A Channel Selection Algorithm of Power Line Communication Network Base on Double-layer Cascade Artificial Neural Network

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Abstract. A crucial issue in Power Line Communication (PLC) networks is how to improve the performance of power line channel in physical layer. In this paper, a multiple input multiple output (MIMO) PLC channel selection algorithm based on a double-layer cascaded artificial neural network model is proposed. After the model is trained, the best channel combination can be selected directly through the channel estimation information. The results show that compared with the communication system without channel selection, the model can improve the channel by 2-3dB, the probability of selecting the best channel is 95.02%, and the training has fast convergence speed and small amount of calculation.

1. Introduction
From the smart grid to the Energy Internet, the traditional power system needs to be further integrated with the information system. Power Line Communication (PLC) as a unique communication to power system, because of its extensive and economical characteristics, has unique advantage in many fields[1]. In order to give full play to the performance of power line channel in physical layer. In this paper, a multiple input multiple-output (MIMO) PLC channel selection algorithm based on a double-layer cascaded artificial neural network model is proposed. After the model is trained, the best channel combination can be selected directly through the channel estimation information. The results show that compared with the communication system without channel selection, the model can improve the channel by 2-3dB, the probability of selecting the best channel is 95.02%, and the training has fast convergence speed and small amount of calculation.

The power line normally consist of three conductors, namely phase (P), neutral (N), and protective earth (PE), so there are three input (output) ports. However, according to the Kirchhoff's law, the sum of the voltage differences between the three lines is zero at the same time[6], so only two channels can be used as the input port at the transmitter. However, the above literature uses both channels, and does not use other channel combinations for signal transmission, so the performance of power line communication can be improved in this way. Babak, N [7] used reinforcement learning algorithm to select the best channel among the available PLC channels without a priori information, so as to
maximize the average utility expressed in data rate. However, it only studies SISO channel, not MIMO channel, so the channel performance can be improved. This paper uses a two-layer cascaded artificial neural network (CANN) model to select the best $2 \times 2$ channel for data transmission from the $3 \times 3$ MIMO power line channels. The results show that, compared with other schemes, the proposed algorithm has higher probability and better transmission performance.

This paper is organized as follows. In Section 2, we describe the MIMO-PLC system and propose the channel selection problem. In Section 3, we briefly review CANN and propose a channel selection algorithm based on double-layer CANN. Numerical results and analyses are presented in Section 4. Section 5 concludes the paper.

2. MIMO-PLC System model

2.1. MIMO channel model

The MIMO PLC system equivalent model is shown in figure 1. The signal is transmitted by the voltage difference between two power lines, so there are three input (or output) ports.

![Figure 1. MIMO-PLC channel model.](image)

The general channel model based on MIMO-PLC is shown in equation (1)

$$s_t = H_t x_t + n_t$$

where $H_t$ and $n_t$ represent the channel gain and noise matrix at $t$-th.

$H_t$ usually has $n$ transmission ports and $m$ reception ports, and the expression is given by

$$H = \begin{bmatrix}
    h_{1,1} & h_{1,2} & \cdots & h_{1,n} \\
    h_{2,1} & h_{2,2} & \cdots & h_{2,n} \\
    \vdots & \vdots & \ddots & \vdots \\
    h_{m,1} & h_{m,2} & \cdots & h_{m,n}
\end{bmatrix}$$

where $h_{n,m}$ is the complex channel transfer function from the $n$-th sending port to the $m$-th receiving port, which obeys the lognormal (LogN) distribution and can be expressed as $h_{n,m} \sim \log N(\mu_n, \sigma^2_n)$.

According to Kirchhoff’s law, two PLC ports are used as transmitters and two PLC ports are used as receivers. Accordingly, the channel matrix is given by

$$H = \begin{bmatrix}
    h_{1,1} & h_{1,2} \\
    h_{2,1} & h_{2,2}
\end{bmatrix}$$

In the above formula, diagonal elements are called common channels, and non diagonal elements are called cross channels.

