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REVIEW PAPER

Artificial Intelligence-Enabled Mode-Locked Fiber Laser: A Review

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Abstract

Owing to their compactness, robustness, low cost, high stability, and diffraction-limited beam quality, mode-locked fiber lasers play an indispensable role in micro/nanomanufacturing, precision metrology, laser spectroscopy, LiDAR, biomedical imaging, optical communication, and soliton physics. Mode-locked fiber lasers are a highly complex nonlinear optical system, and understanding the underlying physical mechanisms or the flexible manipulation of ultrafast laser output is challenging. The traditional research paradigm often relies on known physical models, sophisticated numerical calculations, and exploratory experimental attempts. However, when dealing with several complex issues, these traditional approaches often face limitations and struggles in finding effective solutions. As an emerging data-driven analysis and processing technology, artificial intelligence (AI) has brought new insights into the development of mode-locked fiber lasers. This review highlights the areas where AI exhibits potential in accelerating the development of mode-locked fiber lasers, including nonlinear dynamics prediction, ultrashort pulse characterization, inverse design, and automatic control of mode-locked fiber lasers. Furthermore, the challenges and potential future development are discussed.

Highlights

1. A comprehensive review of the recent progress in AI-enabled mode-locked fiber lasers is provided.
2. The applications of AI algorithms in nonlinear dynamics prediction, ultrashort pulse characterization, inverse design, and automatic control of mode-locked fiber laser are presented.
3. The challenges and potential future development of AI-enabled mode-locked fiber lasers are discussed.

Keywords Artificial intelligence · Mode-locked fiber lasers · Ultrafast optics · Intelligent optimization · Machine learning · Deep learning

1 Introduction

Owing to their compactness, robustness, low cost, and high performance, mode-locked fiber lasers have become a mainstream laser source for generating ultrashort pulse output (time duration is of the order of 10^{-12} s or less) [1–3] and play an indispensable role in various research fields. First, mode-locked fiber lasers have extremely high peak power and beam quality, they can enable precise and efficient material ablation, cutting, and surface structuring, which are suitable for micro/nanomanufacturing and precision machining [4–7]. Second, mode-locked fiber lasers with ultrashort pulses allow efficient excitation of fluorophores and deep penetration into tissue, making them ideal candidates for biomedical imaging and multiphoton microscopy [8–10]. Third, in the frequency domain, mode-locked fiber lasers have equidistant narrow-linewidth modes that can effectively generate optical frequency combs [11–14]. Owing to the good balance between their cost and performance, optical frequency combs based on mode-locked fiber lasers have been widely exploited for precision metrology [15–18], laser spectroscopy [19–21], and LIDAR [22–26]. Fourth, mode-locked fiber lasers can carry rich information across a broad

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spectral range, showing potential as a key component in high-speed optical communication systems and massively parallel optical computation [27, 28]. Last but not least, mode-locked fiber lasers are a highly complex nonlinear system. Different dissipative soliton dynamics (such as soliton molecules, soliton rain, dissipative soliton resonance, and noise-like pulse) could occur by adjusting the gain, loss, dispersion, and nonlinear parameters in the laser cavity to deepen the understanding of soliton physics in the scientific community [29–32].

However, research on mode-locked fiber lasers faces a series of challenges. First, it is difficult to accurately model the pulse propagation process in mode-locked fiber laser, which hinders the prediction of highly complex nonlinear dynamics. The propagation process of light in the fiber laser cavity is usually described by the coupled Ginzburg–Landau equation. Sophisticated numerical simulation based on the split-step Fourier method (SSFM) is typically required to solve this partial differential equation and predict the dynamic process of mode-locked fiber laser [33]. When requiring high model accuracy, the calculation amount would become huge, making the total calculation rather time-consuming. Then, to date, the characterization methods of mode-locked fiber lasers are relatively limited. The time durations of ultrashort pulses generated by mode-locked fiber lasers are on the picosecond or even femtosecond level, which considerably exceed the response speed of electronic devices, such as photodetectors. Frequency-resolved optical gating (FROG), spectral phase interferometry for direct electric-field reconstruction (SPIDER), and dispersion scan (d-scan) can characterize the electric field to some extent, but require complicated inversion algorithm to reconstruct accurate pulse parameters [34]. Next, the on-demand design and controllable fabrication of mode-locked fiber lasers remain a challenge due to the unclear subtle relationships between laser output and variable parameters. Much uncertainty surrounds the existing laser design process, and whether the output of the laser meets the needs is difficult to judge in advance, thus limiting the further application of mode-locked fiber lasers. Finally, as a delicate resonator system, mode-locked fiber laser is very sensitive to external environment fluctuations [35]. In practical applications, the optimized mode-locked state may be disrupted by temperature drift, vibration, and stress. The common solution is to manually search for the optimized state by tuning the mode-locked fiber laser, but this approach is rather difficult and time-consuming. Hence, intelligent automatic control and flexible state switching are urgently needed.

Artificial intelligence (AI) [36] is a wide-ranging branch of computer science concerned with building smart machines capable of performing tasks that typically require human intelligence. As a data-driven automatic learning technology, AI exhibits excellent self-adaptation and avoids unnecessary human intervention. It also has strong nonlinear function fit ability, massively parallel ability, and fast computing speed. To date, AI has demonstrated its superiority in various fields, such as autonomous driving [37], natural language processing [38], medical diagnosis [39], computer vision [40], intelligent manufacturing [41], computational imaging [42], spectral informatics [43], ultrafast photonics [44], and fiber lasers [45].

The rapid development of AI technology provides new opportunities for advancing the progress of mode-locked fiber lasers. As shown in Fig. 1, the four major tasks in AI-enabled mode-locked fiber lasers are nonlinear dynamics prediction, ultrashort pulse characterization, inverse design, and automatic control. In these tasks, there are two types of common requirements: data-driven modeling and model-free optimization. Data-driven modeling learns the complex mapping relationship between input and output nodes from data to build a "black box" and achieve efficient computation. It can serve as the basis for nonlinear dynamics predictions (input: laser parameters and initial perturbation; output: predicted dynamic process), ultrashort pulse characterization (input: measurement data, output: pulse parameter), inverse design (input: on-demand laser output, output: designed laser parameters), and automatic control (input: on-demand laser output, output: in-cavity actuator parameters). Emerging AI technologies, such as feedforward neural network (FNN), convolutional neural network (CNN), recurrent neural network (RNN), reinforcement learning, and autoencoder, are suitable for solving this issue. Meanwhile, model-free optimization tries to directly search in the parameter space to minimize the objective function. Common model-free optimization methods include genetic algorithm, particle swarm algorithm, and simulated annealing algorithm. Owing to its robust performance, low complexity, and low label dependence, model-free optimization is also an attractive route for mode-locked fiber laser applications, such as inverse design and automatic control (minimizing the difference between actual and on-demand laser outputs).

