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Research Paper

Development of Non-Intrusive Load Monitoring of Electricity Load Classification with Low-Frequency Sampling Based on Support Vector Machine

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Abstract

Non-intrusive load monitoring (NILM) is a promising approach to provide energy consumption monitoring of electrical appliances and analysis of current and voltage data with less instrumentation. This paper proposes an electrical load classification model using support vector machine (SVM). SVM was chosen to keep the computational cost low and be able to implement an embedded system. The SVM model was utilized to classify the on/off state of air conditioners, light bulbs, other uncategorized electronics, and their combinations. It utilizes low-frequency sampling data captured every minute, or at a 0.0167 Hz rate. Utilization change in active and reactive power was used as a feature in the model training. The optimal kernel for the model was the radial basis function (RBF) kernel with C and gamma values of 88.587 and 2.336 as hyperparameters, producing a highly accurate model. In testing with real-time conditions, the model classified the on/off state of the electrical loads with 0.93 precision, 0.91 recall, and 0.91 f-score. The results of testing proved that the model can be applied in real time with high accuracy and with an acceptable performance in field implementation using an embedded system.

Keywords: *energy monitoring; load classification; low frequency sampling; non-intrusive load monitoring; support vector machine.*

Introduction

Energy conservation in buildings through energy efficiency optimization is of the utmost importance nowadays, as it is part of climate change mitigation [1,2]. The first step of energy conservation is to monitor energy usage and to profile electrical energy consumption. Thus, the consumer will get information on how much energy they use and why it reaches a particular value. The study by Batra [3] explains that awareness of energy consumption associated with real-time energy observation encourages users to change their energy usage behavior, leading to more sustainable energy consumption. However, the total energy consumption data alone was reported to be ineffective in changing consumers' energy usage behavior [4]. Energy usage measurement at the appliance level is necessary. Although appliance-level energy measurement can yield very accurate results [5], system deployment is expensive [4]. For this problem, non-intrusive load monitoring (NILM) exists as a solution. In addition to the lower measurement costs, the NILM methodology can be proposed to deduce electrical load information and reduce appliance complexity.

NILM is a method for disaggregating total electrical load from one measurement point into individual appliances by using their distinctive characteristics [6]. Load separation can be solved by looking at the load conditions when the utility is turned on/off and operated at varying power states. To classify appliances based on these situations, a certain classification method is needed based on load characteristics. The challenge of NILM lies in determining the characteristics to classify loads. Load characteristics also depend on the frequency of data retrieval. If the data retrieval frequency is high, it is possible to see the load behavior during transient states, whereas if the data retrieval frequency is low, it can only see the behavior at steady state events.

Various NILM approaches have been reported in previous studies. Two common features extracted for disaggregating load are V-I trajectory [7-9] and active and reactive power [10-12]. Although using V-I trajectory results in a faster computation time [7], the introduction of reactive power in addition to active power has been proven to enhance NILM performance [11-13]. The primary objective of NILM is to categorize load based on aggregated consumption data. Machine learning has been widely used to solve such problems. In a supervised learning approach, not only aggregate consumption data are needed but also appliance-level consumption data [14]. The algorithms used in supervised learning NILM include artificial neural network (ANN) [15], deep learning neural network [14,16], k-Nearest Neighbors (kNN) [17], and support vector machine (SVM) [7,18]. In unsupervised learning, the model can learn without prior knowledge of the existing load. Common algorithms used in unsupervised learning NILM are hidden Markov model (HMM) [19], Bayesian network [20], and artificial neural network (ANN) [21]. In addition to the above machine learning methods, Ma et al. [22] developed an algorithm called Multi-Chain NILM (MC-NILM), which integrates models generated by existing algorithms and considers the relation among the models, aiming to improve the disaggregation performance. Kim et al. [23] used a temporal bar graph that arranges the operational time and status of the appliances to extract the inherent features. Moreover, the use of transfer learning was investigated in [8,24-26].

Li et al. [27] proposed an NILM classification model using SVM to detect events generated by electrical equipment from aggregated data. Soelami et al. [28] implemented SVM to predict the electricity consumption of an entire building, while Haq et al. [29] proposed an architecture to analyze the performance of a micro grid. Considering the computational power of the available embedded system, SVM is a suitable method to keep the computational cost low.

In this study, a low-frequency data collection approach was used to classify the load characteristics during steady state. This approach was realized by grouping the data based on active and reactive power. Moreover, it was assumed that no simultaneous appliance condition changes occur during the data collection period. This research focused on the classification of electrical load based on the measurement data of total electric load using SVM so that it can be applied in real time using an embedded system with a similar measurement concept as in [28,29]. The system was tested in a laboratory room, where the load was categorized into several classes, namely air conditioners (AC), light bulbs, uncategorized electronic devices, and their combinations.

Methodology

The research workflow is illustrated in Figure 1. The collected data were current, voltage, and power factor, which were taken from the Electrical Energy Information System (SiElis - *Sistem Informasi Energi Listrik*) implemented at the Energy Management Laboratory, Institut Teknologi Bandung, Bandung, Indonesia. The experimental object of this research was a typical university laboratory in a tropical climate. The connected electricity load consisted of a computer, lighting, and an air conditioning system. The collected data were recorded in a database with a period of one minute.

