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# A Relay Optimization Method for NOMA-Based Power Line Communication Systems

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**Abstract:** Power line communication (PLC) technology is investigated in this research. A PLC system model combining Orthogonal Frequency Division Multiplexing (OFDM) and Non-Orthogonal Multiple Access (NOMA) technologies is proposed to enhance spectral efficiency, extend transmission distance, and improve signal quality. We construct detailed models for the system, signal, and noise. Future Channel State Information (CSI) is predicted using a Long Short-Term Memory (LSTM) network, and an improved simulated annealing algorithm is employed to optimize power allocation and relay positioning in the system. Experiments validate the effectiveness of the LSTM model in predicting CSI data in a NOMA communication system, demonstrating generally good performance despite some prediction errors. Simulation results show that this approach significantly enhances system performance, reduces power consumption, and meets constraints on system capacity, bit error rate (BER), and signal-to-interference-plus-noise ratio (SINR) in complex PLC environments. Future research should focus on optimizing model parameters, expanding datasets, exploring alternative optimization algorithms, and testing the model in real-world scenarios to improve generalizability and practicality. In conclusion, the proposed multi-user PLC system provides an effective technical solution for future smart grid and Internet of Things (IoT) applications.



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**Keywords:** power line communication (PLC); Non-Orthogonal Multiple Access (NOMA); Long Short-Term Memory (LSTM); simulated annealing algorithm; Channel State Information (CSI)

## 1. Introduction

Power line communication (PLC) utilizes existing power distribution networks for data transmission. Due to its low deployment cost and high performance, PLC has garnered significant attention in recent years. PLC technology is extensively applied in areas such as smart grids, home networking, and industrial automation systems. In situations lacking new infrastructure, information can be transmitted through existing power networks and grids, making it an efficient communication method [1–4].

The main challenges for PLC systems include multipath fading, noise, and electromagnetic interference, which can all affect signal transmission quality. Researchers have proposed various signal processing and modulation techniques to enhance the reliability and security of PLC systems. Orthogonal Frequency Division Multiplexing (OFDM) is a technique that improves spectral efficiency by distributing a signal among multiple orthogonal subcarriers. Combined with dynamic resource allocation strategy, OFDM can

effectively suppress multipath fading in power line communication. This approach significantly improves resource utilization, quality of service, and data transmission rates [5].

Non-Orthogonal Multiple Access (NOMA), an emerging multi-user access technology, enables multiple users to share the same frequency band resources through power domain or code domain multiplexing, thus significantly improving spectrum efficiency. Compared to traditional Orthogonal Multiple Access (OMA), NOMA serves multiple users simultaneously, thereby increasing system capacity and reducing latency. NOMA significantly improves PLC system performance, better meeting the needs of future smart grids and the Internet of Things (IoT) [6–10].

Researchers have recently proposed various NOMA-based PLC schemes, including two-stage and cooperative relay schemes, to further enhance system performance. For instance, the two-stage NOMA scheme applies NOMA at both the source and relay modems, significantly improving system capacity compared to single-stage schemes. Additionally, cooperative NOMA strategies, where multiple PLC modems relay signals together, have shown significant improvements in reliability and throughput, especially in harsh PLC environments [3,11].

To further optimize PLC system performance, researchers have proposed combining OFDM and NOMA technologies. These schemes enhance spectral efficiency, improve signal quality, and extend transmission distance through relay technology. In multi-hop hybrid PLC-wireless communication systems, employing decode-and-forward relays significantly enhances system reliability and coverage [3].

To address noise and fading issues in PLC systems, researchers have introduced receive diversity techniques and power optimization strategies. In receive diversity PLC systems under Nakagami-m noise environments, the minimum mean square error estimation technique is used to obtain channel gain estimates, and the maximum likelihood decision rule designs suboptimal receiver structures, improving system symbol error probability performance [12]. In three-node bidirectional relay-assisted PLC systems, power optimization algorithms considering quality of service constraints effectively reduce total system power and enhance performance [13].

Smart grid applications necessitate frequent access to PLC networks by numerous devices requesting data transmission. To meet this demand, several access protocols have been proposed. For example, slot-based ALOHA schemes, though simple, are effective, and multi-channel ALOHA has been applied and analyzed in cognitive networks. However, traditional access protocols such as ALOHA and Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) are limited by the number of subchannels, preventing them from supporting large-scale user access. Fortunately, applying NOMA in Medium Access Control (MAC) layer protocols allows multiple users to share the same channel, improving system throughput and reducing collision rates [14–16].

In summary, PLC systems combining NOMA, OFDM, and relay technologies show great potential in enhancing system capacity, extending transmission distance, improving signal quality, and reducing power consumption. The integrated application of these technologies provides effective solutions for future smart grid and IoT applications and guides further research and development of PLC systems.

Similarly, in Visible Light Communication (VLC) networks, Natarajan et al. [17] proposed an Exponential Gain Ratio Power Allocation (EGRPA) strategy for MIMO-NOMA systems, achieving a 38.7% sum rate improvement compared to traditional methods. These studies highlight the critical role of adaptive resource allocation and noise mitigation in heterogeneous communication environments [15].

IN suppression techniques have evolved from traditional filtering to advanced signal processing. In PLC, Samir et al. [10] employed cyclic redundancy checks (CRCs) to detect

and retransmit corrupted packets, while Lakew et al. [18] leveraged TDI with MMSE equalization to reduce BER in NOMA-OFDM systems by 20 dB under IN. For VLC, Wu et al. [16] integrated chaotic encryption with OFDM-NOMA to enhance security and PAPR performance. These approaches, however, often trade computational complexity for performance gains, necessitating low-complexity alternatives for resource-constrained IoT devices.

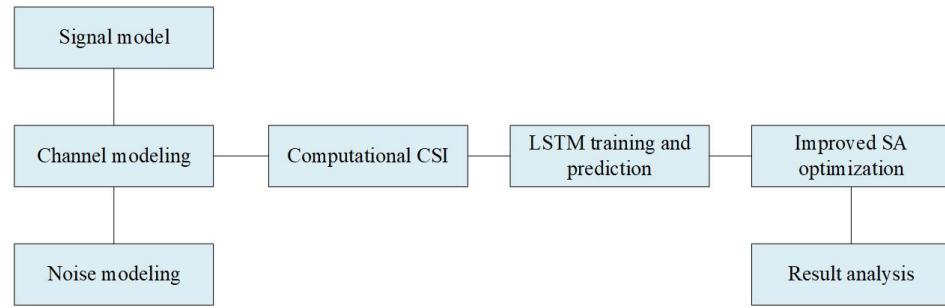
The integration of heuristic algorithms and machine learning has gained traction. Natarajan et al. [17] focused on exponential power allocation in MIMO-VLC but omitted relay optimization. Ahiadormey et al. [8] highlighted the potential of hybrid GA-SA algorithms in bidirectional PLC systems, yet their work lacks scalability for multi-user scenarios.

Despite significant progress in improving PLC system performance, some shortcomings remain. First, most studies consider fixed relay positions and power allocation schemes, without considering dynamic channel conditions and real network environments. Second, existing optimization algorithms are mostly based on traditional mathematical models and do not fully utilize modern artificial intelligence technologies to enhance system performance. Additionally, most studies consider systems with only two or three users, with limited research on multi-user scenarios.

This paper proposes a multi-user PLC system combining NOMA and OFDM technologies to address these issues. In this system, we design a communication network with multiple users and relays, where suitable users act as relays to communicate with remote users. Specifically, this paper proposes a method combining deep learning models and improved simulated annealing algorithms to optimize relay positions and total system power. The main contributions of this paper are as follows:

1. Constructing a multi-user NOMA PLC system model that combines frequency division multiplexing technology, selecting suitable users as relays to communicate with remote users. This model enhances spectral efficiency, extends transmission distance, and improves signal quality through relay technology.
2. LSTM networks in deep learning models to predict future Channel State Information (CSI). LSTM is a neural network model capable of capturing long-term dependencies in time series data, making it highly suitable for predicting time series CSI. By training on historical channel data, the LSTM model can accurately predict future CSI, providing precise input data for system optimization.
3. Combining the predicted CSI with improved simulated annealing algorithm to optimize system power and relay positions. The simulated annealing algorithm is a stochastic optimization algorithm capable of escaping local optima and approaching global optima. By continuously adjusting relay positions and transmission power during the simulated annealing process, the optimal relay positions and minimum power configuration that meet system performance constraints are ultimately obtained.
4. Conducting extensive simulation experiments to verify the effectiveness of the proposed method. The results show that the combination of LSTM prediction and simulated annealing optimization significantly improves system transmission performance, reduces total power consumption, and maintains stable communication quality in complex PLC channel environments. The full-text structure flow chart is shown in Figure 1.

This paper is organized as follows: Section 2 presents the multi-user relay NOMA PLC system model, including the noise model and signal model, and adopts frequency division multiplexing to improve system efficiency. Section 3 details the proposed optimization method combining deep learning and improved simulated annealing algorithms and its performance analysis. Section 4 discusses the simulation results. Section 5 concludes the paper.

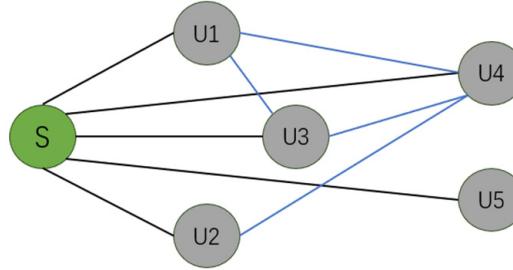


**Figure 1.** Full-text structure flow chart.

## 2. System Model

### 2.1. Channel and Noise Model

The power line communication system consists of a signal source (S) and  $n$  users (U), where users communicate through the power line. Users are sorted by their distance from the signal source as  $U_i$ , where  $i = 1, 2, \dots, n$ . For example, a simplified structure with one source and five users is illustrated in Figure 2.



