Field Trial toward Low-carbon Society in Indonesia

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Developing economies are rapidly pursuing urbanization and industrialization, and the consumption of fossil-fuel-based energy is increasing. Thus, the greenhouse gas emissions of these countries are also expected to increase. Fujitsu is collaborating with the National Institute for Environmental Studies of Japan, Bogor Agricultural University, and the Bandung Institute of Technology of Indonesia, working toward the application of continuous evaluation and field trial of energy-saving measures to model urban/industrial areas in Indonesia. This initiative is unique in that it leverages the technologies and expertise of Fuji Electric Co., Ltd., a company that has a high reputation in Indonesia for data measurement, as well as a local maintenance team. This initiative is also noteworthy for the use of big data analysis and highly reliable energy-saving assessment technology provided by Fujitsu Semiconductor Ltd. These strengths make it possible to select the energy-saving measures best suited for the culture and customs of Indonesia, and to quantify the effectiveness of evaluations using information and communications technology (ICT). We have high hopes that this initiative will lead to the application of large-scale energy-saving measures to urban areas and/or industrial parks as an inspection and field trial. It could thus make significant contributions to achieving a low-carbon society in developing countries. This paper discusses the role of ICT in this field trial.

1. Introduction

The Republic of Indonesia, which is an emerging Asian country, has the world's fourth largest population of 252 million as of 2014, and has been steadily achieving a high level of economic growth of around 5% per annum in recent years.[1] However, owing to the increase in domestic energy consumption accompanying economic growth, domestic energy demand is expected to exceed supply in 2020, and Indonesia faces the urgent task of changing over to an industrial and social structure with high economic efficiency and environmental efficiency.[2] In transforming the energy systems of industry and society, energy-saving measures and the introduction of renewable energy will be required, necessitating the quantitative and continuous monitoring of actual energy consumption conditions to obtain the data required for analysis, assessment, forecasting, and decision-making. To this end, the Government of Indonesia decided to measure and grasp energy consumption using state-of-the-art digital technology in collaboration with universities, research organizations, related ministries, and municipalities in the country. Fujitsu and the National Institute for Environmental Studies of Japan are participating in a research project to build a system to measure energy consumption (hereafter, an energy monitoring system) in Bogor city, Indonesia, in collaboration with such bodies as Bogor Agricultural University and the Bogor Municipal Government, and the system has been in full operation since March 2015.

This paper describes the development of an energy monitoring system using Fujitsu's digital technology, for use especially in developing countries. The establishing of following items was required in the research project.

1) The technologies of the energy monitoring system and network consumption. (Technical elements: Realization and implementation of Internet of Things [IoT] and energy consumption visualization function)
2) A process for the utilization of the measured data by Indonesian and Japanese affiliated entities

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on a collaborative basis. (Technical elements: Establishment of big data analysis method and introduction of energy-saving diagnosis)

3) A method that can be applied deployment over a wide area of the above process flow based on implementation and verification in Bogor. (Technical element: Establishment of an estimation method that extrapolates measurement results and standardizes them)

2. Realization of IoT and energy consumption visualization function

Figure 1 (a) shows the concept of the energy monitoring system, and **Figure 1 (b)** shows the work flow for analyzing and using the measured data.

The measurement targets of energy consumption are electricity and fossil fuel such as gas and heavy oil. In view of the fact that Indonesia has a tropical climate with an average temperature of 26°C or higher throughout the year, air conditioning, OA equipment, and home appliances are assumed to account for the major part of energy consumption, and energy consumption measurement is given priority for such equipment over other types of equipment.

Indonesia has a variety of electric facilities, and thus it is necessary to support two types of power distribution boards for measurement, namely the single-phase 2-wire 220 V type for home use, and the three-phase 4-wire 380 V type for industrial use. A measurement system designed using products and solutions[3] from Fuji Electric Co., Ltd. The company has a track record of data measurement at Indonesian plants as well as a maintenance system. The local operation of the measurement system is being implemented with the support of the company. The measured data is aggregated over Fujitsu's cloud server in Japan via a LAN-to-LAN VPN (virtual private network) over the Internet. Researchers, local governments, citizens, and others involved in this project can check the energy consumption situation in real time by connecting to this cloud server through a smartphone or tablet.

3. Establishment of big data analysis method

Analyses of the daily measurement data are carried out using statistical and engineering methods. **Figure 2** shows the analysis flow.

3.1 Statistical methods

The statistical methods consist in the use of two methods of analysis, "time series analysis" for grasping periodicity and seasonality in energy consumption data, and "regression analysis" for estimating the factors of change in energy consumption and creating models based on these factors.

