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Smart Home Electric Energy Management Using Non-Intrusive Appliance Load Monitoring (NILM)

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ABSTRACT

Reducing the use of electrical energy in everyday life can be done with the awareness of the user. Awareness of using electrical energy can be done by providing information about the use of electricity itself. In developing a smart home with energy management systems or other commercial electronic devices, a tool that can measure or sort electricity usage in buildings and households is needed based on current and voltage units. Measuring and sorting what is meant is separating the total power consumption used as a load of a specific device that can be used by applying the Non-Intrusive Load Monitoring (NILM) technique known as Energy Disaggregation. The results are shown by NILM using the IoT concept data will be sent to the server via the internet using Message Queuing Telemetry Transport (MQTT). The data is processed and given to the user in the form of measurement results for each electronic device connected to the measuring device. From these results, the system can separate the energy from the refrigerator and air conditioner from the total energy consumed at one time. This step is one way to make energy efficient, that an energy management system with iot concept is built.

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1. INTRODUCTION

Electricity consumption is one of the factors that affect a country's economy and climate change, as there is still a significant reliance on fossil fuels as a natural resource for generating electricity. Efficiency in electricity usage can be controlled by monitoring the electricity consumption, where the information is communicated to the users or consumers (Ahmed Zoha 2012; Berges 2011). Traditional energy consumption measurement devices used by the public can only measure the total energy consumption data for each household and cannot measure individual electrical loads of devices. Obtaining load data for each device requires more detailed information. To obtain this information, the Appliance Load Monitoring (ALM) method can be employed (Hart, G. W. 1992). There are two approaches to ALM: Intrusive Load Monitoring (ILM) and Non-Intrusive Load Monitoring (NILM). The NILM method is used as a distributed sensing method and single-point sensing method.

The ILM method is more accurate than NILM in measuring the energy consumption of specific devices compared to NILM. However, its implementation requires high costs, the configuration of multiple sensors, and complex installations for large-scale applications, as the ILM method requires one or more sensors for each device (Ahmed, 2012). The NILM method, on the other hand, only requires one measuring device/sensor for each house or building for the monitoring process. The NILM method can be combined with emerging domains such as the Internet of Things (IoT). Combining the NILM method with the concept of IoT is one of the most relevant alternatives for energy disaggregation, providing a method to separate individual consumption for each electronic device so that the public/users can have a clearer understanding of their electricity consumption.

A brief explanation of the IoT concept being built is the Smart Home, which is a comfortable home arrangement where appliances and home devices can be controlled and monitored automatically from anywhere via the internet. Within the Smart Home, there is an energy management system. Energy management utilizes the NILM method to classify the consumption of each electronic device using the SDM220.

Figure 1. Eastron SDM 220

SDM220 is connected to the Arduino ESP8266 microcontroller, and the data received by the Arduino will be sent to the server via the internet using MQTT. **Figure 2** shows the circuit diagram for the Arduino ESP8266 and SDM220, connected through TTL RS485, which is used to establish serial communication between the Arduino and the sensor. Once the data sent

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by the Arduino is received by the server, it will be processed to match input data with a set of existing data for identification purposes. This process aims to recognize that the data is from a device that is currently powered on or in an "on" status. After the data is successfully identified, the processed data will be sent to the consumer or user.