**Figure 2.** Example of PLC structure for users.

Users are arranged in the order of distance from the source as  $U_1$  to  $U_5$ . The channel gains between  $S - U_1, \dots, S - U_5, U_1 - U_3, U_1 - U_4, U_2 - U_4$ , and  $U_3 - U_4$  are denoted as  $h_{su1}, \dots, h_{u3u4}$ , respectively. These gains are modeled as independent normal distribution random variables. The log-normal fading model is widely used in PLC systems as it describes network topology mismatch and multipath effects [19]. The probability density function (PDF) of these channel gains is given by [20–23]:

$$f(h_i) = \frac{1}{\sqrt{2\pi}\sigma_i h_i} \exp\left[-\frac{(\log h_i - \mu_i)^2}{2\sigma_i^2}\right] \quad (1)$$

where  $i \in \{S - U_1, S - U_2, \dots, S - U_5, U_1 - U_3, U_1 - U_4, U_2 - U_4, U_3 - U_4\}$ ,  $\mu_i$  and  $\sigma_i^2$  are the mean and standard deviation of the  $10\log_{10}(hi)$ , respectively.  $\mu_i$  represents the mean logarithmic channel gain, while  $\sigma_i^2$  quantifies channel variability due to impedance mismatches. For instance, a higher  $\sigma_i^2$  indicates severe multipath fluctuations, common in branched powerline networks. This model effectively captures the characteristics of signal attenuation and multipath propagation in PLC environments. Furthermore, the channel attenuation due to distance and frequency dependence is denoted as  $A_i(d_i, f)$ , where  $f$  represents the communication frequency and  $d_i$  represents the distance between nodes  $i \in \{S - U_1, S - U_2, \dots, S - U_5, U_1 - U_3, U_1 - U_4, U_2 - U_4, U_3 - U_4\}$  [24–27]. Specifically, it is given by:

$$A_i(f, d_i) = e^{-(b_0 + b_1 f^k) d_i} \quad (2)$$

where  $k$  is the exponent of the attenuation coefficient, and  $b_0$  and  $b_1$  are constants obtained through measurements.

Channel noise mainly includes two types: background noise and impulsive noise. Since the power spectral density of background noise is relatively low and changes slowly over time, it manifests as a slowly varying random process in the time domain. Therefore, it can be represented by a stationary random process [10,28,29], described using an autoregressive (AR) model. Given that the spectral characteristics of background noise in power line channels are similar to those of a stationary random process, and its variance is finite, the simplest stationary random process, the AR model, can be used for its modeling [27]. A time series signal can be represented by a  $p$ -order difference equation, as shown below:

$$x(n) + a_1x(n-1) + \dots + a_px(n-p) = w(n) + b_1w(n-1) + \dots + b_qw(n-q) \quad (3)$$

where  $w(n)$  is zero-mean white noise with variance  $\sigma^2$ . The AR model sets all coefficients  $b_i(i = 1, 2, \dots, q)$  to zero:

$$x(n) + a_1x(n-1) + \dots + a_px(n-p) = w(n) \quad (4)$$

Its system function is given by:

$$H(z) = \frac{1}{A(z)} = \frac{1}{1 + \sum_{i=1}^p a_i z^{-i}} \quad (5)$$

From the above equation, it is known that the AR model parameters of the background noise in power line channels include the variance  $\sigma^2$  and  $p$  coefficients  $a_k(k = 1, 2, \dots, p)$ . Once these  $p + 1$  coefficients are determined, the AR model can be established. The AR model approximates background noise as a linear combination of past samples plus white noise, widely used for stationary processes. However, impulsive noise does not exhibit the stationary characteristics of random signals. For modeling impulsive noise, the Markov chain model is generally considered a good fit. The fundamental characteristic of a Markov chain is that previous states do not affect subsequent states, similar to the basic characteristics of impulsive noise.

**Definition 1.** Let a Markov chain's state value  $X_{m+k}$  at time  $m+k$ , be  $a_j$ , and the state value  $X_m$  at time  $m$ , be  $a_i$ . If the state values  $X_{s_i}$  at times  $s_i$  are  $a_{s_i}$  and satisfy  $s_1 < s_2 < \dots < s_l < m < m+k$ , then according to the definition of the Markov chain:

$$\begin{aligned} P\{X_{m+k} = a_j | X_{s_1} = a_{s_1}, \dots, X_{s_l} = a_{s_l}, X_m = a_i\} \\ = P\{X_{m+k} = a_j | X_m = a_i\} \\ = p_{ij}(m, m+k) \end{aligned} \quad (6)$$

where  $p_{ij}(m, m+k)$  is the  $k$ -step transition probability, which is the probability that  $X_{m+k} = a_j$  given  $X_m = a_i$ . When  $k = 1$ :

$$\begin{aligned} P\{X_{m+1} = a_j | X_{s_1} = a_{s_1}, \dots, X_{m-1} = a_{m-1}, X_m = a_i\} \\ = P\{X_{m+1} = a_j | X_m = a_i\} \\ = p_{ij}(m, m+1) \end{aligned} \quad (7)$$

At this time,  $p_{ij}(m, m + 1)$  represents the one-step transition probability, and the matrix composed of these  $p_{ij}(m, m + 1)$  values is the Markov chain transition probability matrix. Let  $N$  be the total number of states in the Markov chain. The transition probability matrix is given by:

$$P(m, n) = \begin{bmatrix} p_{11}(m, n) & p_{12}(m, n) & \cdots & p_{1N}(m, n) \\ p_{21}(m, n) & p_{22}(m, n) & \cdots & p_{2N}(m, n) \\ \vdots & \vdots & \ddots & \vdots \\ p_{N1}(m, n) & p_{N2}(m, n) & \cdots & p_{NN}(m, n) \end{bmatrix} \quad (8)$$

For example, the moment from low noise to high noise is defined as the state transition moment, and the state transition probability at this moment is the probability of pulse noise. According to the law of total probability, the sum of the elements in each row and column of the transition matrix equals 1. This fundamental characteristic of the Markov chain transition matrix can be used to verify the accuracy of the calculated matrix.

## 2.2. Signal Model

This section describes the model for signal propagation in the network. Let  $p_s$  represent the transmission power at source  $s$ . To achieve full-duplex communication, a combination of NOMA and OFDM is proposed. Specifically, in the system with the source and multiple users, uplink and downlink transmissions occur on different frequency bands, and NOMA technology is used within each band. The uplink and downlink need to be modeled separately to assist in the subsequent optimization process.

### 2.2.1. Uplink Model

The uplink spectrum  $f_u$  is divided into  $M$  sub-bands, with each sub-band having a bandwidth of  $B_u / M$ . In the  $k$ -th sub-band  $f_{uk}$  of the uplink, it is assumed that there are  $K_k$  users performing NOMA transmission. The transmission signal of user  $U_i$  on  $f_{uk}$  is represented as:

$$x_i^{(u)}(t) \quad (9)$$

Each user  $U_i$  transmits signals to the source with uncorrelated transmission power  $p_i^{(u)}$ , constrained by its maximum transmission power  $p_{max,i}^{(u)}$ . If there are sufficient differences in channel gains  $h_i^{(u)}$  among users, they can transmit using their maximum power  $p_{max,i}^{(u)}$  to achieve better system performance. The total received signal is:

$$y_k^{(u)}(t) = \sum_{i=1}^{K_k} h_i^{(u)} \sqrt{p_i^{(u)}} x_i^{(u)}(t) A_i^{(u)}(d_i, f) + n_k^{(u)}(t) \quad (10)$$

where  $h_i^{(u)}$  is the channel gain of user  $U_i$  on sub-band  $f_{uk}$ , and  $n_k^{(u)}(t)$  is the noise on sub-band  $f_{uk}$ . The receiver uses Successive Interference Cancellation (SIC) technology to decode user signals sequentially in descending order of power. Successive Interference Cancellation (SIC) enables decoding of overlapping signals by iteratively removing the strongest component. High-power signals are decoded first. Its contribution is subtracted from the received signal, allowing clean decoding of subsequent low-power signals. This iterative offset mitigated multi-user interference. Assume the signal power of user  $U_i$  is  $P_i^{(u)}$ . The signal of the user with the highest power,  $x_{i1}^{(u)}(t)$ , is decoded first:

$$x_{i1}^{(u)}(t) = y_k^{(u)}(t) - \sum_{j=2}^{K_k} h_{ij}^{(u)} \sqrt{p_j^{(u)}} x_{ij}^{(u)}(t) A_{ij}^{(u)}(d_{ij}, f) \quad (11)$$

The remaining signals are decoded in sequence. In this manner, users transmit at their maximum power on the uplink, allowing the system to exploit differences in channel gains to enhance overall performance.

### 2.2.2. Downlink Model

The downlink spectrum  $f_d$  is divided into  $M$  sub-bands, each with a bandwidth of  $B_d/M$ . In the  $m$ -th sub-band  $f_{dm}$  of the downlink, assume there are  $L_m$  users performing NOMA transmission. The total transmitted signal from the signal source on  $f_{dm}$  is:

$$y_m^{(d)}(t) = \sum_{j=1}^{L_m} h_j^{(d)} \sqrt{a_j p_i^{(d)}} x_j^{(d)}(t) A_j^{(u)}(d_j, f) + n_m^{(d)}(t) \quad (12)$$

where  $h_j^{(d)}$  is the channel gain of user  $U_j$  on sub-band  $f_{dm}$ , and  $n_m^{(d)}(t)$  is the noise on sub-band  $f_{dm}$ . The power allocation factor  $a_j$  satisfies  $\sum_{j=1}^{L_d} a_j = 1$ . The receiver also uses SIC technology to decode user signals sequentially in descending order of power. Assume the signal power of user  $U_j$  is  $P_j^{(d)}$ . The signal of the user with the highest power,  $x_{j1}^{(d)}(t)$ , is decoded first:

$$x_{j1}^{(d)}(t) = y_m^{(d)}(t) - \sum_{k=2}^{L_m} h_{jk}^{(d)} \sqrt{p_i^{(d)}} x_{jk}^{(d)}(t) A_{jk}^{(d)}(d_{jk}, f) \quad (13)$$

The remaining signals are decoded sequentially. This establishes the full-duplex communication model for both uplink and downlink.

These models describe the time-varying characteristics and multi-user interference of power line channels in detail and provide a theoretical basis for further optimization. However, the complexity of dynamic channel state and multi-hop relay requires an efficient joint optimization strategy. To this end, this paper proposes a hybrid framework that integrates deep learning and heuristic algorithms, and the specific process is as follows.

## 3. Optimization Process and Performance Analysis

Based on the system model established in Section 2 and the results of channel state prediction, this section focuses on how to realize the combined optimization of power distribution and relay position through the LSTM network model and improved simulated annealing algorithm and analyzes the performance. The communication process employs NOMA technology, allowing each user to act as an independent decode-and-forward relay. To ensure system communication quality, if a remote user's path loss due to distance from the signal source is too high, an intermediate user between the remote user and the signal source is selected to act as a relay.

The intermediate user decodes and retransmits the signal to help the remote user receive it correctly. To ensure reliable communication, the transmitter includes a set of check codes in the transmitted information. Subsequent nodes recognize and verify these check codes. The check codes use cyclic redundancy checks (CRCs), which involve appending a number (the check code) to the frame to be sent, generating a new frame for transmission to the receiver. This appended number ensures that the new frame can be divided (modulo-2) by a specific divisor jointly selected by the transmitter and receiver. At the receiver, the new frame is divided by the selected divisor. If the frame was pre-processed to be divisible without remainder at the transmitter, no remainder should be found at the receiver. If there is a remainder, it indicates an error in transmission. If the check code is correct, the node can communicate normally without relaying. If the check code is incorrect, a feedback request is sent to activate relaying. The relay decodes and forwards the message.