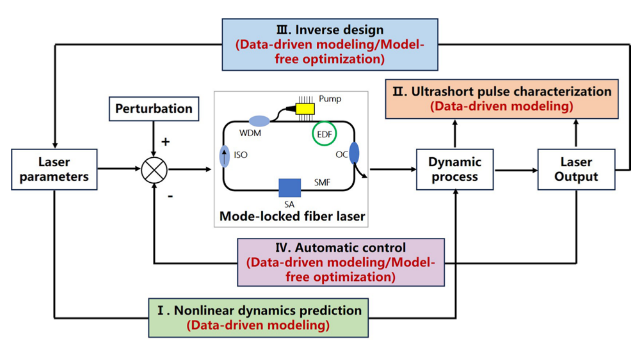

Fig. 1 Typical AI-enabled tasks in mode-locked fiber lasers

It can also be used as an auxiliary algorithm to optimize the hyperparameters of the data-driven model.

In this paper, the recent progresses of AI-enabled mode-locked fiber lasers are reviewed, especially the interdisciplinary research of nonlinear dynamics prediction, ultrashort pulse characterization, inverse design, and automatic control. Finally, the challenges and potential future development are discussed.

2 Nonlinear dynamics prediction

Mode-locked fiber lasers are dissipative nonlinear systems whose dynamic processes are complex, highly nonlinear, and highly dimensional. The accurate prediction of nonlinear dynamics in mode-locked fiber lasers is the basis for optimizing their design and understanding the underlying soliton physics. The pulse propagation model in optical fibers can be described by the Ginzburg–Landau equation [33], which is a partial differential equation. Conventional numerical solution methods are based on the SSFM, which suffers from a relatively large amount of calculation and slow calculation speed. With the in-depth study of the dynamic process of mode-locked lasers [30], the demand for effective prediction methods to study the in-cavity pulse evolution has increased. However, as the pulse signal iteratively propagates in the fiber cavity, the mode-locked fiber laser is extremely sensitive to parameter changes and external perturbations, which puts forward higher requirements on the accuracy of pulse propagation modeling. With the development of AI technology, deep learning is expected to predict the complex dynamic process of mode-locked fiber lasers in an efficient data-driven manner, eventually eliminating the sophisticated numerical calculation required by conventional methods. It has great potential for promoting theoretical research on mode-locked fiber lasers.

The efficient solution of partial differential equations is a key problem in conventional pulse propagation modeling and nonlinear dynamic prediction. In scientific computing, AI has shown the advantage of solving such equations. An emerging algorithm is the physics-informed neural network (PINN) [46], and its structure is shown in Fig. 2a. PINN integrates physical information into deep learning, allowing the latter to directly learn the solution of the partial differential equation from the data without mesh deformation problems. Compared with conventional numerical algorithms, PINN has improved computational efficiency. Additionally, PINN reduces the dependency on extensive data collection and labeling efforts, making it suitable for scenarios with limited data availability. In recent years, PINN has made great achievements in modeling the dynamic propagation of optical pulses in fiber. Jiang et al. [47] used PINN to solve the nonlinear Schrödinger equation for learning nonlinear dynamics in fiber optics. The physical mechanisms, including dispersion, self-phase modulation, and high-order nonlinearity, are carried out with PINN to investigate the soliton and multi-pulse propagations. The results show that the computational complexity of PINN is generally two orders of magnitude lower than that of SSFM. The function of PINN can be further extended by introducing extra physical law [48], proposing new net structures [49], and optimizing model training [50]. With these modified algorithms, the behavior of vector solitons can be effectively predicted, as shown in Fig. 3a.

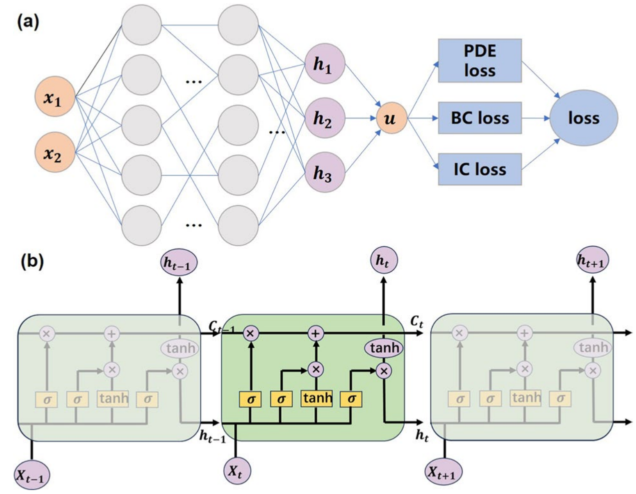

Fig. 2 Deep learning architecture for modeling the dynamic propagation of optical pulse in fiber. **a** PINN. **b** LSTM

Although PINN provides an efficient solution to partial differential equations, it is highly dependent on known physical mechanisms, and the model training is relatively difficult. By contrast, a purely data-driven method based on RNN can learn system dynamical behavior from a set of training data without any prior knowledge [51, 52]. As a unique type of RNN architecture, long short-term memory (LSTM) introduces a gate mechanism to control the flow and loss of features to solve the long-term dependence problem of conventional RNN (Fig. 2b). LSTM has been widely used to solve the sequence prediction problem. In mode-locked fiber lasers, the evolved pulse of each roundtrip can form a long sequence. Thus, LSTM is quite suitable for the nonlinear dynamics prediction of mode-locked fiber lasers.

