

Machine learning assisted zero-area pulse design in an open quantum system

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Accurate and precise quantum control is crucial for quantum information processing. Zero-area pulse control, originally developed for closed systems, has played a significant role in driving quantum systems toward desired states. However, its effectiveness is often compromised by environmental noise. Traditional methods can find optimal pulses for fixed environmental parameters, and they need to be recalculated again once the environmental parameters change. Here, we propose a supervised learning (SL)-based protocol to design optimal zero-area pulses in noisy environments. By including environmental parameters as input during training, the neural network (NN) learns to generate effective controls for various environmental parameters. We demonstrate the protocol using quantum state transmission through a spin chain governed by a non-Markovian master equation. The SL-optimized pulses significantly enhance transmission fidelity compared to ideal pulses, with greater improvements observed at higher system-bath coupling and temperature, where more optimization space exists. Interestingly, fidelity first increases and then decreases with stronger Markovianity, suggesting that highly Markovian environments limit control performance. We also compare the SL method with a genetic algorithm, and the similar results confirm the accuracy and generalization ability of the NN-based approach.

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I. INTRODUCTION

Quantum control achieves the target state from certain initial states through the precise manipulation of the system [1]. Dynamical decoupling [2–4] is an efficient control strategy and has been widely used in numerous quantum information processing tasks. The zero-area pulse, which belongs to the category of dynamical decoupling, shows promise for precise quantum control. It alternates between positive and negative intensities, and the integration of the pulse in the time domain is zero. By applying the Feshbach PQ partitioning technique of decomposing the n -dimensional state vector into the one-dimensional state vector P and the $(n-1)$ -dimensional state vector Q [5], the ideal zero-area pulse control conditions have been theoretically derived [5,6]. The effective expedited holonomic quantum computation [7], almost exact quantum state transfer [8], and adiabatic speedup [9] can be obtained via zero-area pulse control.

A closed system is a theoretical idealization, and in practice, the environment inevitably plays a role during quantum

information processing. In reality, control capabilities are often weakened due to environmental interactions [5,10]. Therefore, it is essential to consider these effects—for example, through the use of the non-Markovian quantum state diffusion (QSD) equation [11–13]. The master equation for a bosonic bath has been derived for both zero temperature [11] and finite temperature [14]. The influence of the bath on the system can be characterized by environmental parameters such as system-bath coupling strength, bath temperature, and bath characteristic frequency. When applying the ideal zero-area pulse to the system in open quantum scenarios—such as quantum state transfer through a spin chain [15] or adiabatic speedup [16], control tends to perform well in a weak environment [17]. However, the transmission or adiabatic fidelity gradually decreases with increasing system-bath coupling strength [18], bath temperature, or bath characteristic frequency [16].

To enhance the controllability of the zero-area pulse in an open system, the bath parameters must be considered in the control design. However, a theoretical derivation becomes challenging due to the infinite degrees of freedom of the environment. Traditional optimization techniques such as stochastic gradient descent (SGD) [19], adaptive moment estimation (Adam) [20], and genetic algorithm (GA) [21] have been employed to address quantum optimization tasks. For example, SGD has been used to design the pulse for control of adiabatic speedup in a non-Markovian open qutrit system [22]. However, these traditional algorithms can only

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solve optimization problems for a specific environment—that is, when the environmental parameters are fixed. If the environment changes, the optimization must be recalculated. With the rapid development of artificial intelligence (AI), optimal control has gradually shifted from traditional techniques to AI-driven approaches. Methods such as neural network (NN)-based deep reinforcement learning [23] and supervised learning (SL) [24] are increasingly being applied in this context. The NN is capable of finding the relationship between input and output parameters based on large-scale datasets [25]. Leveraging the powerful generalization capabilities of NNs, quantum algorithms adaptable to different environments have been proposed [26]. However, in our control tasks, the zero-area pulse constraint must be taken into account during the design process. By carefully recording the environmental parameters along with the corresponding period, a dataset can be constructed where the output represents the pulse intensity. Specifically, we employ an SL algorithm to design zero-area pulses tailored to specific environmental parameters. Once the NN is well trained, it can generate the optimal pulse for given conditions. As an example, we demonstrate the effectiveness of the SL-designed control pulse through the transmission of quantum states in a spin chain. Quantum state transfer (QST) through spin chains has been extensively studied [8,27–29], and it is well known that transmission fidelity decreases in the presence of a noisy bath [30]. We show that the transmission fidelity can be significantly enhanced using the optimized zero-area pulse, compared to the ideal pulse case. Defining fidelity improvement as the difference between the fidelity obtained with the optimized zero-area pulse and that with the ideal pulse, we find that the improvement in fidelity increases with stronger interaction or higher temperature parameters. A stronger environment thus offers greater potential for improvement. However, for fidelity improvement as the characteristic frequency increases, a peak is observed, indicating that the control loses its effectiveness in a near-Markovian regime. To verify the accuracy of the NN's generalization ability, we use GA to perform the same task and compare the results obtained from both algorithms. We find that the fidelities are nearly identical for the same environmental parameters.

