Research on Non-intrusive Load Decomposition Based on FHMM

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Abstract. Non-intrusive load monitoring and decomposition, as one of the important parts of intelligent power utilization system, can deeply analyze users’ internal load components and obtain user’s electricity consumption information from different scales, which is of great significance to users and power companies. In this paper, a non-intrusive load decomposition method based on factorial hidden Markov model using low frequency data is proposed. Kmeans-II algorithm is used to cluster the working state of a single load, the results of which are used to calculate the parameters of the HMM for individual load model. The total load model is represented by a factorial hidden Markov model, which transforms the load decomposition into an optimization problem with maximum probability. The improved Viterbi algorithm based on event detection is proposed to solve this optimization problem, so as to obtain the working state sequence and realize load decomposition. Finally, the correctness and practicability of the method are verified by an example.

1. Introduction

Non-intrusive load monitoring and disaggregation (NILMD) refers to the analysis of the components and status of various loads in power system and the acquisition of power consumption information through the collection of electrical parameters at the terminal of power system [1]. As one of the most important technologies of smart grid, Non-intrusive load decomposition technology breaks the current situation that the traditional load monitoring can only measure the total load power consumption, and reduces the cost of intrusive load monitoring.

Compared with the traditional intrusive load monitoring, NILMD has lower economic cost and stronger practicability [2]. Therefore, NILMD has attracted wide attention since it was proposed. In recent years, thanks to the development of smart grid, it has become a burning issue for scholars at home and abroad [3-6]. However, the research on NILMD in China is not enough, and there is still a large space for improvement. The accuracy of load decomposition method based on NILMD framework mainly depends on the differentiation of load’s characteristics. With the improvement of software and hardware technology and the development of computing level, more and more researchers are committed to explore more load characteristics and new methods to improve the accuracy of the algorithm. The hidden Markov model (HMM) and its variants are widely used to model the load’s operation behavior [7, 8]. In spite of many studies on load decomposition at present, there are still problems in which highly fluctuating loads are difficult to be modeled and analyzed, and the accuracy of load decomposition with low-frequency sampling data is low.
Aiming at these problems, a load decomposition algorithm based on Factorial Hidden Markov Model (FHMM) is proposed. As a variants of HMM, FHMM assumes that there are multiple Markov chains in the system, forming a trust network composed of several layers. FHMM can make statistical modeling and classification for information in a time span, especially for non-stationary sequence analysis with poor reproducibility. In this paper, the problem of load state decomposition is constructed as a FHMM decoding problem to solve the optimal state combination, and the load state is solved by improving and extending the Viterbi algorithm in the FHMM problem.

2. Establishment of Load Decomposition Model

2.1. Single Power Load Model

Under different operation conditions, the electric parameters of power load, such as current amplitude, active power and reactive power, are different, but they always show the inherent characteristics under the same operation condition. The operation process of power load can be regarded as a series of state transition, which is consistent with the hidden Markov model.

The single load model is demonstrated with an example of the working process of a washing machine, as shown in Figure 1. The working state of the power load can be described by the finite state set \( S\{s_1, s_2, \cdots, s_K\} \), where \( K \) refers to the number of the device’s working states. The discrete time series \( Q\{q_1, q_2, \cdots, q_t\} \) represent the operation process of load, where \( q_t \ (q_t \in S) \) denotes the device’s state at time \( t \), and \( T \) is the length of operation time. The output active power of the load state can be represented by \( O\{o_1, o_2, \cdots, o_t\} \), where \( o_t \) denotes the output active power of the load at time \( t \), or a vector containing multi-dimensional load characteristics. In this model, the state sequence \( S \) is a Markov chain, and the state transition has Markov properties and can’t be observed. Therefore, the single load model of on/off equipment and finite state equipment can be expressed as \( \lambda = (\pi, A, B) \).

