A Non-intrusive home load identification method based on adaptive reinforcement learning algorithm

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Abstract. At present, the load data collection of residential users mainly starts from the lower acquisition frequency, so the non-intrusive home load identification method based on low frequency sampling has attracted wide attention. However, low-frequency sampling has a low recognition accuracy when the training data set is small. Therefore, a non-intrusive home load identification method based on adaptive KNN reinforcement learning algorithm is proposed. The method firstly analyzes the state of the electrical appliance by KNN to obtain the initial HMM model, and then solves the HMM model by adaptive KNN reinforcement learning algorithm to obtain the optimal state transition strategy. This method reduces the model pair data. The dependence improves the recognition accuracy of the model and the adaptability to new data. Finally, the experimental verification is carried out by the low frequency data set AMPds. The results show that the method improves the state recognition accuracy of the electrical appliance and enhances the adaptability of the algorithm to new data.

1. Introduction
With the development of smart grids, power systems are increasingly demanding data interaction and information mining. Non-intrusive load monitoring can provide real-time and accurate user power load status information, which is essential for power system planning, load forecasting and market regulation, and has broad development prospects in the field of load monitoring and energy analysis [1]. The non-intrusive load monitoring system provides key data support for the two-way interaction between the power grid and the user, deep mining of user information, and analysis of household energy consumption by mining user load data [2-3]. The main idea of non-intrusive load monitoring is to collect and analyze information such as voltage, current, or power through sensors installed at the power supply inlet, extract corresponding electrical characteristics, and then analyze the operating state of the user's internal load [4-5].
Non-intrusive load monitoring has low economic cost and strong practicability, so it has attracted widespread attention in the field of smart grid, and many scholars have studied the NILM method. Wu et al. [6] first constructed the de-mixing matrix through the whitening total current signal, and then proposed a non-intrusive home load identification method based on the negative entropy maximization criterion. Finally, the recognition results were analyzed by the constructed evaluation function. Sun et al. [7] proposed a non-intrusive home load identification method based on dynamic adaptive particle swarm optimization algorithm. The load characteristics of power feature and total harmonic distortion coefficient are used as the objective function of dynamic adaptive particle swarm optimization
algorithm. Breschi et al. [8] first designed a set of jump models to describe the consumption behavior of each appliance, and then proposed a load identification method based on the dynamic programming filtering algorithm. Qi et al. [9] takes the steady-state current and the steady-state voltage as load characteristics, and then combines the local average decomposition and model matching to identify the internal electrical state of the user. Lin et al. [10] proposed a non-intrusive load identification method based on quadratic programming in order to improve the accuracy of recognition.

At present, most of the non-intrusive load monitoring research is based on high-frequency sampling, but high-frequency sampling has high hardware requirements and high economic costs. Moreover, the load data collection of residential users mainly starts from the lower acquisition frequency, so high-frequency sampling is not conducive to the promotion of non-intrusive load monitoring. And existing models based on low-frequency sampling also have problems such as low recognition accuracy and poor system stability. This paper proposes a non-intrusive home load recognition method based on adaptive KNN reinforcement learning algorithm. The adaptive KNN reinforcement learning algorithm is used to solve the HMM model, which reduces the dependence of the model on a large amount of data and improves the model's Identify accuracy and adaptability to new data.

2. Research Methods

2.1. Non-invasive household load identification system

The key technologies implemented by the non-intrusive home load identification system include: Load monitoring and Identification technology, Information communication technology and Data deep mining technology. Load monitoring and Identification is the real-time status of the user's internal load through the information analysis at the user's entrance. The information communication technology is to realize the two-way interaction between the power grid and the user. And the Data deep mining technology can further mine the user's power load data information. As shown in Figure 1, the non-intrusive home load identification system collects user real-time voltage and current information at the user entrance, obtains the user's internal load information by analyzing the characteristics of the load, and then uploads the user load information to the data center through the communication network. After the data center obtain the user side information, the user load information is further analyzed and mined to obtain the user's power usage rules and abnormal power usage behaviors. And the user side and the power grid side are provided with support for flexible interaction services such as energy efficiency management and demand response.

![Figure 1. Non-invasive home load identification system](image-url)
2.2. NILM method based on adaptive reinforcement learning

2.2.1. Reinforcement Learning. Reinforcement learning obtains Enhanced signals in the interaction with the environment, and learns by strengthening the signal in a "trial and error" way. Enhanced signals is an evaluation of the current action in the environment, rather than letting the reinforcement learning system perform the correct action. Because the external environment provides very little information, the reinforcement learning system must learn on its own experience. In this way, the reinforcement learning system gains knowledge in the interaction with the environment, and then dynamically adjusts the parameters to improve the action strategy to adapt to the new environment [11].