As shown in Fig. 3b, LSTM is effective for modeling the dynamic propagation of optical pulse in single-mode fibers [53] and multimode fibers [54], laying the foundation for predicting the complex nonlinear dynamics of mode-locked fiber lasers. The nonlinear Schrödinger physics model was also combined with LSTM to reduce dependency on abundant labeled data [55]. In 2022, He et al. [56] combined LSTM with a dense network for soliton dynamics prediction in mode-locked fiber lasers. On the basis of the

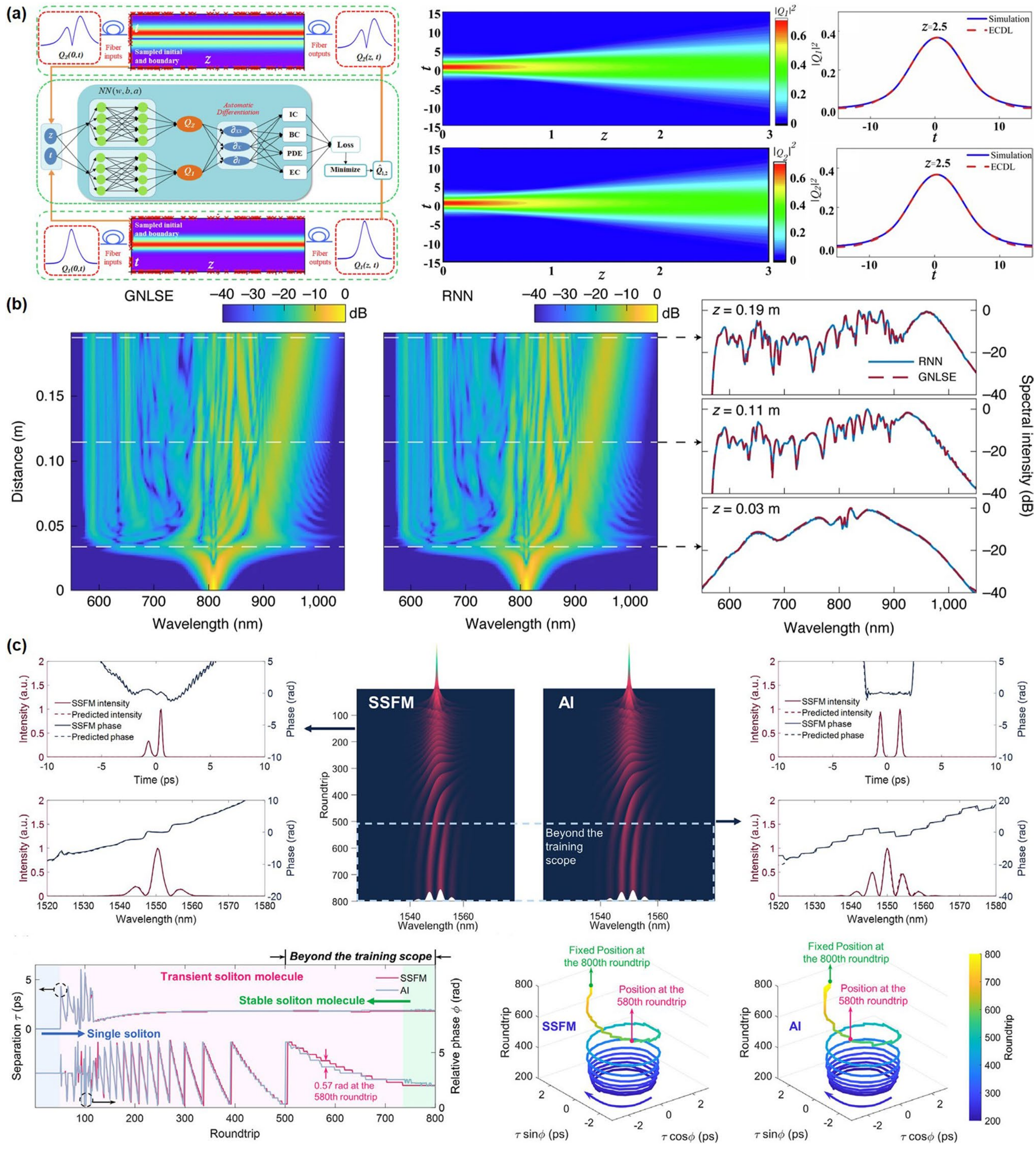

Fig. 3 AI-enabled nonlinear dynamics prediction. **a** Soliton evolution process predicted by PINN (with permission from [48] © Elsevier). **b** Supercontinuum generation process predicted by LSTM (with permission from [53] © The Optical Society). **c** Build-up dynamics of mode-locked fiber lasers predicted by LSTM (with permission from [57] © Wiley)

particle characteristics of soliton interaction, the separation and relative phase between solitons are used as characteristic parameters to predict the nonlinear dynamics. In 2023, Pu et al. [57] exploited LSTM for the fast and accurate nonlinear dynamics prediction of mode-locked fiber lasers and achieved generalization over different cavity settings using a prior information feeding method. The speed of the proposed AI model inferring 500 roundtrips is about 146 times faster than that of SSFM (Fig. 3c). Fang et al. [58] proposed a Bi-LSTM method with an attentional mechanism to predict the dynamics of solitons from the detuning steady state to a stable mode-locked state.

In addition to PINN and LSTM, FNN with fully connected network architecture [59–62] has been successfully used for the end-to-end dynamics prediction of nonlinear optical fiber systems. CNN with cascaded convolution layers and pooling layers has also been introduced to further simplify the training process. Yang et al. [63] proposed a convolutional feature separation modeling method with low complexity and strong, highly accurate generalization ability. Sui et al. [64] proposed a compressed CNN to accurately predict the initial pulse distribution of the nonlinear optical fiber system with different initial widths and powers. Gautam et al. [65] used a CNN model based on knowledge distillation to learn the pulse evolution in the nonlinear fiber; this model uses few trainable parameters to obtain good generalization and a fast convergence rate. Liu et al. [66] used a convolutional autoencoder neural network to reduce data dimension and reconstruct soliton dynamics in mode-locked fiber lasers. The average similarity between the reconstructed and original spectra is more than 99%.