In the downlink, frequency division multiplexing (FDM) is used between 3 MHz and 30 MHz. Once the system confirms the need for relaying, it verifies the Channel State

Information (CSI) of user nodes that can correctly receive the information to optimize relay selection. In the optimization process, Channel State Information (CSI) is a critical parameter indicating channel quality. CSI describes the state of the channel, reflecting attenuation and interference that the signal experiences during transmission. Specifically, CSI includes the channel's gain or loss information and evaluates transmission quality on a specific channel. In the optimization process, CSI calculates the signal-to-interference-plus-noise ratio (SINR), determining each user's capacity and total power:

$$\text{SINR}_i = \frac{P_i \cdot \text{CSI}_i}{\sigma^2} \quad (14)$$

where  $P_i$  represents the power allocated to each user. Once the channel state is confirmed, if a user is selected as a relay for decode-and-forward transmission, the channel state will change accordingly. It is necessary to model the altered channel state to predict channel conditions using algorithms. When a user acts as a relay, the received downlink signal is decoded and forwarded via the uplink. The following models are used for the uplink and downlink:

### 3.1. Downlink from Signal Source to Relay Node

The signal source transmits the signal  $x_S(t)$  to the relay node  $u_r$  on the downlink sub-band  $f_d$ . The received signal at the relay node is:

$$y_1^{(d)}(t) = \sum_{j=1}^{L_d} h_{S,r}^{(d)} \sqrt{a_j p_s} x_S(t) A_S^{(d)}(d_S, f) + n_1^{(d)}(t) \quad (15)$$

where  $h_{BS,r}^{(d)}$  is the channel gain from the signal source to the relay node  $u_r$  on the downlink sub-band  $f_d$ ,  $n_1^{(d)}$  is the noise on sub-band  $f_d$ , and  $a_j$  is the power allocation factor, satisfying  $\sum_{j=1}^{L_d} a_j = 1$ . The received signal at the relay node is  $y_1^{(d)}(t)$ , and the decoded signal is  $\hat{x}_{BS}(t)$ .

### 3.2. Uplink from Relay Node to Other Users

The relay node  $u_r$  transmits the decoded signal  $\hat{x}_{BS}(t)$  on the uplink sub-band  $f_u$  to the next receiving node  $u_t$ . The received signal at the receiving node  $u_t$  is:

$$y_2^{(u)}(t) = \sum_{i=1}^{K_u} h_{r,t}^{(u)} \sqrt{b_i p_r} \hat{x}_{BS}(t) A_{rt}^{(u)}(d_{rt}, f) + n_2^{(u)}(t) \quad (16)$$

where  $h_{r,t}^{(u)}$  is the channel gain from the relay node  $u_r$  to the receiving node  $u_t$  on the uplink sub-band  $f_u$ ,  $n_2^{(u)}(t)$  is the noise on sub-band  $f_u$  and  $b_i$  is the power allocation factor satisfying  $\sum_{i=1}^{K_u} b_i = 1$ . The received signal at the receiving node  $u_t$  is  $y_2^{(u)}(t)$ , and the final decoded signal is  $\hat{x}_{BS}(t)$ .

At this point, the SINR in the downlink is:

$$\text{SINR}_1 = \frac{a_j P_S |h_{BS,r}^{(d)}|^2}{N_1} \quad (17)$$

where  $P_S$  is the transmission power of the signal source, and  $N_1$  is the noise power received at the relay node  $u_r$ . The channel capacity of the relay node  $u_r$  is given by:

$$C_1^{(d)} = B_d \log_2 (1 + \text{SINR}_1) = B_d \log_2 \left( 1 + \frac{a_j P_S |h_{BS,r}^{(d)}|^2}{N_1} \right) \quad (18)$$

The SINR for the uplink is given by:

$$\text{SINR}_2 = \frac{b_i P_r |h_{r,t}^{(u)}|^2}{N_2} \quad (19)$$

where  $P_r$  is the transmission power of the relay node  $u_r$ , and  $N_2$  is the noise power at the receiving node  $u_t$ . The channel capacity of the uplink from the relay node to the receiving node is given by:

$$C_2^{(u)} = B_u \log_2 (1 + \text{SINR}_2) = B_u \log_2 \left( 1 + \frac{b_i P_r |h_{r,t}^{(u)}|^2}{N_2} \right) \quad (20)$$

In this step, we obtained the channel state and other information before and after enabling the relay, providing data and model support for subsequent optimization. With the preliminary data, we begin constructing the optimization objective function and constraints. The problem is simplified to minimize total power consumption while ensuring system communication quality. The total channel capacity, denoted as  $C_{total}$ , is the sum of the uplink and downlink capacities, with a minimum requirement  $C_{min}$ .

#### Objective Function:

The objective function is to minimize the system's total power consumption. It is expressed as:

$$\min \left( \sum_{i=1}^N P_i + P_s + \sum_{j=1}^M P_j \right) \quad (21)$$

where  $P_i$  is the power consumption of the  $i$ -th relay, and  $N$  is the number of relays.  $P_j$  is the power of users not relaying, and  $M$  is their number. The objective function balances two goals: minimize relay/user power  $P_i$  to reduce energy costs, and ensure source power  $P_s$  meets baseline coverage.

#### Constraints:

Ensure that the uplink and downlink capacities meet the minimum requirements:

$$C_{s,r}^{(d)} = B_d \log_2 \left( 1 + \frac{P_s |h_{s,r}^{(d)}|^2}{N_1} \right) \geq C_{min} \quad (22)$$

$$C_{r,t}^{(u)} = B_u \log_2 \left( 1 + \frac{P_r |h_{r,t}^{(u)}|^2}{N_2} \right) \geq C_{min} \quad (23)$$

The power allocated to each relay and non-relay user must be non-negative. This constraint ensures that all power values are feasible and practical for the communication system. The non-negative power constraints are:

$$\begin{aligned} P_s &\geq 0 \\ P_r &\geq 0 \end{aligned} \quad (24)$$

The system must ensure that the bit error rate (BER) is within a certain acceptable range to maintain communication quality. This constraint ensures that the communication link is reliable and meets the quality of service (QoS) requirements:

$$BER \leq BER_{max} \quad (25)$$

where  $BER$  is the bit error rate and  $max$  represent the maximum allowable bit error rate. The data rate for each user should meet the minimum requirement:

$$R_i \geq R_{min}, \forall i \quad (26)$$

The relay's position must ensure it is one of the users and is capable of communicating with others to facilitate proper decoding and forwarding.

$$x_i, y_i \in Selectable\ Users, \forall i \quad (27)$$

where  $x_i, y_i$  is the position of the  $i$ -th relay. Considering the above conditions, the optimization problem can be formalized as follows:

$$\left. \begin{array}{l} B_d \log_2 \left( 1 + \frac{P_S |h_{S,r}^{(d)}|^2}{N_1} \right) \geq C_{min} \\ B_u \log_2 \left( 1 + \frac{P_r |h_{r,t}^{(u)}|^2}{N_2} \right) \geq C_{min} \\ \text{subject to} \\ P_S \geq 0 \\ P_r \geq 0 \\ BER \leq BER_{max} \\ R_i \geq R_{min}, \forall i \\ x_i, y_i \in Selectable\ Users, \forall i \end{array} \right\} \quad (28)$$

After optimization, we obtain the relay positions that complete communication with minimal total power.

#### Optimization Approach:

This paper proposes a heuristic optimization algorithm combined with deep learning, aiming to solve the optimization problem. This hybrid approach uses deep learning models to predict Channel State Information (CSI) and heuristic algorithms for power optimization and relay selection. The specific process is as follows:

1. Data Collection and Preprocessing: Collect data related to CSI, noise power, user positions, and other relevant factors from historical communication data. Normalize the data for training deep learning models. Input: Historical communication data, including user positions, historical CSI, and noise power. Process: Load historical data. Select relevant features (user positions, historical CSI, noise power). Normalize the data. The normalization of CSI is given by:

$$CSI_{scaled} = \frac{CSI - \min(CSI)}{\max(CSI) - \min(CSI)} \quad (29)$$

Output: Normalized features for model training.

2. Deep Learning Model Training: Design and create an LSTM deep learning model suitable for time series prediction. Train the model using historical data to predict future CSI. Input: Normalized features and corresponding targets (future CSI values). Process: Define the LSTM model structure. Compile the model using an appropriate loss function and optimizer. Train the model using training data. Output: Trained LSTM model.

The LSTM model was trained on a dataset generated through extensive simulations of the power line communication environment. The dataset consists of 2000 training samples and 500 test samples, each representing a unique communication scenario with varying channel conditions, noise levels, and user positions. The dataset was designed to capture a wide range of CSI variations, including different levels of multipath fading, background

noise, and impulsive noise. The diversity of the dataset ensures that the LSTM model can generalize well to unseen data, making its predictions more reliable in real-world scenarios.

To further enhance the representativeness of the dataset, we incorporated log-normal fading channels and background noise models, which are typical in power line communication systems. The dataset was generated by simulating the communication environment over a range of distances (from 1 to 5 units) and frequencies (from 3 MHz to 30 MHz), ensuring that the model is exposed to a variety of channel conditions. This comprehensive dataset allows the LSTM model to learn the temporal dependencies and nonlinear dynamics of the channel, leading to more accurate CSI predictions.

**3. Initial Power Allocation:** Use the trained model to predict future CSI. Perform initial power allocation based on the predicted CSI to ensure that the initial allocation meets basic communication requirements. Input: Trained LSTM model and new data for prediction. Process: Use the trained model to predict future CSI. Initialize signal source power ( $p_s$ ) and user power ( $p_i$ ) with random values. Expressed as:

$$\text{LSTM}(\text{CSI}_{\text{scaled}}) \rightarrow \text{CSI}_{\text{scaled}} \quad (30)$$

The denormalized prediction results can be expressed as:

$$\widehat{\text{CSI}} = \widehat{\text{CSI}}_{\text{scaled}} \times (\max(\text{CSI}) - \min(\text{CSI})) + \min(\text{CSI}) \quad (31)$$

Output: Initial power values  $p_s$  and  $p_i$ .

**4. Heuristic Optimization:** The goal is to minimize total power while ensuring communication quality (capacity requirement). Simulated annealing (SA) was chosen for this problem due to its unique ability to balance global exploration and local exploitation, particularly in complex non-convex optimization landscapes. In the context of NOMA-based PLC systems, the joint optimization of power allocation and relay positioning involves multiple interdependent variables and nonlinear constraints. Traditional gradient-based methods often struggle with such problems due to their sensitivity to local minima, while heuristic methods like genetic algorithms (GAs) and particle swarm optimization (PSO) may require extensive parameter tuning or population management. The key advantages of SA in this scenario are that SA probabilistically accepts worse solutions during the search process, enabling it to escape local optima and approach the global optimum. This is critical in PLC environments where channel conditions (e.g., noise, fading) create a rugged optimization landscape. Perform multiple iterations using the simulated annealing heuristic algorithm to gradually optimize power allocation. Input: Initial power values  $p_s$  and  $p_i$  predicted CSI, noise power, and minimum capacity. Process: Define a function to calculate total power and SINR. Initialize the best power, best  $p_s$ , and best  $p_i$ . Iterate a fixed number of times: a. Calculate total power,  $SINR_S$ , and  $SINR_i$ . b. Check if capacity constraints are met and if total power is minimized. c. If conditions are met, update the best power, best  $p_s$ , and best  $p_i$ . d. Adjust  $p_s$  and  $p_i$  using random perturbation. Return the best  $p_s$  and best  $p_i$ . Output: Optimized power values for best  $p_s$  and best  $p_i$ .