1) Time series analysis

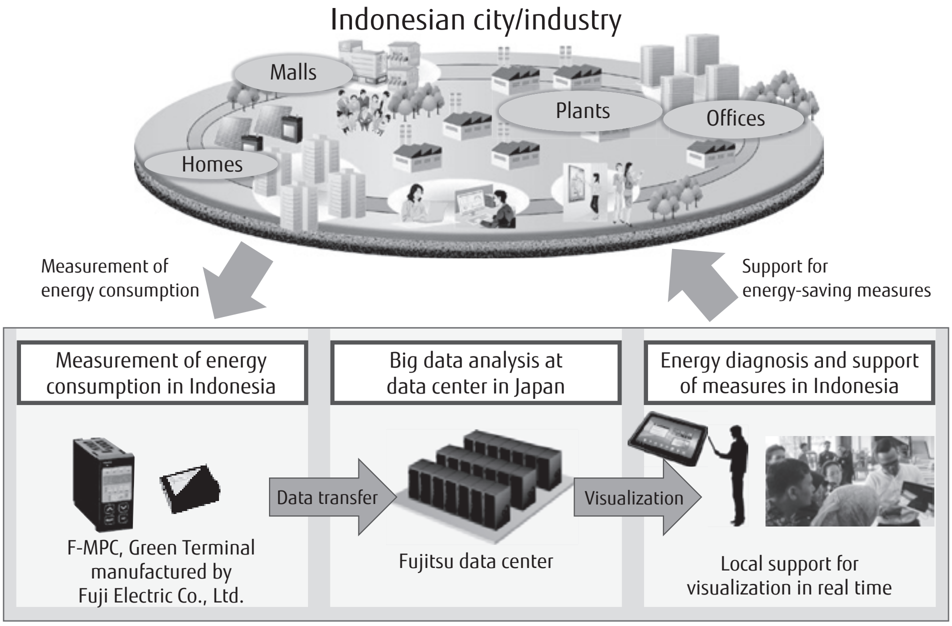
A time series whose statistical properties (average, variance) are independent of time is called a stationary time series, and a time series whose statistical properties are dependent on time is called a non-stationary times series. The autoregressive (AR) model and moving average (MA) model can be applied to stationary time series, and the autoregressive moving average (ARMA) model, which combines the two above models, is described with the following equation.[4)]

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \psi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

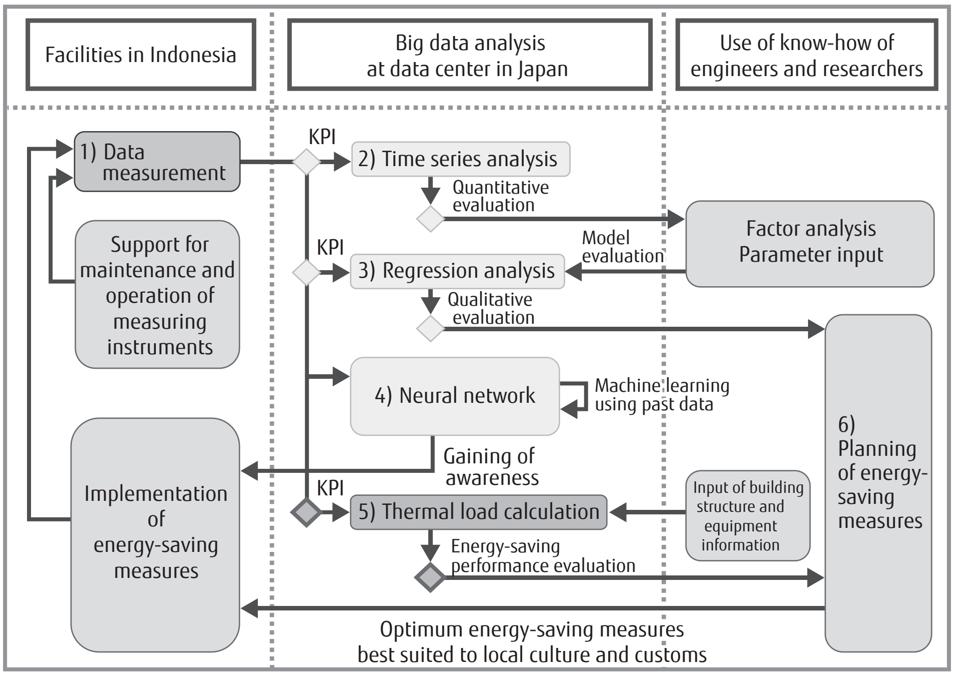
This model combines an AR model of order p and an MA model of order q, where X is power consumption, ψ and θ are parameters, and ε_t is a residual error term that constitutes a random number term that follows a normal distribution with zero mean.