3 Ultrashort pulse characterization

The time durations of ultrashort pulses generated by mode-locked fiber lasers are on the order of picosecond or even femtosecond level. Thus, the characterization of mode-locked fiber lasers allows for the examination of the ultrafast phenomenon and the exploration of new physical mechanisms. However, comprehensively characterizing the output of mode-locked fiber lasers with high speed, resolution, and accuracy is challenging due to the limited response bandwidth of existing photoelectric sensors and the insufficient processing level of analog/digital circuits.

The accurate inversion of the pulse phase must be achieved to completely characterize the electric field of ultrashort pulses. The common time-domain electric-field characterization methods include FROG, SPIDER, and d-scan. However, these methods typically require complex experimental configuration and sophisticated nonlinear devices, have limited signal-to-noise ratio (SNR), and commonly necessitate complicated reconstruction algorithms. When the amount of data is large, a large amount of computing resources and time are required for accurate electric-field reconstruction. The rapid development of AI technology has brought new hope for solving the above problems.

In 1996, Krumbügel et al. [67] proved that an FNN could directly obtain the intensity and phase of a pulse from the FROG trace of a pulse. Although the performance of FNN was limited, it opened up new ideas for researchers. In 2018, Zahavy et al. [68] reconstructed the ultrashort optical pulse by a deep neural network with convolutional and fully connected layers called deepFROG (Fig. 4a), which outperforms the other methods under low SNR. In 2019, Kleinert et al. [69] used a DenseNet to perform ultrashort pulse reconstruction based on d-scan traces. This method showed an excellent tolerance against noisy conditions, and the retrieval took only 16 ms, thus enabling video-rate reconstructions.

With the development of nonlinear optics, computational imaging, and ultrafast photonics, pulse characterization methods based on deep learning have been enriched continuously. In 2020, Ziv et al. [72] proposed a simple all-line system for ultrashort pulse reconstruction from sum-frequency field interference measurements. This system inverts the nonlinear interference pattern to pulse mapping by employing the CNN, thus achieving a good performance. Xiong et al. [73] proposed a self-referenced method of characterizing the spectral phases of ultrashort pulses with a multimode fiber. They combined CNN with compressive sensing by representing the spectral phase on a sparse basis to dramatically reduce the number of parameters to be predicted by the neural network. Kolesnichenko et al. [74] demonstrated an approach to characterize ultrashort pulses from 1D interferometric correction time traces using CNN. The results implied that rapid ultrashort pulse characterization can be achieved using a simple experimental setup with only one delay stage, a single-channel detector, and a spectrometer.

Different from the slow characterization method based on commercial spectrum analyzers and autocorrelators, dispersive Fourier transform (DFT) [75] has been proposed to track the pulse-to-pulse spectral evolution. DFT has revolutionized the time-resolved pulse characterization. In Fig. 4b, Kokhanovskiy et al. [70] predicted the temporal characteristics (temporal width, optical spectrum, and RF spectrum) of ultrashort pulses by employing a DFT trace and supervised machine learning, which considerably reduced the system complexity. In 2020, to obtain further information within the DFT data, Li et al. [71] trained a residual CNN to retrieve the separation and relative phase of solitons in three- and six-soliton molecules from the DFT data, providing an effective method for exploring complex soliton molecule dynamics (Fig. 4(c)). The performance of three deep CNN networks (VGG, ResNets, and DenseNets) for studying the internal dynamics evolution of soliton molecules with real-time spectral interference was also compared and discussed [76].

4 Inverse design

The inverse design of mode-locked fiber lasers is important for generating on-demand laser output. Common parameters to be optimized include net group velocity dispersion,