II. MODEL AND METHODS

We now consider a bosonic bath model with Hamiltonian $H_b = \sum_k \omega_k b_k^\dagger b_k$, which can consist of phonons in a solid lattice or the radiation field at finite temperature. We take $\hbar = 1$ throughout. ω_k is the k th mode frequency of the baths $b_k^\dagger$ and b_k . The system-bath interaction can be written as $H_{\text{int}} = \sum_k (g_k^* L^\dagger b_k + g_k L b_k^\dagger)$, where L and g_k represent the Lindblad operator and coupling strength between the system and the k th mode of the bath, respectively. Now the total Hamiltonian is $H_{\text{tot}} = H_s + H_b + H_{\text{int}}$.

With the help of QSD equation approach, the non-Markovian master equation can be obtained [31]:

$$\begin{aligned} \frac{\partial}{\partial t} \rho_s = & -i[H_s, \rho_s] + [L, \rho_s \bar{O}_z^\dagger(t)] - [L^\dagger, \bar{O}_z(t) \rho_s] \\ & + [L^\dagger, \rho_s \bar{O}_w^\dagger(t)] - [L, \bar{O}_w(t) \rho_s]. \end{aligned} \quad (1)$$

Here, $\bar{O}_{z(w)}(t) = \int_0^t ds \alpha_{z(w)}(t-s) O_{z(w)}(t,s)$. O operator is an ansatz and $\alpha_{z(w)}(t-s)$ denotes the correlation function. For details, see Ref. [12].

For the Lorentz-Drude model with spectral density $J(\omega) = \frac{\Gamma}{\pi} \frac{\omega}{1+(\frac{\omega}{\gamma})^2}$ [32–34]. Here, Γ and γ denote system-bath coupling strength and bath characteristic frequency, respectively. In the weak system-bath coupling and high temperature approximations, we obtain [15]

$$\alpha_z(t-s) = \Gamma T \Lambda(t,s) + i\Gamma \dot{\Lambda}(t,s), \quad (2)$$

$$\alpha_w(t-s) = \Gamma T \Lambda(t,s). \quad (3)$$

Here, $\Lambda(t,s) = (\gamma/2) e^{-\gamma|t-s|}$ denotes the Ornstein-Uhlenbeck correlation function. T is the bath temperature. The bath correlation function [12] is

$$\begin{aligned} \alpha(t-s) &= \alpha_w(t-s) + \alpha_z(t-s) \\ &= \frac{\Gamma \gamma^2}{2} (2T/\gamma - i) e^{-\gamma|t-s|}, \end{aligned} \quad (4)$$

which is in accordance with the results in Ref. [35].

Using the Lorentz-Drude model, we obtain the following equations [20]:

$$\begin{aligned} \frac{\partial \bar{O}_z}{\partial t} = & \left(\frac{\Gamma T \gamma}{2} - \frac{i\Gamma \gamma^2}{2} \right) L - \gamma \bar{O}_z \\ & - [iH_s + L^\dagger \bar{O}_z + L \bar{O}_w, \bar{O}_z], \end{aligned} \quad (5)$$

$$\frac{\partial \bar{O}_w}{\partial t} = \frac{\Gamma T \gamma}{2} L^\dagger - \gamma \bar{O}_w - [iH_s + L^\dagger \bar{O}_z + L \bar{O}_w, \bar{O}_w]. \quad (6)$$

By Eqs. (1), (5), and (6), we can solve the non-Markovian dynamics of the system.

When $\gamma \rightarrow \infty$, it corresponds to the Markovian case: $\bar{O}_z = (\Gamma T \gamma/2) L$ and $\bar{O}_w = (\Gamma T \gamma/2) L^\dagger$. The master equation in Eq. (1) becomes [31]

$$\begin{aligned} \frac{\partial}{\partial t} \rho_s = & -i[H_s, \rho_s] + \frac{\Gamma T}{2} (2L \rho_s L^\dagger - L^\dagger L \rho_s - \rho_s L^\dagger L \\ & + 2L^\dagger \rho_s L - L L^\dagger \rho_s - \rho_s L L^\dagger). \end{aligned} \quad (7)$$

In this paper, we take the QST through a one-dimensional XY spin chain as an example. The system Hamiltonian reads [36]

$$H_s = \sum_{i=1}^{N-1} J_{i,i+1} (\sigma_i^x \sigma_{i+1}^x + \sigma_i^y \sigma_{i+1}^y), \quad (8)$$

where $J_{i,i+1}$ denotes the strength of the coupling between the two spins of the nearest neighbor, and σ_i ($i = x, y$) are Pauli operators. The perfect state transfer (PST) requires $J_{i,i+1} = -\sqrt{i(N-i)}$ [28,29], and N is the number of spins. In this paper, we will investigate the QST through a uniform chain $J_{i,i+1} = -1$.

