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Research on the dynamic networking of smart meters based on characteristics of the collected data

Yaxin HUANG, Yunlian SUN*, **Xiaodi ZHANG**
School of Electrical Engineering, Faculty of Engineering, Wuhan University, Wuhan, China

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Abstract: In order to accurately collect the electricity usage information from the smart meter which uses the power line for communication, this paper proposes the method of dynamic networking to enhance the reliability of the smart meter communication. We shall firstly establish a logical topology between the smart meter and the concentrator with reference to their communication paths within the power supply range of the same transformer, and then grade smart meters, and choose the relay for each level network based on the selection methods of relay, and finally use the improved ant colony algorithm to choose the optimal communication path for smart meters in the communicref1ref1ation range of multiple relays. Although the optimal path can be discovered quickly in this way, it cannot establish other communication paths in time when the collected data are abnormal. Therefore, on the basis of the characteristics of data, this paper uses the probabilistic neural network to determine the integrity of the data collected. If the collected data is abnormal, we will reconstruct communication network by choosing a new communication path between concentrator and smart meters. By means of the MATLAB simulation, we can automatically organize the network to improve the reliability of communication between the concentrator and smart meters, which is of great significance for the concentrator to collect the users' electricity usage information.

Key words: Power line, dynamic networking, logical topology, the ant colony algorithm, the characteristics of data

1. Introduction

Smart meters are the next generation of electricity meters and offer a range of intelligent functions. For example, they can communicate directly with the electricity information acquisition system based on the power line communication, meaning there will be no need for the energy supplier to visit our home to read the meter. With the large-scale use of smart meters, the electricity information acquisition system becomes the largest automatic measurement system of electric energy, and the accurate collection of information from smart meters is the key to its normal operation. In actual work, abnormal communication of the smart meter was found to be the main reason that it could not be accurately collected. Therefore, in order to ensure accurate collection of the information of smart meters, this paper focuses on improving the reliability of smart meter communication. Because existing wiring has the advantages of wide coverage, low cost, no rewiring, and data can be transmitted to every device connected to the power-line network when using the existing wiring to provide data communication access [1], the power line communication is widely used in the information collection of remote smart meters [2]. Nevertheless, on account of the characteristics of low-voltage power line carrier communication, such as strong noise interference, large signal attenuation, and uneven distribution

*Correspondence: ylsun@whu.edu.cn

of carrier signals [3], concentrator cannot communicate directly with all smart meters. Therefore, in order to guarantee the concentrator to communicate with all the smart meters within the power supply range of the same transformer, the communication distance between the concentrator and the smart meter needs to be increased.

A literature review [4–7] reveals that networking can augment communication distance between the concentrator and smart meters. However, in the experiment, there will be signal conflicts leading to communication failures, and if the abnormal data collected are not detected in time, it will communicate in accordance with the original communication path, which will cause failure of collecting users' electricity usage information and affect the measurement of the automation system's normal operation. Therefore, the main task of this study is to overcome the signal conflict problem in the networking of smart meters and the detection of abnormal information. When the same smart meter belongs to multiple relay communication ranges, the improved ant colony algorithm is used to select the optimal path for smart meters, which can effectively avoid communication failures caused by signal conflicts. In order to accurately and quickly detect the collected abnormal information, this paper divides the collected data information of smart meters into different combinations, and inputs different combinations of data into the intelligent algorithms such as back propagation (BP), general regression neural network(GRNN), and probabilistic neural network (PNN) for training. By comparing the running time and detection accuracy of different data combinations in these three algorithms, the optimal feature combinations are selected as the power information eigenvalues, and through experimental comparison, PNN has the shortest running time with the highest detection accuracy. Therefore, the collected feature values of power consumption information are input into the PNN for detection, and when the information collected through the original communication path is abnormal, the improved ant colony algorithm can quickly find other paths for communication.

2. The communication principle and implementation

The concentrator can connect with the smart meter within the power supply range of the same transformer through the power line, as is shown in Figure 1. Ideally, the concentrator can communicate immediately with all smart meters within the power supply range of the same transformer. However, in practice, with the rise of communication distance between the concentrator and smart meter, the multipath effect, and the increase of signal attenuation, the concentrator will fail to establish straightway communication with smart meter. For the sake of improving communication distance, we choose the appropriate smart meter as a relay, and thereby increase the communication distance between the concentrator and the smart meter, and ensure the communication between the concentrator and the remote smart meter. The relay has the function of forwarding packet of the concentrator to other smart meters that cannot communicate with concentrator directly, which helps to complete the communication between the concentrator and all smart meters within the power supply range of the same transformer.

