Non-intrusive load monitoring based on bagging decision trees and the selective features for commercial building loads

Omar Al-Khadher
Faculty of Engineering, Universiti Pertahanan Nasional Malaysia
Kuala Lumpur, Malaysia
O.khadher@hotmail.com

Azharudin Mukhtaruddin
Faculty of Engineering, Universiti Pertahanan Nasional Malaysia
Kuala Lumpur, Malaysia
azharudin@upnm.edu.my

Fakroul Ridzuan Hashim
Faculty of Engineering, Universiti Pertahanan Nasional Malaysia
Kuala Lumpur, Malaysia
fakroul@upnm.edu.my

Muhammad Mokhzaini Azizan
Faculty of Engineering and Built Environment, Universiti Sains Islam Malaysia
Negeri Sembilan, Malaysia
mokhzainiazizan@usim.edu.my

Hussin Mamat
School of Aerospace Engineering, Universiti Sains Malaysia
Penang, Malaysia
hussinm@usm.my

Naouras Saleh
Faculty of Electrical Engineering, Universiti Malaysia Perlis
Perlis, Malaysia
naouras@studentmail.unimap.edu.my

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***Abstract*— A non-intrusive load monitoring (NILM) system, also called an energy disaggregation system, allows obtaining information relating to the power absorption of individual appliances connected to a user, through the use of voltage and current transducers positioned at its connection point to the grid. In this paper, the collected data for the NILM system are obtained from four three-phase loads, namely two chillers and two induction motors with a high sampling rate. The proposed method showed all the possible features based on the transient state to be extracted and examined to select the efficient features for commercial building loads by using a bagging decision trees (BDT) classifier. Current, and harmonics features proved that can easily classify the loads rather than the other features.**

***Keywords*— Non-intrusive load monitoring (NILM), Commercial buildings, Chillers, Induction motors, transient-state features, Bagging decision trees**

I. Introduction

Energy conservation and emission reduction have emerged as critical challenges in light of the ongoing degradation of the global environment and the growing shortage of renewable energy sources. About 40% of worldwide electricity use comes from homes and businesses, and at least a third of the world's carbon dioxide emissions come from the electricity used to power buildings [1]. Reducing energy use in buildings, both commercial and residential, is a major contributor to improving energy efficiency. To achieve this goal, one must monitor and evaluate the power consumption characteristics of the equipment currently placed in the buildings. Depending on the application, one may be interested in estimating the overall energy consumed by devices over a certain period, the operating schedule of a specific device, the power consumption profile at a given time step, or the assessment of electrical dependability [2].

An energy disaggregation system, or non-intrusive load monitoring (NILM). By placing voltage and current transducers at a user's point of connection to the grid, data on the power consumption of specific appliances may be gleaned, beginning with the measurement of total power or, in some cases, just the current [3]. The price of heat, ventilation, and air conditioning (HVAC) systems monitoring and diagnostics may be drastically reduced with the help of NILM. For example, the number of installed sensors on packaged air conditioners might be decreased, lowering the capital and installation expenses of remote monitoring systems dramatically [4].

Most of the researchers focus on residential buildings rather than commercial buildings due to several limitations such as a large number of appliances, the similarity of appliances, and lack of published datasets. In this paper, we concentrate to implement the NILM model for commercial buildings based on the transient state features and bagging decision tree classifier to select the best features for the most consumed loads in the commercial buildings.

II. Literature Review

Machine learning and pattern recognition are effective and frequently utilized methodologies for a broad range of NILM research topics, namely appliance classification. To solve the appliance identification challenge, many researchers turn to classification tasks that are guided by training data that contains ground truth labels for previously collected appliance measurements [5].