The conditions used in this study can be stated as follows. The data collection interval was one minute, the system observed in steady state, and the low-frequency features changed both in active and reactive power. The data from electric measurement were treated with pre-processing procedures such as data cleaning, feature creation, and feature selection. Each data point was given a particular class label that characterizes the equipment used, namely light bulbs, air conditioners, uncategorized electronic devices, and their combinations. These features were normalized in the same range. Furthermore, kernel selection was an essential step in the SVR process modeling. Kernels such as linear, polynomial, RBF, and sigmoid kernels with C and gamma parameters were investigated to obtain the best model using a search-cross validation grid.

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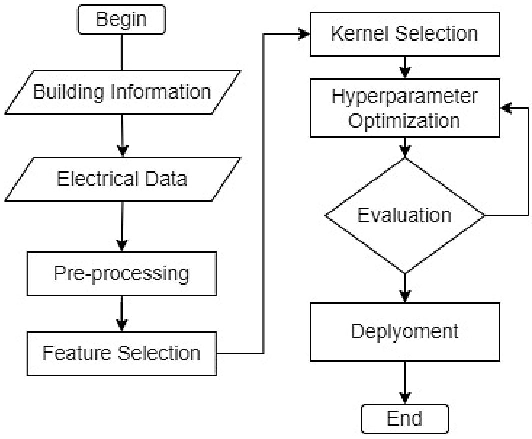

Figure 1 Data-driven building electricity consumption model workflow.

The first step was to collect data for the training process. Data retrieval was carried out on the light bulbs, air conditioners, uncategorized devices and their combinations. In this study ten classes were created. Class 0 was the group of uncategorized equipment other than light bulbs and air conditioners. Classes 1, 2, 3, and 4 were designated for the number of operating light bulbs respectively. Class 5 refers to the condition when only the AC is operating. Furthermore, Classes 6 to 9 are combinations of classes 1, 2, 3, 4, and 5. The value stored in the database was the RMS value of the measurement by the power meter. The current, voltage, and power factor data were processed to obtain the features of active power and reactive power.

The value of active power (P) can be calculated by multiplying the current (I), voltage (V), and power factor (PF) as in Eq. (1). To obtain the reactive power (Q), the relationship between apparent power and active power was used, as in Eq. (2).

$$P = V \times I \times PF \tag{1}$$

$$Q = \sqrt{(V \times I)^2 - P^2} \tag{2}$$

After the training data were prepared, the next stage was to make an appliance classification model to classify appliances according to their class. The first stage was to input the model features in the program as training data for active power and reactive power that were labeled with the corresponding classes. In this study, six types of kernels were used, namely linear, grade-two polynomial, grade-three polynomial, grade-four polynomial, RBF, and sigmoid. The multiple kernels were used to increase the likelihood of getting the best model. After the kernel was selected, iteration was carried out to find the proper hyperparameter combination to maximize the model's quality. In this study, 18,446 data points were obtained and then divided into two sets. For training, 15,566 data points were used, while the remaining 2,880 were used for testing. Furthermore, the training data were further divided so that one set was used as test data and the remaining set (k-1) as training data with K-fold cross-validation. Thus, there were K iterations for each hyperparameter combination. To find the best combination of hyperparameters, a grid search was used for C and gamma values in a range between 0.01 and 1000. This process was carried out until the highest accuracy was obtained, after which the parameters were applied in the SVM model.

After obtaining the best estimation model, the next step was to carry out validation. The data were tested sequentially according to the day of the week to check whether it could estimate the on/off condition of the device. Based on the device condition, it is possible to calculate the operating time of the device, namely the on and off period multiplied by the average energy per minute. The validated model will then be selected at the final stage, using a confusion matrix.

SVM is a binary classification method equipped with the kernel approach to deal with high-dimensional data. Various strategies to address SVMs for multiclassification problems are expressed in [30], including one-versus-the-rest, pair-wise classification, and the multiclassification formulation. The principle of SVM is to separate multiple groups of data using a boundary field that has the best margin, minimum value of which indicates the best boundary plane. Following [7], suppose the input data $\boldsymbol{x}_i \in R^n$ with n is number of features and $i = 1, 2, \ldots, l$ represent the data number. The output vector is $\boldsymbol{y}$, with $\boldsymbol{y} \in R^l$ and $y_i \in \{-1,1\}$. The maximum margin can be obtained by solving the problem in Eq. (3) subject to the constraints given by Eq. (4).

$$\min_{w,b,\xi} \frac{1}{2}|\mathbf{w}|^2 + C \sum_{i=1}^{n} \xi_i \tag{3}$$

$$y_i(\mathbf{w} \cdot \phi(\mathbf{x}_i) + b) \geq 1 - \xi_i, \quad \xi \geq 0, \tag{4}$$

where $\phi(\boldsymbol{x}_i)$ is the kernel function, C is a regularization parameter, and ξ are slack variables. Finally, the classification function f gives the solution to the classification problem formulated previously.

$$f(\boldsymbol{x}_i) = sgn\left(\sum_{i=1}^{l} \mathbf{w} \cdot \phi(\boldsymbol{x}_i) + b\right). \tag{5}$$

Experimental Setup

Figure 2 shows the measurement system scheme, called SiElis, used in this study, which has a similar measurement concept as [28,29]. The intelligent electronic devices (IED) consisted of a power meter, a communication interface, and an embedded system as local data concentrators.

