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***Abstract*— Considering the importance of energy and the necessity of its management, this paper examines residential energy disaggregation/non-intrusive load monitoring. Support Vector Machine (SVM) has been proposed as one of the most powerful machine learning applications to solve this problem. The advantage of this method over other methods is the feature extraction of data and their classification based on recognized patterns. The proposed method is conducted on two REDD and AMPds datasets, which are related to real-world measurements. In the proposed method, SVM is trained by each of the characteristics of a particular electrical appliance. Then, the trained network shows the closest recognition to identify the given electrical appliance and predict the total power consumption of homes. The accuracy obtained for the datasets shows the applicability of the proposed method for load disaggregation**.

Keywords— Load disaggregation, non-intrusive load monitoring, machine learning, support vector machine (SVM).

I. Introduction

Energy - consumption management is required for dealing with environmental issues and deceasing emission. Data on type, amount and time of domestic usage are useful for reaching the decent aims. Energy data of each appliance is advantageous for various goals such as reducing power consumption, detecting performance deficiencies, enhancing electric usage profile via load deployment, and load forecasting [1], [2].

Intrusive load monitoring (ILM) is one of the methods to acquire each electrical appliance's power consumption [3]. In the ILM method, a measurement device is installed between the appliance and the socket. This method is undesirable since its implementation is expensive, and it disturbs customers' privacy. However, the other approach known as non-intrusive load monitoring (NILM) is a desirable concept, on which extensive research has been initiated since 1992 [4].

The total consumption of appliances is the input of NILM problem, and the goal is to extract each appliance's usage in time, which is called load disaggregation. Four steps are followed in NILM methods; a) data acquisition, b) event detection, c) feature extraction, d) electrical appliance identification [2]. Curves of load current, immediate admittance, active and reactive power, instantaneous power, and the switching transients are transient or steady-state features used for implementing load/energy disaggregation. Steady-state features need to be used to rebuild the power consumption of any electrical appliance over time. However, as the most of the special features of power consumption data are lost in steady-state, the transient state features are more appropriate for the goal of electrical appliance types recognition [5].

In studies different approaches for improve the NILM in residential load disaggregation based on machine learning and artificial intelligence methods [6], and optimization-based methods [3], [7] are proposed.

The evolutionary genetic algorithm is proposed in [7] to solve load disaggregation problem identified as a knapsack problem for recognition of only appliances with two modes (on or off) of operation. Optimization-based load disaggregation method is proposed in [3], in which the problem is introduced as an integer nonlinear optimization problem with the proposed state transition constraint. In [8], three different hybrid structures incorporating recurrent network structures and convolutional neural network (CNN) have been used to estimate the power consumption of electrical appliances.

In [1], a load disaggregation method based on Cepstrum smoothing has been used for recognition of concurrent states (on and off) of multiple appliances. A event-based solution has been suggested in [9] for improve NILM, in which multiple signatures including active, reactive, and distortion powers are utilized. In [10], an approach based on information coding has been proposed for residential load disaggregation, in which devices with similar power draws are recognized.

An unsupervised approach called principal component analysis (PCA) has been presented in [5] to improve NILM in residential load disaggregation. In [11], the graph signal processing-based NILM has been expanded without the need for training. The Cross-Entropy method is used to formulate the load disaggregation problem as a constrained optimization problem in [12], and a new penalty method is used to solve the problem. Hidden Markov model has been used to model each residential electrical appliance and improve the NILM

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problems in [13]. Each appliance is modelled using the hidden Markov model to acquire the load model in [14], and iterative fuzzy c-means is exploited to get the number of hidden states. In [14], additive factorial approximate method for improving NILM and assessment the consumption of household electrical appliances is presented.

In [2], each appliance is modelled as auto - associative neural network, in which transient power signals obtained from the events (on/off) are used. Residential load disaggregation via deep CNN for identifying multi-state devices and by considering low-frequency power data as input has been performed in [15]. Transform learning solution has been suggested in [16] for improving the NILM. Deep Learning applications have been utilized in [17] for load disaggregation of residential electrical devices.

Most of the above-mentioned methods for solving the load disaggregation problem require some complicated computational methods that are not practically possible for everyone. In some cases, the load disaggregation is performed using high frequency data, in which, the high percentage of data features is lost.