2.1. The selection of relay

The transmission distance between the concentrator and the smart meter is 200 m to 400 m, while the same distance between the smart meters is about 30 m. Because of their communication distance, the concentrator cannot communicate directly with all smart meters, so the smart meter in the experiment area is hierarchically selected as the relay. First, establish a connection between the concentrator and the smart meter, and among the smart meters within the range of communication distance. Then the smart meter directly establishing communication with concentrator and other smart meters will be the first-level relay. If the smart meter is able to establish communication with the next-level smart meter and the first-level relay, the smart meter is then utilized as the second-level relay. In this way, the other level relays are identified in sequence finally. The specific schematic diagram is listed in Figure 2.

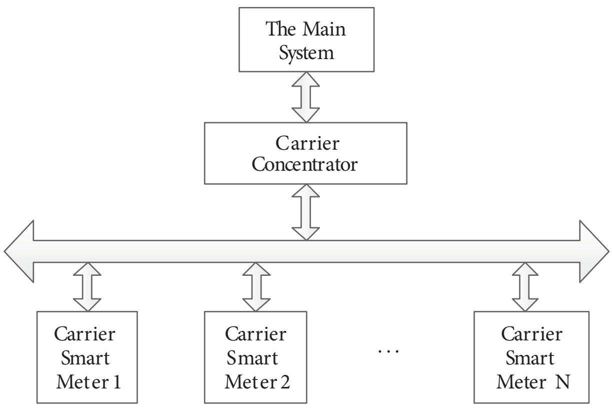

Figure 1. The reading system structure of power carrier meter.

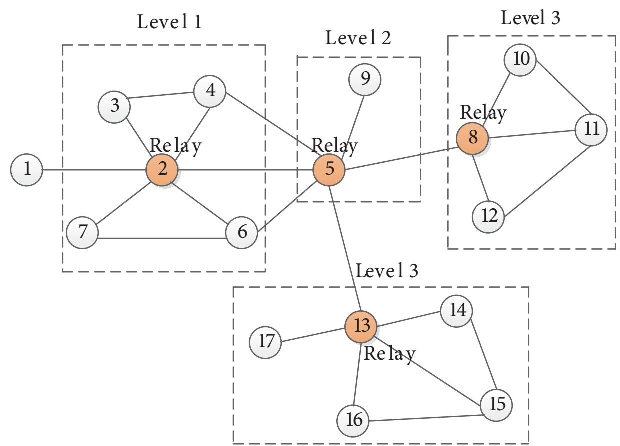

Figure 2. The reading system structure of power carrier meter.

Figure 3 is the logical topology structure of the concentrator and smart meter of an experimental area of the southern power grid after choosing the relay. Con1 is a concentrator, M is a smart meter that is not selected as a relay, and R is a smart meter that is selected as a relay.