In recent works, due to the existence of more complicated categories of devices and the difficulty of recognizing a single event on the power curve, Simon et al. [2] demonstrated why residential NILM algorithms are ineffective when applied to commercial buildings. Alan et al. [6] tested the NILM system's capacity to separate electrical loads by installing it in three commercial buildings. As a result of the system's general incapability to recognize individual loads, three key factors consistently make NILM challenging: the sheer number and variety of loads, the challenge of interpreting subtle shifts in energy consumption, and the failure to recognize loads that are constantly drawing power. To increase the academic and industrial interest in analyzing the electrical consumption of commercial buildings. Simon et al. [7] proposed a model for generating realistic synthetic current waveforms by making use of both publicly available datasets and our private dataset that is collected from real commercial buildings. The experiments show that the generated data resemble real datasets. Yi et al. [8] suggested the NILM approach for industrial customers' harmonic source loads based on the principle of single-channel blind source separation to isolate the impedance signal of the harmonic source load from the integrated equivalent impedance signal. The results show a low requirement on data quantity and quality, high resistance to noise, and strong adaptability. Zhaowen et al. [9] presented a set of industrial NILM method based on the motor starting

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transient process. The results demonstrated the technique can solve the problem that it is challenging to distinguish devices with similar power to induction motors.

However, due to the lack of research on commercial buildings, researchers tend to residential buildings. NILM system approaches for residential buildings can be considered to know the concept of the framework of NILM and not be applied to commercial buildings which may lead to inaccurate results. Recently, Li et al. [10] presented a new appliance identification method in residential buildings based on time-frequency analysis and particle swarm optimization algorithm with the Support Vector Machines (PSO-SVM). The result confirms that the proposed NILM system is robust. Ju-Song [11] presented a non-intrusive load monitoring method based on feature fusion. The proposed method can identify unknown loads and can dynamically expand the load feature database.

III. The Proposed Model of NILM

After collecting and pre-processing data, the proposed NILM system obtains the features based on electrical parameters including voltage (V), current (I), real power (P), reactive power (Q), apparent power (S), power factor (PF), harmonics, and total harmonic distortion (THD). The proposed system uses a bagging decision tree classifier to identify the loads. To evaluate the NILM model, the evaluation metrics need to be used if the model can be effective and accurate for classification. Figure 1 presents the proposed NILM system.

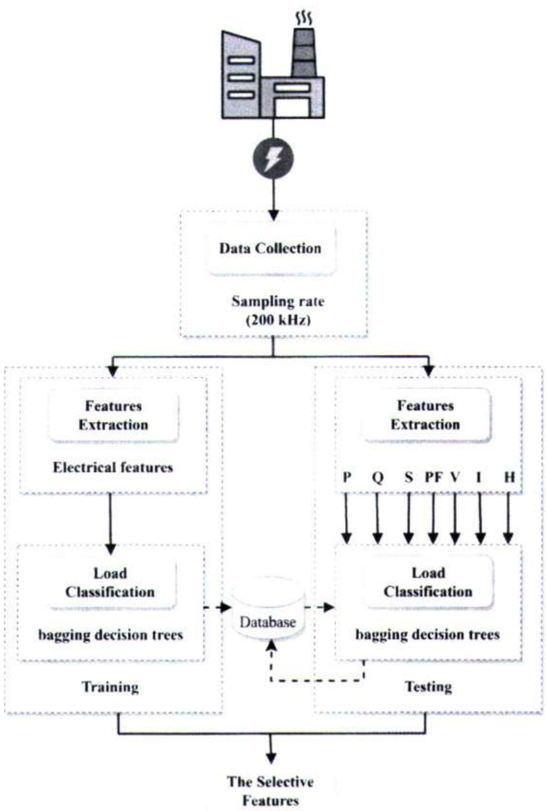

Fig. 2. The scheme of the proposed NILM system.

A. Data Collection and pre-processing

In this study, the raw signal of four loads are two induction motors (IMs), and two chillers (CHs) were collected by using Fluke 435 II energy analyzer from 7:30 AM to 10:00 PM for two days. Where each load has three-phase and the total loads are 12 loads to be classified. The sampling frequency is 200 kHz to capture the transient state of the parameters and the most crucial is obtaining the high order harmonics due to having the nonlinear loads and this will ease the classification of loads in this study. Figure 2 shows the graphical of the experimental setup.