The autoregressive integrated moving average (ARIMA) model, which approximates a stationary time series by removing differences with previous values because the previous values affect the value at a given point in time, is applied to the analysis of non-stationary time series. In this paper, we decided to carry out an analysis using a seasonal autoregressive integrated moving average (SARIMA) model that adds a seasonal variation component to ARIMA.

Figure 3 shows the results of SARIMA analysis of the power consumption measurement results for offices in Bogor, Indonesia. From the top, the results are classified as measurement data, seasonality, periodicity, and residual error, as obtained for power consumption in 1-hour units from January 1, 2015 to June 30, 2016. It should be noted that measurement started on January 19, 2015. With regard to seasonality, Indonesia has a tropical climate with an average temperature of 26°C or higher throughout the year, so energy consumption tends to be constant throughout the year at around 1.4 kWh. The decrease in power



(a) Energy monitoring system concept



KPI: Key performance indicator

(b) Work flow

Figure 1
Continuous evaluation and field trial of the effect of energy-saving measures.

consumption in July 2015 is due to the influence of a long vacation peculiar to the Muslim faith called Lebaran, which is celebrated after Ramadan (fasting month). In terms of periodicity, a constant cycle with fluctuation range of about 3.0 kWh tends to be seen. This result indicates that model evaluation using only seasonality and periodicity is not possible owing to the large influence of the residual error term because the

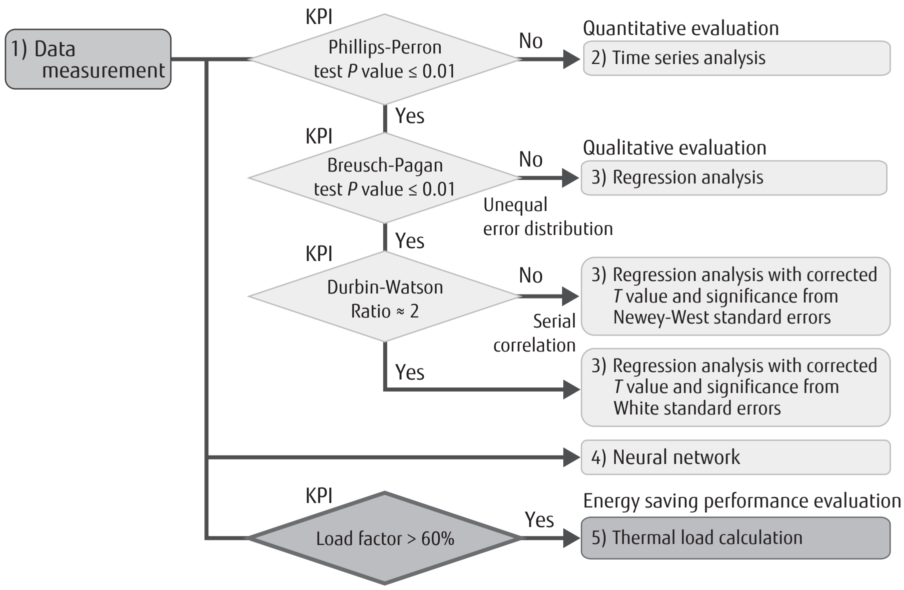


Figure 2
Analysis flow.

