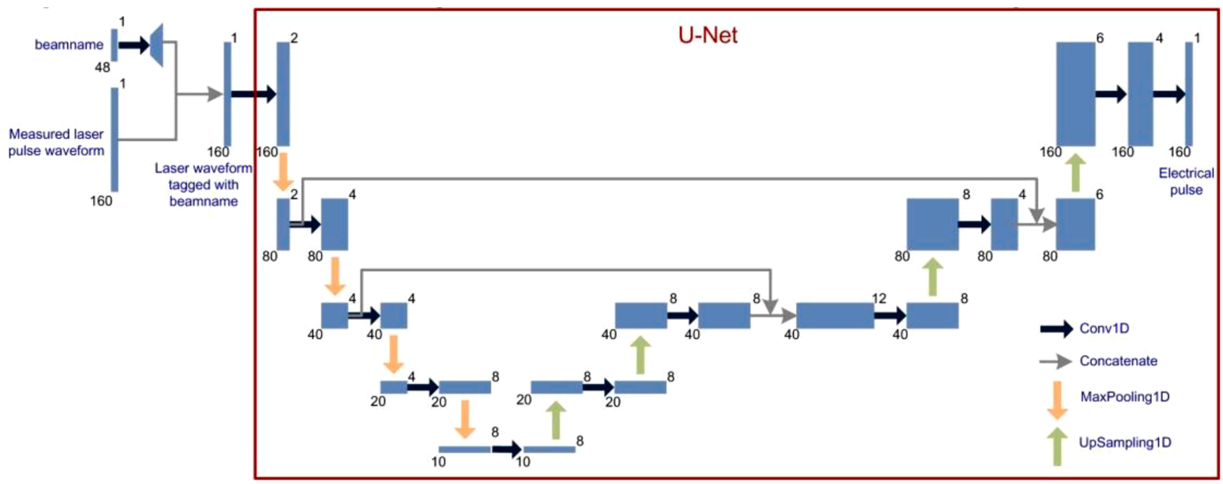

Fig. 3. Procedure of iterative way and schematic of directly predicting by deep learning.

data, producing a loss value of electrical pulse, which should be minimized in the training process. The loss function designed for this case involves an absolute error and a gradient error to insure a high training speed. α is the weight of gradient error, which is set empirically at the value of 0.001 according to training trial. Optimizer helps update the network's weights by using loss value and optimization scheme of Adam [18]. The formula of loss function is expressed in Eq. (1).

$$Loss = \sum_{i=1}^{N} \left| y_i - y_i^{'} \right| + \alpha \sum_{i=1}^{N} \left| \frac{\Delta y_i - \Delta y_i^{'}}{\Delta t_i} \right| \tag{1}$$

Where y_i is the true electrical pulse, $y_i^{'}$ is the predicted electrical pulse, $\Delta t_i$is time interval equaling to one electrical impulse.

2.4. Modal training

The training process was implemented by Python 3.6 on a workstation, using Keras framework with Tensorflow backend. 902 pairs of training data and 139 pairs of validation data anticipated in training process. In order to monitor the accuracy of the model on data it has never seen before, the model was trained for 500 epochs in batches of 500 stochastic pairs of samples supplemented by data augmentation. Loss and accuracy after every epoch was monitored at the same time. As Fig. 4 shown, the training and validation loss are both decreasing round every epoch without appearing overfitting. The above all training process took approximately 3 h 28 min.

Finally, the accuracy of this model was evaluated on 141 sets of test data. The predicted electrical pulses are calculated by model with inputting measured laser pulse waveforms from test data. The mean absolute percentage error (MAPE) expressed as Eq. (2) and root mean square error (RMSE) expressed as Eq. (3) are shown in Fig. 5, evaluating the accuracy [16] between the predicted and test data, which performs an averaged MAPE of 2.78 % and RMSE of 0.42 % . It is a high accuracy of direct reversing transformation.

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left(\left| \frac{y_i^{'} - y_i}{y_i} \right| \right) \tag{2}$$

$$RMSE = \sqrt{\sum_{i=1}^{N} \left(\frac{y_i^{'} - y_i}{y_i} \right)^2 \Big/ N} \tag{3}$$

3. Application

3.1. Application effects

Now the trained model is integrated to pulse-shaping system on facility in Refs. [19,20] and works well. Consistently, the hard wares work in the condition as same as the historical data archived. The electrical impulse generator is adjustable in the span of 0–0.35 V. Laser wavelength is 1053 nm. The feedback point is located after an electro-optic modulator and several amplifiers at output energy of approximately 10 μJ, measuring laser pulse waveform by a photoelectric detector with