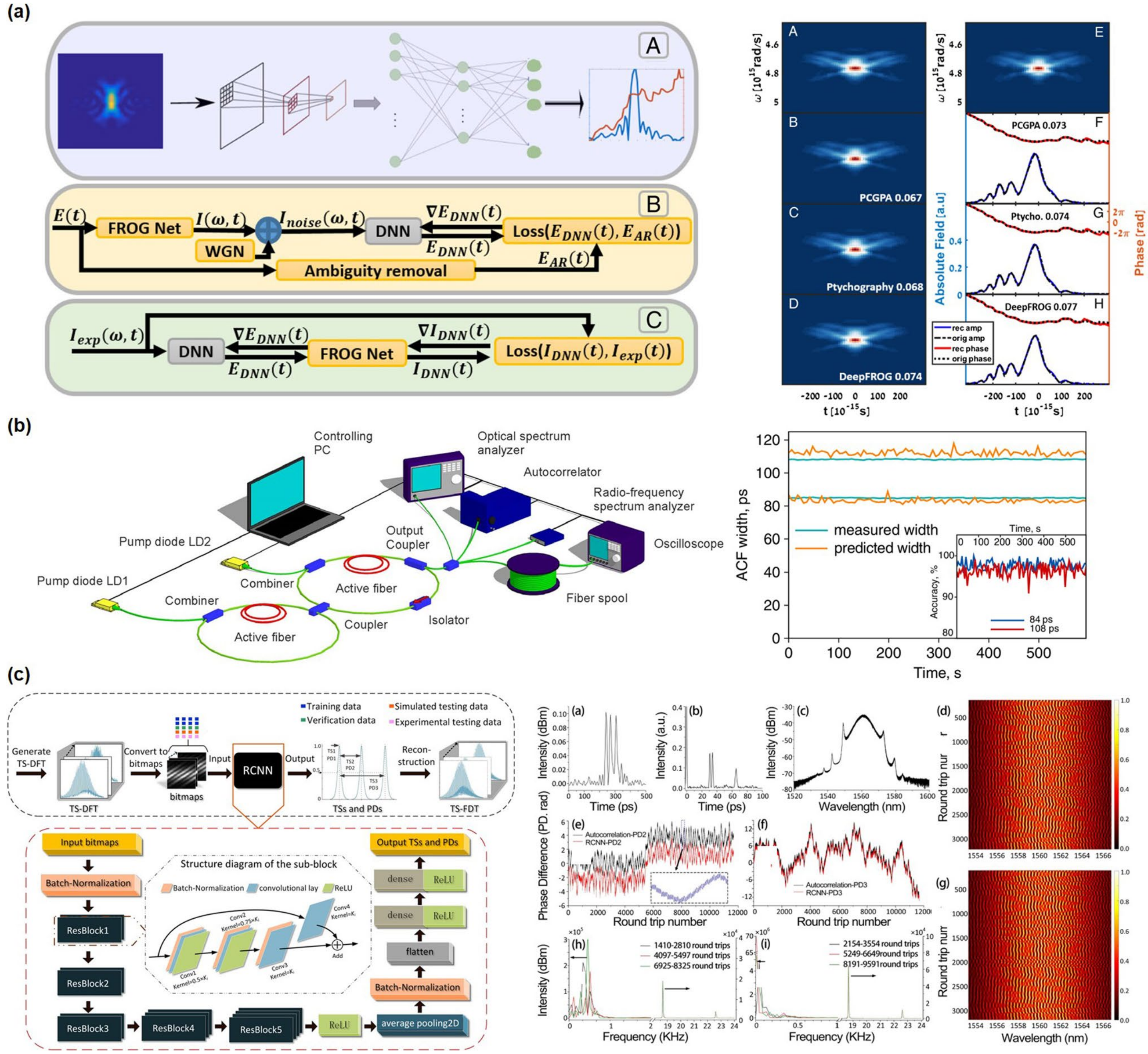

Fig. 4 Ultrashort pulse characterization with deep learning. **a** Deep learning reconstruction of the ultrashort pulse (with permission from [68] © The Optical Society). **b** Pulse width characterization (with permission from [70] © The Optical Society). **c** Soliton dynamics characterization (with permission from [71] © AIP Publishing)

total cavity length, pump power, loss, and polarization state. Owing to the unclear relationship between the final laser output and these parameters, no explicit theory has been established to guide the on-demand design of mode-locked fiber lasers. Conventional laser designs must traverse the entire parameter space to find the optimal parameter setting. This process is time-consuming and requires human intervention. When the parameter space to be optimized is highly dimensional, the global optimal solution becomes difficult to find accurately. In actual ultrafast laser systems, optical amplifiers and supercontinuum generation modules are commonly cascaded after mode-locked fiber lasers to further increase the degree of freedom of the pulse output; however, this step further increases the difficulty of the optimization problem (as shown in Fig. 5). AI has a natural advantage in solving such complex optimization problems and has been successfully introduced in the inverse design of mode-locked fiber lasers.

As shown in Fig. 6a, Kokhanovskiy et al. [77] proposed the design of mode-locked fiber lasers based on a particle swarm optimization algorithm, which can determine the laser cavity architectures with on-demand pulse duration in the range of 1.5–105 ps and spectral width in the range 0.1–20.5 nm. Bahloul et al. [78] used a genetic algorithm

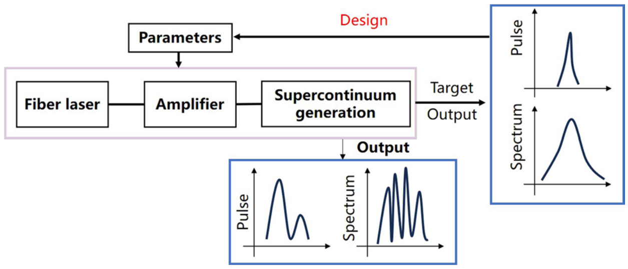

Fig. 5 Inverse design of mode-locked fiber lasers

to optimize the cavity parameters to obtain a high-energy rectangular pulse operating in the dissipative soliton resonance regime. As shown in Fig. 6b, Feehan et al. [79] used an improved genetic algorithm and intuitive optimization loss function to automatically design the cavity parameters of experimental mode-locked fiber lasers. This method achieved exceptional accuracy using minimal prior knowledge. Chen et al. [80] proposed an online machine learning method based on the Gaussian process (GP) to determine the parameters of mode-locked fiber lasers for generating on-demand dissipative solitons. The GP learner iteratively searches the target parameters according to the optimization strategy until the desired cavity parameters are determined.

Apart from the seed source, success was also achieved in the reverse design of the optical amplifier and supercontinuum generation module. In 2020, Zibar et al. [81] demonstrated a high-precision pumping setup for arbitrary Raman gain spectrum using multilayer neural networks. With the