The QST process is as follows. First prepare the left spin at the up state, and rest of the spins at the down state; therefore, the initial state of system can be expressed as $|\Psi_s(0)\rangle = |1\rangle = |100 \dots 0\rangle$. The target state is $|N\rangle = |000 \dots 1\rangle$. The transmission fidelity is defined as $F(t) = \sqrt{\langle N | \rho_s(t) | N \rangle}$, where $\rho_s(t)$ denotes the reduced density matrix of the system. Clearly, if $F = 1$, the up state has been successfully transferred from

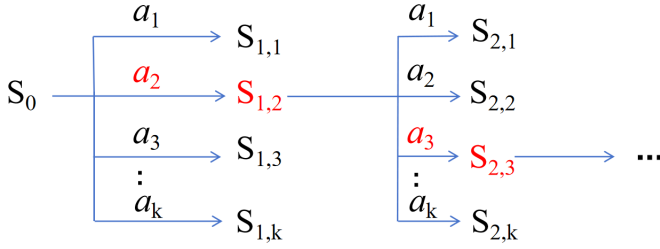


FIG. 1. The diagram of dataset construction by greedy algorithm. S_0 denotes the initial state and a_i ($i = 1, 2, \dots, k$) denotes the value of pulse intensity (action). $S_{i',i}$ ($i' = 1, 2, 3$ and $i = 1, 2, \dots, k$) denotes the output state obtained by a_i at the end of i' th period.

site 1 to site N . However, F cannot reach 1 in a uniform chain even without noise for $N \geq 4$ due to dispersion [37], and the noise will decrease the fidelity as well [5]. Quantum control has been implemented to enhance the transmission fidelity [8]. In this paper, we apply a leakage elimination operator (LEO) Hamiltonian to improve the transmission fidelity. The LEO Hamiltonian includes a sequence of control pulse. The function of the LEO Hamiltonian is to guarantee that the quantum system evolves through a desired channel. We choose $|\Psi(t)\rangle = \exp(-iH_{\text{PST}}t)|1\rangle$ as the evolution channel, H_{PST} is the Hamiltonian with PST couplings, and the LEO Hamiltonian can be described as [38]

$$H_{\text{LEO}} = c(t)|\Psi(t)\rangle\langle\Psi(t)|. \quad (9)$$

Here, $c(t)$ denotes the control function and $|\Psi(t)\rangle$ is the target state. By designing $c(t)$, which satisfy certain conditions [5], the near PST can be obtained in closed systems. For rectangular case, the ideal pulse condition is [5]

$$I\tau = 2k\pi, \quad k = 1, 2, 3, \dots \quad (10)$$

Here, I is the pulse intensity and τ is the pulse half period. In open quantum systems, these ideal pulse conditions will lose their effectiveness [5,9]. In this paper, we use SL to design optimal zero-area pulse for certain environmental parameters.

The first step for SL is to construct a large-scale dataset. In SL, the dataset is divided into input samples and output labels, and the goal is to find the mapping relationship between the samples and labels. The strategy we apply to construct dataset is inspired by greedy algorithm that can take the best or optimal choice in the current state at each step of the choice, with the hope that the last result will be the best or optimal. Figure 1 shows the process of the dataset construction by greedy algorithm. Suppose the pulse has P periods; the total transmission process is also divided into P periods. In the first period, several discrete actions $I_1 \in [a_1, a_2, \dots, a_k]$ are chosen to be pulse intensity. Try each action in I_1 and at the end of this period we obtain output state that is expressed as $S_{1,n}$ ($n = 1, 2, \dots, k$). For each $S_{1,n}$, we calculate fidelity. Assume that in the first period, $S_{1,2}$ leads to the highest fidelity. Then, we record $S_{1,2}$ and the corresponding action a_2 . In the next period, $S_{1,2}$ will be the initial state and repeat the above procedures until all periods are considered. Finally, when the transmission ends, we obtain the optimized pulse sequence.