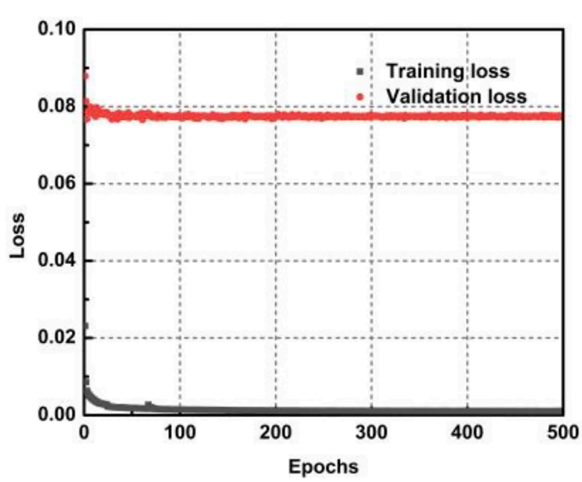

Fig. 4. Training and validation loss.

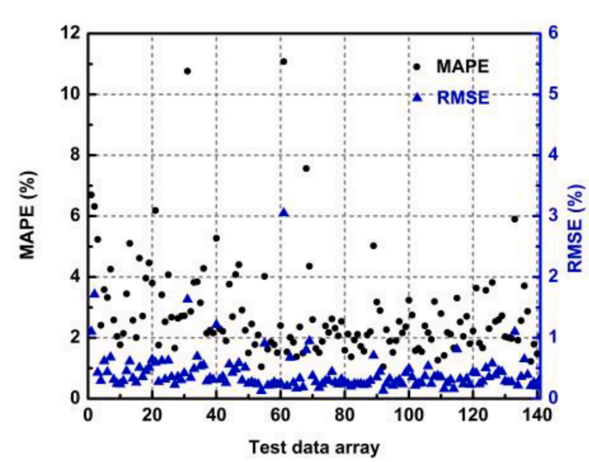

Fig. 5. The prediction accuracy on test data.

a response wavelength from 300 to 1100 nm and a response time of 60 ps, and a digitizing oscilloscope with a responding frequency of 8 GHz.

Figs. 6–8 reveals the application results by deep learning model. For the multiple beamlets on facility and finite layout here, 6 beamlets from different bundles are represented in Fig. 6. The red line is the goal waveform with a contrast ratio from 14:1 to 16:1 between the highest peak and the first platform, the blue line is the laser pulse waveform generated by predicted electrical pulse. Noted that, in the application scenario, the prediction accuracy is also evaluated by RMSE [13], which is between the laser pulse waveform and the goal waveform. The model directly shapes the laser pulse waveform in less than 5 s at an accuracy of 11.88 %, 8.97 %, 13.44 %, 12.07 %, 12.11 %, 14.34 % RMSE, which is a high accuracy for such complex waveform. Comparing with iterative method in Fig. 7(a) for beam 2, it started from large deviance of 50.73 % RMSE and took 20 iterative rounds to reach an accuracy of 6.75 %, exceeding the prediction accuracy of 8.97 % for the first time. Even if model loses shot due to its not well learning, as illustrated in beam 4–6, we immediately switched into iterative way, which has become our applying strategy. As Fig. 7(b) displayed for beam 4, laser pulse waveform was continued to be optimized to 8.69 % RMSE after only 4 iterative rounds, saving almost 80 % time. So, though in the situation that the model did not work so well, it could largely decrease iterative rounds and saved much time. Fig. 8 displays the application effects for some other pulse waveform shapes on beam 2. The prediction in Fig. 8(a) met the goal so well, with the contrast ratio higher than 40:1 during the first nanosecond and higher than 30:1 during the second nanosecond. But Fig. 8(b) came out large deviance from the goal, dominating at the sudden steps, which also appeared in waveform in Fig. 6. It would be quickly fixed by iterative relay nonetheless.

4. Discussions

As illustrated in Ref [13], the higher contrast the waveform is, the more iterative rounds it takes. Usually, the iterative way takes around 15 rounds for arbitray low-contrast pulse waveforms. But for pulse waveform of higher contrast ratio, e.g. higher than 15:1, it needs more rounds. The results in Figs. 6–8 demonstrate an excellent performance of the deep learning model for different beamlets, and also high accuracy for high-contrast pulse waveform mostly. For the not well prediction, our short-term strategy is first deep learning prediction and then iterative way, which is effective to guarantee both efficiency and accuracy. Undoubtedly, the long-term job is increasing prediction accuracy by reinforcing data quality, gathering more data and optimizing modal, forming a virtuous cycle between training and prediction. The final goal is approximately 100 % meeting demands by deep learning prediction in less than 5 s, eliminating iterations.