In this paper, a machine learning-based method called Support Vector Machine (SVM) is utilized to recognize, classify, and disaggregate patterns related to the power consumption of household electrical appliances. To implement the suggested solution, the low-frequency data of power measurements at the meter relevant to two real-world electricity appliance consumption datasets is utilized. This method, in addition to recognition inherent patterns of data and classify them, perfectly fits with the practical paradigm of this issue. In order to reach the high performance of results in this paper, constraints such as considering transient state data for each appliance and the operation state of each appliance with a single state are assumed.

The rest of this paper is arranged as: In section II, structure and formulation of SVM is illustrated. Section III describes in detail the studied cases in this paper. The design of SVM and simulation results are presented in Section IV. Finally, section V is conclusion.

II. Support Vector Machine (SVM)

Support vector machine (SVM) was proposed in 1995 by Cortes and Vapnik as a machine learning method. On the foundation of a statistical learning principle, SVM is a useful technique for pattern recognition, classification, and solving the regression problems [18], [19]. SVM has been applied to solve the problems of dependency estimation between data, forecasting various types of models, and designing intelligent machines. A set of samples, where each sample has features is used as a training database for SVM input [20]. For data separation and classification, SVM needs to an optimal separating hyperplane. This optimal hyperplane is obtained by maximizing the margin between the separating data. Fig. 1 depicts the hyperplane H that separates the two data classes.

The optimized hyperplane can be expressed in the form of mathematical formulas as [21]:

$$b + w^t x_i = 0 \tag{1}$$

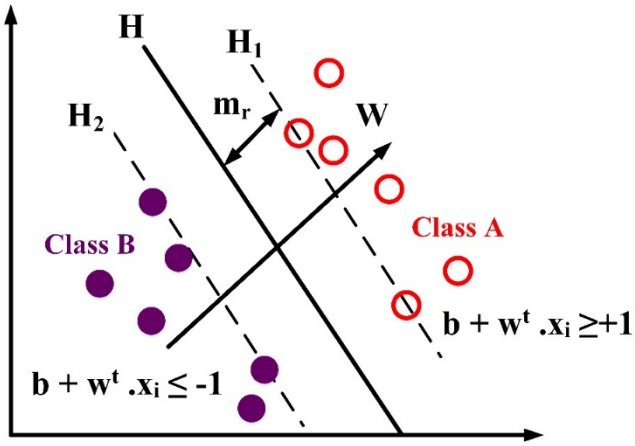

Fig. 1. Separation of two classes by SVM

where b represents the bias, w is a normal vector in the hyperplane, and X is an input vector.

The support vectors equations of each class are given as follow [21]:

$$\begin{cases} b + W^T.X_i = +1, & for\ d_i = +1 \\ b + W^T.X_i = -1, & for\ d_i = -1 \end{cases} \tag{2}$$

where d_i corresponds to the relevant class, i.e., $d_i = +1$ for class A and $d_i = -1$ for class B.

Training data of classes A and B are the result of following inequalities:

$$d_i(b + w^t x_i) \geq 1 \tag{3}$$

SVM classification tries to find the superficial surface with the largest margin and optimal hyperplane. This optimization problem is given as [20], [21]:

minimizing $\frac{1}{2}\|w\|^2$ such that

$$d_i(b + W^t.X_i) \geq 1, for \quad i = 1, 2, \dots, k. \tag{4}$$

The ultimate intention function can be obtained via the following equation [21]:

$$f(x) = sign\left(\sum_{i=1}^{N} a_{0,i}(x^T x_i) + b\right) \tag{5}$$

where x is the input vector to be categorized and N defines the support vector numbers gained in training operation. The non-negative parameters $a_{0,i}$ are used to depict support vectors among input vectors. Fig 2 illustrate the SWM flowchart.