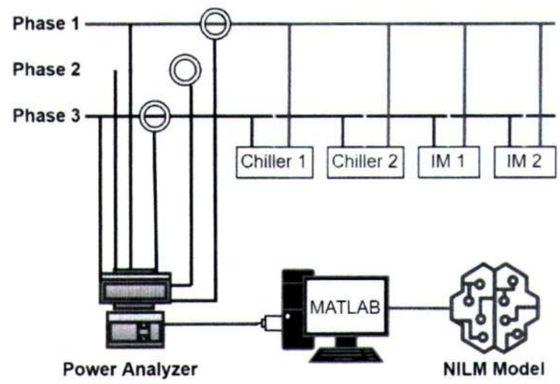

Fig. 1. The experimental setup.

There are three types of loads in NILM called single state (Type-I), multi-state (Type-II), and infinite state (Type-III). IMs are considered Type-II appliances while CHs as Type-III appliances due to the changes in the power during the operation time. Table I shows the parameters of IMs that have been used in this study.

TABLE I. THE MAIN PARAMETERS OF THREE-PHASE IM

Parameter	Value
Power	75 kW (100 HP)
Voltage	415 V
Frequency	50 Hz
Speed	1475 RPM
Pole pairs	4
Frame size	250 MC

All signals need to be standardized which is a scaling feature technique where the values are centered around the mean with a unit standard deviation. This indicates that the attribute's mean becomes zero, and the resulting distribution has a standard deviation of one. The standardizing formula is as follows:

$$S = \frac{S-\mu\,(S)}{\sigma\,(S)} \tag{1}$$

Which S is the feature from the data, μ is the mean of the feature values and σ is the standard deviation of the feature values.

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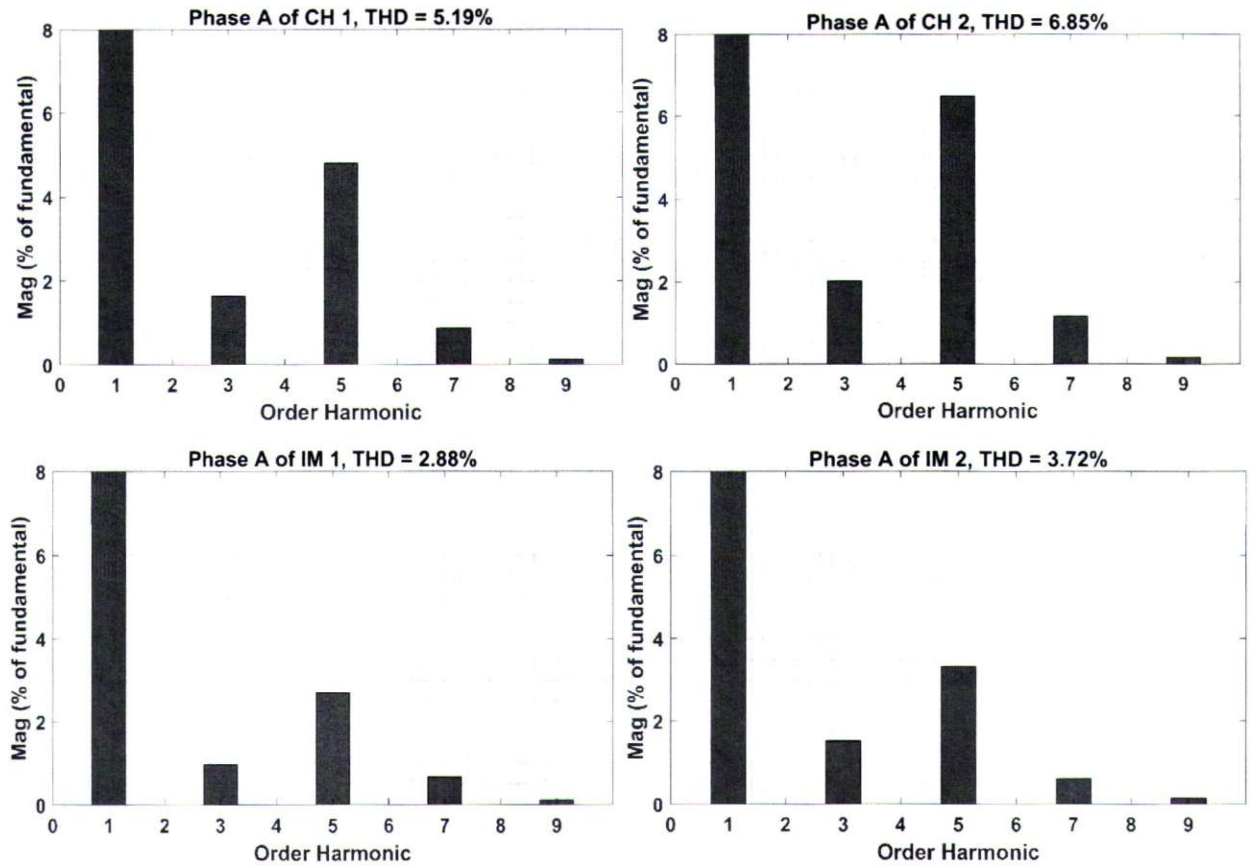