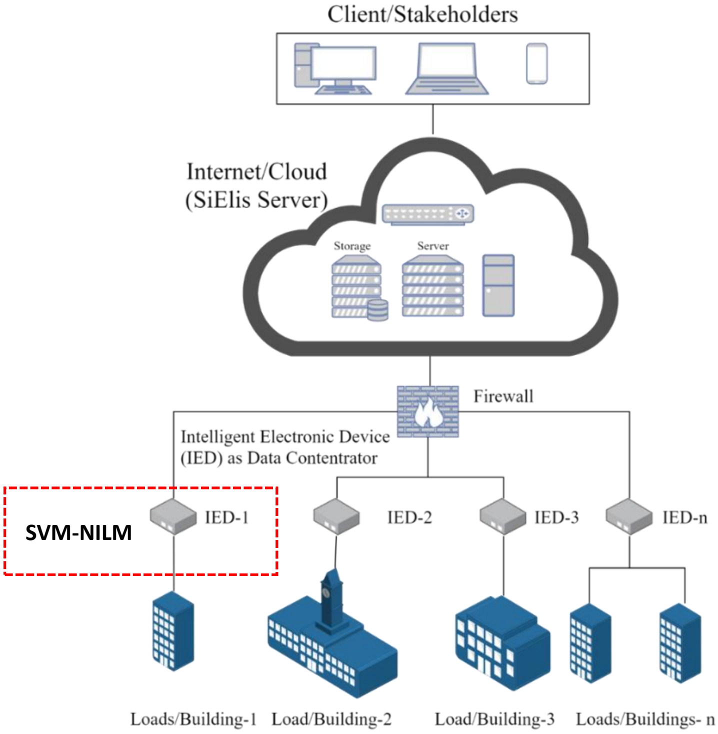

Figure 2 SiElis – Electricity Information System Concept.

The measurement system collects real-time electricity consumption data and sends it to a historical database installed on a cloud server. Complete device descriptions are utilized for non-intrusive appliance load monitoring purposes, where the IED is responsible for monitoring the energy consumption of the electrical appliance and performing load classification without the use of intrusive sensors. The IED system is supported by a cloud server to ensure that the information transfer process operates in real time and to store the historical database.

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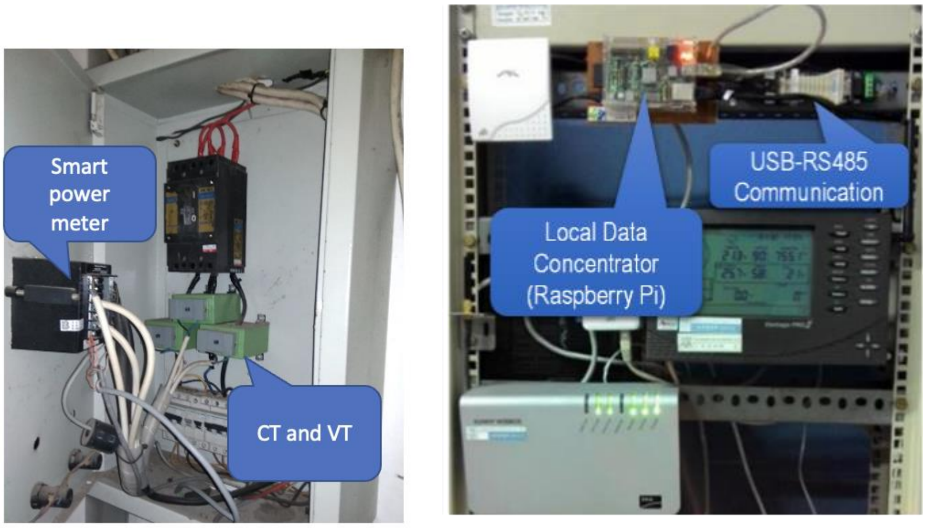


(a) (b)

Figure 3 (a) IED - CT, VT sensor & smart power meter; (b) IED – data concentrator.

Figures 3(a) and 3(b) depict the implementation of the IEDs inside the building's electrical panel. Figure 3(a) shows the voltage transformer (VT) and current transformer (CT) that took voltage and current measurements respectively from the load point to the smart power meter. VT and CT sensors were the main responsible measurement devices, recording analog data. Subsequently, the smart power meter measuring devices converted the analog to digital data related to several electrical parameters such as the average of three-phase currents, the current of each phase, the line-to-line voltage, the line to neutral voltage, the voltage between phases, each phase voltage, the average power factor, each phase power factor, and the frequency.