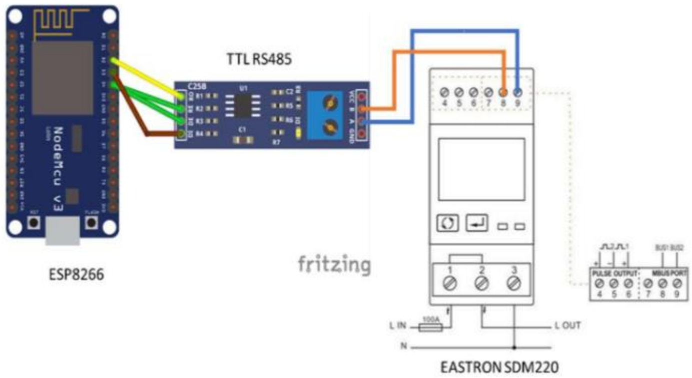

Figure 2. Schematic of the Arduino ESP8266 and Eastron SDM 220 circuit

2. METHOD

This research uses a quantitative method. The classification accuracy of each electronic device's consumption is determined using the NILM method. The main function of NILM is to obtain specific information from an electronic device non-intrusively (Carrie A. 2013). Information is collected on the main input and then divided to generate results in the form of active time and power used by a device to describe the obtained information. In this research, the aim is to obtain information on the electricity consumption and power on/offload used by a refrigerator under single steady-stage conditions. The research stages are derived from the phases used in the NILM method (L Ma 2019), which are as follows:

A. Data acquisitions dan preprocesing

Data acquisition is used to obtain total load measurements from a load meter device (L Ma 2019). There are various electric metering devices available in the market, and in this research, the Eastron SDM220 is used.

B. Features extraction

The load meter device detects the status transition changes (ON/OFF) of the measured device by analyzing the changes in power levels. These events can be defined in terms of temporary and steady-state changes.

C. Training

In the NILM method, the training or pre-learning phase is a prerequisite that must be carried out. In the disaggregation algorithm, labeled data is required for the data to be learned based on the specific models of the electronic devices to be recognized.

D. Data disaggregation

In the supervised disaggregation algorithm for NILM, it can be categorized into recognition methods or optimization methods. It involves sorting data for disaggregation purposes or classifying electrical equipment as either on or off.

3. RESULT AND DISCUSSION

A. Data acquisitions dan preprocesing

Generally, the sampling rate of a power meter can be classified as low-frequency meters and high-frequency meters, which are used to differentiate the data features that will be extracted from the acquired data (D. Egarter 2016). In power measurement devices, typically three values are measured: voltage, current, and power factor. Low-frequency meters are used to capture the steady-state electricity consumption. High-frequency meters aim to capture temporary conditions and collect highly detailed and specific data to obtain more specific load data (Darby S 2006). The data is obtained from the power meter using the ESP8266 microcontroller, which communicates with the TTL RS485 module. The data obtained by the microcontroller is sent to the server over the internet through an MQTT gateway. An example of the data can be seen in Table 1, which represents data from a collection of loads for various electronic devices measured by the power meter at each time, where active power is measured in kilowatts (kW), reactive power is measured in Volts-Amps-Reactive, and voltage is measured in volts (V).

Table 1. Example data from a collection of data from a power meter

Time Active	Power (kW)	Reactive Energy (VAR)	Voltage
1/1/2019 0:00	489	654	162
1/1/2019 0:00	997	158	417
1/1/2019 0:00	712	262	805
1/1/2019 0:00	382	896	214
1/1/2019 0:00	525	792	116
1/1/2019 0:00	391	423	773
1/1/2019 0:00	846	531	80

B. Features extraction

Several methods to detect changes in power consumption levels can be seen in (D. Egarter 2016); (Ehrhardt-Martinez 2010); (GW Hart 1992). And to differentiate transient events from steady-state and transient events based on feature extraction from the used methods. After data acquisition, the next process is to process raw data (voltage and waveform) to calculate power (Maucelli et al 1996). After processing the raw data, the next step is to detect events/transitions from the power consumption status of the measured electronic device (for example, from On to Off status). The module detects the ON/OFF transition of the electronic device based on the rate of power change used. An example of data obtained for the load obtained from one identified device (refrigerator).

Table 2. Example of active power data of a refrigerator

Time Power	Active (kW)
2019-04-18 09:22:13-04:00	6.000000
2019-04-18 09:22:16-04:00	6.000000
2019-04-18 09:22:20-04:00	6.000000
2019-04-18 09:22:23-04:00	6.100000
2019-04-18 09:22:26-04:00	6.612903

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C. Training

The main elements of NILM can be divided into four parts: Hardware, which utilizes an electric meter with an RS485 TTL communication module connected to a microcontroller (Youssef, T. 2017). The microcontroller obtains the active power sampling rate at 1Hz from the meter and stores the data in its memory. Event Detection uses three types of monitored data to detect any changes in real active power. The software event detection can identify power changes or other electrical parameter changes. A transition of active power from high to low can be determined when an electronic device is turned on, and a transition from low to high can be observed when the electronic device is turned off. Mathematically, this can be expressed as the following equation (1):