Fig. 3. The harmonics order for two CHs and two IMs from Phase A.

B. *Features Extraction*

According to recent studies, The transient-state was used especially to extract the unique harmonic characteristics among similar loads more than power derivatives such as P, Q, S, and PF. When the loads overlap, the classification becomes tough on the classifiers where which leads to a negative result. The harmonics prove that when having similar loads can be added to avoid overlapping which is more accurate than active power and reactive power features.

This study will use all the possible features to prove the best features for IMs and CHs that can be used for the NILM system. Figure 4 shows the active power signatures of two chillers and two induction motors. To illustrate, the CHs have 3 compressors, which each compressor will be operated based on the response demand of the building that will need and these compressors do not have a specific time to be on, which will be a challenge to classify the loads. The operations of the commercial loads are all used at the same time and turned off at the end of the day.

In this study, P, Q, S, PF, V, I, and harmonics were used. Event harmonics will be not considered due to the symmetry relationship as well as including harmonics reaches up to 21st may bring out a poor result because these lower harmonics may carry the same values and leads to inaccurate classification. Figure 3 shows the harmonics of the loads for phase A.

C. *Load Classification*

The most well-known and competitive decision tree extensions are bagging, random forest, and AdaBoost, with bagging requiring three stages to complete. The first step involves creating subsets of the original data by dividing the columns and rows into subsets of data. Step 2 is to develop classifiers for each group of data, using the same or different classifiers for each piece of data. When it comes down to it, the best classifier is selected from among all classifiers in step 3 by a simple majority vote. To prevent over-fitting due to high variation during decision tree model training, the bagging decision tree model is used [12]. The maximum number of splits is 200891 and the number of learners is 30 in this model.

One day will be considered as training data and the other day will be considered as testing data to examine the strength of the classifier and select the superior features for similar loads. Moreover, we labeled the data as follows:

- Chiller 1 = 1.
- Chiller 2 = 2.
- Induction motor 1 = 3.
- Induction motor 2 = 4.

D. *Evaluation metrics of load identification*

It is very important to use an appropriate evaluation index to evaluate the effect of NILM. Therefore, the accuracy of load identification and disaggregate can be measured by identifying the target electrical appliances [13]. Table II presents the confusion matrix where TP is the true positive, FP is the false positive, TN is the true negative and FN is the false negative.

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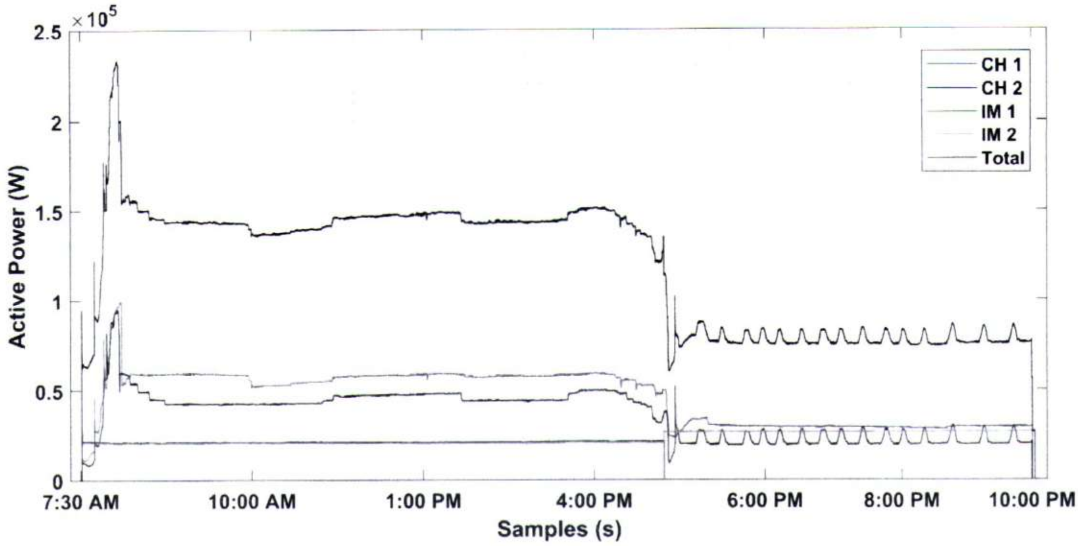