The data flow of the IED system was as follows. Data from the PM1200 smart power meter were collected using a Raspberry Pi 3, as shown in Figure 3(b). It utilized a two-wire half duplex RS485-to-USB converter interface as physical layer and a Modbus RTU as communication layer. The data acquisition algorithm in the Raspberry Pi 3 utilized *pymodbus* python library programming to capture digital data from the Modbus RTU with respect to *modbus_id* and *modbus_address* of the smart power meter. Variable digital data for each electrical device were formatted and stored in a local MySQL database. Using the TCP/IP protocol and structured query language (SQL), the formatted data model was forwarded to the cloud MySQL database for reporting and user interface purposes. All the mentioned routines were programmed to send and store the data every minute using cronjob in the operating system, as mentioned in IEC Standard 61724, which is between 1 and 10 minutes per monitored data [31].

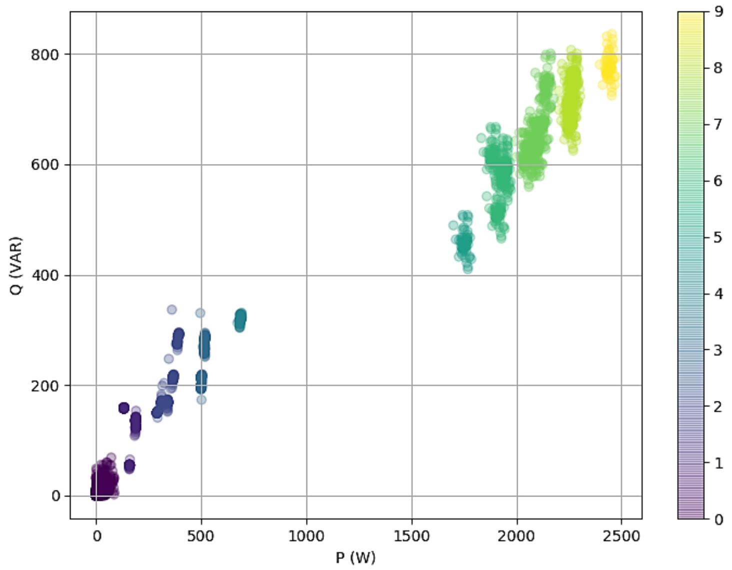
Result and Discussion

The active and reactive power consumption intervals were the chosen features selected to train the model. Table 1 shows the power consumption interval of each class from the power meter readings, which included the maximum, minimum, and average power. Class 0 was designated for any load conditions where power consumption is below the value for Class 1 and above the value for Class 9. Figure 4(a) presents the active and reactive power relation for all classes, while Figure 4(b) shows the standardized value.

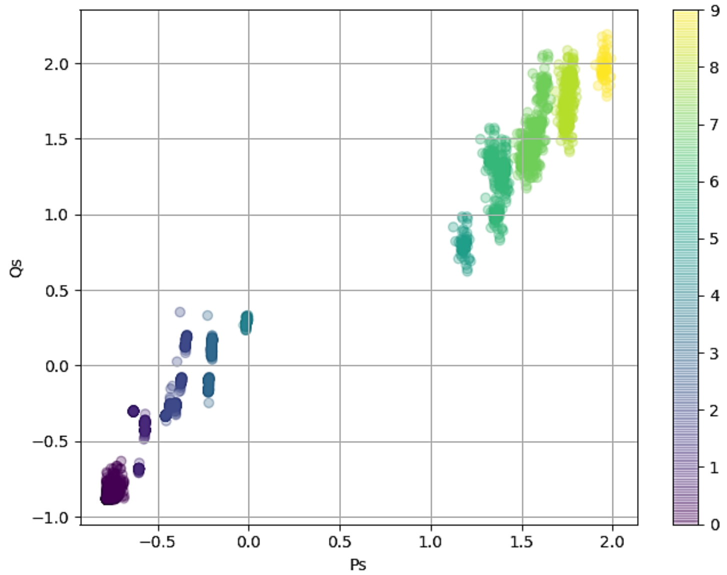
The machine-learning models were built on six kernels: second- to fourth-degree polynomial, RBF, and sigmoid. The grid search algorithm was employed to find the optimal parameter combination. It searched for the optimal C and gamma parameters from 0.01 to 1,000 values. Upon completion, every optimized model passed through five-fold cross-validation to evaluate the model's precision, accuracy, and recall. The optimal model parameters and the result of the five-fold cross-validation are summarized in Table 2.

Table 1 Active power data and reactive power for each class.

Class	Maximum		Minimum		Average	
	P	Q	P	Q	P	Q
1	191.02	159.57	132.08	47.53	166.67	114.89
2	396.39	336.56	285.77	141.10	336.82	193.63
3	563.34	344.37	464.44	173.46	506.97	244.29
4	693.76	330.99	659.11	282.38	671.09	299.21
5	1,837.90	619.09	1,376.82	409.73	1,783.66	521.65
6	2,009.34	818.18	1,833.66	465.42	1,953.46	646.25
7	2,197.15	908.01	1,994.44	558.96	2,119.16	711.85
8	2,380.35	972.72	2,202.21	624.34	2,290.84	770.22
9	2,481.77	877.02	2,397.52	724.10	2,458.06	813.04



(a)



(b)

Figure 4 PQ-plane: (a) real value (b) standardized value.