$\Delta P = Pt2 - Pt1$ (1)

ΔP : Change in active power

Pt1 : Steady-state active power at time t1

Pt2 : Steady-state active power at time t2

To perform training using the REDD dataset, an example of data for a refrigerator can be seen in Table 3 and Table 4

Table 3. Example of active power data of a refrigerator

Time Power	Active
2019-04-18 09:22:13-04:00	6.0
2019-04-18 09:22:16-04:00	6.0
2019-04-18 09:22:20-04:00	6.0
2019-04-18 09:22:23-04:00	6.0
2019-04-18 09:22:26-04:00	6.0

Table 4. Example of power apparent of a refrigerator

Time Power	Apparent
2019-04-18 09:22:13-04:00	342.820007
2019-04-18 09:22:16-04:00	344.559998
2019-04-18 09:22:20-04:00	345.140015
2019-04-18 09:22:23-04:00	341.679993
2019-04-18 09:22:26-04:00	341.029999

D. Data disaggregation

In this study, the data used involves a refrigerator with a capacity of 5.8 cu.ft. Optimization method: In this research, the comparison of feature extraction results of unknown electronic devices present in the database is performed, aiming to find the closest match with the data to be identified.

minP(t) - (2)

On the equation (2),

P(t) : Total change value of active power obtained from the meter at time t.

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Ai : Status of load i (0: on and 1: off).

Pi : Active power of load i.

N : Number of loads in the system.

e(t) : Tolerance error.

The recognition method is the most commonly used matching method for disaggregation. In the database of electronic devices, many unique features are used to determine the structure and parameters of the recognition algorithm. To identify loads, the steady-state transition of active power can be depicted in the form of P-Q. In mathematical terms, it can be expressed as the following equation (3)

$(\Delta P - Pk) + (\Delta Q - Qk) = e$ if $\Delta P > 0$ (Device On),

$(\Delta P - Pk) + (\Delta Q - Qk) = e$ if $\Delta P < 0$ (Device On) (3)

On the equation (3) where:

ΔP : Change in active power,
ΔQ : Change in reactive power,
Pk : Data collection of active power from k,
Qk : Data collection of reactive power from k,
e : Tolerance error.

In **Figure 4**, the prediction results between the dataset and the ground truth data/input from the power meter are shown. The results indicate a graph with similar patterns in each high and low phase. Thus, it is possible to identify the incoming input data with values that are almost identical to the dataset. The information presented is the prediction of power consumption from electronic devices through the disaggregation (Egarter, D et al 2015) module and the data is sent to the server via the internet using the MQTT gateway. The system design can be seen in **Figure 3**.

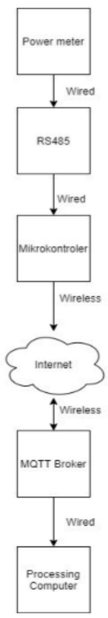

Figure 3. Design of the IoT electricity management system

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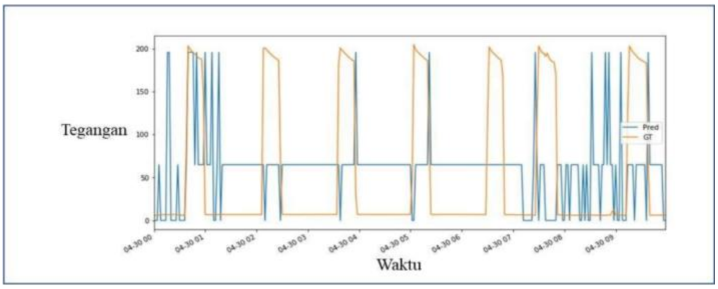

Figure 4. Visualization of prediction results between datasets and input data

4. CONCLUSION

The result of this research is that the system can identify the electrical energy used by electronic devices, specifically the refrigerator, from the total energy used at a specific time (Iqbal J. et al). The information is continuously obtained from the refrigerator's consumption. If this data is further utilized, there is a possibility of energy savings, for example, by creating a planning system for defrosting the refrigerator. If this method is implemented for lights and other electronic devices, it will enable more efficient electricity usage by utilizing data to schedule the usage of electronic devices only when necessary.