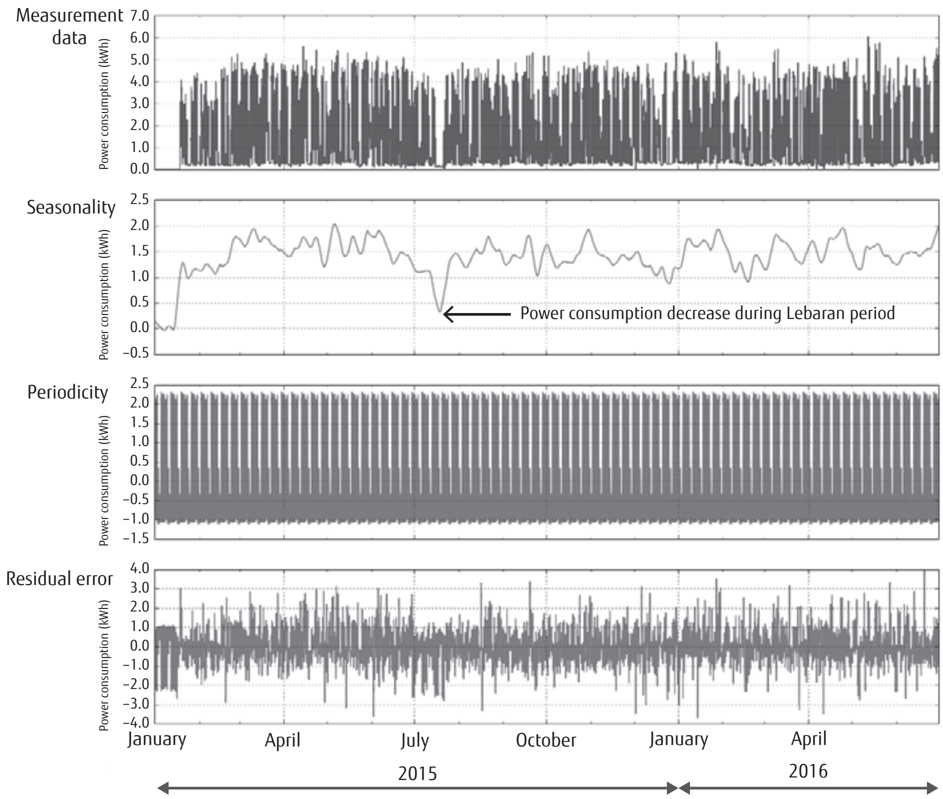


Figure 3
Evaluation with SARIMA.

P value is 0.01 in the Phillips-Perron test. The factors of change of seasonality, periodicity, and residual error are described in the next section.

2) Regression analysis

The factors of the seasonality and periodicity of energy consumption described in the previous section were analyzed using regression analysis. In this section, we describe the results of applying a multiple regression analysis model, which is a linear regression analysis that describes multiple factors of change.

The multiple regression analysis model, which is used for listing the factors of change from the on-site situation and grasping the influence of each factor, can be described by the following equation.[5)]

$$y = \beta_0 + \sum_{i=1}^{m} \beta_i x_i + \varepsilon$$

This is a multiple regression model of order m, where y is the power consumption, x is the activity time, β is a parameter, and ε is a residual error term. In this project, of the measurement points of the data used in time series analysis, for the quantitative data, we selected the temperature as a factor of change, and for the qualitative data, we selected the activity time of facilities (9:00 to 18:00 on business days) as a factor of change, using the Akaike's Information Criteria (AIC).[4), 5)] For the temperature data, we used the 1-hour interval values for Bogor provided by the Open Weather Map.

Table 1 shows the analysis results for the degree of contribution of each multiple regression analysis factor according to the Newey-West standard errors. **Figure 4** shows the results predicted using the model based on the above for the one-month period from May 17, 2016 to June 16, 2016. The vertical axis of the graph represents the electric power consumption (kWh). When fitting constants by the multiple regression analysis model with the range of temperatures from 0°C to 50°C as normal values, power consumption is described as follows.

Power consumption (kWh)
= 2.57 × activity coefficient (0 or 1)
+ 0.09 × temperature (°C) − 1.88

From the results in Table 1, the facts that the absolute value of value T is 2 or greater and value P is 0.01 or lower indicate that periodicity of power consumption depends on human activity and seasonality depends on temperature as factors of change. However, analysis applying the flow shown in Figure 2, using the Breusch-Pagan test (P value: 2.2×10^{-16}) and Durbin-Watson test (DW ratio: 0.93), showed unequal error distribution and serial correlation. The fact that coefficient of determination R^2 is 0.72, thus smaller than 1, shows that the variables of human activity (periodicity) and temperature (seasonality) on their own are insufficient for model evaluation. In the future, more accurate model

Table 1
Multiple regression analysis model (coefficient of determination R^2 = 0.72).

Factor of change	β value	Standard error	T value	P value
Intercept	−1.88	0.51	−3.67	2.6×10^{-4}
Activity time	2.57	0.16	16.33	$< 2.2 \times 10^{-16}$
Temperature	0.09	0.02	4.69	3.3×10^{-6}

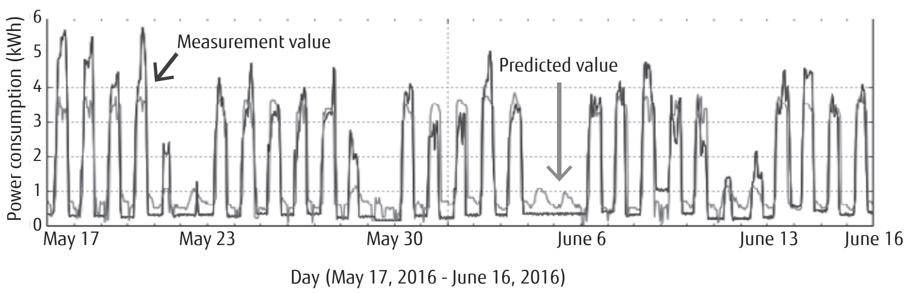


Figure 4
Predictive model evaluation.

evaluation is expected through measurement of qualitative data (residual error) of social elements such as the number of people staying in the office.