After building the dataset, we begin to construct the NN. Figure 2 shows the structure of our model. Except for Γ , γ , and T , we add the number of period i as input parameter. The

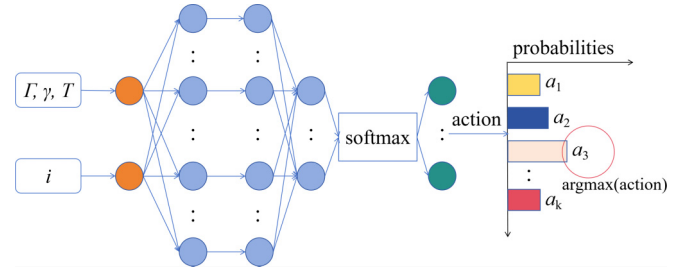


FIG. 2. The structure of the NN. The input parameters include environmental parameters Γ , γ , T , and number of period i . The network will output a probability distribution that each action is selected, and choose the action with the highest probability as optimized pulse in this period.

pulse design task can be solved as classification task. When we bring the collected dataset into the NN, it can find an accurate map between input and output. For each combination of Γ , γ , T , and i , the model will output a distribution of possibilities with the help of *softmax* activation. The action with highest possibility is selected. As a classification task, cross-entropy loss function $\text{Loss} = -\sum_{i=1}^n p(x_i) \log_2 q(x_i)$ is widely used. Here, p denotes the expected distribution of possibilities and q is the actual distribution. By minimizing Loss in each epoch, we will obtain a high-accuracy model.

III. RESULTS AND DISCUSSIONS

In this section, we will introduce the strategy for pulse design in detail. We choose the Lindblad operator $L = \sum_{i=1}^N \sigma_i^-$. Here, $\sigma_i^- = (\sigma_i^x - i\sigma_i^y)/2$ is the lowering operator of i th spin, and we set $N = 4$ as an example. At first, based on the ideal rectangular pulse in Eq. (10), we try to improve the transmission fidelity through tuning the pulse intensity in each period. Take the pulse half period $\tau = \pi/24$ and the total evolution time $T_{\text{tot}} = \pi/4$. According to Eq. (10), the ideal pulse intensity will be $I = 48$ and the pulse will have three periods. Now our target is to design a pulse sequence that can perform well in an environment. For training the NN, we take the parameters $\Gamma \in (0, 0.1]$, $\gamma \in (0, 10]$, $T \in (20, 40]$, and the intervals are 0.01, 0.5, and 0.2, respectively. So, the dataset includes $10 \times 20 \times 100 = 20\,000$ sets of environmental parameters. Besides, since $P = 3$, for each set of environmental parameter, the pulse sequence $\mathbf{I} = [I_1, I_2, I_3]$. So, the dataset has 60 000 sets of data.

Since we use rectangular pulse, the pulse intensity is constant in the first half-period, and in the second-half period, the pulse intensity has a negative value. For certain Γ , γ , and T , we choose one action and let the system evolves under the control. Assume the density matrix of initial state is $\rho(0)$. In the first period, we try a pulse intensity and obtain the corresponding density matrix ρ_1 and the fidelity F_1 . Then, we reset the matrix to ρ_0 and try another pulse intensity; we obtain ρ_2 and F_2 . Repeat the above procedure until all allowed pulse intensities are tried. We record ρ_i with the highest fidelity and the corresponding pulse intensity I_1 . In the next period, let the initial matrix be ρ_i , which is recorded in the first period, and repeat the procedure in the first period. Finally, for one set of environmental parameters, we obtain the data $[\Gamma, \gamma, T, i, I_i]$.

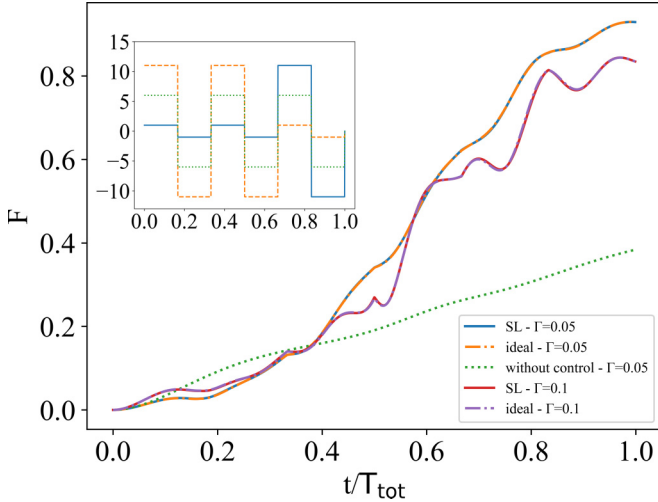


FIG. 3. The fidelity F vs the rescaled time t/T_{tot} ($T_{\text{tot}} = \pi/4$) for $\Gamma, \gamma = 5$, and $T = 40$. The control pulse is presented in the upper left corner. The green line denotes the ideal pulse, and the blue and orange lines denote the optimized pulse obtained by SL for $\Gamma = 0.05$ and 0.1 , respectively.