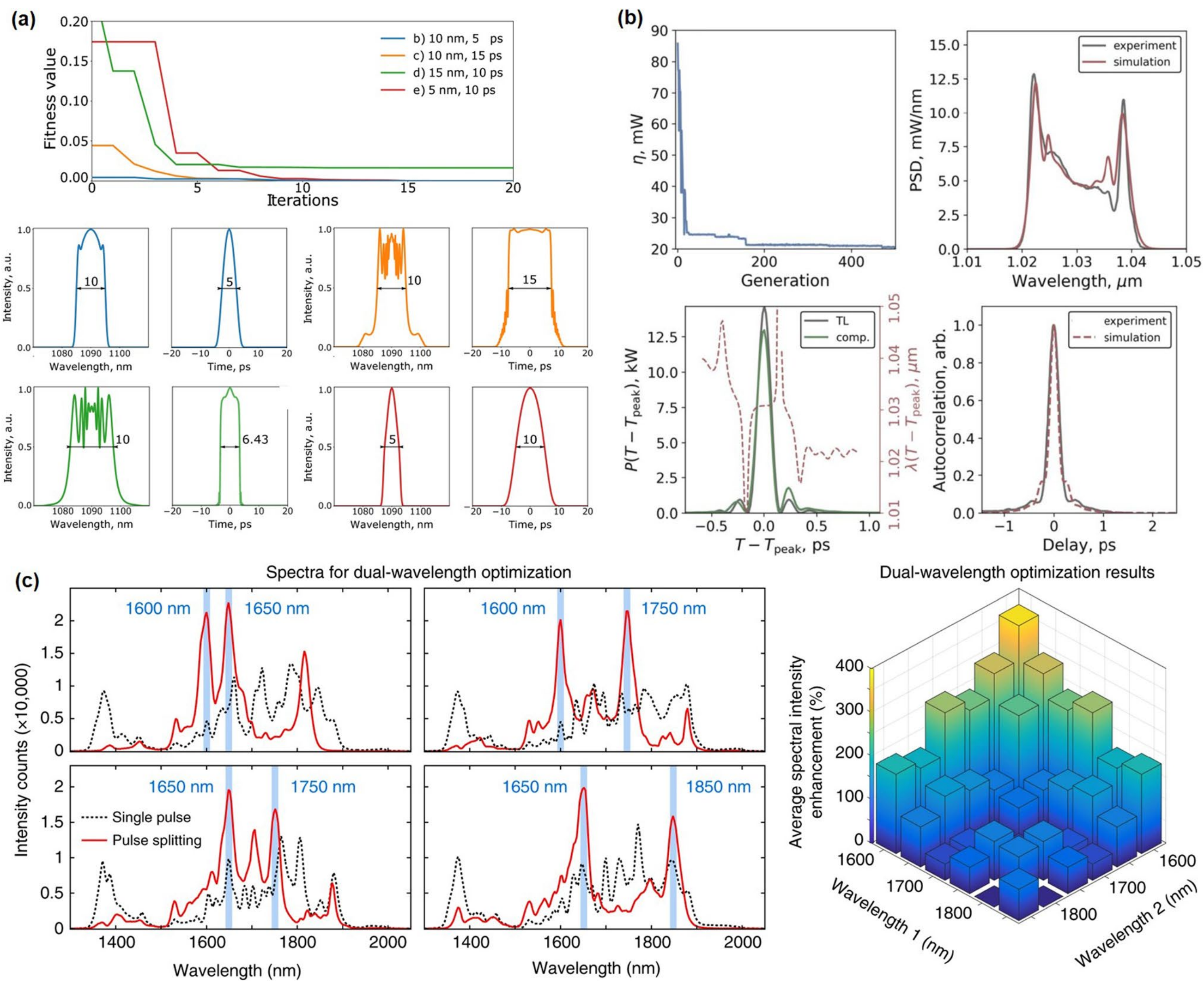

Fig. 6 AI-enabled inverse design of the mode-locked fiber lasers. **a** Inverse design of mode-locked fiber laser by particle swarm optimization algorithm (with permission from [77] © Springer Nature). **b** Computer-automated design of mode-locked fiber lasers (with permission from [79] © The optical Society). **c** Customizing supercontinuum generation via on-chip adaptive temporal pulse-splitting (with permission from [83] © Springer Nature)

use of four pumps and a 100-km span, the maximum errors for the numerical and experimental values exhibit mean and standard deviation of 0.46 and 0.35 dB and 0.20 and 0.17 dB, respectively. Zhang et al. [82] presented a design of optical microstructure fibers that have group velocity dispersion and effective nonlinear coefficient tailored for supercontinuum generation by using a hybrid approach that combines a genetic algorithm with pulse propagation modeling. As shown in Fig. 6c, Wetzel et al. [83] used an actively controlled photonic chip to generate supercontinuum and applied the genetic algorithm to customize nonlinear interactions and manipulate the patterns of ultrashort pulses.

5 Automatic control

Mode-locked fiber lasers have the potential for large-scale application in various fields, such as industrial manufacturing, medical treatment, and scientific research, due to their simple configuration and low cost. However, mode-locked fiber lasers are a delicate resonator system that is very sensitive to parameter drift and external environment perturbation. In practical applications, temperature drift, vibration, and stress may disrupt the optimized mode-locked state, causing performance degradation or even loss of the mode-locked state. For example, for mode-locked fiber lasers based on nonlinear polarization rotation (NPR), environment perturbation can directly affect the balance among dispersion, nonlinearity, gain, and loss, thus creating obstacles to practical applications.

As shown in Fig. 7, mode-locked fiber lasers are expected to maintain the target state even under complex external perturbation. An electronically controlled polarization controller can be used to traverse all possible polarization states for searching on-demand mode-locked states [84, 85]. Although tuning to the desired state is guaranteed, this method is highly inefficient, and this open-loop system has difficulty adapting to complex environmental changes. AI algorithms are expected to enable self-tuning and efficient updates for on-demand mode-locked states. Through the monitoring of the output of the mode-locked fiber lasers, the current operating state can be accurately perceived, and an intelligent decision can be made on the next action. This closed-loop system enables the robust automatic control of the mode-locked fiber lasers and can intelligently adapt to the changes in the external environment.

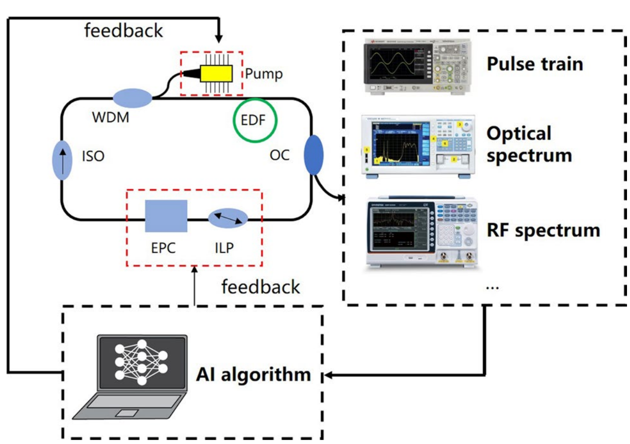

Fig. 7 Automatic control of mode-locked fiber laser

For the automatic control of mode-locked fiber lasers, intelligent optimization algorithms are first applied to the self-tuning of mode-locked lasers. In 2013, Brunton et al. [86] proposed a multiparameter extremum-seeking control algorithm with a physically achievable objective function to realize the optimal mode-locked state. This algorithm can track the locally maximal mode-locked state under significant disturbances. In 2015, Andral et al. [87] experimentally proved the ability of genetic algorithms to autotune mode-locked fiber lasers. They also emphasized the importance of carefully designing the merit function, which constitutes a prerequisite for the predetermined goal. In 2020, Pu et al. [88] adopted the ultrafast DFT as the spectral discrimination criterion, combined it with the genetic algorithm, and realized the real-time control of the spectrum width and shape of the mode-locked fiber pulses. In addition to evolutionary algorithms, expertise can also guide the search for an on-demand mode-locked state. In 2019, Pu et al. [89] proposed a programmable mode-locked laser based on a human-like algorithm (Fig. 8a). The laser can be automatically locked onto desired operation states. The shortest initial mode-locking time and recovery time from detachment are only 0.22 s and 14.8 ms, respectively.