1. \( \pi \) describes the probability of the initial state of the load, ie.
   \[
   \pi_i = P(q_1 = s_i), 1 \leq i \leq K. \tag{1}
   \]

2. \( A \) is the matrix of state transition probability,
   \[
   A = \{a_{ij}, 1 \leq i, j \leq K\}, \tag{2}
   \]
   \( a_{ij} \) denotes the transfer probability of the load from state \( i \) to state \( j \), ie.
   \[
   a_{ij} = P(q_t = s_j | q_{t-1} = s_i). \tag{3}
   \]

3. \( B \) refers to the emission probability matrix,
   \[
   b = \{b_k(o_l), 1 \leq k \leq K, 1 \leq l \leq T\}, \tag{4}
   \]
   where \( b_k(o_l) \) describes the output probability of the load from state \( k \) to observation \( o_l \). According to the law of statistics, it is reasonable to assume that the observation value \( O \) is a random variable and obeys the normal distribution, so the mean and variance can be calculated to determine its parameters. The formula is as follows:
   \[
   p(o | q) = \frac{1}{\sqrt{(2\pi)^m |\Sigma|}} e^{-\frac{1}{2}(o-\mu)^T \Sigma^{-1}(o-\mu)}, \tag{5}
   \]
   where: \( m \) is the dimension of the observed value \( O \); \( \mu \) is the mean value of load’s output in a certain state; \( \Sigma \) is the covariance square of the observation vector. Normally, the observed multi-dimensional load characteristics of the electrical load are independent of each other, so the covariance matrix \( \Sigma \) is a diagonal matrix of the p-order.
2.2. FHMM Load Model

FHMM can be used to model and analyze the load decomposition problem with multiple power loads. Each equipment can be modeled based on HMM: for the load $i \in N$, there are two sequences to describe the load model, where $Q\{q_1^i, q_2^i, \ldots, q_{T_q}^i\}$ represents the operating state and $O\{o_1^i, o_2^i, \ldots, o_{T_o}^i\}$ represents the observation sequence. But the power of a single load in this model is unobservable, and what can be observed is the total load active power $O\{o_1, o_2, \ldots, o_{T_o}\}$ at the power entrance. The total model structure is shown in Figure 2.

Compared with HMM model, the parameters of the total load model FHMM can be defined as $\Lambda = (\Pi, A, B)$, similarly:

1. $\Pi$ describes the initial state probability of the model, i.e.
   \[\Pi_i = p\{q_1^i = s_1, q_2^i = s_2, \ldots, q_{T_q}^i = s_{T_q}\}, 1 \leq i \leq K'.\] (6)
2. $A$ denotes the state transition probability,
   \[p\{q_i | q_{i-1}\} = p\{q_1^i, q_2^i, \ldots, q_{T_q}^i | q_1^{i-1}, q_2^{i-1}, \ldots, q_{T_q}^{i-1}\}.\] (7)
3. $B$ refers to the emission probability,
   \[p(O_i | q_i) = p\{O_i | q_1^i, q_2^i, \ldots, q_{T_q}^i\}.\] (8)

3. Model Solution

3.1. Determination of Load State Numbers——Kmeans-II

In order to estimate HMM’s parameters through the observed data (load power), the operating state of the load must be determined first. Considering that the output power of the load in the same state will fluctuate in a certain range, Kmeans-II clustering algorithm is used to cluster the state to obtain the output in the corresponding state.

K-means II algorithm is an improvement based on K-means++ algorithm [9]. This algorithm randomly selects an initial point and then calculates the initial cost $\psi$ (refers to the distance from the nearest center point) after the selected initial center is determined. After that, process the $\log(\psi)$ times
iterations, give the current center set, sample $x$ by the probability \( \frac{\log^2 (x,P)}{\phi X (P)} \), add the selected $x$ to the initialization center and update $\phi X (P)$.