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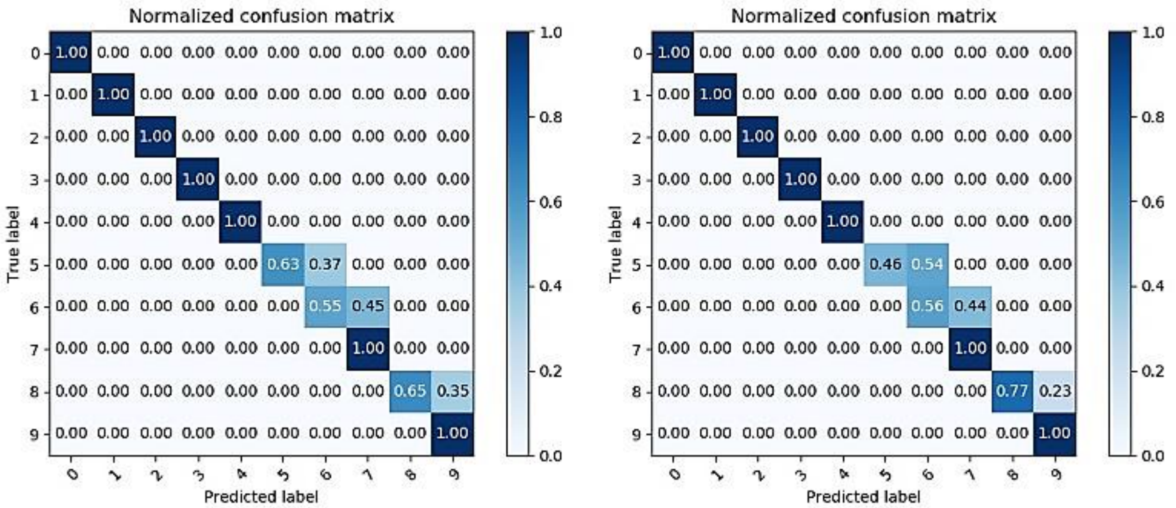
Table 2 Model validation

	C	Gamma	Accuracy	Precision	Recall	F-score
linear	26.367	-	0.997	0.889	0.875	0.882
poly-2	0.01	48.329	0.997	0.845	0.856	0.850
poly-3	0.01	26.367	0.991	0.772	0.781	0.776
poly-4	0.01	26.367	0.982	0.776	0.779	0.777
sigmoid	1,000	0.034	0.998	0.893	0.879	0.885
rbf	88.587	2.336	0.998	0.889	0.883	0.885

Shown in Table 2 are the top-three precisions models: sigmoid (0.893), linear (0.889), RBF (0.889), while RBF (0.883) and sigmoid (0.879) were the top two for recall. For the f-score, the models based on RBF and the sigmoid kernel had the highest value, at 0.885. Based on the three evaluation parameters, RBF and sigmoid kernel competed for the optimal kernel. To determine which of the two should be chosen, further evaluation based on accuracy distribution was done in the form of confusion matrices.



(a) (b)

Figure 5 Confusion matrix modeling results with (a) RBF and (b) sigmoid kernels.

The confusion matrix represents the distribution of model accuracy for load classes, as depicted in Figure 5. For Class 5, Class 6, and Class 8 there were differences in the accuracy distribution between RBF and sigmoid. The NILM classification model is expected to provide accurate predictions for each class label. We can observe that RBF had a better accuracy distribution than sigmoid, therefore we selected it for deployment in the next research phase. Figure 6 shows the decision regions of the SVM model using the RBF kernel.

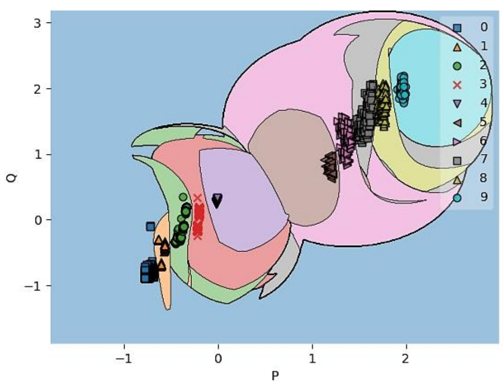


Figure 6 Normalized decision region modeling result with RBF kernel.

The model with the RBF kernel was deployed to predict the test data created based on the scenario shown in Table 3. Each class operated for a certain period in a day. The model was deployed to estimate the load condition based on the scenario above. Based on the above testing scenario, the model successfully predicted the load conditions, yielding a precision value of 0.93, recall of 0.91, and an f-score of 0.91.

Table 3 Test scenario.