In order to adapt to more complex environment and task, machine learning can be employed to achieve automatic control of mode-locked fiber lasers. In 2014, Fu et al. [90] demonstrated an efficient, self-tuning laser using machine learning and sparse representation. L1-norm optimization was applied to classify the birefringence of the fiber laser, and this method performs well even in the presence of noise. Servo-control motors can be used to adjust the wave plates and polarizers to the optimal positions obtained from the toroidal search. In 2018, Baumerster et al. [91] first demonstrated the integration of a deep learning architecture with model predictive control (MPC). Deep learning can be used to approximate the unknown fiber birefringence and establish the dynamics model of the laser. Meanwhile, MPC control law can be utilized to maintain high-energy pulses against random birefringence drift. In 2020, Sun et al. [92] applied a deep Q-learning network (DQN) to automatic control mode-locked fiber lasers. They further integrated transfer learning to help the deep reinforcement learning algorithm quickly learn new parameter systems

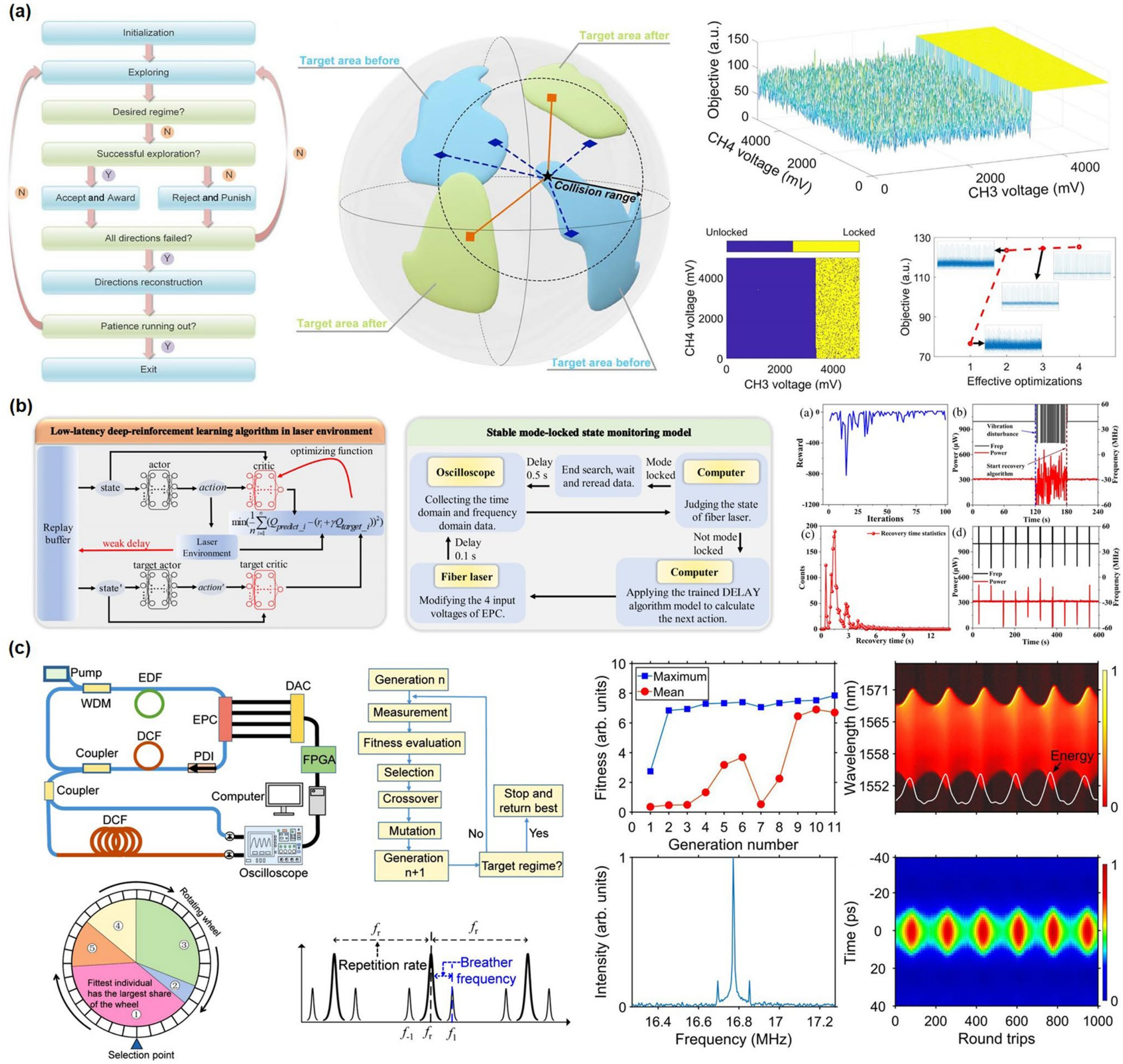

Fig. 8 AI-enabled automatic control of the mode-locked fiber lasers. **a** Programmable mode-locked laser based on a human-like algorithm (with permission from [89] © The Optical Society). **b** Low-latency deep reinforcement learning algorithm for ultrafast fiber lasers (with permission from [97] © Chinese Laser Press). **c** Intelligent breathing solitons generated using a genetic algorithm (with permission from [100] © Wiley)

and generalize their control rights. In 2022, Kokhanovskiy et al. [93] used double DQN to learn the dynamic adjustment strategy of cavity parameters and generate stable solitons in mode-locked fiber lasers. The algorithm learns the hysteresis phenomena (represented by different optical pump adjustment trajectories) of different pump power thresholds under a mode-locked state. Li et al. [94] presented a spectrum series learning-based model combining deep reinforcement learning and LSTM networks for the state searching and switching of mode-locked fiber lasers. The switch of the mode-locked state is realized by a predictive neural network that controls the pump power. The algorithm uses an average of only 690 ms to obtain a stable mode-locked state, which is one order of magnitude less than that of the conventional method.