In this case, the ideal pulse intensity is 48; then, we limit the pulse intensity in $[47.5, 48.5]$, and the interval is 0.1 .

Figure 3 plots the fidelity and optimized pulse versus rescaled time t/T_{tot} . We set $\gamma = 5$ and $T = 40$ fixed. The three distinguishable curves are $\Gamma = 0.05, 0.1$ with optimized pulses and without optimized pulses, from top to bottom. We can see that with increasing Γ , the fidelity decreases. Meanwhile, compared to free evolution, pulse control significantly improves the fidelity. However, the fidelity under pulses designed with SL is almost equal to ideal pulses. The reason may lie in that the optimal parameters are only three intensities of pulses, which do not provide enough space for tuning. In the upper left corner, we plot the pulse designed by SL. To make it easier to distinguish, we map the pulse intensity with 1 in the ordinate corresponding to 47.5 in the pulse intensity, and 11 in the ordinate corresponding to 48.5 in the pulse intensity.

Since the above strategy is not effective, we add more adjustable parameters for the zero-area pulse. Here, inspired by the Fourier expansion of the rectangular pulse, we consider a combinatorial pulse, which can be written as

$$c(t) = \frac{4}{\pi} \sum_{i=1}^k I_i \sin[(2i-1)\omega t]. \quad (11)$$

Here, $\omega = 2\pi/\Delta t$ and $\Delta t = T_{\text{tot}}/3$. Note that when $I_1 = I_2 = \dots = I_k$ and $k \rightarrow \infty$, it is the rectangular pulse. In our work, we consider the first ten terms ($k = 10$). Each term has its corresponding pulse intensity I_i , so the pulse sequence is $\mathbf{I} = [I_1, I_2, I_3, \dots, I_{10}]$. The ranges of the environmental parameters are the same as in above strategy. So, we have 200 000 sets of data. We train NN and the default parameters are presented in Table I. Figure 4 plots the accuracy of both training and test sets versus the number of epochs for combinatorial pulse. We can see that after 20 epochs, the NN converges.

TABLE I. The default parameters of NN.

Parameters	Combinatorial pulse
Number of allowed actions	7
Batch size	80
Neurons per hidden layer	256/128/64/32
Percentage of test set	0.05
Optimizer	Adam
Learning rate	0.001
Number of epochs	100
Activation function	softmax

The strategy for dataset construction is similar with the rectangular pulse case. The adjustable parameters of pulse are now $I_1, I_2, \dots, I_{10}$. In this case, we limit the pulse intensity in $[0, \pm 40, \pm 50, \pm 60]$. Assume the density matrix of initial state is $\rho(0)$. For certain Γ, γ , and T , we try a pulse intensity and let the system completes the transmission process from $t = 0$ to $t = \pi/4$. Then, we obtain F_1 . After that we reset the matrix to ρ_0 and try another pulse intensity, we obtain F_2 . Repeat the above procedure until all allowed pulse intensities are tried. We record the highest fidelity and the corresponding pulse intensity I_1 . Next, we need to find suitable I_2 ; we reset the matrix to $\rho(0)$; and repeat the procedure we use to obtain I_1 . In this step, I_1 is fixed to be what we have obtained before, and on the basis of I_1 , we try to obtain I_2 . Note that when we consider I_i , from I_1 to I_{i-1} all are fixed. Finally, for one set of environmental parameters, we obtain the data $[\Gamma, \gamma, T, i, I_i]$.

Figure 5 plots the fidelity versus the rescaled time t/T_{tot} for different environmental parameters with ideal and combinatorial pulses, respectively. In Fig. 5(a), $\gamma = 5$ and $T = 40$. We can see that with Γ increases, the fidelity decreases. When $\Gamma = 0.05$, the final fidelity $F(T_{\text{tot}})$ is less than 0.4 without pulse control. With pulse control, the fidelity improves greatly, reaching 0.93 with both ideal and combinatorial pulses. In this case, since the environment is weak, ideal and combinatorial pulses obtain similar final fidelity. When $\Gamma = 0.1$, the fidelity improvement with combinatorial pulse is significantly higher than ideal pulse. In Fig. 5(b), $\Gamma = 0.05$ and $T = 40$. When $\gamma = 5$, the combinatorial and ideal pulses also obtain similar final fidelity. When γ increases, the improvement

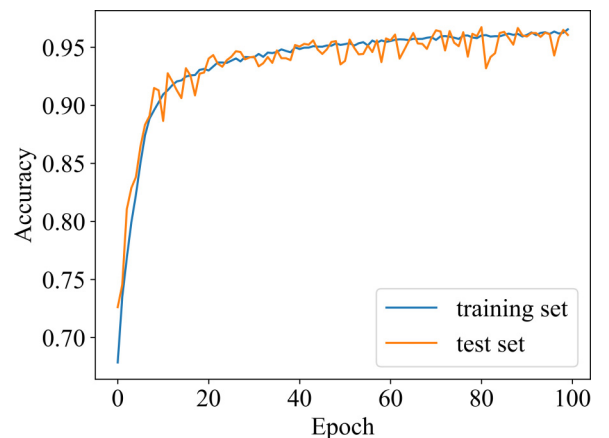


FIG. 4. The training process of NN for combinatorial pulse.