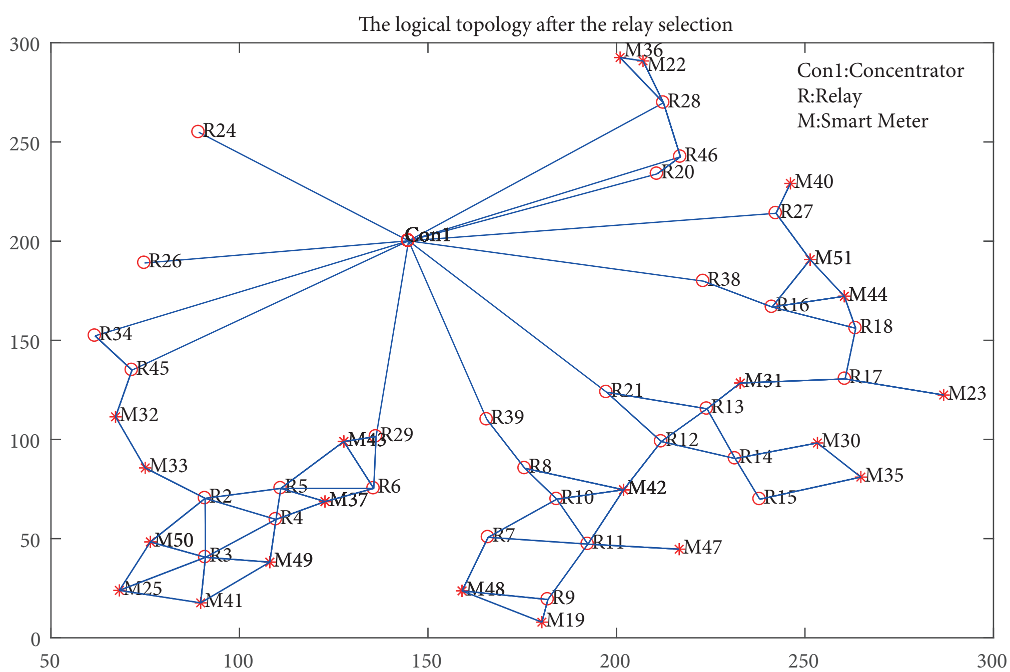

Figure 3. The reading system structure of power carrier meter.

2.2. The communication process between concentrator and smart meters

In the experiment, each smart meter has a unique physical address. First, the addresses of smart meters are stored in the concentrator, by using the modified ant colony algorithm to search for the optimal path of communication in the logical topology of the experimental area. Then, we set the relay forwarding address in turn by the communication path, and the forwarding address is in the message sent by the concentrator, such as the communication path for the $1-2-3$(1: concentrator; 2: the No.2 smart meter as the relay; 3: the No.3 smart meter). The No.2 smart meter receives the message format of the concentrator as listed in Figure 4.

Part A is the receiving part of the No.2 smart meter, and performs the forwarding function, which transmits part B directly to the No.3 smart meter. Figure 5 shows the format of the message received by the No.3 smart meter. Data transmission can be carried out after receiving the message forwarded by No.2, and finally the communication between concentrator and the No.3 smart meter can be established.

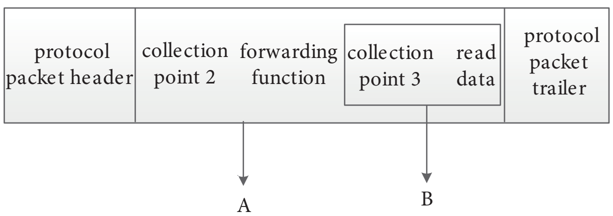

Figure 4. The message format of the meter 2 received from the concentrator.

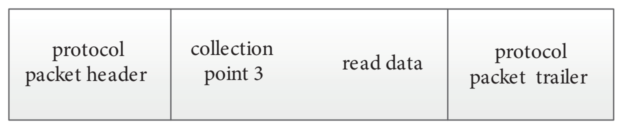

Figure 5. No. 3 smarter meter receives the message format forwarded by the meter 2.

3. Methods

To ensure the normal communication, when smart meters belong to the multiple relays, they need to select the optimal communication path for communication, so as to prevent information conflict. Based on the literature review [8–11], we selected a reformative ant colony algorithm to pick out the optimal communication path of smart meters.

3.1. The principle of ant colony algorithm

In line with the behavior of ants looking for food, Italian scholars, Bonabeau et al., put forward the basic model of the ant colony algorithm in 1991 [12]. It was found that the ants release a kind of special secretion named pheromone in the process of searching food to find paths [12, 13]. When a new intersection is encountered, the path is randomly selected, and pheromone is released. The longer the path is selected, the less pheromone is released. When other ants encounter the crossroads, the probability of choosing the path with the larger pheromone is bigger. Along with the increasing number of ants choosing this path, the pheromone rises gradually. However, with the passing of time, the pheromone of other paths gradually decreases, and finally the optimal path is figured out. When obstacles are encountered in the path of the ant colony to the destination, the ants can quickly find the optimal path again.

3.2. Ant colony algorithm implementation

The location setting and updating method of pheromone are of great significance to the success of a search. The ant colony algorithm uses pheromone to attract ants to choose, with the assistance of pheromone update including the global update and local update. The local update refers to that the path of pheromone is reduced after ants pass, and the local update aims to increase the probability of ants searching the impassable path, and achieve the goal of global search. Local pheromone update follows ants' search, and the pheromone update formula is:

$$\tau_{ij} = (1-\xi)\tau_{ij}, \tag{1}$$

where τ_{ij} is the value of the pheromone on point (i,j) , and ξ is the attenuation coefficient of pheromone.