For linearly non-detachable data to become a high dimensional space, a vector - mapping function $\varphi(x)$ is used. This transform allows data classification to be made using linear hyperplane. The decision function can be corrected as [20], [21]:

$$f(x) = sign\left(\sum_{i=1}^{N} a_{0,i}\left(\varphi(x)\varphi(x_i)\right) + b\right) \tag{6}$$

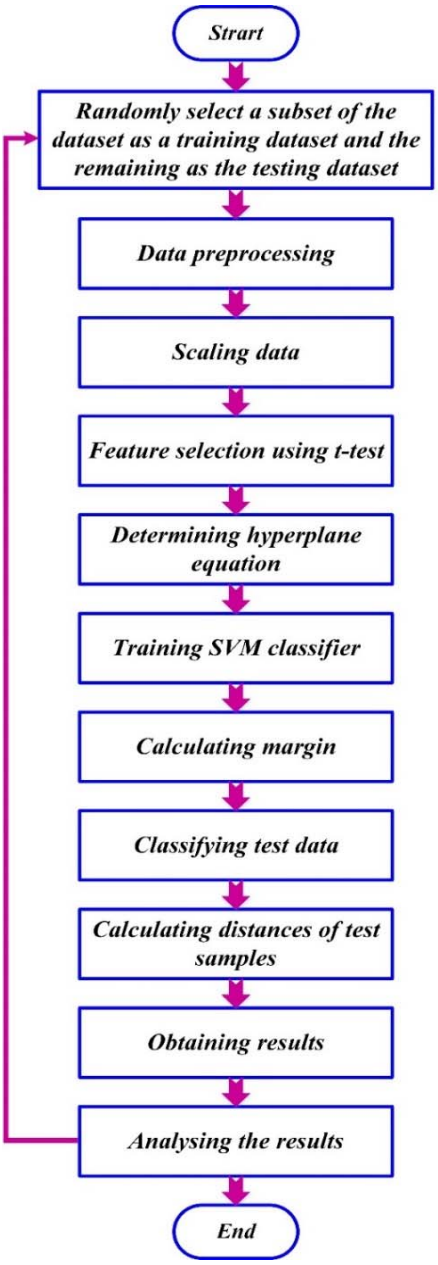

Fig. 2. Flowchart of SVM

The inner kernel function is adopted to separate the nonlinear data and reduce the numerical optimization complexity in a high-dimensional space, The kernel functions are usually defined as $K(x,y) = \varphi(x)\varphi(y)$. There are several types of kernel function used for separating and classifying nonlinear data in SVM such as radial - basis function (RBF), Gaussian, linear, and polynomial. In this paper, we use the polynomial kernel function, which is expressed as [20], [21]:

$$K(x,x_j) = \left(x^T.x_j + 1\right)^n, n > 0 \tag{7}$$

III. Case Study

In this paper, REDD dataset [22] including the power consumption monitoring of six homes in Massachusetts, United States for two weeks at three-second intervals and the AMPds dataset [23] involving power consumption reading of a home unit in Vancouver, British Columbia, Canada for 2 years at one-minute intervals are used. Since this dataset is relevant to real-world utilize, this dataset has been usage in most researchs in NILM fields. For the proposed solution, the power consumption of the 8 electrical appliances from AMPds dataset and for REDD dataset, only the power consumption of 11 electrical appliances in the first house were used. The specifications of the electrical appliances are described in Table I.

IV. Simulation Results

To load disaggregation, identification and classification of the features available for each appliance's power consumption is essential. This classification is done via SVM. To do this, it is necessary to properly design the SVR and create a database. In this paper, the power consumption curves of each appliance are considered as the input of the SVM. Eight power consumption curves of each appliance at specific times have been considered to collect data as input. Each sample from the AMPds dataset is related to one week (5040 min) and the samples from the REDD dataset have been considered for one days (1440 min). For example, Fig. 3 demonstrates the samples of considered data related to the power consumption of the two appliances as the network input. Some Indexes should be intended as targets, for which, in this study the type of household electrical appliances considered as target. Table I illustrates the target number for each electrical appliance related to its power consumption in two studied cases.

TABLE I. Target Numbers for Each Electrical Appliance in Two Studied Cases

AMPds Dataset		REDD House 1	
Appliances Type	*Target*	*Appliances Type*	*Target*
Clothes Dryer	1	Washer Dryer	1
Clothes Washer	2	Dishwasher	2
Dishwasher	3	Heat	3
Wall Oven	4	Stove	4
Fridge	5	Lighting	5
Furnace	6	Microwave	6
Heat Pump	7	Oven	7
Hot Water	8	Refrigerator	8
-	-	Kitchen out-less	9
-	-	Bathroom GFI	10
-	-	Unmetered	11