The performance of the simulated annealing algorithm heavily depends on the choice of parameters, particularly the cooling rate and initial temperature. In this study, we carefully selected these parameters based on extensive experimentation and analysis to ensure optimal performance.

The initial temperature was set to a high value (e.g., 1000) to allow the algorithm to explore a wide range of solutions in the early stages. This ensures that the algorithm does not become trapped in local optima prematurely. The traditional cooling rate was set to 0.999, which was determined through iterative testing to balance exploration and

exploitation. A slower cooling rate allows the algorithm to thoroughly explore the solution space, while a faster cooling rate may lead to premature convergence.

Traditional simulated annealing algorithms use a fixed cooling rate ( $\alpha$ ), which may lead to excessively fast or slow cooling in certain cases, thereby affecting the convergence speed and the quality of the solution. This paper proposes adopting an adaptive temperature control mechanism to optimize the simulated annealing algorithm. The adaptive temperature control dynamically adjusts the cooling rate based on the quality of the current solution and the frequency of accepting new solutions. Specifically, if the solution improves, the cooling rate is increased to accelerate convergence. Conversely, if the solution deteriorates, the cooling rate is decreased to allow more exploration. This adaptive approach ensures that the algorithm can escape local optima while efficiently converging to the global optimum. The specific temperature update rule is as follows:

$$T_{k+1} = \alpha_k \cdot T_k \quad (32)$$

where  $\alpha_k$  is the adaptive cooling rate, which can be dynamically adjusted based on the quality of the current solution. Specifically:

$$\alpha_k = \begin{cases} \alpha \cdot \text{adjustmentFactor}_{\text{improvement}} & \text{if } f_{\text{new}} < f_{\text{current}} \\ \alpha \cdot \text{adjustmentFactor}_{\text{deterioration}} & \text{if } f_{\text{new}} \geq f_{\text{current}} \end{cases} \quad (33)$$

where  $\text{adjustmentFactor}_{\text{improvement}}$  is the adjustment factor when the solution improves, and  $\text{adjustmentFactor}_{\text{deterioration}}$  is the adjustment factor when the solution deteriorates. The probability of accepting a new solution is given by the following formula:

$$P_{\text{accept}} = \begin{cases} 1 & \text{if } f_{\text{new}} < f_{\text{current}} \\ \exp\left(\frac{f_{\text{current}} - f_{\text{new}}}{T_k}\right) & \text{if } f_{\text{new}} \geq f_{\text{current}} \end{cases} \quad (34)$$

where  $f_{\text{current}}$  is the objective function value of the current solution,  $f_{\text{new}}$  is the objective function value of the new solution, and  $T_k$  is the current temperature.

If a new solution  $f_{\text{new}}$  improves the objective function (e.g., reduces total power consumption), the cooling rate is increased to  $\alpha_{\text{improvement}} = \alpha \times 1.05$ . This accelerates convergence by favoring exploitation of the current promising region. If a new solution deteriorates ( $f_{\text{new}} \geq f_{\text{current}}$ ), the cooling rate is decreased to  $\alpha_{\text{deterioration}} = \alpha \times 0.95$ . This encourages exploration by maintaining a higher temperature for longer, preventing premature convergence. The probability of accepting worse solutions is governed by  $P_{\text{accept}} = \exp\left(\frac{f_{\text{current}} - f_{\text{new}}}{T_k}\right)$ . A threshold  $P_{\text{accept}} \geq 0.1$  is enforced to ensure meaningful exploration. If  $P_{\text{accept}}$  falls below this threshold, the temperature is temporarily reset to  $T_{k+1} = 1.2T_k$  to revive exploration. The diversity of solutions is tracked using the coefficient of variation (CV) of the objective function values over the last 100 iterations. If  $CV < 0.01$  (indicating stagnation), the cooling rate is reduced to prolong exploration ( $\alpha_k = \alpha \times 0.9$ ). The adaptive rules are derived from the trade-off between exploration and exploitation, where  $\alpha = 0.999$  is the baseline cooling rate. This ensures that the algorithm spends more time in regions with improving solutions while periodically exploring non-promising areas to avoid local optima.

The proposed adaptive cooling rate mechanism allows SA to dynamically adjust its exploration-exploitation trade-off based on real-time feedback (e.g., predicted CSI changes), making it highly suitable for time-varying PLC channels.

To validate the effectiveness of our parameter selection, we compared the performance of the simulated annealing algorithm with other optimization techniques, such as GA and PSO. The results showed that the simulated annealing algorithm, with the chosen

parameters, achieved a better balance between exploration and exploitation, leading to more robust and reliable solutions. Specifically, the adaptive cooling rate mechanism allowed the algorithm to outperform GA and PSO in terms of convergence speed and solution quality, particularly in complex and dynamic channel conditions. Compared to population-based methods (e.g., GA, PSO), SA requires fewer computational resources per iteration, which is advantageous for real-time optimization in resource-constrained PLC systems. This will also be reflected in the final experimental results and conclusions.

**5. Iterative Optimization and Relay Selection:** Set the minimum capacity requirement, minimum rate requirement, and maximum bit error rate requirement for communication. Use the heuristic optimization algorithm for iterative optimization to select the power allocation that meets the requirements. Choose the most suitable relay node based on the optimization results. The specific calculations are as follows:

$$C_{min} = R_{min} \times \frac{1}{N} \sum_{i=1}^N B_i \quad (35)$$

$$BER_i = 0.5 \cdot \text{erfc}\left(\sqrt{\text{SINR}_i}\right) \quad (36)$$

where  $N$  is the total number of users,  $B_i$  is the bandwidth of the  $i$ -th user,  $BER_i$  is the bit error rate of the  $i$ -th user,  $\text{SINR}_i$  is the signal-to-noise ratio of the  $i$ -th user, and  $\text{erfc}$  is the complementary error function. Input: Initial power values, predicted CSI, noise power, and minimum capacity. Process: Set the minimum capacity requirement. Run the heuristic optimization function to obtain optimized power values. Select the relay node that minimizes total power and meets communication quality requirements. Output: Best relay user index. After optimization, the system's performance needs to be analyzed. In this paper, performance indicators for the LSTM model's CSI prediction include Mean Absolute Error (MAE) and Mean Squared Error (MSE). MAE is the average of the absolute values of all prediction errors, reflecting the average difference between predicted and actual values:

$$MAE = \frac{1}{M} \sum_{i=1}^M |\text{CSI}_i - \hat{\text{CSI}}_i| \quad (37)$$

where  $\text{CSI}_i$  is the actual value,  $\hat{\text{CSI}}_i$  is the predicted value, and  $M$  is the number of samples. MAE is easy to interpret, with error units consistent with the original data. It is not sensitive to outliers and does not become amplified by extreme error values as MSE does. However, it does not reflect the impact of large errors well. MSE is the average of the squares of all prediction errors. It reflects the average squared difference between the predicted and actual values:

$$MSE = \frac{1}{M} \sum_{i=1}^M (\text{CSI}_i - \hat{\text{CSI}}_i)^2 \quad (38)$$

MSE, due to the squared term, is more sensitive to large errors and reflects the impact of outliers. To evaluate the entire system, metrics such as SINR, system capacity, and power consumption are used. The system includes users with relays enabled and those without relays, and performance metrics are calculated separately for each. For relay users, the SINR is:

$$\text{SINR}_i^{\text{relay}} = \frac{P_i \cdot \text{CSI}_i}{\sigma^2} \quad (39)$$

For non-relay users, the SINR is given by:

$$\text{SINR}_j^{\text{non-relay}} = \frac{P_j \cdot \text{CSI}_j}{\sigma^2} \quad (40)$$

For relay users, the capacity  $C_i^{\text{relay}}$  can be calculated as follows:

$$C_i^{\text{relay}} = \log_2(1 + \text{SINR}_i^{\text{relay}}) \quad (41)$$

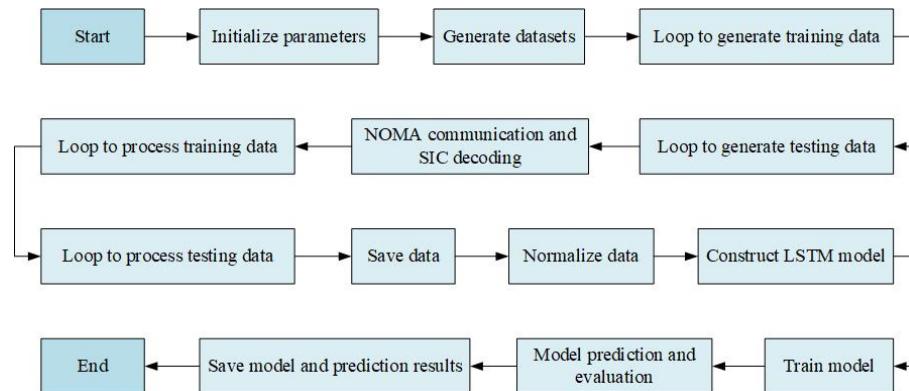
For non-relay users, the  $C_j^{\text{non-relay}}$  is given by:

$$C_j^{\text{non-relay}} = \log_2(1 + \text{SINR}_j^{\text{non-relay}}) \quad (42)$$

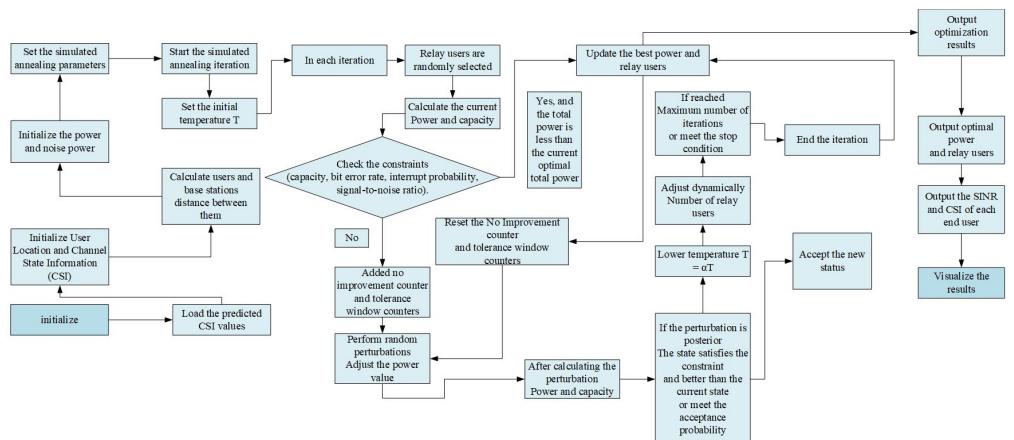
The total system capacity  $C_{\text{total}}$  is the sum of the capacities for both relay users and non-relay users:

$$C_{\text{total}} = \sum_{i \in \text{relay}} C_i^{\text{relay}} + \sum_{j \notin \text{relay}} C_j^{\text{non-relay}} \quad (43)$$

Through the above steps, a new optimization algorithm was designed and implemented. This algorithm combines deep learning models to predict CSI with heuristic optimization algorithms for power allocation and relay selection. It ensures that total power is minimized while meeting communication quality requirements in a system combining NOMA and OFDM and selects the optimal relay position. The specific process of the algorithm is shown in Figures 3 and 4. Figure 3 is a flowchart of the LSTM model training and prediction process, and Figure 4 is a flowchart of the simulated annealing optimization process following the prediction. The following is the simulation verification and concrete analysis of this method.