5. Summary

A method of pulse waveform shaping by deep learning prediction is proposed in this paper. By gathering historical data pairs of electrical pulse and laser pulse waveforms, solving data insufficiency and designing U-Net neural network, a deep learning modal is trained and successfully applied on facility. Now, the pulse waveform shaping system is capable of shaping and qualifying most of laser pulse waveforms directly in less than 5 s at an accuracy of less than 15 % RMSE, some even better than 10 %. To fix the unqualified outputs and also keep the robustness of the system, a strategy of first deep learning prediction and then iterative way is established, cutting down roughly 80 % time

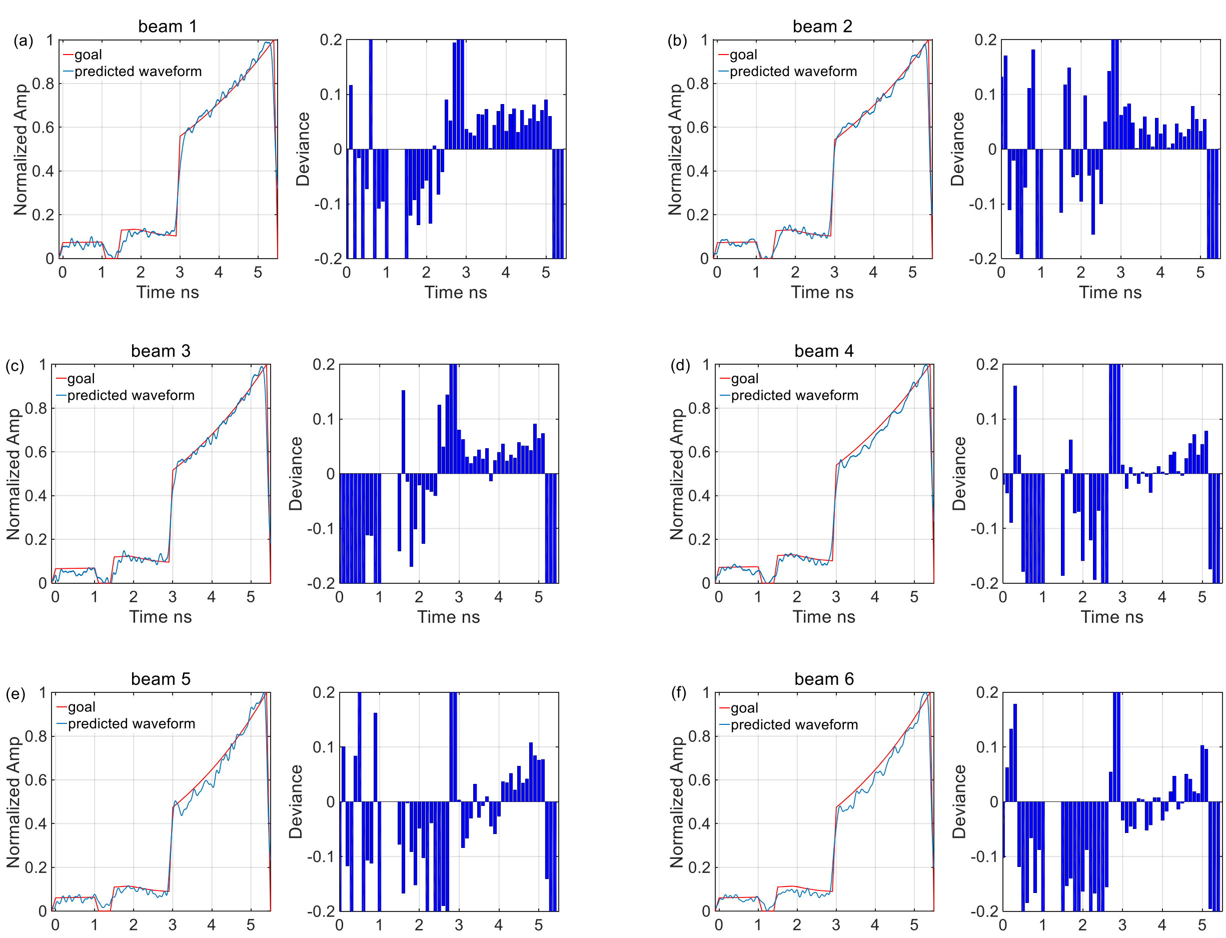

Fig. 6. Laser pulse waveform shaping on different beamlets by deep learning model.