Fig. 4. Singatures of chillers and induction motors including the total power constmption.

TABLE II. CONFUSION MATRIX

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

To evaluate the disaggregated appliances' features and how the classifier identifies the loads effectively based on bagging decision trees are precision (P), recall (R), accuracy (Acc), and F-measure (f1).

$$recall = \frac{TP}{TP+FN} \tag{2}$$

$$precision = \frac{TP}{TP+FP} \tag{3}$$

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$F_{measure} = 2 * \frac{precision * recall}{precision+recall} \tag{5}$$

The performance of the model and analyzing the whole features will be discussed in the next section.

IV. Results and Discussion

In this paper, all the electrical features based on bagging decision trees and the transient states are used for the load classification to prove the efficient features of the chillers and induction motors in commercial buildings.

The results of the testing data are presented in Table III. In the beginning, the P feature showed satisfactory accuracy, and this is because some of the similar phase signatures can be overlapped, while when Q feature is added the classification improved with a 14.7% increase. Even though P, Q, S, and PF features have a high accuracy may not improve the classification but increase the computing and complexity. So, the difference in the accuracy between P-Q features and adding S and PF features are slight with 1.2%.

The current feature showed the lowest accuracy among the other features, which cannot be used as a single feature for these types of loads, especially with chillers (Type-III), where adding the V feature can enhance the classification but still have overlapping due to the equality of voltage for all the loads. The current and harmonics demonstrated the highest one due to the unique values of the loads with 99.7% accuracy. Current and harmonics features proved and overcome the other features. The average classification

TABLE III. COMPARSION OF ELECTRICAL FEATURES BASED ON COMMERCIAL BUILDING LOADS

Feature	Phase A			Phase B			Phase C		
	Recall	*Precision*	*Accuracy*	*Recall*	*Precision*	*Accuracy*	*Recall*	*Precision*	*Accuracy*
P	76.5%	77.83%	75.6%	80.68%	80.78%	79.2%	64.38%	65.33%	63.5%
P and Q	93.83%	93.5%	93.4%	86.55%	86%	83.8%	87.8%	87.2%	85.7%
P, Q, S and PF	93.28%	92.68%	92.5%	89.85%	88.88%	87.8%	90.6%	89.43%	89.5%
I	79%	82.8%	82.6%	77.75%	83.23%	82.1%	53.9%	56.7%	61.5%
I and V	77%	81.23%	80.6%	80.8%	84.45%	83.9%	57.73%	58.23%	61.9%
I and harmonics	98.2%	97.9%	**97.5%**	95.9%	97.2%	**96.7%**	99.15%	98.65%	**98.9%**