Global update means that when ants finish a path search, the length of the path is taken as the evaluation value, and the shortest path is selected from the path set to aggrandize the pheromone value of each node in the shortest path. The pheromone update formula is listed as follows:

$$\tau_{ij} = (1-\rho)\tau_{ij} + \rho\Delta\tau_{ij}, \tag{2}$$

$$\Delta\tau_{ij} = \frac{K}{\min(length(m))}, \tag{3}$$

where $length(m)$ is the path length passed by the mth ant, ρ is the pheromone update coefficient, and K is the coefficient.

When ants go from the current point to the next point, the heuristic function is applied to calculate the feasibility of the next selectable point in the visual area. The heuristic function is:

$$H(i,j) = D(i,j)^{\omega_1} \cdot S(i,j)^{\omega_2} \cdot Q(i,j)^{\omega^3}, \tag{4}$$

where $D(i,j)$ is the path length between two points; $S(i,j)$ is a security factor. When the selected point is unobtainable, the value is 0. When the selected point can be reachable, the value is 1. $Q(i,j)$ is the path length of the next point to the target point; ω_1, ω_2, and ω_3 are coefficients, representing the importance of the above factors.

$$D(i,j) = \sqrt{(x_a-x_b)^2 + (y_a-y_b)^2}, \tag{5}$$

where a is the current point, and b is the next point.

$$Q(i,j) = \sqrt{(x_b-x_d)^2 + (y_b-y_d)^2}, \tag{6}$$

where b is the next point, and d is the target point. The choice of the next point p_{i+1} of the ants at the current point p_i is determined by the selection probability $p_{i+1,j}$.

$$p_{i+1,j} = \begin{cases} \frac{\tau_{i+1,j}H_{i+1,j}}{\sum \tau_{i+1,j}H_{i+1,j}}, & feasible\ point \\ 0, & infeasible\ point \end{cases} \tag{7}$$

where $\tau_{i+1,j}$ is the pheromone value of the point $p_{i+1,j}$.

Through the experiment, when smart meters in the two or more relays' communication range fail to judge forward and backward directions on the communication branch, ants can easily be reciprocated in two nodes. With the reciprocating movement, the pheromone will accumulate, which will result in an infinite loop and the failure to find the target node. Consequently, the direction decision function is introduced into the heuristic function to overcome this cycle reciprocating motion.

$$DY_j = |y_a - y_d|, \tag{8}$$

$$DY_j = |y_b - y_d|, \tag{9}$$

$$Dne = \sqrt{(x_d - x_b)^2 + (y_d - y_b)^2}, \tag{10}$$

$$Dno = \sqrt{(x_d - x_a)^2 + (y_d - y_a)^2}. \tag{11}$$

The heuristic function is improved to:

$$H(i,j) = D(i,j)^{\omega_1} \cdot S(i,j)^{\omega_2} \cdot Q(i,j)^{\omega^3} \cdot W^{\omega_4}, \tag{12}$$

where ω_4 is the coefficient. If $DY_{j+1} < DY_j$ or $Dne < Dno$, $W = 1$ or $W = 0$.

It can effectively assist ants to seek out the best path after adding the direction function. Moreover, this paper sets the route taboo table that the ants cannot go back after passing through a point. The ant can find its destination successfully in some areas where the direction function fails. Through the taboo table, the paths they have passed could be ruled out so as to find the destination. Through this method, we selected the optimal communication path for the smart meter in the logic topology after the relay selection. For example, some optimal communication paths of smart meters are shown in Table 1. Figure 6 shows the simulation of the No. 19 and No. 25 smart meters, and the change trend of their best fitness value are shown in Figure 7.

Table 1. The optimal communication path of smart meter to concentrator.