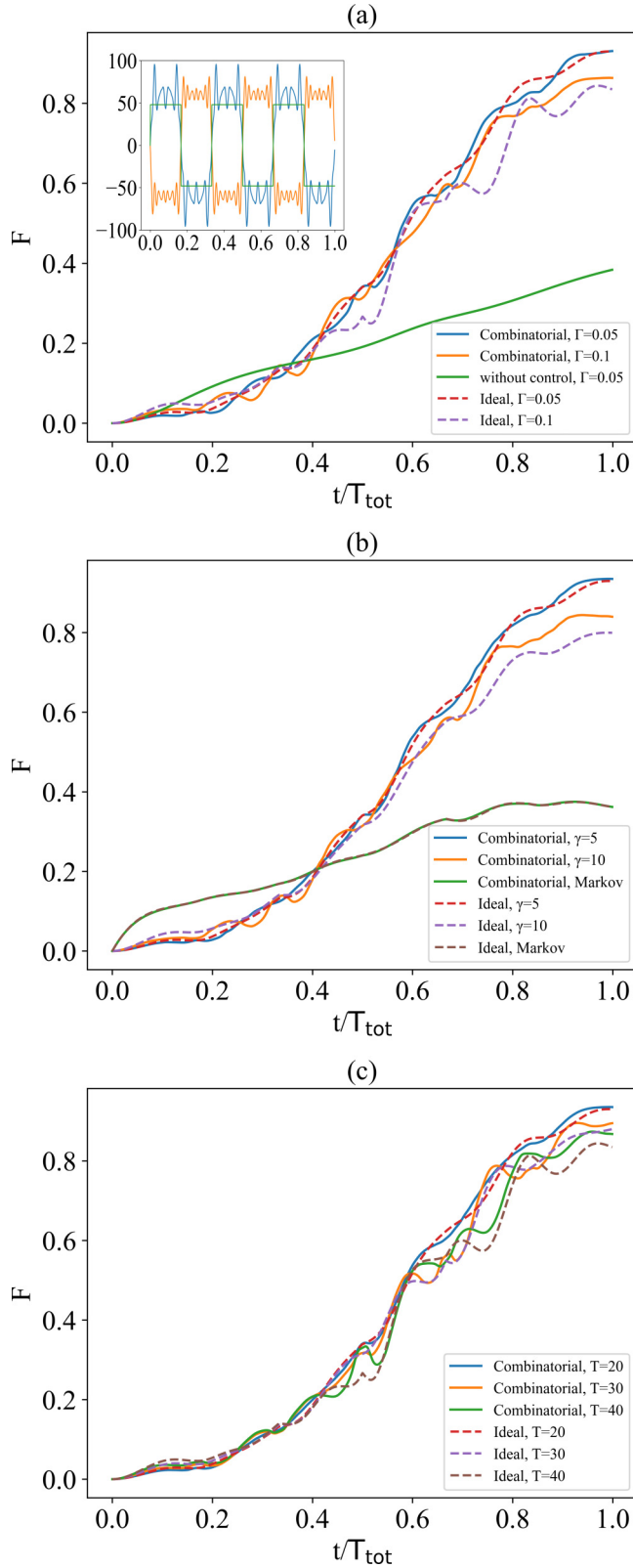


FIG. 5. The fidelity F vs the rescaled time t/T_{tot} ($T_{\text{tot}} = \pi/4$) with ideal and optimized pulses for different parameters (a) Γ , $\gamma = 5$ and $T = 40$; (b) γ , $\Gamma = 0.05$ and $T = 40$; (c) T , $\Gamma = 0.1$ and $\gamma = 5$. The upper left corner of panel a presents the ideal and optimized pulses; the green line denotes the ideal pulse, and the blue and orange curves denote optimized pulses for $\Gamma = 0.05$ and 0.1 , respectively. $N = 4$.