3) Machine learning technology

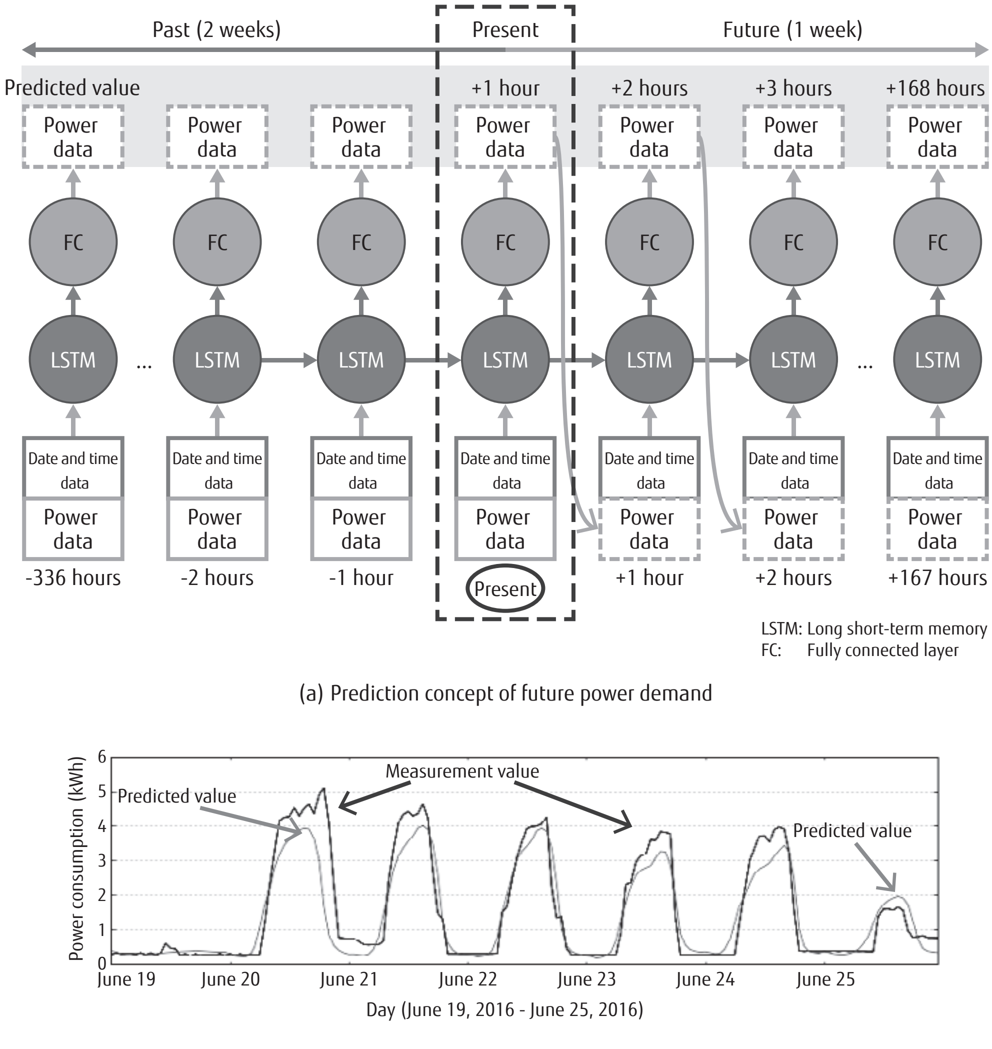
Machine learning is a method to predict the future from past time series data. In this section, we describe the results of applying machine learning using a recursive neural network. A general neural network is described by the following equation.[6]

$$z = f\left(\sum_{i=1} \omega_i x_i(t) - h\right),\ f(v) = \frac{1}{1+e^{-v}}$$

where z is the output of the neural network, x is the input, ω is a parameter, and $f(v)$ is the activation function that mimics the behavior of neurons. In this project, long short-term memory (LSTM)[7] was adopted for the storage of data input in the past (**Figure 5**).

Figure 5 (a) shows the concept of a recursive neural network using the LSTM created in this project. This is a model that predicts power consumption for the following week based on the power consumption and date and time data of the past two weeks, assuming that the date and time data (day of the week, human activity, etc.) are known.