The steps of the algorithm are as follows:

1. randomly initialize a center point $P$
2. calculate initial cost $\psi=\phi X (P)$
3. for $M(\log \psi)$ times do
   4. $P' \leftarrow$ sample each point $x \in X$ independently with probability $p_x = \frac{\log^2 (x,P)}{\phi X (P)}$
   5. $P = P \cup P'$
   6. end for
7. for $x \in P$, assign a weight value $w_x$ to all points in $p$, which represents the number of points closest to the $x$ point
8. Using the local $K$-means++ algorithm to cluster the $K$ clustering centers of these candidate points

The difference between this algorithm and $K$-means++ algorithm is that each iteration of $K$means-II samples multiple center points instead of one center point, and each iteration does not depend on each other, so we can deal with this iterative process in parallel. Since the number of center points generated by this process is much smaller than the number of input data points, step 8 can quickly find $k$ initialization center points by the local $k$-means++ algorithm.

3.2. Parameter Estimation of FHMM Model

The clustering results with labels are obtained through clustering the running status of individual appliances with the $K$-means II algorithm. The label matrix is $l = \{ l_1, l_2, \ldots, l_T \}$. Three parameter matrices $\pi, A, B$ can be calculated according to the clustering result. The calculation formulas are as follows:

\[
\pi_i = \frac{\sum l_i = i}{T}, \quad i = 0, 1, 2 \cdots K,
\]
\[
a_{ij} = \frac{\sum l_{i-1} = i, l_i = j}{T-1}, \quad i, j = 0, 1, 2 \cdots K.
\]
\[
\mu_i = \frac{\sum O(l_i = i)}{\sum l_i = i}, \quad \sigma_i = \sqrt{\frac{\sum (O(l_i = i) - \mu_i)^2}{\sum l_i = i}}.
\]

In the FHMM-based total load model, because of the independence of individual Markov state chains, the initial state probability and state transition probability in the model parameters can be expressed as:

\[
\pi = \prod_{i=1}^{N} \pi_i^i, \quad p(q_i | q_{i-1}) = \prod_{i=1}^{N} p(q_i^i | q_{i-1}^i).
\]

The total active power sequence in the power load model can be obtained by linear superposition of the output of each hidden Markov mode.

\[
O = \sum_{i=1}^{N} O_i^i.
\]

The observation of load corresponding state satisfies $O \sim N(\mu, \Sigma)$, where

\[
\mu = \sum_{i=1}^{N} \mu_i^i, \quad \Sigma = \sum_{i=1}^{N} \Sigma_i^i.
\]
3.3. Solution of FHMM Model

After establishing the load model, the problem of non-intrusive load decomposition can be described as follows: given the FHMM model parameters of the load, the most likely operation state of each electrical appliance \( z_t = \{ q^1_t, q^2_t, \cdots, q^N_t \} \) can be solved by observing the power data \( O \) obtained at the power supply entrance. So load decomposition becomes an optimization problem to solve the maximum probability.

For a single appliance \( i \in N \), under a given HMM model \( \lambda = (\pi, A, B) \), the conditional joint probability of its observed and implicit states can be calculated as follows:

\[
p(O, Z | \lambda) = p(z_1 | \pi) \cdot p(o_1 | z_1, B) \cdot \prod_{t=2}^{T} \left( p(z_t | z_{t-1}, A) \cdot p(o_t | z_t, B) \right),
\]

where \( z_t = \{ q^1_t, q^2_t, \cdots, q^N_t \} \) is the implicit state at time \( t \), which contains multiple Markov state transition chains. Using the independence of Markov chain in FHMM, the optimization objective can be written as:

\[
p(O, Z | \lambda) = \prod_{t=1}^{N} p(z'_{i t} | \pi) \cdot \prod_{t=2}^{T} \prod_{i=1}^{N} p(z'_{t} | z'_{t-1}, A) \cdot \prod_{t=1}^{T} p(o_t | z_t, B).
\]

Such a probability formula can take logarithm on both sides of the equation at the same time, so as to facilitate programming and calculation.