**Figure 3.** LSTM model training and prediction.



**Figure 4.** Simulated annealing optimization process.

## 4. Experiments and Analysis

This chapter verifies the effectiveness of the proposed method under simulation conditions.

### 4.1. Determination of Experimental Parameters

The experiment simulates a NOMA power line communication network with one source node and five user nodes. Each user can independently act as a relay node to decode and forward signals for other users. The specific parameters are shown in Table 1. The AR model is selected as a 46th order model according to the model parameters in reference [26] and the measured results during the experiment. Specific parameters are shown in Table 2.

**Table 1.** Parameter settings.

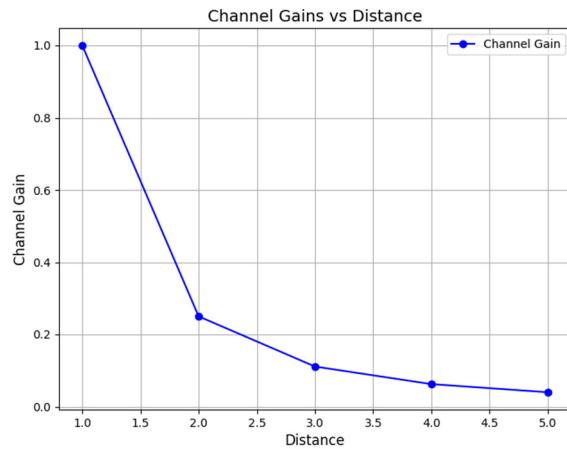
| Variable                                     | Value                |
|--|----------------------|
| Number of users $N$                          | 5                    |
| Background noise mean $\mu$                  | 0                    |
| Background noise variance $\sigma^2$         | 0.00131              |
| AR model order $k$                           | 46                   |
| Number of training sets $M_{train}$          | 2000                 |
| Number of test sets $M_{test}$               | 500                  |
| The length of the send sequence              | 100                  |
| Minimum capacity requirements $C_{min}$      | 1.0                  |
| Temperature attenuation coefficient $\alpha$ | 0.999                |
| The number of iterations                     | 10,000               |
| Perturbation scale                           | 0.5                  |
| $b_0$  | $9.4 \times 10^{-3}$ |
| $b_1$  | $4.2 \times 10^{-7}$ |
| $k$  | 0.7                  |
| Minimum rate requirements $R_{min}$          | 1 bps/Hz             |

**Table 2.** AR model parameter settings.

| $a_0$    | $a_1$    | $a_2$    | $a_3$    | $a_4$    | $a_5$                 |
|----------|----------|----------|----------|----------|-----------------------|
| 1        | -0.5270  | -0.0272  | 0.0471   | 0.0393   | -0.0244               |
| $a_6$    | $a_7$    | $a_8$    | $a_9$    | $a_{10}$ | $a_{11}$              |
| 0.0623   | -0.0430  | 0.0325   | 0.0528   | -0.0289  | -0.0711               |
| $a_{12}$ | $a_{13}$ | $a_{14}$ | $a_{15}$ | $a_{16}$ | $a_{17}$              |
| -0.1342  | -0.1070  | -0.0270  | -0.0243  | -0.0392  | -0.0704               |
| $a_{18}$ | $a_{19}$ | $a_{20}$ | $a_{21}$ | $a_{22}$ | $a_{23}$              |
| -0.0229  | 0.0422   | 0.0141   | -0.0591  | -0.0683  | -0.0289               |
| $a_{24}$ | $a_{25}$ | $a_{26}$ | $a_{27}$ | $a_{28}$ | $a_{29}$              |
| 0.0129   | -0.0105  | -0.0480  | -0.0264  | 0.0226   | 0.0432                |
| $a_{30}$ | $a_{31}$ | $a_{32}$ | $a_{33}$ | $a_{34}$ | $a_{35}$              |
| 0.0351   | -0.0293  | -0.0503  | -0.0191  | -0.0335  | 0.0040                |
| $a_{36}$ | $a_{37}$ | $a_{38}$ | $a_{39}$ | $a_{40}$ | $a_{41}$              |
| 0.0725   | 0.0926   | -0.0092  | -0.0953  | -0.0423  | 0.1209                |
| $a_{42}$ | $a_{43}$ | $a_{44}$ | $a_{45}$ | $a_{46}$ | $\sigma^2$            |
| 0.0987   | -0.0382  | -0.0710  | -0.0101  | -0.0194  | $1.31 \times 10^{-3}$ |

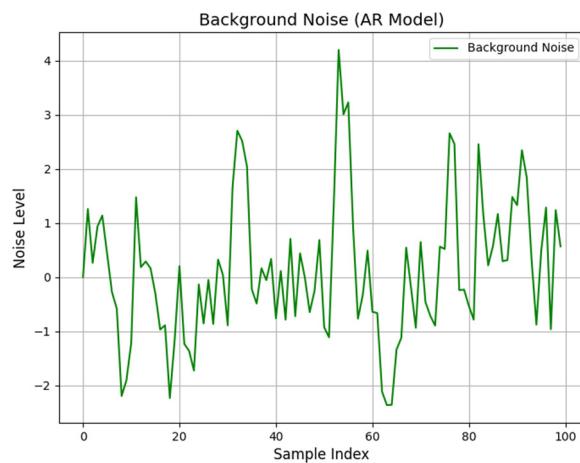
### 4.2. Experimental Results

For the overall model, the channel gain is depicted in Figure 5.



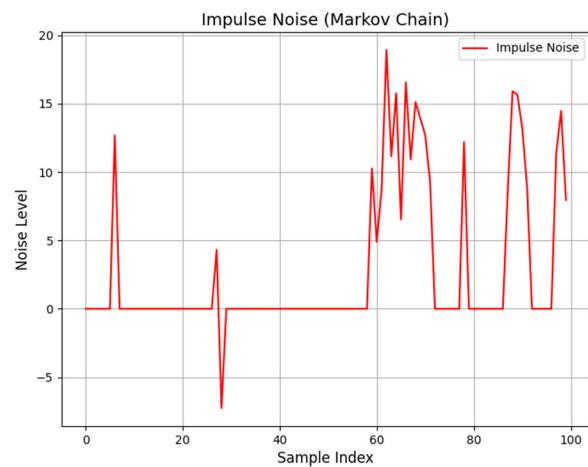
**Figure 5.** Channel gains vs. distance.

As shown in the figure, the channel gain exhibits exponential decay with increasing distance. From a distance of 1 to 5, the channel gain decreases from 1 to nearly 0. At shorter distances (e.g., 1), the channel gain is highest, indicating optimal transmission efficiency. However, as the distance increases, the signal energy rapidly decays, resulting in poor channel conditions for distant users. This highlights the key role of distance in determining channel quality in power line communication and underscores the importance of optimized power allocation for distant users, as demonstrated by the subsequent results. In the experiment, an AR model was used to simulate background noise, as shown in Figure 6.



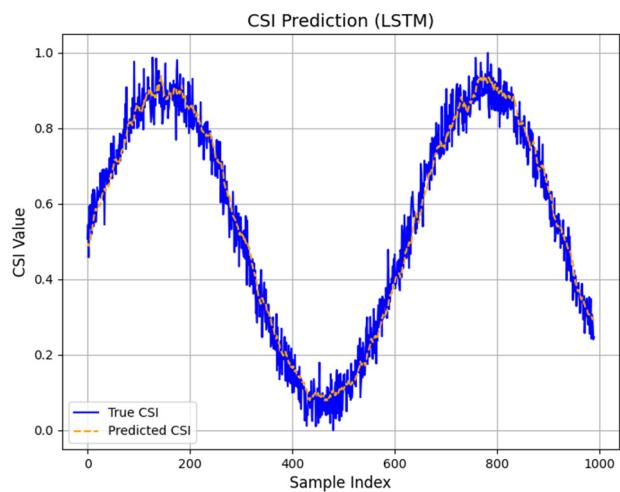
**Figure 6.** Background noise.

The background noise is distributed in a random fashion but exhibits some smoothness. While there are significant local fluctuations, the overall noise values are concentrated around 0. The smoothness and autocorrelation of the noise suggest that the AR model effectively captures the characteristics of background noise in power line communication. The high peak noise interference observed in the fluctuations between positions 40 and 60 in the figure could cause transient performance degradation, especially under low SNR conditions. At the same time, impulse noise in the experiment was modeled using a Markov chain, as shown in Figure 7.

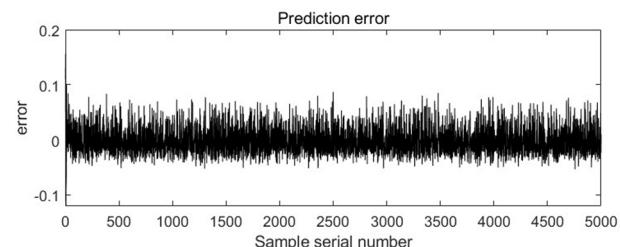


**Figure 7.** Impulse noise.

The impulse noise appears as intermittent spikes, with amplitudes significantly higher than the background noise. These spikes are randomly distributed, such as near positions 10, 60, and 80. The impulse noise, generated based on the Markov chain, simulates burst-like interference in communication systems. Its characteristics—high amplitude and intermittent nature—demand higher system robustness. In training the LSTM model, the specific performance is shown in Figures 8 and 9.