5. AUTHOR'S NOTE

The authors declare that there are no conflicts of interest associated with the publication of this article. The authors also ensure that this paper is free from plagiarism.

6. REFERENCES

Zoha, A., Gluhak, A., Imran, M. A., and Rajasegarar, S. (2012). Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey. Sensors, 12(12), 16838-16866.Berges, M.; Goldman, E.; Matthews, H.S.; Soibelman, L.; and Anderson, K. (2011) User-centered non-intrusive electricity load monitoring for residential buildings. j. comput. *Civil Eng, 25, 471–480.*

Carrie Armel, K.; Gupta, A.; Shrimali, G.; Albert, A. (2013). Is disaggregation the holy grail of energy efficiency? the case of electricity. *Energ. Policy 52, 213–234.*

Egarter, D., and Elmenreich, W. (2015, March). Autonomous load disaggregation approach based on active power measurements. In 2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops) (pp. 293-298). IEEE.

Ehrhardt-Martinez, K.; Donnelly, K.A.; and Laitner (2010)., J.A.Advanced metering initiatives and residential feedback programs: a meta-review for household electricity-saving opportunities; *Technical Report E105 for American Council for an Energy-Efficient Economy (ACEE): Washington, DC, USA.*

Hart, G. W. (1992). Nonintrusive appliance load monitoring. Proceedings of the IEEE, 80(12), 1870-1891.Guizien Martin (2021). Desagregación del consumo eléctrico e identificación de dispositivos en hogares en el contexto de monitorización no intrusiva (NILM) utilizando Deep Learning. *repositorio.comillas.edu*

DOI: https://doi.org/10.17509/seict.v2i1.34572
p- ISSN 2774-1656 e- ISSN 2774-1699

J Ranjan. Object user recognition in multi-person homes (2015). *UbiComp/ISWC'15 Adjunct: Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers*

J Raya and J CerdaA (2014). Low frequency power-based event alignment method for trained NILM systems. *IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC) DOI: 10.1109/ROPEC34556.2014*

L Ma, P Schegner (2019). State duration-based event detection for domestic power disaggregation. *IEEE Milan PowerTech*

Ghosh, S., Chatterjee, A., and Chatterjee, D. (2021). An improved load feature extraction technique for smart Homes using fuzzy-based NILM. *IEEE Transactions on Instrumentation and Measurement, 70, 1-9.*

Jürgel, M., and Mass, J. (2019). Non-Intrusive Load Monitoring in the OpenHAB smart home framework. A bachelor’s thesis of University of Tartu.Youssef, T. (2017). *Co-design of Security Aware Power System Distribution Architecture as Cyber Physical System.*

Iqbal, J., Khan, M., Talha, M., Farman, H., Jan, B., Muhammad, A., and Khattak, H. A. (2018). A generic internet of things architecture for controlling electrical energy consumption in smart homes. *Sustainable cities and society, 43, 443-450. 1-39*

Del Mar, P. (2013). Motor load detection for voltage transient based non-intrusive load monitoring. *Doctoral dissertation, University of Delaware.*

Khanchuea, K., and Siripokarpirom, R. (2019, March). A multi-protocol IoT gateway and WiFi/BLE sensor nodes for smart home and building automation: Design and implementation. *In 2019 10th International Conference of Information and Communication Technology for Embedded Systems (IC-ICTES) (pp. 1-6). IEEE.*

Mauceli, E., Geng, Z. K., Hamilton, W. O., Johnson, W. W., Merkowitz, S., Morse, A., ... and Solomonson, N. (1996). The Allegro gravitational wave detector: Data acquisition and analysis. *Physical Review D, 54(2), 1264.*

DOI: https://doi.org/10.17509/seict.v2i1.34572
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