\[
p(O, Z | \lambda) = \sum_{i=1}^{N} \ln p(z'_{i t} | \pi) + \ln p(o_1 | z_1, B) + \sum_{t=2}^{T} \left( \sum_{i=1}^{N} \ln p(z'_{t} | z'_{t-1}, A) + \ln p(o_t | z_t, B) \right)
\]

Such problems can be solved with dynamic programming. Viterbi algorithm is often used in standard HMM problems, which is a kind of dynamic programming. Therefore, Viterbi algorithm is extended and improved in combination with event detection in this paper, so that it can be applied to FHMM to solve the total load decomposition problem.

The state change of the electric equipment is usually called load event. Load events can be detected by analyzing the change of total load power \([10]\). Since the state of the device remains unchanged between two adjacent load events, it is reasonable to consider the state of the electrical equipment only when the load event occurs, which greatly reduces the number of state sequences that Viterbi algorithm needs to traverse and reduces the computational complexity.

Assuming that the total load power sequence \( O \{ o_1, o_2, \cdots, o_T, \cdots, o_T \} \) contains \( M \) load events, where the occurrence time of the \( n \)-th load event is \( t_n \), then \( q_i = q_{i-1}, n \in \{1, 2, \cdots, M\} \). The total load power sequence \( O \) is divided into \( D \) (\( D=M+1 \)) segments by \( M \) load events. Let \( t_0 = 1, t_{d+1} = T + 1 \), then the starting point of the total load power sequence of the \( d \)-th segment is \( t_d \), the end point is \( t_d - 1, \) and the length is \( t_d - t_{d-1} - 1 \), where \( d \in \{1, 2, \cdots, D\} \).

Similar to the Viterbi algorithm, two auxiliary variables \( \delta_d (i) \) and \( \phi_d (j) \) are defined, where \( \delta_d (i) \) denotes the maximum probability of generating the observed sequence \( \{ o_1, o_2, \cdots, o_t \} \) along the path \( Q \{ q_1, q_1, \cdots, q_d \} \) (and \( q_d = s_j \)), and \( q_d \) represents the state of the \( d \)-th sequence and \( \phi_d (j) \) represents the state of the \( d \)-1th sequence that maximizes a.

The steps of the improved Viterbi algorithm proposed in this paper are as follows:

1. Initialization

\[
\delta_1 (q_0) = \sum_{i=1}^{N} \ln p(q_1^i) + (l_1 - 1) \cdot \ln p(q_1^i | q_0^i) + \ln p(o_1 | q_1^1, q_1^2, \cdots, q_1^N) \cdot \phi_1 (q_1) = 0.
\]
(2) Recursive computation
\[
\delta_d^*(q_d) = \max_{q_{d-1}} \left\{ \delta_{d-1}^*(q_{d-1}) + \sum_{i=1}^{N} \ln p(q'_d | q'_d) + (I_d - 1) \sum_{i=1}^{N} \ln p(q_d' | q_d') + \sum_{t=1}^{I_d - 1} \ln p(o_t | q_t) \right\}.
\]
\[
\varphi_d(q_d) = \arg \max_{q_{d-1}} \left\{ \delta_{d-1}^*(q_{d-1}) + \sum_{i=1}^{N} \ln p(q'_d | q'_d) \right\}.
\]
(19)

(3) Termination
\[
Q^*_D = \arg \max_{q_d} \delta_D^*(q_d).
\]
(20)

(4) Path backtracking
\[
Q^*_D = \varphi_{d+1}(Q^*_{d+1}), d = D - 1, D - 2, \ldots, 1.
\]
(21)

Through the above steps, the optimal state sequence \( Q \) of electric equipment corresponding to the given total load power sequence \( O \) can be obtained. Since the output of load depends on its state, it can be directly obtained.