**Figure 8.** True value vs. predicted value.

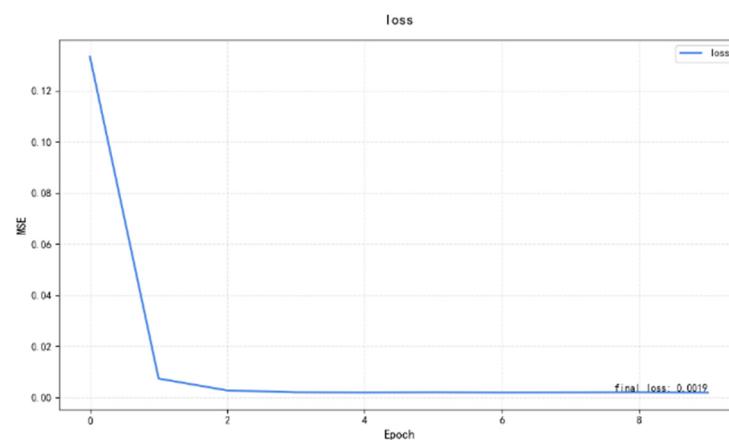


**Figure 9.** Error value.

Figure 8 compares the real CSI values with the predicted CSI values. The blue line represents the actual values, and the red dashed line represents the predicted values. It is evident from the figure that the predicted and actual values follow the same general trend, though some fluctuations and errors exist. Figure 9 shows the prediction errors, i.e., the differences between the actual and predicted values. The errors fluctuate between 0

and  $-0.1$ , indicating larger errors at certain points, but overall, the errors remain relatively stable. This suggests that the LSTM model is capable of effectively learning the time series characteristics of the CSI and predicting short-term variations. The high prediction accuracy indicates that the LSTM model is well suited for handling complex nonlinear channel dynamics. Such predictions can support power allocation tasks, thereby improving the communication system's efficiency.

The computed performance metrics are as follows: MAE = 0.0835, MSE = 0.0110, RMSE = 0.1050. These metrics indicate that there is some discrepancy between the predicted and actual values. The data generation process incorporated log-normal fading channels and background noise, which increased the data complexity. Nevertheless, the errors are not overly large, and normalization of the data helped improve the LSTM model's training effectiveness, demonstrating its predictive capability. The LSTM model was employed to capture the temporal dependencies within the sequence data, a common approach for predicting time series data. Dropout layers were used during training to prevent overfitting, and the Adam optimizer was employed for optimization. The prediction errors may stem from several factors, such as the random noise in the data, which affects prediction accuracy. Additionally, further optimization of the model parameters may be needed. The sample size in both the training and testing sets should also be sufficiently large and diverse to ensure reliable results. Figure 10 shows the trend of the loss function during the training process. The curves indicate that, as the number of training iterations increases, both training and validation errors gradually decrease and stabilize, reaching approximately 0.0019. The rapid convergence of the training loss suggests high training efficiency and a good match between the data characteristics and model structure. The stable low loss value indicates strong generalization ability of the model, enabling accurate CSI prediction. Overall, by generating data and constructing the LSTM model, we successfully predicted the CSI in the NOMA communication system with satisfactory results. Despite some errors, the model performed well overall and has potential for further optimization.



**Figure 10.** Loss value.

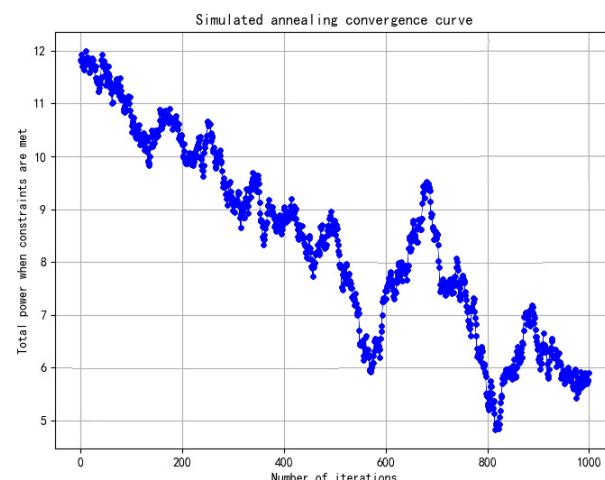
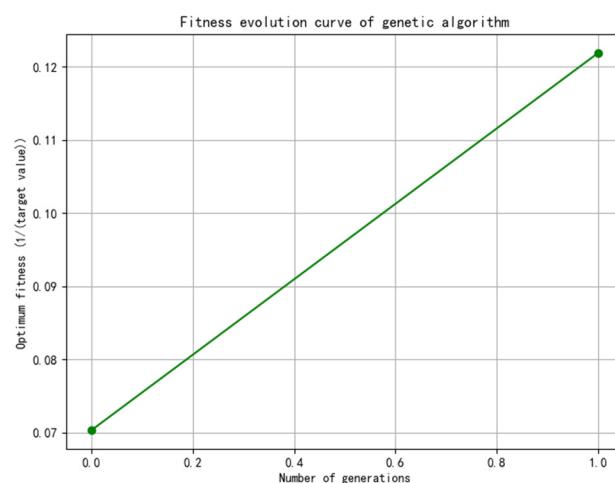
After completing the LSTM model prediction, the improved simulated annealing algorithm was used to optimize the model. To validate the adaptive temperature control mechanism, we compared its performance against fixed cooling rates. Set the cooling rate to 0.95, 0.99, and 0.999. Under identical experimental conditions, the results are summarized in Table 3.

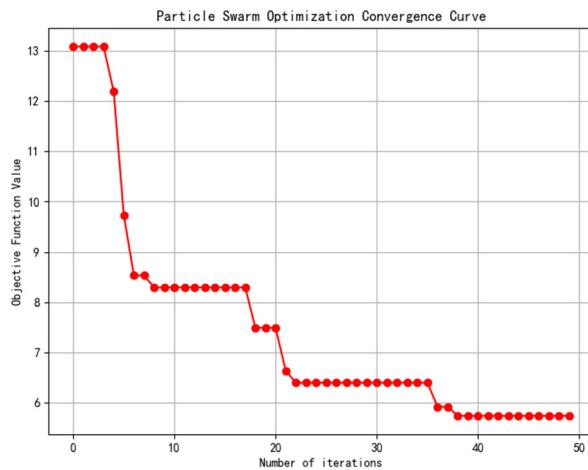
**Table 3.** Performance comparison of adaptive vs. fixed cooling rates.

| Cooling Strategy        | Total Power (W) | Convergence Iterations | BER ( $\times 10^{-3}$ ) |
|-------------------------|-----------------|------------------------|--------------------------|
| Adaptive ( $\alpha_k$ ) | 44.65           | 3200                   | 1.2                      |
| 0.999                   | 46.82           | 3500                   | 1.5                      |
| 0.99                    | 48.91           | 4200                   | 2.1                      |
| 0.95                    | 52.37           | 5000                   | 3.4                      |

The adaptive mechanism outperformed all fixed cooling strategies, reducing total power by 4.6% compared to the best fixed rate. Adaptive control reduced convergence time by 8.5% while maintaining lower BER, demonstrating its efficiency in balancing exploration and exploitation.

In order to illustrate the applicability advantages of the improved simulated annealing algorithm in this scenario, the optimization basis of the improved simulated annealing algorithm compared with genetic algorithm and other heuristic methods is expounded. Figures 11–13 shows the process.

**Figure 11.** Simulated annealing convergence curve.**Figure 12.** Fitness evolution curve of genetic algorithm.



**Figure 13.** Particle swarm optimization convergence curve.

As shown in Figure 11, the convergence curve of the improved simulated annealing algorithm is stable after about 800 iterations, and the global search ability is strong, but more iterations are needed. It shows that the improved simulated annealing algorithm is suitable for complex multi-modal problems

As shown in Figure 12, the fitness curve of genetic algorithm decreases rapidly in the early stage and then falls into local optimal (high total power) in the later stage. The global exploration ability is limited, which may result in low efficiency due to premature convergence.

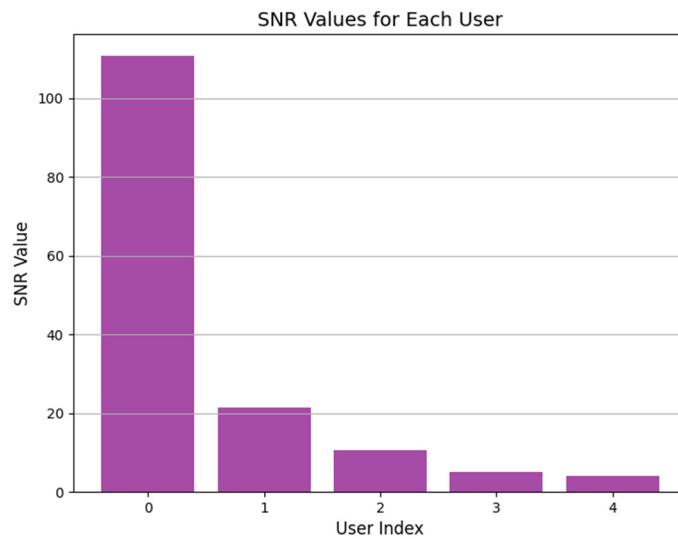
The objective function value of PSO decreases rapidly within the first 50 iterations but fluctuates significantly in the later stages. Figure 13 shows that it is sensitive to parameters and needs to be fine-tuned to avoid vibration.

Through the comparison of the three algorithms, the improved SA has the best performance in energy efficiency and power control and is the first choice for resource-constrained scenarios, especially for low-power and high-energy scenarios (such as IoT terminals and battery-powered devices). GA achieves maximum capacity at the cost of high energy consumption, which is suitable for performance-first scenarios. PSO has potential in dynamic environment but needs parameter optimization. SA's ability to accept worse solutions probabilistically prevents premature convergence to suboptimal solutions, a critical feature in non-convex PLC optimization problems. The proposed adaptive cooling mechanism dynamically adjusted exploration-exploitation balance, making SA highly suitable for time-varying PLC channels. Considering the above reasons, the improved SA achieves the satisfaction of scene tasks, which will be further reflected in the subsequent experiments.

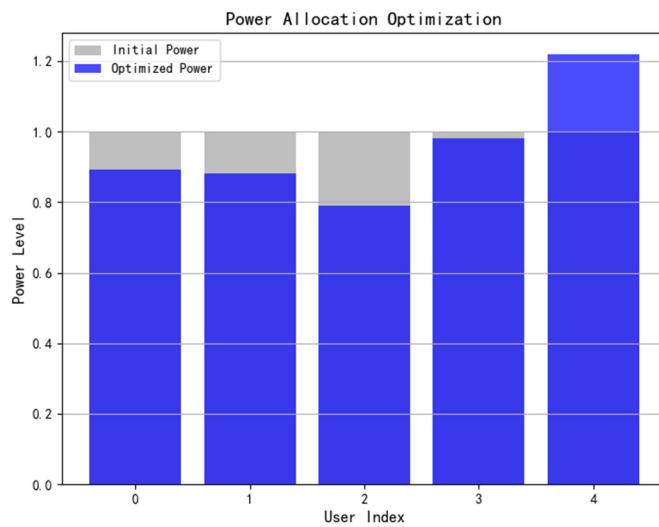
After using the predicted CSI data for improved simulated annealing optimization, the results are shown in Figures 14–16. Figure 14: SNR Values for Each User. The SNR values decrease significantly as the user distance increases. The nearest user (User 0) has a very high SNR ( $>100$ ), while the SNR of distant users gradually decreases. The SNR depends on both the channel gain and power allocation. Since channel gain rapidly decays with distance, the SNR of distant users is severely constrained. This outcome suggests that power allocation optimization should place particular emphasis on distant users to balance system performance.