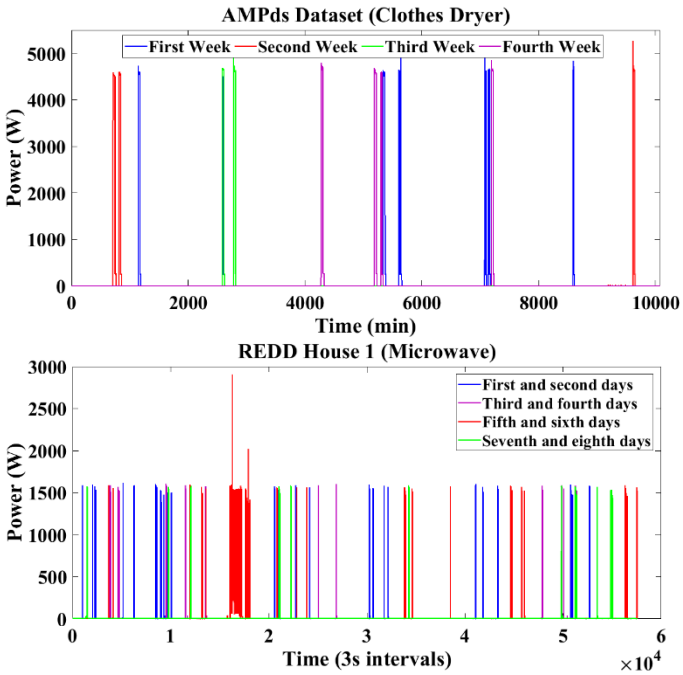

Fig. 3. Considered data for the power consumption of the two appliances

Having prepared the SVM design, it is time to use the inputs. At this point, the data should be divided into training data and testing data. In this study, in both datasets, 70% of data have been considered as training dataset and 30% as testing dataset. Training dataset is utilized to regulate the network parameters (weights of connections between neurons) via comparing network output and target. After network training, test dataset is used as input to the trained network to approve generalization characteristics of the network. The accuracy and efficiency of training and testing results at this stage can guarantee the use of the trained network for identifying and classifying new and unknown data. Fig. 4 and Fig. 5 describe the results of both training and testing the network by the AMPds and REDD datasets to fit regression between appliance type and power consumption of each appliance and classifying the power consumption of each electrical appliance, respectively. These Figs show excellent correlation and good overlap between the target data and the output of the designed SVM with 100% and 98.97% accuracy for training and testing operations by the AMPds dataset, and 98.96% and 98.2% accuracy for the training and testing operations by the REDD dataset. In These Figs, training and testing errors were shows in the forms of mean squared error (MSE), root mean square error (RMSE) and in the form of histogram. The inclination of these errors to zero indicates the accuracy and efficiency of the network in classifying data in training and testing stages.

After training, the network is saved as a black box. The features and patterns contained in the training data constitute this black box. After that, the saved network will be able to identify new and unknown data for the relevant class, given the training and identification of the nature and data patterns. Now, to test the trained network, we consider some of the electrical power consumption data from both databases that were not included in the training data. To do this, data were considered from the power consumption of each electrical appliance during a short period of time. Table II shows the characteristics of these data and the response and prediction of SVM in detecting the power consumption of each electrical appliance. The results presented in Table II show the ability of the proposed method to detect and classify the power consumption of each electrical device in different homes. But disaggregation the power consumption of each electrical appliance from the general home power consumption is the main idea in NILM. That's why, the power consumption samples of whole-house have been considered, each of which representing 120 min (two hours). This data must be utilized as input for the saved network. Fig. 6 represents a plotted examples of the whole-home power consumption of each dataset and Table III describes the specifications of these samples and the results of the identification and classification via SVM for each of these samples. Based on the results in Tables III and IV, it can be concluded that if an SVM is properly trained, it will be able to easily identify and classify test data or any new data with best performance and high accuracy. Accordingly, the trained networks by data on the power consumption related to each electrical appliance in this paper were able to easily disaggregate and classify for the total home power consumption samples from each dataset using prior training.