Learning was conducted using the power consumption between the data measurement points used in the time series analysis: January 19, 2015 and May 31, 2016. Figure 5 (b) shows an example in which



(a) Prediction concept of future power demand

(b) Predictive evaluation of future power demand

Figure 5
Machine learning using a recursive neural network.

data for the two weeks from June 5 to June 18, 2016 are input and the week from June 19 is predicted. The vertical axis of the graph represents the power consumption per hour. Looking at the prediction results, we see that although regular changes are captured between measured values and predicted values, there are differences in demand peaks. These are the differences between past behavioral patterns referenced for prediction and actual behavior. They show how awareness can be achieved among users by showing them in real time the changes due to forgetting to turn lights off and to equipment abnormality, and the effects of the implementation of energy-saving measures.

3.2 Engineering methods

As the engineering method, quantitative analysis of the heat balance of buildings was carried out based on the measured power data. The heat balance during cooling can be described by the following equation.[8)]

$$Q_{AC} = Q_S + Q_L = Q_{IN} + Q_{EX}$$

$$E_{AC} = \frac{Q_{AC}}{COP}$$

Q_{AC}: Cooling load (W)
Q_S: Amount of heat required to lower indoor temperature (sensible heat) (W)
Q_L: Amount of heat required to lower indoor humidity (latent heat) (W)
Q_{IN}: Amount of heat from indoors (W)
Q_{EX}: Amount of heat from outdoors (W)
E_{AC}: Power consumption for cooling by air-conditioning (W)
COP: Air-conditioning performance value (The higher the value, the higher the efficiency)

Figure 6 shows these relationships as a concept.

In this project, first, under the premise that when the air conditioner load factor is high, it is close to the *COP* catalogs value[9)], cooling load Q_{AC} was obtained from the power consumption of the air conditioner and the *COP* catalog value. Then, from the power consumption of the household electrical appliances in the room and the human body load, amount of heat from indoors Q_{IN} was obtained, and the amount of heat from outdoors Q_{EX} was evaluated. For the office where the data shown in Figure 3 was measured, thermal load calculation was performed for 1 hour from 14:00 to 15:00, and **Table 2** compares the thermal load calculation results and power consumption ratio. The heat amount was taken to be the value divided by the total floor area, the air temperature 31.6°C, and the humidity 52%. Further, the load factor of the air conditioning indicates the ratio between the power consumption of

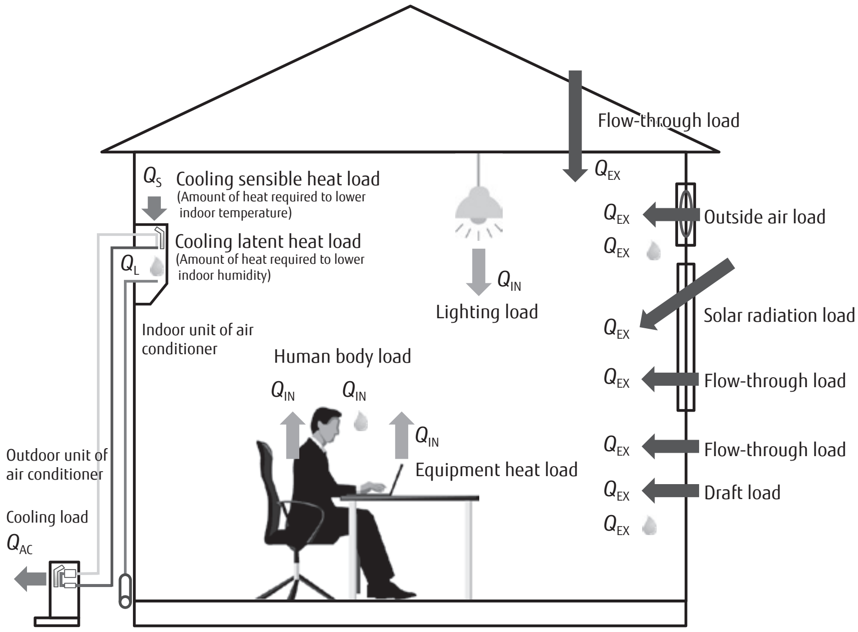


Figure 6
Conceptual diagram of cooling load.

Table 2
Thermal load calculation (97% air conditioning load factor) and power consumption ratio.

Load	Heating value (W/m²)	Ratio (%)
Cooling load Q_{AC}	55	
Amount of heat from indoors Q_{IN}	8	15
Amount of heat from outdoors Q_{EX}	47	85

Equipment	Ratio (%)
Air conditioner	87
Electric outlet	10
Lighting	3

the catalog value of the air conditioner and the actual power consumption.