Smart meter	ρ	ξ	K	The communication path	Optimum fitness value
M19	0.2	0.5	100	M19-R9-R11-R10-R8-R39-Con1	202.2727
M22	0.2	0.5	100	M22-R28-Con1	118.8043
M23	0.2	0.5	100	M23-R17-R18-R16-R38-Con1	180.9245
M25	0.2	0.5	100	M25-R3-R4-R5-R6-R29-Con1	220.5960
M30	0.2	0.5	100	M30-R14-R12-R21-Con1	166.0190
M31	0.2	0.5	100	M31-R13-R21-Con1	136.2590
M32	0.2	0.5	100	M32-R45-Con1	122.0851
M33	0.2	0.5	100	M33-R2-R5-R6-R29-Con1	192.6514
M35	0.2	0.5	100	M35-R15-R14-R12-R21-Con1	193.4152

In Figure 6, the yellow lines are the communication paths between the smart meters of No. 19 and No. 25 and the concentrator. It can be seen that after the ant colony algorithm path optimization, each smart meter has only one communication branch. Because in the process of establishing communication between the concentrator and the smart meters, when a relay belongs to multiple upper-layer relay communication ranges, it is found that after the ant colony algorithm path optimization, each smart meter has only one communication branch, the problem of signal collision when multiple relays communicate with the same meter at the same time is avoided. And Table 1 shows the specific communication path relayed by the smart meter. According to the changes of the optimum fitness of the No. 25 smart meter and the No. 19 smart meter in Figure 7, the number of iterations using the improved ant colony algorithm to find the optimal path is smaller than the same without improvement, which can accelerate the search speed and expedite the networking of the smart meters.

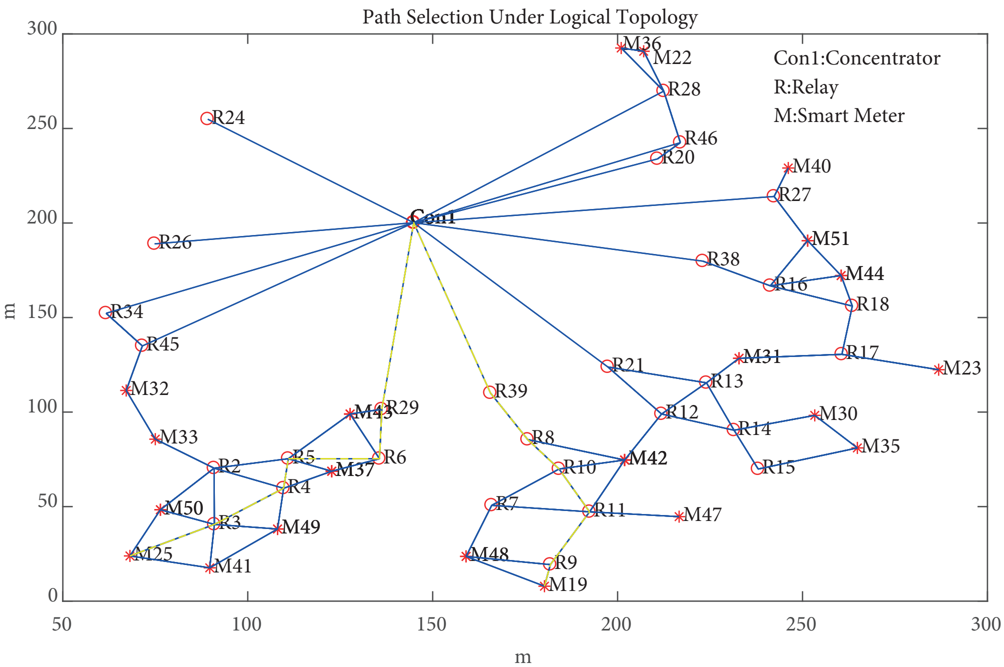

Figure 6. The path selection of No.19 meter and No.25 meter.

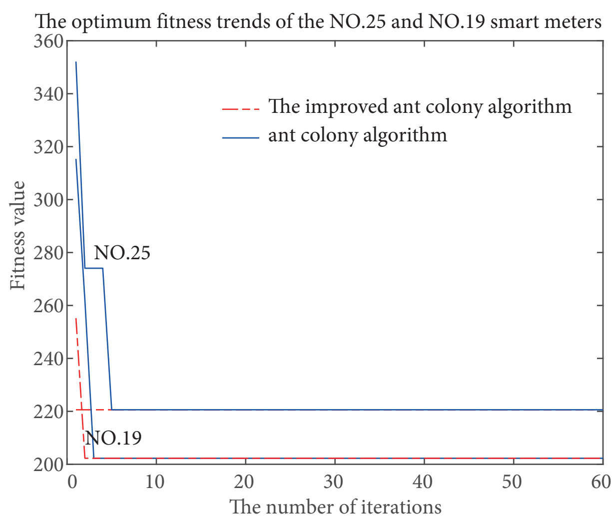

Figure 7. The best fitness trend of the No.19 and No.25 smart meters.