The decision-making process of reinforcement learning can be seen as a process of Markov decision, which can be simply expressed as \( \varphi = (S, A, P, R) \), where S is a finite state set, A is a finite set of actions, P is the transition probability matrix, and R is the return of the completed action. Reinforcement learning mainly evaluates the value of each state or action through the state value function and the action value function, then selects the strategy. The state value function represents the expected return from the current state in accordance with the current strategy, that is \( V(s) = E(R_t | S_t = s) \). The state behavior value function represents the expectation return of the current strategy after performing an action from the current state, that is \( Q(s, a) = E(R_t | S_t = s, A_t = a) \). In the function \( R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + ... + \gamma^{T-t-1} r_T \), it indicates the cumulative return from time t [12]. In this paper, the optimal state value function \( V^*(s) \) and the optimal action value function \( Q^*(s, a) \) are calculated by the Bellman optimal equation. The function is as follows:

\[
V^*(s) = \max_a \sum_{s'} P_{a|s} \left[ R_{a|s} + \gamma V^*(s') \right]
\]

(1)

\[
Q^*(s, a) = \sum_{s'} P_{a|s} \left[ R_{a|s} + \gamma \max_{a'} Q^*(s', a') \right]
\]

(2)

In the function, \( P_{a|s} \) indicates the probability that execution action a will transition from state s to s'. \( R_{a|s} \) indicates the return of execution action a from state s to s'.

In the process of Agent interaction with the environment, the value function is updated. In this paper, the classic Sarsa algorithm is used to update the value function. The Sarsa primitive value function update formula is:

\[
Q(s, a_t) = Q(s, a_t) + \alpha (R_{a_t} + \gamma Q(s', a_t) - Q(s, a_t))
\]

(3)

This paper first analyzes the load state through KNN algorithm and establishes a home HMM model with M loads, that is \( \lambda = (X, Y, T, O, \pi) \). X is a finite set of states, Y is a finite set of observations, T is a state transition probability matrix, O is the observation matrix, and \( \pi \) is the initial probability vector. Based on the HMM model established in this paper, the optimal state value function and the optimal action value function can be rewritten as:

\[
V^*(x_t) = \max_{y_t} \sum_{x_{t+1}} T_{y|x} [O_{y} + \gamma V^*(x_{t+1})]
\]

(4)

\[
Q^*(x_t, y_t) = \sum_{x_{t+1}} T_{y|x} [O_{y} + \gamma \max_{y_{t+1}} Q^*(x_{t+1}, y_{t+1})]
\]

(5)

Then the corresponding value function update formula can be rewritten as:
2.2.2. **Adaptive KNN Reinforcement Learning Algorithm (AD-KNN-RL).** The adaptive KNN reinforcement learning algorithm proposed in this paper combines the KNN algorithm with reinforcement learning, classifies the state of the load through KNN, establishes the state space, and then updates it through reinforcement learning. The reinforcement learning is learned through the enhanced signal of the environment, and when the new data is input, the parameter improvement action plan can be dynamically adjusted to adapt to the environment, so the prior knowledge is less dependent. The adaptive KNN reinforcement learning algorithm is divided into two parts: state space learning and value function learning. The state space learning determines whether to add the new state to the new state space representative point by judging whether the minimum distance between the newly appearing state and the existing discrete state is greater than the distance threshold. The value function learning calculates the corresponding action value function according to the known degree of the current state, and selects the action according to the value and moves to the next state; at the same time, calculates the corresponding update amount according to the known degree of the next state. The algorithm in this paper estimates the state behavior values of k neighbors in the current state. The algorithm in this paper uses the state behavior values of the k nearest neighbors of the current state \( x_i \) to estimate \( Q(x_i, y_i) \).

Assume that the set of k-nearest neighbors of the state \( x_i \) is expressed as:

\[
K = \{x_1, x_2, ..., x_k\}
\]

Then calculate the distance between k neighbors \( x_1, x_2, x_3, ..., x_k \) and the current state \( x_i \):

\[
d = d(x_i, x_j), x_j \in K
\]

Calculate the distance set:

\[
D = \{d(x_i, x_1), d(x_i, x_2), ..., d(x_i, x_k)\}
\]

Finally, calculate the weight set and the neighbor point contribution ratio set:

\[
W = \left\{ w_1, w_2, ..., w_k \right\}, w_j = \frac{1}{1 + (d(x_i, x_j))^2}, 1 \leq j \leq k
\]

\[
G = \left\{ g_1, g_2, ..., g_k \right\}, g_j = \frac{w_j}{\sum_{j=1}^{k} w_j}, 1 \leq j \leq k
\]

Then the optimal state value function and the action value function can be rewritten as:

\[
V^*(x_i) = \max_{y_i} \sum_{y_i} g_j \left[ O_j + \gamma V^*(x_j) \right]
\]

\[
Q^*(x_i, y_i) = \sum_{y_i} g_j \left[ O_j + \gamma \max_{y_j} Q^*(x_j, y_j) \right]
\]

Then the corresponding value function update formula can be rewritten as:

\[
Q(x_i, y_i, t+1) = Q(x_i, y_i, t) + \alpha \left[ O_j + \gamma \sum_{y_j} g_j Q(x_j, y_j, t) - Q(x_i, y_i, t) \right]
\]
2.2.3. NILM method based on adaptive KNN reinforcement learning algorithm. The algorithm first inputs the historical data of each power load and analyzes the load state through KNN algorithm, then generates the initial HMM model. It solve the optimal state transition strategy through the adaptive KNN reinforcement learning algorithm. The algorithm flow is shown in Figure 2, the detailed steps are as follows:

Step 1: Input each load power data and initial parameters, perform cluster analysis by KNN algorithm, and generate an initial HMM model.