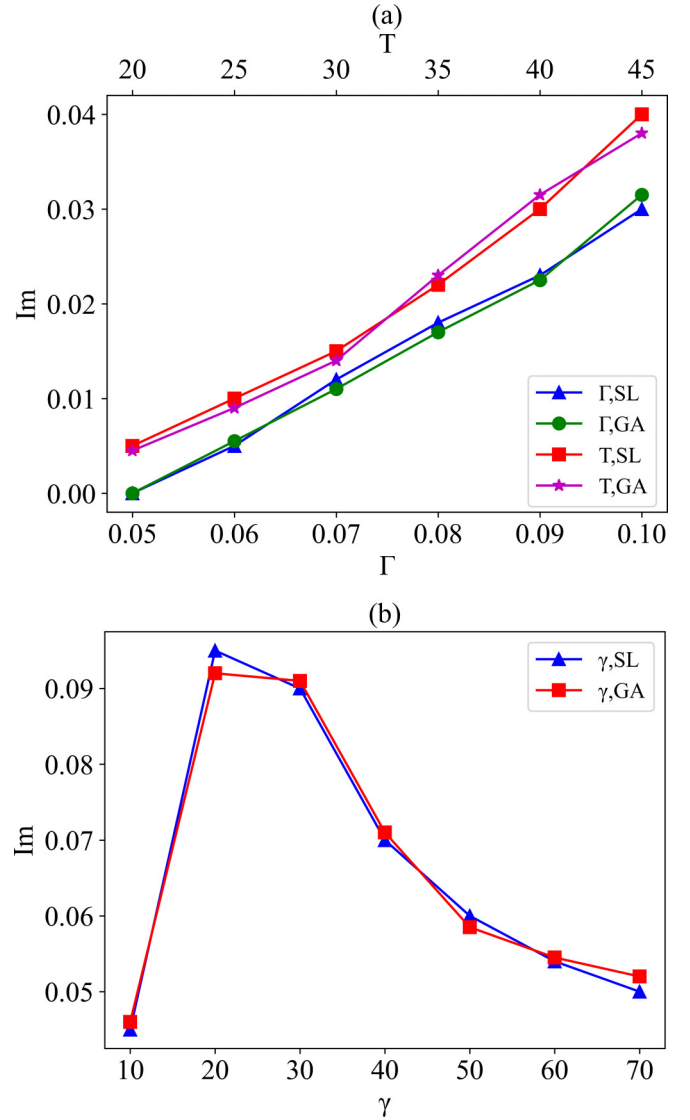


FIG. 6. The fidelity improvement Im at $t = \pi/4$ vs (a) Γ and (b) γ for both SL and GA. $N = 4$.

increases. However, when the environment is Markovian ($\gamma \rightarrow \infty$), SL obtains similar fidelity compared with ideal pulse. In Fig. 5(c), $\Gamma = 0.1$ and $\gamma = 5$. We can also see that with temperature getting higher, the fidelity is lower as expected, and the improvement in fidelity increases as T increases.

From Fig. 5, we can see that when the environment is weak (small Γ , T , and γ), the fidelity improvement is not significant. But with increasing Γ , T , and γ , it becomes bigger except for big γ . In order to show the fidelity improvement for the combinatorial pulse than ideal pulse, we introduce the fidelity improvement $\text{Im} = F_{\text{op}}(T_{\text{tot}}) - F_{\text{id}}(T_{\text{tot}})$. Here, $F_{\text{op}}(T_{\text{tot}})$ is the final fidelity obtained by optimized pulse and $F_{\text{id}}(T_{\text{tot}})$ is the final fidelity obtained by ideal pulse. Figure 6(a) plots the fidelity improvement Im versus Γ and T . We can see that the value of Im increases as these environmental parameters increase. It verifies that a more strong environment provides more space for the fidelity improvement by tuning the ideal pulse, which has also been observed via the traditional Adam