Appliances	Class	State ON	State OFF
Others	0	-	-
Light 1	1	07:00	07:30
Light 2	1	07:35	08:05
Light 3	1	08:10	08:40
Light 4	1	08:45	09:15
Light 1+2	2	09:20	09:50
Light 1+3	2	09:55	10:25
Light 1+4	2	10:30	11:00
Light 2+3	2	11:05	11:35
Light 2+4	2	11:40	12:10
Light 3+4	2	12:15	12:45
Light 1+2+3	3	12:50	13:20
Light 1+2+4	3	13:25	13:55
Light 1+3+4	3	14:00	14:30
Light 2+3+4	3	14:35	15:05
Light 1+2+3+4	4	15:10	15:40
AC	5	12:30	15:50
Light 1+AC	6	15:55	16:10
Light 2+AC	6	16:15	16:30
Light 3+AC	6	16:35	16:50
Light 4+AC	6	16:55	17:10
Light 1+2+AC	7	17:15	17:30
Light 1+3+AC	7	17:35	17:50
Light 1+4+AC	7	17:55	18:10
Light 2+3+AC	7	18:15	18:30
Light 2+4+AC	7	18:35	18:50
Light 3+4+AC	7	18:55	19:10
Light 1+2+3+AC	8	19:15	19:30
Light 1+2+4+AC	8	19:35	19:50
Light 1+3+4+AC	8	19:55	20:10
Light 2+3+4+AC	8	20:15	20:30
Light 1+2+3+4+AC	9	20:35	20:50

However, since these evaluation parameters do not provide information about the model's distribution accuracy, a confusion matrix showing the model's performance for each class was required. The confusion matrix for the data test is shown Figure 7. Based on Figure 7, the model yielded a satisfactory result given the limited number of training data available. Previous work has also attempted to use SVM for NILM purposes [7]. The author utilized 16.5kHz V-I data and low-frequency (1-3) Hz apparent power data, but our model achieved a similar performance even with a 0.0167Hz sampling rate. Additionally, the proposed approach with a simple SVM algorithm means the computational load for real-time application is considerably low. The proposed approach makes a compromise in terms of accuracy, with an f-score of 0.91, when compared with a more computationally expensive approach as investigated by Moradzadeh et al. [16] with a 0.96 f-score. Our algorithm did not perform well when the difference between the load profiles was too small to be detected by the SVM algorithm. However, the result of this study is in line with Hu et al. [17], who found that to obtain a light-weight NILM algorithm, one needs a low sampling rate. The priority of our approach was a low computation effort and acceptable performance in field implementation, therefore the obtained result is acceptable.

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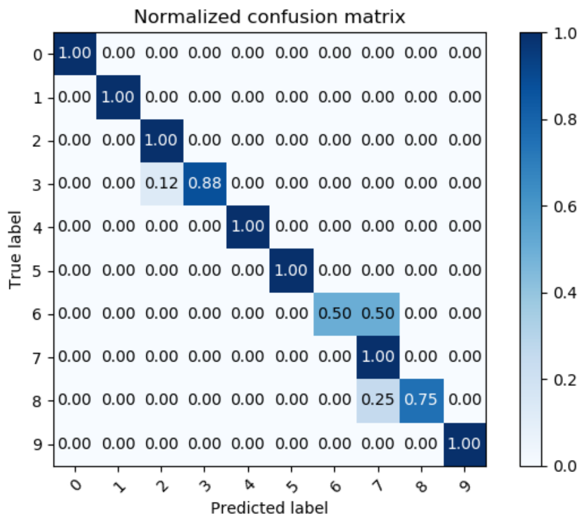

Figure 7 Confusion matrix of the deployed model.

Although the model performed very well, estimation errors were found for Classes 3, 6, and 8. Data that should have been classified as Class 3 were estimated as Class 2, as indicated by the 0.88 and 0.12 values. The confusion matrix value of 0.5 for Class 6 indicated that half of its data were incorrectly estimated as Class 7, which resulted in a value of 0.75. For Class 8, some of the data were incorrectly identified as Class 7, reducing the confusion value to 0.75. By referring to Table 3 and Figure 7, we can conclude that the model was unable to differentiate between classes when they were different by one light bulb. Classes 3-4, 6-7, and 8-9 were all different by only a single light bulb.

Conclusions

In this research, load conditions resulting from electrical appliances consisting of an air conditioner, light bulbs, uncategorized devices, and their combinations were classified into ten classes. The classification modeling by using a support vector machine obtained the optimal result by using an RBF kernel using parameters C = 88.587 and gamma = 2.336, with accuracy = 0.998, precision = 0.88, recall = 0.88, and f-score = 0.88. The model with the RBF kernel was deployed to predict the test data created based on a test. The model could predict the load condition with a precision of 0.93, recall of 0.91, and an f-score of 0.91, which are promising results. However, due to small differences, the model was unsuccessful in distinguishing classes that only differed by a single light bulb.

The proposed approach with an SVM algorithm means the computational cost for real-time application is considerably low, while the characteristics of the appliances in the form of active power and reactive power could be used as features for a classification model with a low data count frequency (0.0167 Hz or 1 minute). With a low data count frequency, the appliances can be classified by taking advantage of the feature changes in a steady state. The results proved that the proposed method can be applied in real time with acceptable performance in field implementation using an embedded system.