In addition to controlling the in-cavity polarization state of NPR-based mode-locked fiber lasers, AI technology is effective for nonlinear amplifier loop mirror (NALM)-based mode-locked fiber lasers and saturable absorber (SA)-based mode-locked fiber lasers. Kokhanovskiy et al. [95] and

Woodward et al. [96] used a genetic algorithm to control the laser operation state by adjusting the pump power. As shown in Fig. 8b, Yan et al. [97] proposed a low-latency deep reinforcement learning algorithm based on deep deterministic policy gradients for SA-based mode-locked fiber lasers. The algorithm consists of two actor neural networks and two critic neural networks, which can provide strategies to modify the in-cavity polarization state and evaluate the effect of the actor network. The average mode-locking recovery time of the network model after training is only 1.948s.

Beyond fundamental mode-locking, mode-locked fiber lasers can experience rich regimes by manipulating the balance among gain, dispersion, and nonlinearity. AI technology has also been used in the automatic control of Q-switching [98], Q-switching mode-locking [89], harmonic mode-locking [89], dissipative solitons [99], and breathing solitons [100] (Fig. 8c). Furthermore, the AI-enabled automatic control is feasible for mode-locked lasers in the 2-μm band [101] and single-cavity dual-comb lasers [102], showing the strong adaptability of AI to different types of lasers.

6 Discussion

Mode-locked fiber lasers are a highly complex nonlinear ultrafast optical system that is very sensitive to internal parameters and external perturbation. The traditional research paradigm often relies on known physical models, sophisticated numerical calculations, and exploratory experimental attempts. However, when dealing with many complex issues, these traditional approaches often face limitations and struggle to find effective solutions. For example, efficient and high-precision nonlinear dynamics prediction, accurate ultrashort pulse characterization, on-demand inverse design, and robust automatic control involve unclear physics models, a substantial amount of complex calculations, and limited instrument performance. In recent years, AI for science has set off an upsurge. AI has irreplaceable advantages in solving multivariable complex nonlinear problems, bringing new opportunities for scientific research on mode-locked fiber lasers. Despite the above great achievements, the following challenges remain:

In the nonlinear dynamics prediction of mode-locked fiber lasers, current AI technology still rely on the known physical model and existing numerical methods to generate labeled data set. Hence, the prediction model cannot surpass the existing knowledge of human beings. In addition, most of the current works are focused on making numerical calculations efficient. Further mining and revealing the intrinsic physical mechanism of mode-locked fiber lasers have not been attempted. In this sense, the potential of AI has not been fully realized. Therefore, realizing the full integration of big data, physical mechanisms, and prior experience to discover unknown valuable physical laws is a challenge for the future.

In ultrashort pulse reconstruction, current AI technologies have only played an auxiliary role. AI-enabled ultrashort pulse reconstruction has not completely reformed the conventional pulse characterization instruments and methodologies. Elegantly simplifying the existing characterization configuration would be beneficial for comprehensive, fast, and accurate ultrashort pulse characterization. In addition, AI technology is mainly used for data postprocessing and cannot fully realize the effective encoding–decoding of information. In recent years, the joint optimization of optical measurement systems and postprocessing algorithms has become a trend for improving the performance of spectrometers and optical imaging systems. Hence, the co-design of the characterization instrument and postprocessing algorithms based on emerging AI technologies would be a promising direction in the future.

In the inverse design of mode-locked fiber lasers, some AI-based inverse design methods have already been proposed. However, whether these existing model-free inverse design methods have sufficient generalization and interpretability remains questionable. In particular, the mapping relationship between fiber laser output and actual controllable laser parameters remains unclear. At present, the mainstream inverse design of mode-locked fiber lasers still relies on expert experience and trial–error improvement iteration. This situation is partly because the constraints of real conditions are difficult to fully consider. Fortunately, AI technology is still developing rapidly, and a systematic and highly interpretable theory of inverse design for mode-locked fiber lasers is expected to be established in the future.

In the automatic control of mode-locked lasers, the existing methods are mainly based on complete expert experience (such as human-like algorithms) or complete data-driven strategy (such as model-free evolutionary algorithm and machine learning). These methods all have their own insurmountable limitations. For further improvement in the effect of automatic control, the accurate and comprehensive digitization of the expert experience and its integration with physical mechanisms and data-driven models is a potential research direction.

Although AI can achieve many unprecedented functions and applications, it also has limitations. First, too much reliance on data. AI technology, particularly those represented by deep learning, typically requires cumbersome dataset construction and time-consuming model training process, which could bring additional costs. These costs should be carefully considered in practical applications. Moreover, when the amount of data is insufficient, the data quality is poor, or the dataset is unbalanced, the performance of the AI algorithm would greatly decline, and its benefits over conventional methods would diminish. Then, tricky overfitting and limited generalization. AI algorithm is commonly difficult to adapt to the change of the research object or even realize the dynamic transfer of the scene. Given the huge cost of retraining a new data-driven model, the practicability of the AI algorithm should be further improved. Next, "black box" properties and insufficient interpretability. The "black-box" model of AI technology can always give a result, but this result may not meet our needs. Therefore, the uncertainty analysis and interpretability exploration of AI models is an important development direction. Finally, the insufficient use of prior knowledge. The comprehensive digital representation of human knowledge is a very challenging problem. It is expected that knowledge and data can be fully integrated so that the AI model learns more efficiently from data and is not bound by existing experience.

With the rapid development of AI technology in numerous applications, an increasing number of researchers have engaged in this rapidly developing field. The emergence of new technologies is expected to solve the current limitations of AI-enabled mode-locked lasers. For example, small sample learning [103] can effectively use a small amount of data for training, which can considerably reduce labeling and training costs. Lightweight deep learning [104] allows the easy deployment of AI technology, thus improving its competitiveness compared with conventional methods for field-deployed applications. Transfer learning can transfer learned models to new tasks, which reduces the cost of retraining and is promising to improve the generalization of AI. Explainable AI [105] can provide new ways to evaluate the uncertainty of AI models, enabling the discovery of new laws of physics and the expansion of human knowledge. Knowledge graph [106] is able of representing and organizing knowledge in a graphical structure, which is potential to reveal the relationship between entities, infer hidden knowledge, handle complex query questions, and support intelligent decisions. It is believed that with the development of AI technology, AI-enabled mode-locked fiber lasers can break through current limitations and advance the applications in micro/nanomanufacturing, precision metrology, laser spectroscopy, LiDAR, biomedical imaging, optical communication, and soliton physics.

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Availability of data and materials The authors declare that all data supporting the findings of this study are available within the article.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

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