For example, in the process of relaying to the upper-layer relay by the R3 relay, the No. 25 smart meter can directly find the upper-layer relay R4 to communicate through the improved ant colony algorithm. As a result, the networking speed of the smart meter is improved.

3.3. Presented reasons for the dynamic networking based on the data characteristics

From the simulation results, we can see that the ant colony algorithm helps find out the optimal communication path quickly. However, in the process of the experiment, due to the signal attenuation in the channel, collected data information will be abnormal.When the collected information is abnormal, it indicates that the original communication branch has too much interference and is not suitable for continuing communication. The above ant colony algorithm is required to find other branches for communication. However, if the abnormal information cannot be judged in time, a new communication path will not be established, and it will communicate in accordance with the original communication path, which will cause the failure of users' electricity usage information collection.

In order to detect abnormal data accurately and timely, by comparing the algorithms in the literature [14, 15] in the experiment, the PNN has the shortest running time with the highest detection accuracy. Therefore, we selected the probability neural network to detect the collected data. Due to the fact that some of the information collected from the smart meter has little influence on the detection result of the abnormal information, and when the training data is relatively large, it will cause system redundancy. Therefore, in order to reduce the dimension of the sample, the main information collected in this paper is combined in different ways. By analyzing the running time and accuracy of different combinations, the optimal combination is used as the characteristic value of the data information of the smart meter. Table 2 in the following give the detection results of the main information combinations.

3.4. The basic principle and model of the probability neural network

Probabilistic neural network has the good classification performance and global optimization, and thus it can be widely used in the field of detection and classification [16–18]. The structural model of PNN is shown in Figure 8, which is divided into four layers: input layer, sample layer (also called model layer), the summation layer, and output layer (also called competitive layer). The hierarchical model of the PNNs is proposed by Specht based on the Bayesian classification rule and the probability density function of Parzen [16]. The main idea is to use Bayes decision rule (the least expected risk of error classification) to part decision space in the multidimensional input space. It is a feed-forward network model that is based on the statistical principle and uses the window function of Parzen as the activation function.

The basic principle of the PNN: assuming that there are two types of patterns θ_A and θ_B, and for the sample input vector $X = (x_1, x_2, \ldots x_n)$ to be judged, according to Bayes minimum risk criterion [19]:

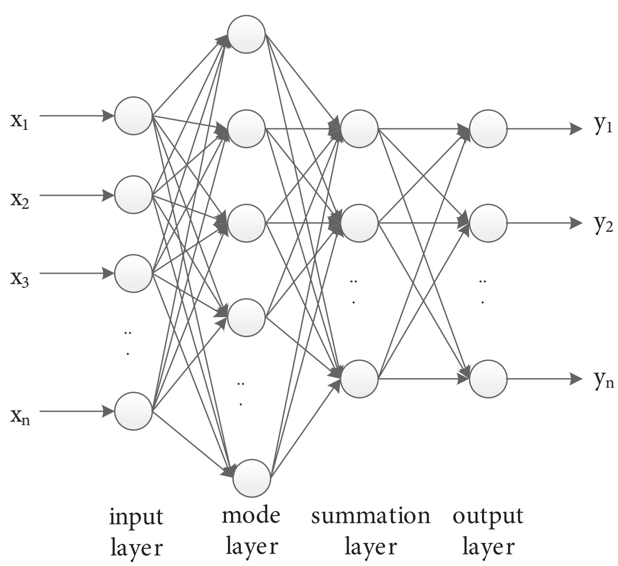

Figure 8. The model structure diagram of PNN.