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References

[1] Chel, A. & Kaushik, G., *Renewable Energy Technologies for Sustainable Development Of Energy Efficient Building*, Alexandria Engineering Journal, **57**(2), pp. 655-669, Jun. 2018. doi: 10.1016/J.AEJ.2017.02.027.

[2] Mi, Z., Guan, D., Liu, Z., Liu, J., Viguié, V., Fromer, N. & Wang, Y., *Cities: The Core of Climate Change Mitigation*, J Clean Prod, **207**, pp. 582-589, Jan. 2019. doi: 10.1016/J.JCLEPRO.2018.10.034.

[3] Batra, N., Parson, O., Berges, M., Singh, A. & Rogers, A., *A Comparison of Non-Intrusive Load Monitoring Methods for Commercial and Residential Buildings*, CoRR, vol. abs/1408.6, 2014.

[4] Gopinath, R., Kumar, M., Joshua, C.P.C, & Srinivas, K., *Energy Management Using Non-Intrusive Load Monitoring Techniques – State-Of-The-Art and Future Research Directions*, Sustain Cities Soc, **62**, no. June, p. 102411, 2020, doi: 10.1016/j.scs.2020.102411.

[5] Nalmpantis, C. & Vrakas, D., *Machine Learning Approaches for Non-Intrusive Load Monitoring: From Qualitative to Quantitative Comparation*, Artif Intell Rev, **52**(1), pp. 217-243, Jun. 2019. doi: 10.1007/S10462-018-9613-7/TABLES/3.

[6] Hosseini, S.S., Agbossou, K., Kelouwani, S., & Cardenas, A., *Non-Intrusive Load Monitoring Through Home Energy Management Systems: A Comprehensive Review*, Renewable and Sustainable Energy Reviews, **79**, no. May, pp. 1266–1274, 2017, doi: 10.1016/j.rser.2017.05.096.

[7] Wang, A.L., Chen, B.X., Wang, C.G. & Hua, D., *Non-Intrusive Load Monitoring Algorithm Based on Features Of V–I Trajectory*, Electric Power Systems Research, **157**, pp. 134-144, Apr. 2018. doi: 10.1016/J.EPSR.2017.12.012.

[8] Liu, Y., Wang, X. & You, W., *Non-Intrusive Load Monitoring by Voltage–Current Trajectory Enabled Transfer Learning*, IEEE Trans Smart Grid, **10**(5), pp. 5609-5619, Sep. 2018. doi: 10.1109/TSG.2018.2888581.

[9] Baets, L.D., Develder, C., Dhaene, T. & Deschrijver, D., *Detection of Unidentified Appliances In Non-Intrusive Load Monitoring Using Siamese Neural Networks*, International Journal of Electrical Power & Energy Systems, **104**, pp. 645-653, Jan. 2019. doi: 10.1016/J.IJEPES.2018.07.026.

[10] Bonfigli, R., Principi, E., Fagiani, M., Severini, M., Squartini, S. & Piazza, F., *Non-intrusive Load Monitoring by Using Active and Reactive Power in Additive Factorial Hidden Markov Models*, Appl Energy, **208**, pp. 1590-1607, Dec. 2017. doi: 10.1016/J.APENERGY.2017.08.203.

[11] Valenti, M., Bonfigli, R., Principi, E. & Squartini, S., *Exploiting the Reactive Power in Deep Neural Models for Non-Intrusive Load Monitoring*, Proceedings of the International Joint Conference on Neural Networks, vol. 2018-July, Oct. 2018, doi: 10.1109/IJCNN.2018.8489271.

[12] Wittmann, F.M., Lopez, J.C. & Rider, M.J., *Nonintrusive Load Monitoring Algorithm Using Mixed-Integer Linear Programming*, IEEE Transactions on Consumer Electronics, **64**(2), pp. 180-187, May 2018. doi: 10.1109/TCE.2018.2843292.

[13] Houidi, S., Auger, F., Sethom, H.B.A., Fourer, D. & Miègeville, L., *Multivariate Event Detection Methods for Non-Intrusive Load Monitoring in Smart Homes and Residential Buildings*, Energy Build, **208**, 109624, Feb. 2020. doi: 10.1016/J.ENBUILD.2019.109624.

[14] Zheng, Z., Chen, H. & Luo, X., *A Supervised Event-Based Non-Intrusive Load Monitoring for Non-Linear Appliances*, Sustainability 2018, **10**(4), 1001, Mar. 2018. doi: 10.3390/SU10041001.

[15] Lin, Y.H., & Hu, Y. C., *Electrical Energy Management Based on a Hybrid Artificial Neural Network-Particle Swarm Optimization-Integrated Two-Stage Non-Intrusive Load Monitoring Process in Smart Homes*, Processes 2018, **6**(12), p. 236, Nov. 2018, doi: 10.3390/PR6120236.

[16] Moradzadeh, A., Mohammadi-Ivatloo, B., Abapour, M., Anvari-Moghaddam, A., Farkoush, S.G. & Rhee, S.B., *A practical solution based on Convolutional Neural Network for Non-Intrusive Load Monitoring*, J Ambient Intell Humaniz Comput, **12**(10), pp. 9775-9789, Oct. 2021. doi: 10.1007/S12652-020-02720-6/TABLES/5.