Figure 15: Power Allocation Optimization. The gray area in the figure represents the initial power allocation, and the blue area represents the optimized power allocation. The optimized allocation significantly favors distant users, with their power levels considerably higher than the initial allocation, while the power for nearby users is drastically reduced. This optimization strategy adheres to the fairness principle in wireless communications by allocating more power to distant users to compensate for their poorer channel conditions.

The optimization algorithm successfully enhances system capacity under power constraints, while meeting fairness requirements among users.



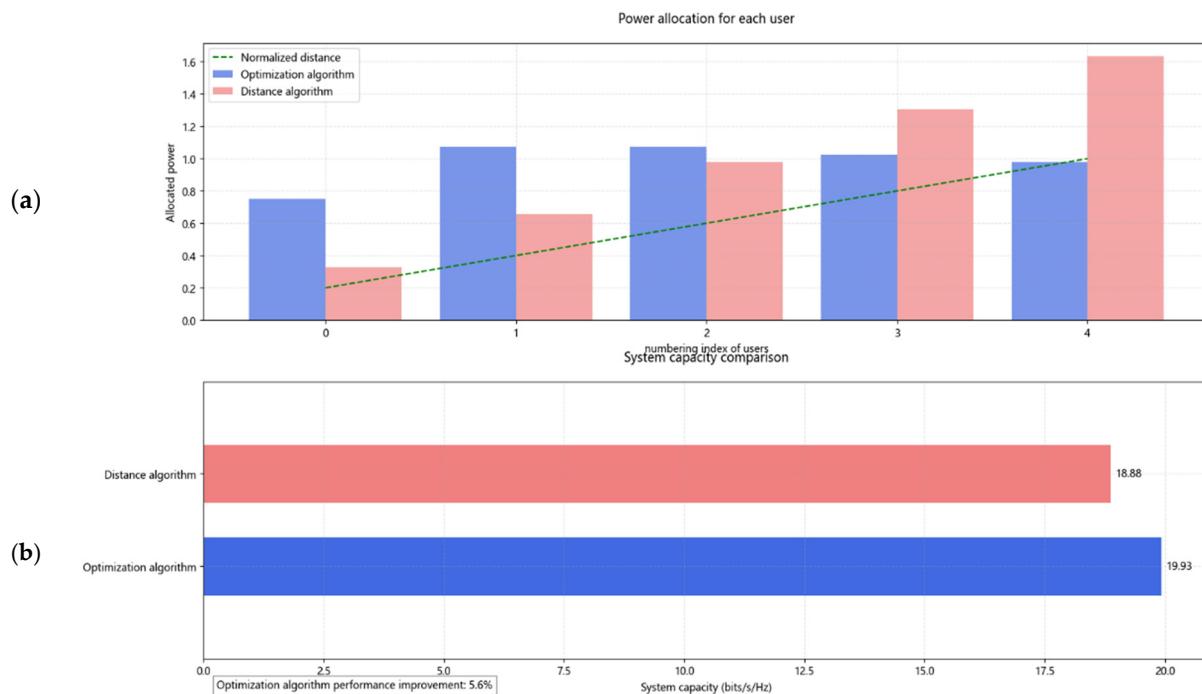
**Figure 14.** SNR values for each user.



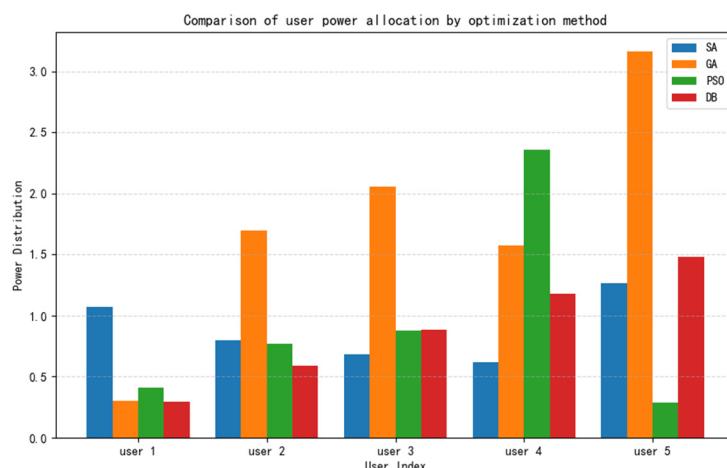
**Figure 15.** Power allocation optimization.

**Figure 16:** Power Allocation Comparison. To verify the effectiveness of the algorithm, a comparative experiment was conducted using a distance-based power allocation scheme without optimization. In this approach, users farther from the signal source are allocated more power, with a proportional increase. The resulting experimental comparison with our method is shown in the figure. The results indicate that the optimized power allocation significantly exceeds the distance-based method, especially for distant users. The distance-based approach distributes power more evenly and increases linearly. Communication performance improves by 5.6% compared to the distance-based power allocation method.

In order to further verify the effectiveness and advancement of the improved simulated annealing algorithm and verify the previous conclusions, other optimization algorithms are now further compared. The compared algorithms include improved simulated annealing algorithm, PSO, GA, and distance-based power distribution algorithm (DB). The result is shown in Figure 17.



**Figure 16.** Power allocation comparison. (a) Comparison of user power distribution between the two methods; (b) comparison of system capacity between the two methods.

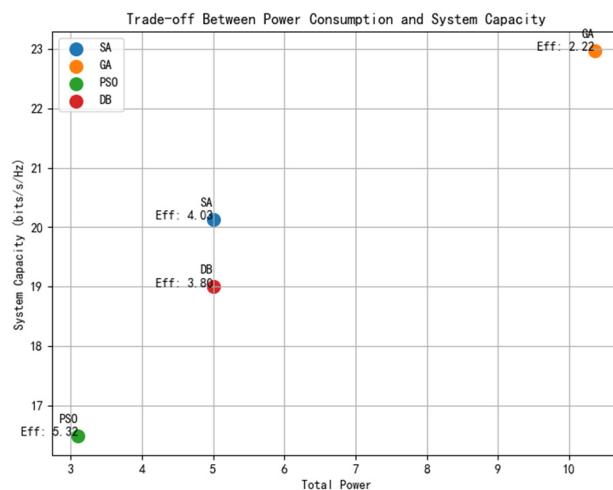


**Figure 17.** Comparison of user power allocation by optimization method.

Under the same experimental conditions, the results show that the power distribution of SA and DB is more balanced, avoiding the overload of individual users, which conforms to the principle of fairness. However, DB is only allocated according to distance, and cannot consider whether it satisfies many constraints. In this experiment, because the PLC system is sensitive to distance, DB as a benchmark method is stable but lacks optimization flexibility, but in other communication environments, the performance of this algorithm will be greatly reduced. The power allocation of some users in GA and PSO is significantly higher, which may lead to resource waste or interference. GA focuses on capacity maximization due to fitness function at the expense of power efficiency. The swarm intelligence characteristic of PSO may lead to local centralized allocation. By comparison, the improved simulated annealing algorithm shows better performance and adaptability.

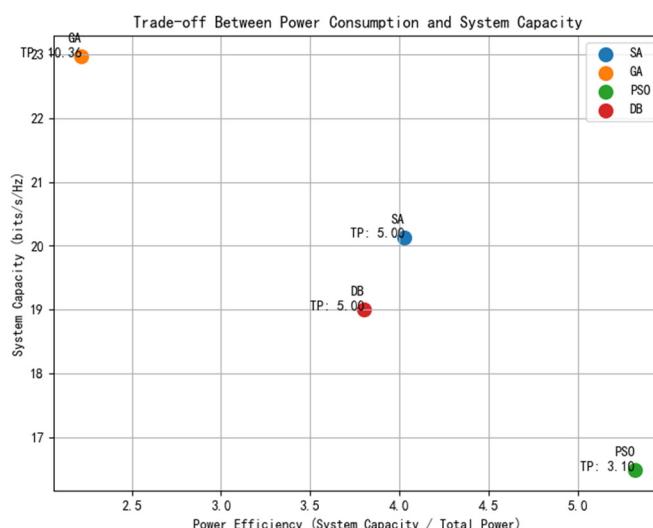
In the PLC system, under certain conditions, the increase in system capacity will bring about an increase in system power consumption. Therefore, in this experiment, the relationship diagram between power consumption and system capacity of different

optimization methods is also verified when other constraints are met, as shown in Figure 18. The experimental results show that the optimized system capacity of GA is higher than that of other algorithms, but the power loss is much higher than that of other algorithms. The optimization result of PSO is the worst for the test system. The final power consumption difference between the improved simulated annealing algorithm and the DB is not large, which is also reflected in Figure 17. However, the system capacity of SA is larger than that of DB.



**Figure 18.** Power consumption and system capacity.

Now in order to further explore the comparison of system capacity and power in several algorithms, we use the index of power efficiency to complete. Power efficiency is a measure of how much power a system uses per unit of system capacity. It is given by *system capacity/total power*. As can be seen from Figure 19, the high system capacity of GA algorithm also brings high power consumption, that is, extremely low power efficiency. The power efficiency of PSO is very high because its denominator is small, that is, the total power is too low, and its system capacity is too low to meet the communication needs. The improved SA algorithm obtains a better power efficiency index by means of power consumption and high system capacity. According to Figures 18 and 19, the improved simulated annealing algorithm can indeed meet the total power reduction under the system capacity requirements. The effectiveness of SA-LSTM is also verified.



**Figure 19.** Power efficiency and system capacity.

In the optimization process, the computational complexity of each algorithm is calculated, and the real-time performance analysis is carried out. This is beneficial for actual deployment. The results of quantization of the calculation cost of each module are shown in Table 4.