2.2. Noise model of power line system

The noise in the power line can be divided into background noise and impulse noise[8], in which the impulse noise is generally caused by the instantaneous switch of power equipment in the power supply.
network. Impulse noise has short duration and high intensity. When it occurs, it will cause serious data transmission errors. Common impulse noise models include general Gaussian Mixture (GM) model[9], Bernoulli Gaussian model[10], Middleton class A model[11], etc. In this paper, Bernoulli Gaussian noise model is adopted. The probability density distribution of noise $n_t$ can be modelled as follows[10]

$$G_t(v) = (1 - p)G(w_t; 0, \sigma^2_{n,t}) + pG(i_t; 0, \sigma^2_{i,t})$$

(4)

where $w_t$ and $i_t$ refers to background noise and impulse noise, and their distributions satisfy Gaussian distribution $G(0, \sigma^2_{n,t})$ and $G(0, \sigma^2_{i,t})$, $p$ is the probability of impulse noise, $G(\bullet)$ is the Gaussian probability density function.

Therefore, in MIMO-PLC, the channel capacity can be expressed as

$$C = \log_2 \left( \det \left( I_{N_T} + \frac{\rho}{N_T} H^H H \right) \right)$$

(5)

where $\rho$ is the signal-to-noise ratio (SNR) in the channel.

3. Channel Selection Algorithm Based on Cascaded Artificial Neural Network

The general mathematical expression of CANN [12] is

$$a^k = f^k \left( \sum_{i=1}^{n-1} W_i^k a^i + W_0^k p + b^k \right)$$

(6)

where $n$ is the number of neural network layers, the number of rows of $W$ is the number of neurons in each layer, and the number of columns is the hidden layer weight matrix of the number of input individuals, $b$ is the column vector of hidden layer bias with the same number of rows as $W$, $a$ is the output vector of each layer, $p$ is the input vector, $f$ is the activation function.

Next, this paper will analyse in detail the training process of the CANN and the operation process in the system:

Step 1 extracts the eigenvalues from the channel state information as the training set. First, assume that there are $m$ channel state information samples $\{(H_i)_{m=1}^m\}$, and extract the real eigenvalue $d^w_i$ from the training set

$$d = \left[ \text{vec}(\hat{H})^T \right]$$

(7)

where $\text{vec}(\bullet)$ represents the vectorization of the matrix and matrix $\hat{H}$ is the modulo operator with the matrix $H$.

Step 2 in order to avoid significant deviation in the training set, the eigenvalues need to be normalized to obtain the 1-by-$n$-dimensional vector $\hat{d}^w_i$

$$\hat{d}^w_i = \frac{d^w_i - E(d^w_i)}{\max(d^w) - \min(d^w)}, i = 1, 2, ..., m$$

(8)

Get trained data set $D = \{\hat{d}_1^w, \hat{d}_2^w, ..., \hat{d}_m^w\}$.

Step 3 label each feature vector
\[ y^* = \arg \max_{i} \left\{ \log \det \left( I_{N_r} + H H^H \frac{\rho}{N_T} \right) \right\} \]  

(9)

where \( \rho \) is the signal-to-noise ratio, \( N_r \) is the number of send ports. Repeat the above process for each channel state information training sample, the corresponding tag set \( T = \{ y^* \} \) can be finally obtained.

Step 4 puts the data set into the model for training, and the formula of error function is as follows

\[ L(\hat{y}^{(n)}, \hat{y}^{(n)}) = -y^T \log \hat{y} \]  

(10)

Then solve the formula of each layer and update parameters

\[ W^{(l)} \leftarrow W^{(l)} - \beta \left( \frac{1}{N} \sum_{n=1}^{N} \left( \frac{\partial L(\hat{y}^{(n)}, \hat{y}^{(n)})}{\partial W^{(l)}} \right) \right) + \alpha \left( W^{(l)} \right) \]  

\[ b^{(l)} \leftarrow b^{(l)} - \beta \left( \frac{1}{N} \sum_{n=1}^{N} \left( \frac{\partial L(\hat{y}^{(n)}, \hat{y}^{(n)})}{\partial b^{(l)}} \right) \right) \]  

(11)

where \( \beta \) is Learning rate.