$$\begin{aligned} &h_A l_A f_A(X) > h_B l_B f_B(X), X \in \theta_A \\ &h_A l_A f_A(X) < h_B l_B f_B(X), X \in \theta_B \\ &h_A = \frac{n_A}{n}, h_B = \frac{n_B}{n} \end{aligned} \tag{13}$$

where h_A and h_B represent the prior probability of the corresponding pattern category θ_A and θ_B. n_A and n_B are the training sample number of the relevant pattern category θ_A and θ_B. n means the total number of training samples. l_A represents the risk factor for classifying the X of pattern category θ_A into the pattern category θ_B. l_B similarly. $f_A(X)$ and $f_B(X)$ respectively represent the probability density function of the pattern category θ_A and θ_B. In general, probability density function is difficult to be obtained accurately, which often uses the existing input sample vectors to calculate its statistics. The PNN is a method of estimating probability density function on the basis of known random samples. The main idea is that, in the case of a large number of samples, it can continuously and smoothly approximate the original probability density function. The pattern category θ_A can obtain the estimation formula of its probability density function:

$$f_A(X) = \frac{1}{(2\pi)^{p/2}} \cdot \frac{1}{n_A} \cdot \sum_{i=1}^{n_A} \exp\left[\frac{-1(X - X_{Ai})^T (X - X_{Ai})}{2\sigma^2}\right], \tag{14}$$

where p represents the dimension of the input sample vector, and X_{Ai} is the ith training sample in the pattern category θ_A. σ means the smoothing factor.

The output of any neuron in the pattern layer can be expressed as in Eq. (15). The summation layer is the probability estimation which simply adds the output of the pattern layer unit of the same class, and the corresponding probability density function of each mode category is calculated using Eq. (14).

$$f(X, W_i) = \exp\left[-\frac{(X - W_i)^T (X - W_i)}{2\sigma^2}\right] \tag{15}$$

where W_i represents the connection weight between the input layer and the mode layer, and σ represents the smoothing factor, which significantly influences the classification effect.

3.5. The automatic selection method of key parameters of the PNN

In MATLAB simulation, the choice of smoothing factor σ will also impact the judgment result. In order to set the smoothing factor more objectively, in the present study we use the detection accuracy rate of the PNN as the objective function, and then search for the optimal values of the smoothing factor. Using the accuracy as the fitness function, the specific formula is listed as follows:

$$Acy = \frac{n_{A'} + n_{B'}}{N_{dec}}, \tag{16}$$

where Acy is the accuracy rate, and $n_{A'}$ is the sample size of pattern θ_A detected correctly. $n_{B'}$ is the sample size of pattern θ_B detected correctly, and N_{dec} is the test sample size. σ decreases or increases bit by bit according to the step length Δm until the maximum off Acy is reached. Step length Δm varies along with the change trend of accuracy Acy.

$$\Delta(t+1) = Acy(t+1) - Acy(t) \tag{17}$$

where $\Delta(t)$ is the change direction of the correct rate.

$$\sigma(t+1) = \sigma(t) + m \tag{18}$$

$$\begin{cases} \sigma = \sigma(t+1) & \Delta(t+1) \geqslant 0; \\ \sigma = \sigma(t) & \Delta(t+1) < 0. \end{cases} \tag{19}$$

$$\begin{cases} \Delta m = \Delta m & \Delta(t+1) \geqslant 0; \\ \Delta m = -\Delta m & \Delta(t+1) < 0. \end{cases} \tag{20}$$

In accordance with the change direction of accuracy in Eq. (17), the smoothing factor is adjusted dynamically according to step length Δm. In line with the change rule of Δm, we can figure out the prime smoothing factor that makes the finding of smoothing factor more objective.

3.6. The analysis of the collected data

According to the experiment, the data information transmitted by the smart meter to the concentrator are: Co, Ti, El, To, Vt, and so on (Co: collection point, Ti: time, El: electricity consumption of the day, To: total electricity consumption, Vt: voltage). The principal component analysis to reduce the dimension was used in [20], but it eliminated certain crucial but relatively small information in the experiment conducted in the present study. In order to accurately detect the abnormal data, we analyze the model of the main data respectively and find the optimal eigenvalue of the abnormal data. There are 600 groups of experimental data used to model for training, and 100 groups of test data for testing. The simulated data utilized for the experiment are provided by the Yunfu power supply company of China Southern Power Grid. Table 2 shows the detection and judgment of abnormal data for 600 different groups of data.

In the light of the test results given in the table, the accuracy of using the probabilistic neural network to test the collected data is the highest, and there are three combinations of data collected in which the accuracy rate is up to 0.9964. However, with the increase of training samples, severe system redundancy is hard to avoid. In order to reduce the system redundancy and improve the speed of detection, we choose the day power consumption, the total power consumption, and the voltage as the eigenvalues for detection. Because when the detection accuracy rate reaches 0.9964, these three information values are the least in the information feature of the combination. Using them as the feature values of the power information can not only reduce the dimension, improve the detection speed, but also ensure the accuracy of the detection. From the test results shown in Table 2, we observe that these three eigenvalues can quickly and efficiently detect abnormal data information.