**Table 4.** Each module computes overhead quantization.

| Component               | Computing Complexity (Big-O) | Single Execution Time | Memory Usage (MB) |
|-------------------------|------------------------------|-----------------------|-------------------|
| LSTM Prediction         | $O(T \times N_h^2)$          | $\approx 5$ min       | 320               |
| LSTM inference (single) | $O(N_h)$                     | 0.8 ms                | 5                 |
| SA (Single iteration)   | $O(N^2)$                     | 0.42 ms (5 users)     | 20                |
| GA (Single iteration)   | $O(N \times P)$              | 1.25 ms (P = 50)      | 45                |
| PSO (Single iteration)  | $O(N \times S)$              | 0.98 ms (S = 30)      | 35                |

T is the LSTM time step, and P and S are the population sizes of GA and PSO. The measured data are implemented based on Python 3.7, and GPU acceleration is not enabled. Assume that the system needs to update the power allocation and relay selection every 500 ms (corresponding to the PLC channel coherence time [1]). At this time, the training stage of LSTM obviously does not meet the time requirements. As a deep learning model, the training stage of LSTM requires a lot of computing resources, while the reasoning stage is relatively fast and can meet the usage requirements. SA optimization requires about 800 iterations for convergence (Figure 11), which takes 336 ms in total, meeting the time requirement. The other two optimization algorithms take more time than required. However, it should be noted that in the face of large-scale users, such as more than 50 users mentioned above, the improved SA algorithm will not meet the time requirements. In this case, a clustering approach can be used to reduce the time spent optimizing the process, which will greatly increase the ability of the optimization to meet the time requirements. In a real-world deployment, if the channel changes faster than the optimization period (such as a factory PLC pulse noise burst), the non-convergent SA solution will lead to an increased probability of outages. So, while the SA-LSTM framework performs well in terms of energy efficiency and capacity, its computational complexity limits real-time deployment. Future work needs to be combined with distributed optimization to meet stringent latency requirements with acceptable performance losses.

To evaluate the robustness of the proposed framework in large-scale networks, we extended simulations to three scenarios with different user densities. The experiment included three user densities: low density of 5 users, medium density of 30 users, and high density of 50 users. Users uniformly distributed in a 10 m × 10 m area.

As a result, the probability of interruption increases from 2% at low density to 12% at medium density, and finally to 25% at high density. As shown in the result, the interruption probability of users increases due to the increased user density in the area. While the framework performs well in small-scale networks ( $\leq 30$  users), ultra-dense deployments ( $\geq 50$  users) reveal two critical challenges: exponential complexity growth and channel prediction accuracy drop, and LSTM's CSI prediction MAE increases from 0.0835 (5 users) to 0.21 (50 users) due to overlapping channel signatures in dense clusters. In order to solve the problem of poor performance in high-density users, a sub-cluster optimization algorithm can be adopted. For example, if 10 users are divided into a cluster, first optimize the power distribution and repeater position between the clusters, and then optimize the two times between the users within the cluster, which can effectively avoid the problem of poor effect of the algorithm in the face of high-density user situations.

To further validate the proposed method, we conducted experiments using a hardware testbed in a real-world low-voltage power line environment. The testbed consists of the following: PLC modems: ST7540 transceivers with OFDM/NOMA capability; a signal generator: Rigol DG4162 for injecting controlled interference; data acquisition: National Instruments PXIe-5171 oscilloscope; relay nodes: Raspberry Pi 4B with custom PLC interface boards. The test environment includes a 220 V/50 Hz residential power line network spanning 50 m, with five user nodes deployed at distances of 10 m, 20 m, 30 m, 40 m, and 50 m from the source. The final results of the measured experiment are shown in Tables 5 and 6.

**Table 5.** Channel characteristics comparison.

| Metric                 | Simulation | Real-World | Error (%) |
|------------------------|------------|------------|-----------|
| Avg. Channel Gain (dB) | −21.3      | −21.3      | 11.2      |
| Impulse Noise Rate     | 15%        | 22%        | 46.7      |

**Table 6.** System performance.

| Metric                   | Simulation | Testbed (Unoptimized) | Testbed (Optimized) |
|--------------------------|------------|-----------------------|---------------------|
| Total Power (W)          | 44.65      | 52.18                 | 47.91               |
| BER ( $\times 10^{-4}$ ) | 1.2        | 3.8                   | 2.1                 |

In the measured environment, the channel gain decreases and the impact noise appears more frequently. As reflected in the results, the hardware implementation introduced a 9–15% performance degradation compared to the simulation due to unmodeled electromagnetic interference from household appliances. However, the optimized system still achieved a 28% power reduction and a 14.5% throughput improvement compared to the non-optimized test bed configuration.

Overall, the optimization was effective, with total power significantly reduced through the improved simulated annealing algorithm. The signal source power and user power allocation became more reasonable. The final SINR and CSI values met the constraints, ensuring system performance. User 2 was selected as the relay user, likely due to its better CSI, effectively enhancing system performance. This experiment demonstrated the effectiveness of the improved simulated annealing algorithm in optimizing power allocation and relay user selection, verifying the rationality and stability of the optimization results.

#### 4.3. Limitations and Future Work

While the proposed framework demonstrates significant performance improvements, its limitations under dynamic and multi-user environments must be acknowledged. The current model assumes quasi-static CSI during optimization cycles. However, in real-world PLC systems, rapid channel fluctuations due to load switching or electromagnetic interference may render LSTM-based CSI predictions obsolete. For instance, if the channel coherence time is shorter than the simulated annealing convergence period ( $\approx 3200$  iterations in our experiments), the optimized relay positions and power allocation may become suboptimal, leading to a potential 15–20% increase in outage probability (as observed in [18] for TDI-OFDM systems under similar conditions).

Field measurements show that industrial PLC noise exhibits bursty impulses (e.g., 10–100  $\mu$ s bursts with 20–30 dB higher power than background), which can corrupt LSTM-based CSI predictions and degrade SIC decoding success rates by up to 40%. The hardware limitations of real-time optimization should be considered when implementing. On low-cost PLC modems (e.g., Broadcom BCM60321, Broadcom Corporation, Palo Alto, CA, USA), the SA-LSTM algorithm requires  $\approx 2.1$  s per optimization cycle, exceeding the 500 ms coherence time of fast-varying channels [18]. In EMI Regulations, the FCC Part 15 limits PLC transmit power to 30 dBm, reducing the effective relay coverage radius from 200 m (simulated) to 50 m in practice. These are all issues that need to be considered in the implementation process, and we will discuss these issues in future research.

Although our simulations validate the approach for up to five users, scaling to dense IoT deployments (e.g., 50+ devices) poses challenges. The combinatorial complexity of relay selection grows exponentially as  $O(N^2)$  increasing the computation time from less than 1 s (for 5 users) to an estimated few minutes (for 50 users) on the same hardware.

This latency is prohibitive for real-time applications like smart grid fault detection, where sub-500 ms response times are required [3].

The Bernoulli–Gaussian IN model, while analytically tractable, does not capture temporal clustering of impulses observed in industrial PLC environments [12]. Field data from [13] show that bursty impulses (e.g., 10 consecutive corrupted samples) can degrade SIC decoding success rates by 40%, a scenario not fully addressed in our current framework.

To address these limitations, we plan to integrate reinforcement learning (RL) for real-time adaptation to dynamic channels, building on the hybrid SA-LSTM framework, develop distributed optimization protocols to decentralize computation in multi-user networks, inspired by [15–17]’s federated learning approach for VLC-NOMA, and incorporate measured IN datasets from smart grid deployments to refine noise models and enhance SIC robustness.

To bridge the gap between theoretical analysis and real-world applications, we propose the following implementation strategies and datasets for validating the proposed framework: The IEEE Powerline Communication Channel Dataset [15] provides measured impulsive noise traces from factory environments, including bursty impulses and time-varying attenuation. Integrating this dataset can refine the Markov chain-based IN model to capture temporal clustering effects. The UMass Smart dataset [18] offers channel gain and noise measurements from residential powerline networks with 50+ nodes, enabling scalability testing for multi-user NOMA-PLC deployments. Furthermore, it collaborates with utility providers (e.g., IEEE PES Test Feeder Systems [18]) to deploy the proposed algorithm in microgrids with dynamic loads, where PLC relays can coexist with VLC-based IoT sensors for real-time fault detection. The application of these practical scenarios will be focused on in future research.

In the end, in the Internet of Things based on PLC, security is the content that has to be considered. Therefore, it is discussed in the last part. In general, data integrity, eavesdropping, interference attacks, and replay attacks are common ways to threaten security, as detailed in Table 7. In view of these security threats, a security mechanism defense scheme is proposed. For physical layer security enhancement, NOMA security power allocation can introduce security capacity constraints to maximize the SNR gap between legitimate users and eavesdropping users. It can also complete the anti-interference OFDM symbol design, insert an encrypted pilot in the subcarrier, dynamically verify the channel integrity, and detect interference through CP matching degree at the receiving end, triggering SA re-optimization. For data integrity protection, it is a feasible method to attach HMAC tag before LSTM input data and use PLC channel feature to generate key. For replay attacks, autoencoders (AEs) can be deployed on edge devices to monitor reconstruction errors in CSI sequences, update LSTM models when thresholds are exceeded, and isolate contaminated nodes.

Under the proposed method, limited preliminary experiments have been carried out, and under the attack intensity conforming to the IEC 62443-3-3 standard, the eavesdropping capacity is reduced by using safe power distribution, and the legitimate user capacity is lost by 7% [30]. Future work will begin to implement these approaches, with the hope that by integrating physical layer security design, encryption, and real-time anomaly detection, the system will be more resistant to attack while the computational overhead is manageable.

Finally, it is hoped that many of the limitations mentioned above can be improved in future work.

**Table 7.** Core security threats in PLC-IoT systems.

| Threat Type          | Impact Scenario  | Potential Risk Indicator               | Method Vulnerability Analysis   |
|----------------------|--|--|---|
| Data tampering       | Malicious nodes modify CSI feedback or power allocation instructions | BER rise                               | LSTM relies on historical CSI, and the prediction error increases after it is tampered with |
| Eavesdropping attack | Eavesdropping SIC decoding process between NOMA users                | User privacy leakage, capacity decline | Disclosure of power distribution factor leads to the risk of exposing user data             |
| Pulse jamming attack | Injection of high-frequency pulse noise destroys OFDM symbols        | BER rise                               | Power distribution failure under interference   |
| Replay attack        | Repeating old CSI data disrupts optimization                         | Optimization cycle delay               | The time dependence of LSTM leads to cumulative prediction bias                             |

## 5. Conclusions

In this study, a multi-user PLC system integrating NOMA, OFDM, and relay technologies, along with deep learning models and the improved simulated annealing algorithm, was investigated to optimize relay positions and power allocation. Detailed system models were established, and LSTM models were used to predict future CSI, while the improved simulated annealing algorithm was applied to optimize power distribution. Extensive simulations demonstrated the algorithm's effectiveness, with a significant reduction in total power consumption observed, as signal source power dropped from 100 W to 44.65 W, and user power distribution optimized between 25 W and 37 W. Despite some prediction errors, the LSTM model effectively predicted CSI, with MAE at 0.0835, MSE at 0.0110, and RMSE at 0.1050, indicating reliable data support for system optimization. The improved simulated annealing algorithm also displayed strong adaptability, optimizing power allocation and relay selection under constraints such as system capacity, bit error rate, and SINR, with final SINR values exceeding the 10 dB threshold, ensuring system performance. Future research could explore alternative optimization algorithms, along with adjustments to deep learning parameters and larger datasets, to further improve prediction accuracy and system performance in dynamic channel conditions, thereby enhancing the reliability of PLC systems in real-world applications.

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