From the results, the load factor of the air conditioning being close to 100%, it is understood that inverter control is not effective because the air conditioner always operates at the maximum cooling load. Moreover, the ratio of power consumption for air conditioning to total power consumption is high, at 87%. Considering that the amount of heat from outdoors is as high as 85% or more, reduction in power consumption is expected to be achievable by switching to a high *COP* air conditioner and increasing the thermal insulation and air tightness of the building itself. The results show that the energy-saving performance (heat insulation, air tightness) of buildings can be evaluated along with the energy-saving performance (*COP*) of home appliances.

4. Introduction of energy-saving diagnosis

The energy-saving diagnosis carried out at an office in addition to data measurement is described below. The thermal environment of the office as surveyed by thermography is shown in **Figure 7**. Shown on the left side of Figure 7 are photos of the office, and on the right side are photos taken by a thermographic camera. The diagnosis was carried out by Fujitsu Semiconductor Ltd., which has plant facilities know-how. Although the window of the office can be opened and closed, it can be seen that there is a gap even when it is closed as shown in the above figure, and outside air heat penetrates into the room. The figure below shows how external heat penetrates from the ceiling. In this office, the doors of unused rooms are left open, letting warm air flow in from non-air conditioned spaces and causing unnecessary air conditioning load, resulting in insufficient cooling capacity of the air conditioning equipment.

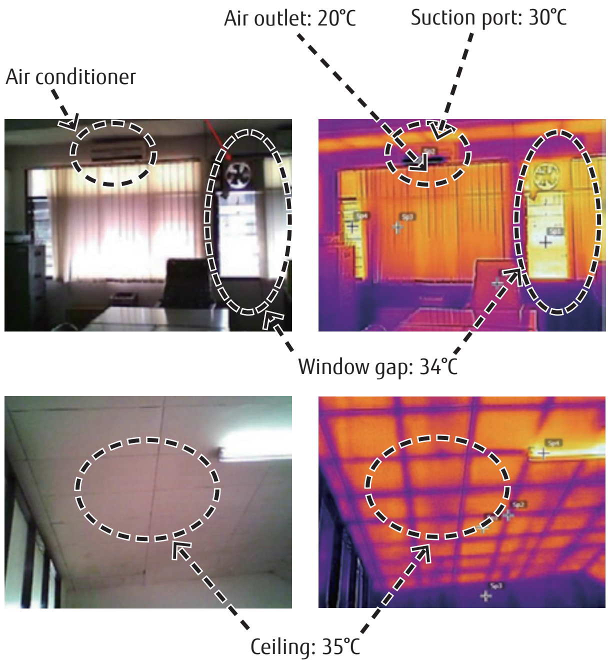


Figure 7
State of energy loss at office.

Reducing power consumption requires the installation of heat insulation on the ceiling and roof, light shielding curtains and blinds, and double windows to prevent heat from entering from the outside, and taking measures to ensure that the doors of unused rooms are closed to prevent cooling of spaces that are not needed. Implementing these measures and thereby being able to change the set temperature of the air conditioners from 25°C to 27°C is expected to reduce power consumption by about 20%.[10] On top of that, further reduction of power consumption can be expected by replacing air conditioners with high-performance ones.

By implementing energy-saving measures appropriate to the climate of Indonesia described in this paper and continuously implementing the work flow shown in Figure 1 (b), it is possible to quantitatively grasp the actual state of energy consumption, and to demonstrate and verify continuously the energy-saving effect that is achieved.

5. Establishment of estimation method for extrapolation to a whole area

The method introduced so far is based on measurement data of a specific facility (point), but in order to disseminate energy-saving measures across a whole country or region, it is necessary to also expand its application to a wider area such as a city or an industrial park. In this paper, we describe an initiative that utilizes open data to estimate power consumption across a wider area. **Figure 8** shows the positioning of power consumption in Bogor. It shows the features of electric power demand in Bogor, as obtained from the compilation of information published by the Statistics Bureau[11] and information from power companies.[12]

Figure 8 (a) shows a comparison of average annual power consumption per capita in the country of Indonesia, Java island, and the city of Bogor. In 2014, Bogor's population was 1.01 million[11], and average per capita power consumption was nearly the same value as that for Indonesia as a whole. As can be seen from the density distribution of the distribution transformers per city block in Figure 8 (b), the density is higher in the central city block areas. Looking at the relationship between population density and power density for each city block of Bogor [Figure 8 (c)], one can see that power density is more a function of facility location than population density.