Through the above steps, the trained network model \( h_{sel} = F^*(d) \) can be obtained.

Then the CANN model can be used to select channel of power line. The system only needs to transform the estimated channel fading matrix into a vector \( H_{d_{13}} \to d^{h_{13}} \). Then, the data is normalized by (8) and treated by the model, and finally we can automatically get the best channel combination

\[ h_{sel} = \arg \max_{i} \left\{ \hat{d}^{h_{i1}} \right\} \]  

(12)

### 4. Simulation Results and Analysis

#### 4.1. Parameter selection

The CANN structure used in this system is shown in Fig 2, including an input layer, an output layer and two hidden layers, each hidden layer has 32 neurons. Table 1 summarizes other super parameters used in some simulations.

| Table 1. Super parameter setting. |   |   |
|-----------------------------------|---|---|
| parameter                        | Value |   |
| Data volume                      | \( 10^5 \) |   |
| Training times                   | 5000 |   |
| Learning rate                    | 0.05 |   |
| Min-performance gradient          | \( 10^{-5} \) |   |
| Modulation mode                  | BPSK |   |
| Demodulation mode                | maximum likelihood |   |

#### 4.2. Analysis of simulation results

In this section, the performance of the proposed algorithm is verified by simulation, and compared with all connected neural network and maximum norm algorithm. Assuming that the channel is lognormal distribution, the receiver and transmitter know the channel state information, and the transmitter has equal power allocation.

Figure 2 shows the change curve of channel capacity of each algorithm with signal-to-noise ratio. It can be seen from the figure that the channel capacity of each algorithm increases with the increase of SNR. It can be seen that in the case of low SNR, the effects of each algorithm are close, and the
performance improvement of each algorithm is different with the increase of SNR. All connected neural network is better than the maximum norm algorithm, but with the increase of SNR, the performance improvement of CANN is more obvious than that of all connected neural network.

Figure 2. Channel capacity of different algorithms.

Figure 3 and figure 4 show the variation curves of bit error rate (BER) and outage probability (OP) of each algorithm. With the increase of channel average SNR, the BER of the system decreases and the OP also decreases. Similar to the conclusion in figure 2, the algorithm proposed in this paper has certain advantages over other algorithms in the performance of channel selection.

It can be obviously seen from figure 2, figure 3 and figure 4 that no matter what algorithm is used, the performance of the system can be greatly improved compared with the system without any channel selection. The proposed algorithm can achieve 2-3dB performance improvement.

Table 2 shows the correct rate (CR) of the CANN in selecting the best channel combination after training under different hidden layers and different numbers of neurons. It can be seen from the table that the performance of the network with two hidden layers is higher than that of one hidden layer, and under the same hidden layer, the selection accuracy increases with the increase of the number of neurons in each layer. However, with the increase of network level and the number of neurons, both training time and running time will increase significantly. Considering comprehensively, the CANN model with two hidden layers and 32 neurons in each hidden layer is selected as the best choice.

| numbers | CR    |
|---------|-------|
|         | 16    | 32    | 64    | 128   |
| One layer | 0.9028 | 0.9174 | 0.9259 | 0.9362 |
| Double layers | 0.9396 | 0.9502 | 0.9533 | 0.9623 |
5. Conclusion
This paper proposes an adaptive channel selection algorithm for PLC networks, where multiple wires are used as communication channels subject to the impulsive and the Gaussian noises. In order to solve the optimal problem, we develop a CANN model by maximizing the sum data rate. In consorting to this, the number of hidden layers and neurons of neural network are further optimized. We compared our model with several other channel selection schemes, and the simulation results reveal that the algorithm can effectively use the spectrum and has the lower computation. This research can further improve the performance of power lines and is expected to undertake important communication tasks in smart grids. The future work includes investigating various aspects of the algorithms such as the selection of relays, power allocation.

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