Step 2: Input the total load power data through the preprocessing, and calculate the weight set and the contribution ratio set of the neighbor points by using equations (10) and (11).

Step 3: According to the current state, calculate the corresponding state value function and action value function through equations (12) and (13), and then select and execute the action through the greedy strategy to move to the next state.

Step 4: Perform state space learning, and update the value function according to formula (14).

Step 5: Change the next state to the current state and return to Step 3 until the last observation value ends.

Step 6: Get the optimal state transition strategy and the status of each load.

![Algorithm flow chart](image-url)

**Figure 2.** Algorithm flow chart

3. Experimental Results and Analysis

3.1. Data Preparation

The experimental data set used in this paper is the public low-frequency data set AMPds [13]. Eight electrical power data were selected from the AMPds data set to train the model, including: Lamps, Dishwashers, HVAC, Refrigerators, Heat Pumps, Televisions, Washing Machines, Dryers. These eight kinds of electrical appliances have various operating modes and different powers, covering various types such as resistance type, motor type and switching power supply type, and have certain representativeness. The total table data is equal to the sum of the power values of the eight electrical...
devices at each moment. In this paper, state recognition accuracy and power squared error are selected as non-intrusive load decomposition evaluation indicators [14-15]. At the same time, three algorithms of HMM, KNN and genetic algorithm (GA) are selected as the comparison algorithm [16-18].

(1) State recognition accuracy

\[
Acc = \frac{S_{correct}}{S_{correct} + S_{incorrect}} \times 100\%
\]

In the formula, \(S_{correct}\) is the number of states that identify the correct state, and \(S_{incorrect}\) is the number of states that identify the error.

(2) Power squared error

\[
RSE = \frac{\sum_{i=1}^{T} (P_i - \tilde{P}_i)^2}{\sum_{i=1}^{T} P_i^2}
\]

In the formula, \(P_i\) is the actual power value at the ith time, and \(\tilde{P}_i\) is the estimated power value at the ith time.

3.2. Results and Analysis

This article is divided into two scenarios for experimentation. Scene 1 is five kinds of electrical appliances, and Scene 2 is eight kinds of electrical appliances, to analyze the influence of the number of electrical appliances on the algorithm. Scene 1 selects appliances as Lamps, Dishwashers, HVAC, Refrigerators, Heat Pumps. And the training data set is a week of data randomly selected from the AMPds data set.

![Figure 3. Scene 1 State recognition accuracy comparison and Power square error comparison](image)

Figure 3 a is a comparison of the recognition accuracy in the Scene 1. It can be seen from the figure that the accuracy of the state recognition of the electrical appliances with simple state changes such as lamps and heat pumps is higher than that of other electrical appliances. The accuracy of electrical identification is generally low for multi-state continuous changes. Relatively speaking, the proposed algorithm the of the recognition accuracy in this paper can reach 95%, and the recognition performance of the algorithm is good. Among them, the HMM’s state recognition accuracy is the worst, which is related to the training data set for one week. The HMM model requires a large amount of prior knowledge [22]. In contrast, the KNN and GA state recognition accuracy has improved, but Obviously, AD-KNN-RL better and the dependence on data is lower.
Figure 3 b is a comparison of the power squared error. It can be seen that the power squared error of the algorithm is also improved. Compared with the other three algorithms, the power square error of the five types of electrical appliances is reduced, further illustrating the superiority of AD-KNN-RL.

Scene 2 added Televisions, Washing Machine and Dryer, which will have certain influence on the recognition accuracy of the algorithm. It can be seen from Figure 4 a and b that the recognition accuracy of the original five kinds of electrical appliances has decreased. The recognition accuracy needs to be improved. Relatively speaking, the recognition accuracy of AD-KNN-RL is the best, and the downward trend is relatively flat, and AD-KNN-RL has better adaptability to new data.

![Figure 4](image_url)

**Figure 4.** Scene 2 State recognition accuracy comparison and Power square error comparison

4. **Conclusion**

Based on the low-frequency sampling, this paper proposes a non-intrusive home load identification method based on adaptive KNN reinforcement learning algorithm. The model can identify the running state of the home load from the low-frequency mixed power signal and realize the non-intrusive load identification. The low-frequency data set AMPds is used to verify the decomposition effect of the algorithm. It can be seen from the comparison of two non-intrusive load decomposition evaluation indicators of state recognition accuracy and power square error. This method can obtain higher load recognition accuracy when the training data set is smaller, and reduce dependent of the model's prior data. And when adding new home load data, the system performance can be stable and adaptable to new data. However, the accuracy of the recognition of the multi-state and continuously changing electrical appliances needs to be improved.

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