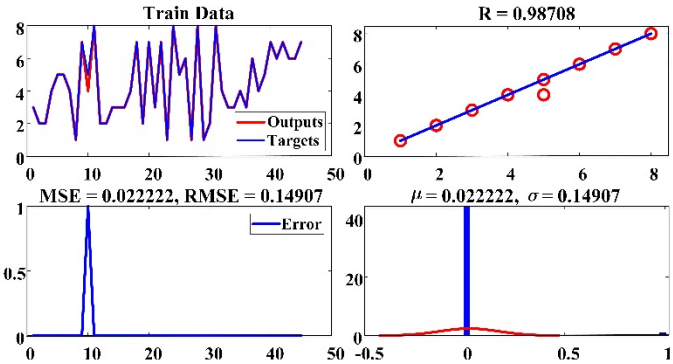

Fig. 4-a. network training results

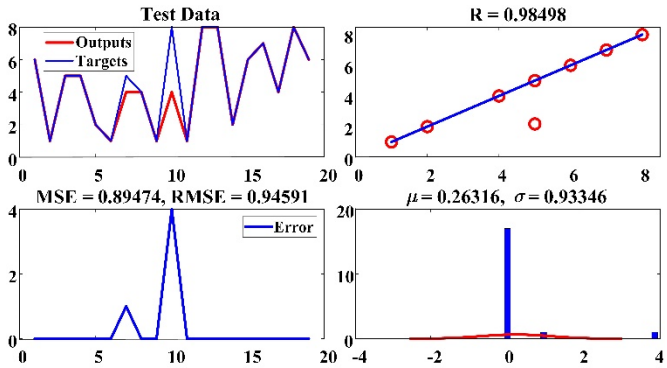

Fig. 4-b. network testing results

Fig. 4. network training and testing results by the AMPds dataset

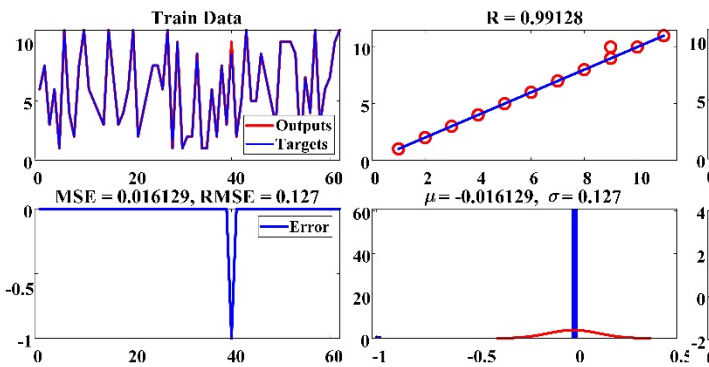

Fig. 5-a. network training results

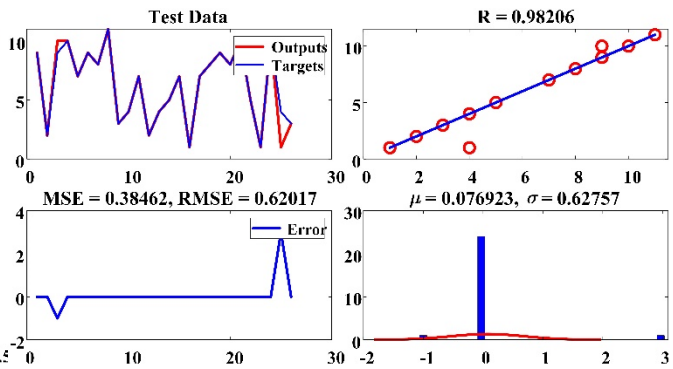

Fig. 5-b. network testing results

Fig. 5. Network training and testing results by the REDD House 1 dataset

TABLE II. NETWORK TEST RESULTS WITH POWER CONSUMPTION DATA OF EACH ELECTRICAL APPLIANCES

AMPds Dataset			REDD House 1		
Target	***The intended time of power consumption***	***SVM Predict***	***Target***	***The intended time of power consumption***	***SVM Predict***
1	Minute 60481 to minute 61921 (1 day)	1	1	Minute 2881 to minute 2940 (1 hour)	1
2	Minute 46081 to minute 48960 (2 day)	2	2	Minute 4321 to minute 4350 (30 min)	2
	Minute 100801 to minute 100920 (2 hour)	2	3	Minute 3601 to minute 3720 (2 hour)	3
3	Minute 80641 to minute 81360 (12 hour)	3	4	Minute 3721 to minute 3765 (45 min)	4
4	Minute 90721 to minute 90750 (30 min)	4	5	Minute 8641 to minute 10080 (1 day)	8
5	Minute 90721 to minute 96480 (4 day)	5	6	Minute 12961 to minute 13140 (3 hour)	6
	Minute 93601 to minute 96480 (2 day)	5	7	Minute 11161 to minute 11250 (90 min)	7
6	Minute 113761 to minute 113820 (1 hour)	6	8	Minute 15301 to minute 16740 (1 day)	8
7	Minute 20161 to minute 30240 (1 week)	7	9	Minute 6481 to minute 6600 (2 hour)	9
8	Minute 100801 to minute 100920 (2 hour)	8	10	Minute 18361 to minute 18420 (1 hour)	10
	Minute 80641 to minute 81360 (12 hour)	8	11	Minute 5760 to minute 5880 (2 hour)	11

TABLE III. SVM PREDICTION RESULTS FOR THE INTENDED DATA OF TOTAL POWER CONSUMPTION OF THE HOME

AMPds Dataset			REDD House 1		
Target	***The intended time of power consumption***	***SVM Predict***	***Target***	***The intended time of power consumption***	***SVM Predict***