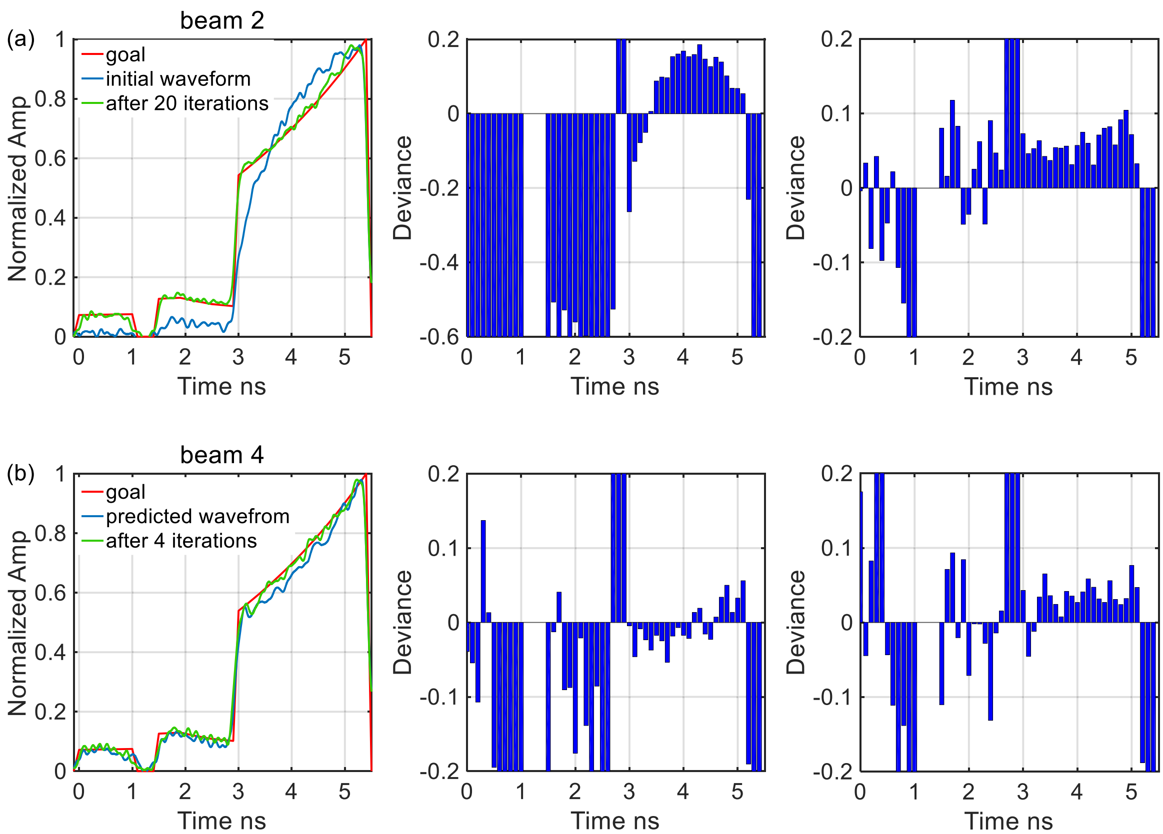

Fig. 7. Laser pulse shaping by iterative method only versus by consorting deep learning model.

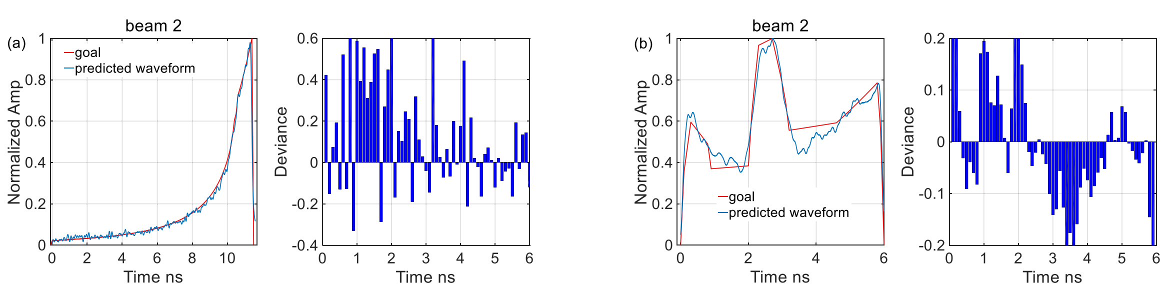

Fig. 8. application of several laser pulse waveforms by deep learning.

consumption. This modal makes a great improvement for facility operation efficiency on pulse waveform shaping process, which solves the urgency of frequent shifts of laser pulse waveform between shots.

Disclosures

The authors declare no conflicts of interest.

CRediT authorship contribution statement

Xiaoxia Huang: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Xiaocheng Tian:** Data curation, Formal analysis. **Yuanchao Geng:** Conceptualization, Methodology. **Huaiwen Guo:** Formal analysis, Validation. **Bowang Zhao:** Validation. **Wei Zhou:** Conceptualization. **Ping Li:** Supervision. **Zhiyu Tian:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that there are no conflicts of interest related to this article.

Data availability

The authors do not have permission to share data.

Funding

This work was supported by the Natural National Science Foundation of China (NSFC) (12275249, 12004352).

Acknowledgments

The authors would like to gratefully acknowledge the auspices of all the colleagues.

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