This paper has presented data and analysis results, taking an office as an example. It has demonstrated the possibility of applying this approach to energy-saving measures across a wider area by selecting and analyzing model facilities from commercial facilities such as eating and drinking, industrial facilities such as plants, and entertainment facilities such as hotels and shopping malls, and applying the results to block districts with similar characteristics and carrying out continuous estimation.

6. Future initiatives

Going forward, using satellite images and deep learning technology,[13] we plan to classify woods, rivers, roads, cars, residences, commercial facilities, industrial facilities, offices, and so on, based on urban images, and obtain data on the number of facilities and their surface area to further improve the accuracy of estimation of energy demand per city block area. We will also expand application of the data collection system and analytical method described in this paper horizontally to a larger scale, and based on the environmental parameters of temperature, humidity, and wind speed, and the location conditions for each city block, select the optimum energy-saving measures for each city and

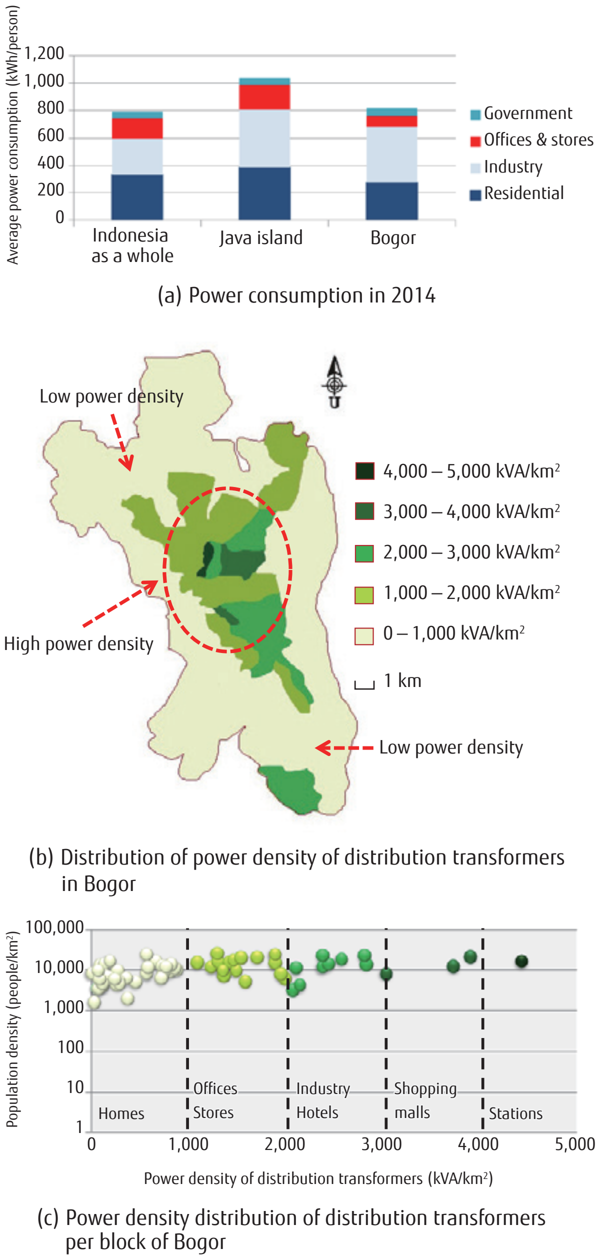


Figure 8
Characteristics of electricity consumption of Bogor.

consider the best path for social implementation.

7. Conclusion

This paper introduced a work flow that combines data analysis and other techniques for the diagnosis and implementation of energy-saving measures, using energy consumption measurement data as the starting point. This content is based on a case study conducted in collaboration with Fujitsu as part of a research project carried out by the Center for Social and Environmental Systems Research of the National Institute for Environmental Studies of Japan,[note] for the Research and Information Office, Policy Planning Division, Global Environment Bureau, Ministry of the Environment of Japan.

In the future, we plan to contribute to the realization of a low-carbon society in developing countries by expanding the scope of activities of this field trial, including the proposed estimation method, for extrapolation to a wide area.

In closing, we would like to express our sincere gratitude to all the people at the Centre for Climate Risk and Opportunity Management in Southeast Asia and the Pacific of Bogor Agricultural University and the Overseas Energy Management Department, Sales Division, Fuji Electric Co., Ltd. for their cooperation in introducing this system.

note) Technology advancement project commission in Indonesia in relation to MRV, etc., for FY2014, 2015, 2016 Joint Credit Mechanism (JCM) promotion.

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