1	Minute 1081 to minute 1200	1	1	Minute 6625 to minute 6745	1
1	Minute 5601 to minute 5720	1	2	Minute 17450 to minute 17570	2
3	Minute 8181 to minute 8300	3	3	Minute 5445 to minute 5565	3
4	Minute 611331 to minute 611450	4	6	Minute 5640 to minute 5760	6
5	Minute 704601 to minute 704720	6	7	Minute 6505 to minute 6625	7
6	Minute 2201 to minute 2320	6	8	Minute 9555 to minute 9675	8
7	Minute 4141 to minute 4260	7	11	Minute 6250 to minute 6370	11

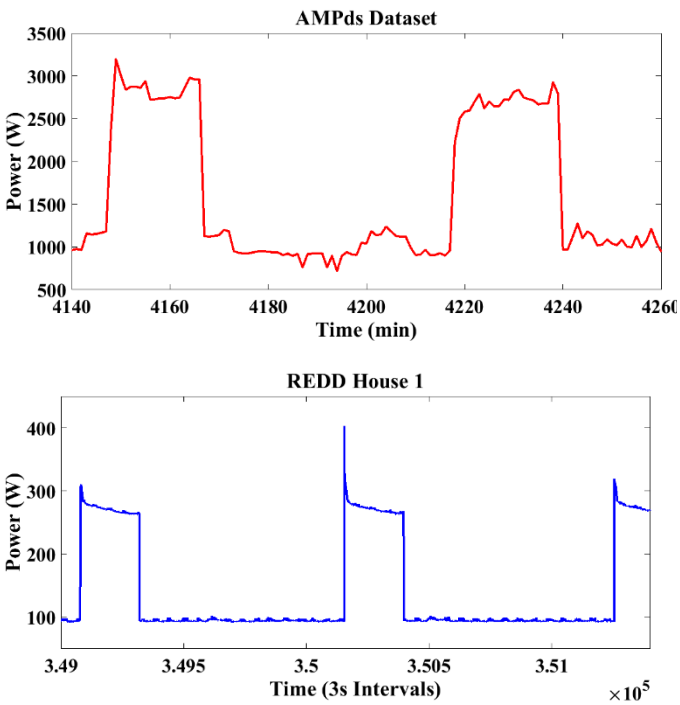

Fig. 6. Examples of total power consumption of the home considered as network inputs

The proposed method has some advantages such as making it possible to use transient state signals from the power consumption of any electrical appliance as input, reducing the computational cost of measuring data, and needless of complex computation in training and testing operations.

V. CONCLUSION

In this paper, a powerful and practical machine learning method called SVM was presented to solve energy/power disaggregation problems for the most challenging type of electrical appliances, especially for those with many pre-programmed functions. The proposed solution developed a post-processing technique to solve the NILM problem of home appliances by training on the characteristics and patterns of power consumption of each household electrical appliance. To implement the suggested solution, low frequency sampling data from REDD and AMPds datasets were used. Using real-world data provided better results in the training and testing stages of the proposed method. The presented results showed the high performance and efficiency of the SVM in solving the residential load/energy disaggregation problems. The proposed method could be applied to all monitored data in the real world.

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