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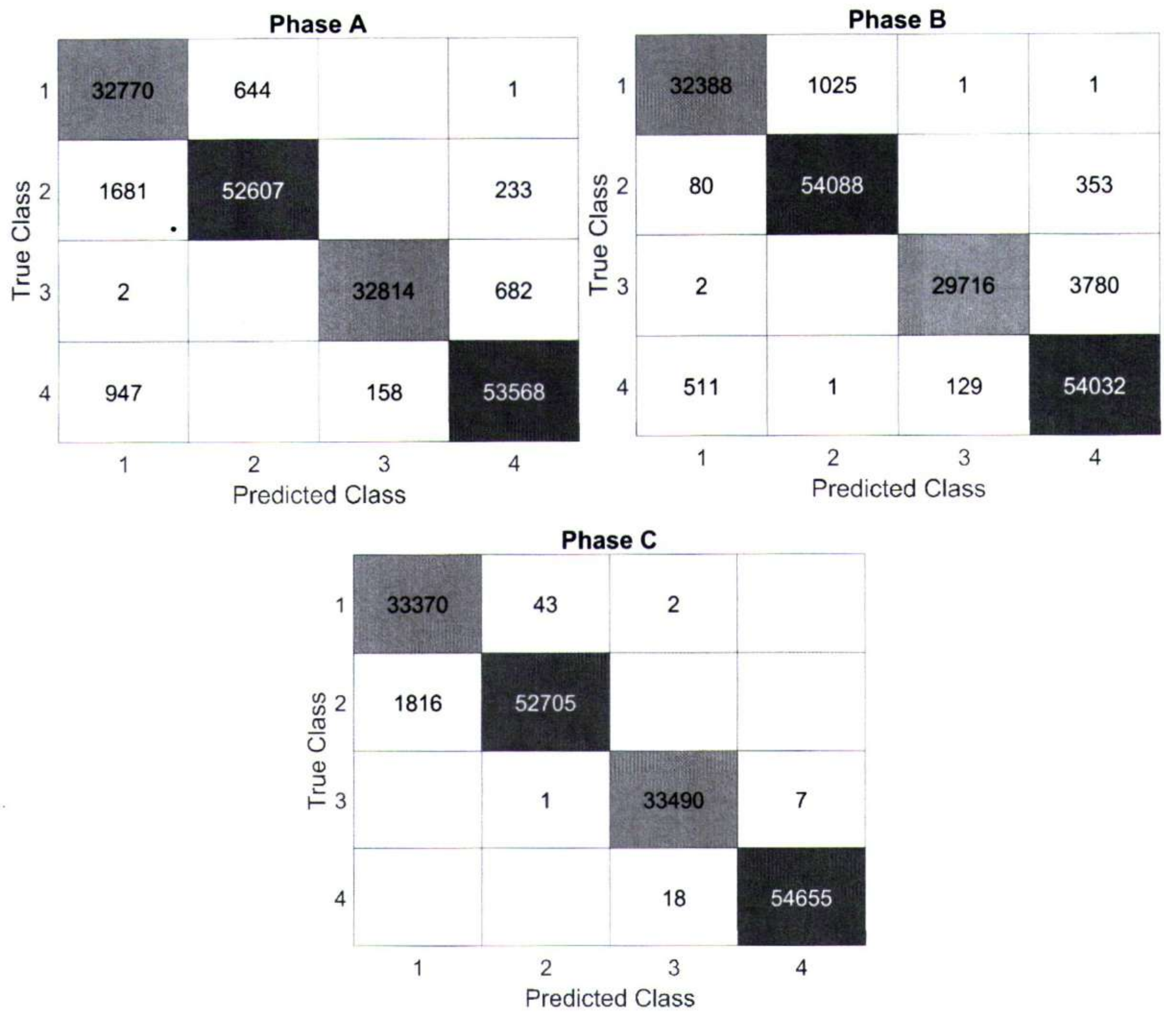

Fig. 5. Test results for each phase based on Current and harmonics.

accuracy can reach 75.9%, while the other features can reach 44.3% or less.

As shown in Figure 5, The identification of each load based on I, THD, and harmonics features demonstrated the lowest rate is 54.91% and the highest is 98.22% for CH1_B and CH 2_A, respectively. Similar loads might overlap but not much if harmonics are used which have the ability to classify the same type of loads with high accuracy. The model can be enhanced if the training data is big, where one day is not enough for training only due to the fluctuation signal of chillers day after day, while IMs have a steady signature and can easily be classified.

V. Conclusion

This paper proposes a BDT method for commercial building loads classification to select the efficient features for two similar chillers and two induction motors. Extracting all the possible electrical features to study and analyze based on transient states. The BDT classifier is capable to classify similar loads. The selective features for type-I and type-III loads are I and harmonics. These features have unique values that make them non-overlapping, while the other features are overlapped and not efficient to be used especially with type-III loads. The results of the classification rate showed a satisfactory accuracy of 75.87% based on I and harmonics. On other hand, the other features demonstrated less than 45%.

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