4. The overall process and results of the experiment

In order to detect the dynamic networking situation when the smart meter information is abnormal, the experimental steps for the dynamic networking of the smart meter are summarized as follows:

1. According to the relay selection method in the text, relay selection is carried out for the logical topology of smart meters. After relay selection, each smart meter has many communication branches.

2. To select the best communication path for each smart meter, this paper starts from the lowest level smart meter. If the smart meter belongs to multiple relay communication ranges, the improved ant colony algorithm is used to perform the optimal path selection and an optimal upper relay is selected for

Table 2. The results of different data information for abnormal data detection.

Combination of information eigenvalues	BP		GRNN		PNN	
	The detection average accuracy	The run time (s)	The detection average accuracy	The run time (s)	The detection average accuracy	The run time (s)
Co	0.5876	0.3432	0.6107	0.9672	0.6214	0.3120
Co, Ti	0.5876	0.1716	0.6107	0.1560	0.6214	0.1716
Co, Ti, El	0.7500	0.1404	0.7250	0.1716	0.8964	0.0468
Co, Ti, El, To	0.7875	0.1404	0.9393	0.0624	0.9964	0.0624
Co, Ti, El, To, Vt	0.8500	0.2652	0.9536	0.0624	0.9964	0.0624
Ti	0.7500	0.1404	0.9286	0.0468	0.9286	0.0468
Ti, El	0.7500	0.1560	0.7357	0.0468	0.7857	0.0468
Ti, El, To	0.7500	0.1560	0.8500	0.0936	0.9643	0.0312
Ti, El, To, Vt	0.7875	0.1716	0.9393	0.0468	0.9964	0.0468
El	0.8500	0.1404	0.7357	0.0468	0.7786	0.0468
El, To	0.7750	0.1872	0.8500	0.0312	0.9643	0.0936
El, To, Vt	0.7875	0.2028	0.9393	0.0468	0.9964	0.0312
To	0.7500	0.1872	0.8500	0.0468	0.9286	0.0312
To, Vt	0.7875	0.1872	0.9393	0.0312	0.9714	0.0624
Vt	0.7875	0.1716	0.9393	0.0468	0.9393	0.0468

communication. Otherwise, communication is established directly. According to this method, we find all the optimal communication branches.

3. From the power consumption information of the smart meter collected by the concentrator, the characteristic values of the power information are selected, and the abnormal values of the power information eigenvalues are detected by PNN.

4. In the process of communication between the concentrator and the smart meter, if the information of the smart meter collected by the concentrator is abnormally detected by the PNN, the improved ant colony algorithm finds communication branches in other suboptimal paths to establish communication.

For instance, when the collected data of the No. 37 smart meter is abnormal, the No. 37 smart meter can quickly establish connection with concentrator through the No. 5 relay. As a consequence, it can automatically network the smart meter according to the characteristics of the data, which improves the reliability of the communication between the smart meter and concentrator.

5. Conclusion and discussion

Through the MATLAB simulation experiment, when there are many communication branches between the smart meter and the concentrator, the improved ant colony algorithm can not only find out the optimal communication path, but also solve the problem of local optimum. Because the path found by the improved ant colony algorithm is unique, the problem of signal collisions in practice can be avoided. Moreover, the dynamic networking of smart meters can solve the problem of communication failure in the communication process based on the characteristics of the collected information. That is, after the information of the smart meter is collected through the original communication path, the characteristic information of the smart meter is input into the probabilistic neural network for detection. When an abnormality is detected, the original communication branch of the smart meter is turned off, and the improved ant colony algorithm is used to find other communication branches to reestablish timely communication with the concentrator, thus avoiding the situation where the collected power information of the smart meter is always abnormal, and improving the communication reliability between the concentrator and the smart meter. It has raised new questions and solutions for the automatic network of the smart meter based on the power line communication, which has a certain guiding significance for the automatic networking.

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Contribution of the authors

Yunlian SUN gave the idea, Yaxin Huang did the experiments and wrote the paper, Xiaodi Zhang gave suggestions.

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