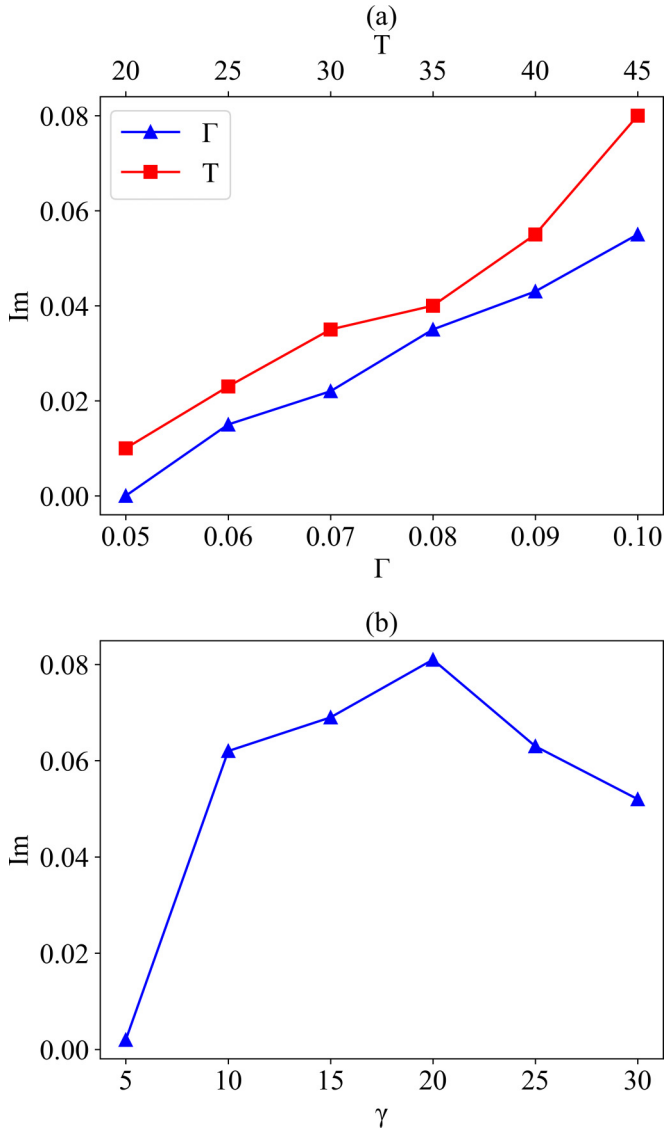


FIG. 7. The fidelity improvement Im at $t = \pi/4$ vs (a) Γ and T ; (b) γ for GA. $N = 6$.

algorithm [15,22]. Figure 6(b) plots the fidelity improvement Im versus γ . The difference is that there is a peak. When $\gamma < 20$, Im increases as γ increases. However, when $\gamma > 20$, larger γ leads to lower Im . In the increasing area of Im , a more Markovian environment will affect the system more and provide more space for improvement. However, when γ becomes extremely large, a Markovian environment means that the information flows quickly from system to environment. Then, it is hard to control the state of the system and the effectiveness of the control is more significant for a more non-Markovian environment [39,40].

When using the SL algorithm, once the NN is well trained, the optimal pulse can be obtained via the generalization ability of NN for any environmental parameters. To check the correctness of the prediction, we use traditional GA to deal with the same task and compare the fidelities given by SL and GA. GA is an evolutionary algorithm used for optimization. It encodes potential solutions as individuals (chromosomes)

with parameters (genes). The goal is to evolve better solutions through natural selection, crossover, and mutation. We choose GA because compared to the algorithms based on gradient descent like Adam and SGD, the algorithm takes into account multiple individuals in the population and has the ability to perform parallel calculations; as a result, GA converges faster while searching for the optimal solution globally. The calculation results of GA are also plotted in Fig. 6. From Fig. 6, we can see that similar results are obtained for both SL and GA, verifying the correctness of the NN-based SL algorithm, except for some specific environmental parameters.

We only consider $N = 4$ in the above discussion. With increasing N , the increase of time for dataset construction will be exponential as 2^N . For big N , SL is no longer efficient, even for $N = 5$. GA has the ability to perform parallel calculation and can be used for bigger N . Here, we use GA to deal with $N = 6$. Figure 7 shows the fidelity improvement Im versus parameters Γ , γ , and T at time $t = \pi/4$ via GA-designed pulse. As expected, a similar behavior to that shown in Fig. 6 was observed with $N = 4$.

IV. CONCLUSION

Zero-area pulse control is an effective strategy for performing quantum information processing tasks. However, ideal pulse conditions are only suitable for closed systems. In open systems, these conditions must be adjusted to mitigate environmental noise. In this paper, we use both SL and GA to find the optimized zero-area pulse in a noisy environment. As an example, we consider quantum state transmission through a one-dimensional XY uniform spin chain, which is immersed in a non-Markovian heat bath. The dynamics are described by a non-Markovian quantum master equation. For the modified rectangular pulse, we find that fidelity improvement cannot be achieved by simply tuning the intensity. We then use a combinatorial function with more adjustable parameters, and the results show that the fidelity can be significantly enhanced by these combinatorial pulses compared to the ideal pulse. The fidelity improvement increases with the parameters Γ and T , as expected, since a stronger environment provides more potential for improvement. However, for the parameter γ , the fidelity improvement first increases and then decreases, indicating that the control's effectiveness weakens in a more Markovian environment. We also use GA to solve the same design task and find that the fidelities obtained from both algorithms are nearly identical. Finally, leveraging the parallel computation capability of GA, we design the optimal pulse for large N . The dependence of fidelity improvement on environmental parameters is evident for larger N . Our paper provides a general strategy for optimal control design based on given environmental parameters.

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DATA AVAILABILITY

The data that support the findings of this article are not publicly available. The data are available from the authors upon reasonable request.

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