[17] Hu, M., Tao, S., Fan, H., Li, X., Sun, Y. & Sun, J., *Non-Intrusive Load Monitoring for Residential Appliances with Ultra-Sparse Sample and Real-Time Computation*, Sensors, **21**(16), pp. 1-18, 2021. doi: 10.3390/s21165366.

[18] Hernandez, A.S., Ballado, A.H. & Heredia, A.P.D., *Development of a Non-Intrusive Load Monitoring (NILM) with Unknown Loads using Support Vector Machine*, 2021 IEEE International Conference on Automatic Control and Intelligent Systems, I2CACIS 2021 - Proceedings, pp. 203-207, Jun. 2021. doi: 10.1109/I2CACIS52118.2021.9495876.

DOI: 10.5614/j.eng.technol.sci.2023.55.2.1

[19] Salem, H., Sayed-Mouchaweh, M. & Tagina, M., *Unsupervised Bayesian Non-Parametric Approach for Non-Intrusive Load Monitoring Base on Time Of Usage*, Neurocomputing, **435**, pp. 239–252, May 2021, doi: 10.1016/J.NEUCOM.2020.12.096.

[20] Mostafavi, S. & Cox, R. W., *An Unsupervised Approach in Learning Load Patterns for Non-Intrusive Load Monitoring*, Proceedings of the 2017 IEEE 14th International Conference on Networking, Sensing and Control, ICNSC 2017, pp. 631–636, Aug. 2017, doi: 10.1109/ICNSC.2017.8000164.

[21] Brucke, K., Arens, S., Telle, J.S., Steens, T., Hanke, B., Maydell, K.v. & Agert, C., *A Non-Intrusive Load Monitoring Approach for Very Short-Term Power Predictions in Commercial Buildings*, Appl Energy, **292**, p. 116860, Jun. 2021, doi: 10.1016/J.APENERGY.2021.116860.

[22] Ma, H., Jia, J., Yang, X., Zhu, W. & Zhang, H., *Mc-Nilm: A Multi-Chain Disaggregation Method for Nilm*, Energies (Basel), **14**(14), pp. 1–14, 2021, doi: 10.3390/en14144331.

[23] Kim, H. & Lim, S., *Temporal Patternization of Power Signatures for Appliance Classification in Nilm*, Energies (Basel), **14**(10), 2021, doi: 10.3390/en14102931.

[24] Houidi, S., Fourer, D., Auger, F., Sethom, H.B.A., & Miègeville, L., *Comparative Evaluation of Non-Intrusive Load Monitoring Methods Using Relevant Features and Transfer Learning*, Energies (Basel), **14**(9), pp. 1–28, 2021, doi: 10.3390/en14092726.

[25] D'Incecco, M., Squartini, S., & Zhong, M., *Transfer Learning for Non-Intrusive Load Monitoring*, IEEE Trans Smart Grid, **11**(2), pp. 1419–1429, Mar. 2020, doi: 10.1109/TSG.2019.2938068.

[26] Li, Y., Liu, Y., Zhang, Z., Shi, F., Li, G. & Wang, K., *Non-intrusive Load Monitoring Method Based on Transfer Learning and Sequence-to-point Model*, Proceedings - 2021 IEEE Sustainable Power and Energy Conference: Energy Transition for Carbon Neutrality, iSPEC 2021, pp. 2366–2370, 2021, doi: 10.1109/ISPEC53008.2021.9735675.

[27] Li, Y., Yang, Y., Sima, K., Li, B., Sun, T., & Li, X., *Non-Intrusive Load Monitoring Based on Harmonic Characteristics*, Procedia Comput Sci, **183**, pp. 776–782, 2021, doi: 10.1016/j.procs.2021.02.128.

[28] Soelami, F.X.N, Utama, P.H.K, Haq, I.N., Pradipta, J., Leksono, E. & Wasesa, M., *Data Driven Building Electricity Consumption Model Using Support Vector Regression*, Journal of Engineering and Technological Sciences, **53**(3), 2021, doi: 10.5614/j.eng.technol.sci.2021.53.3.13.

[29] Haq, I.N., Kurniadi, D., Leksono, E. & Yuliarto, B., *Performance Analysis of Energy Storage in Smart Microgrid Based on Historical Data of Individual Battery Temperature and Voltage Changes*, Journal of Engineering and Technological Sciences, **51**(2), pp. 149–169, 2019, doi: 10.5614/j.eng.technol.sci.2019.51.2.1.

[30] Awad, M. & Khanna, R., *Support Vector Machines for Classification,in Efficient Learning Machines*, Berkeley, CA: Apress, 2015, pp. 39–66. doi: 10.1007/978-1-4302-5990-9_3.

[31] Zhang, P., Li, W., Li, S., Wang, Y. & Xiao, W., *Reliability Assessment of Photovoltaic Power Systems: Review of Current Status and Future Perspectives*, Appl Energy, **104**, pp. 822–833, Apr. 2013, doi: 10.1016/j.apenergy.2012.12.010.

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