4. Example analysis
In order to verify the effectiveness of the FHMM-based non-intrusive load decomposition algorithm, the Reference Energy Disaggregation Dataset (REDD) [11] was used for analysis. The data set collected a total of 9 to 24 electrical equipment load data of six households in the United States, including several load characteristic signals such as voltage, current and power. The REDD data set contains two bus load sampling signals for each family, as well as the load sampling signals of each electric equipment on the same bus. Therefore, it is very suitable as experimental data to verify the performance of the load decomposition algorithm. In this paper, F-measure is used as the performance evaluation index of load decomposition algorithm and F-measure is the harmonic average of precision and recall [12]. The formulas are as follows:
\[
P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN}, \quad F = \frac{2 \times P \times R}{P + R}
\]
(22)

In the formula, \( TP \) denotes the number of positive classes predicted as positive classes; \( FP \) denotes the number of negative classes predicted as positive classes; and \( FN \) denotes the number of positive classes predicted as negative classes. For on / off devices, the on state is a positive example and the off state is a negative example; for multi-state devices, the specified working state is a positive example and the rest are negative examples.

Select some common or high-power electrical appliances as the experimental object, and decompose the load with 4-week sampling data. The data of the first three weeks are used as training samples to get the equipment’s working state and estimate the model parameters. The fourth week data is used as a test set to decompose the load. Due to the large number of intermittent periods in the use of household equipment, it is easy to identify the off state, which leads to the high accuracy of load decomposition and does not reflect the effective performance of load decomposition method. Therefore, the off state of the equipment is eliminated in the calculation of the evaluation index. Some results of household load decomposition are shown in Table 2, while the AFAMP decomposition method [13] is presented as a comparison.

| Table 1. Load decomposition results. |
|--------------------------------------|
| Load       | States (W) | Improved FHMM | AFAMAP |
|------------|------------|---------------|--------|
|            |            | P          | R      | F        | P        | R      | F        |
| refrigerator | 49, 192, 418 | 0.9026 | 0.9637 | 0.9321 | 0.8864 | 0.9645 | 0.9238 |
| microwave   | 355, 1350  | 0.8347 | 0.9982 | 0.9092 | 0.4915 | 0.9876 | 0.6564 |
| lighting    | 81, 279    | 0.8364 | 0.9055 | 0.8696 | 0.6871 | 0.9572 | 0.8000 |
| dishwasher  | 232, 1060  | 0.7631 | 0.8926 | 0.8228 | 0.1099 | 0.7238 | 0.1908 |
| washer_dryer | 136,436    | 0.6918 | 0.9932 | 0.8155 | 0.8527 | 0.9645 | 0.9052 |
| bathroom_gfi | 15,304,608,1150,1595 | 0.9684 | 0.9535 | 0.9609 | 0.9562 | 0.9849 | 0.9703 |
It can be seen from Table 1 that when the load decomposition is performed by the method of this paper, the F-Measure value of most electrical appliances is higher than the AFAMAP algorithm and are all above 0.8. The result of load decomposition is accurate and reliable. Compared with the AFAMAP algorithm, the load state identified by clustering in this paper is more accurate, and the Viterbi algorithm is improved on the basis of event detection, which can effectively improve precision.

5. Conclusion
Aiming at the current difficulties in load decomposition research, a non-intrusive load decomposition algorithm based on FHMM using low frequency data is proposed. Hidden Markov models are used to describe a single load model, and Kmeans-II is used to cluster the running state of a single load, and the clustering results are used to estimate the parameters of the HMM. The total load model is represented by a factorial hidden Markov model, which transforms the load decomposition into an optimization problem with maximum probability. The improved Viterbi algorithm based on event detection is used to solve this optimization problem and realize load decomposition. Finally, the correctness and practicability of the method are verified with an example. However, the algorithm in this paper is greatly affected by the unmodeled load. In the future work, we can consider using more external information to improve the accuracy of the algorithm and find a way to add unmodeled loads to make the load model more perfect.

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