J. Eng. Technol. Sci., Vol. 53, No. 3, 2021, 210313

Data Driven Building Electricity Consumption Model Using Support Vector Regression

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Highlights:

- Electricity consumption prediction using external variables as features.
- Data driven model of electricity consumption using machine learning.
- Building electricity consumption patterns.
- IoT-based electricity information system.

Abstract. Every building has certain electricity consumption patterns that depend on its usage. Building electricity budget planning requires a consumption forecast to determine the baseline electricity load and to support energy management decisions. In this study, an algorithm to model building electricity consumption was developed. The algorithm is based on the support vector regression (SVR) method. Data of electricity consumption from the past five years from a selected building object in ITB campus were used. The dataset unexpectedly exhibited a large number of anomalous points. Therefore, a tolerance limit of hourly average energy consumption was defined to obtain good quality training data. Various tolerance limits were investigated, that is 15% (Type 1), 30% (Type 2), and 0% (Type 0). The optimal model was selected based on the criteria of mean absolute percentage error (MAPE) < 20% and root mean square error (RMSE) < 10 kWh. Type 1 data was selected based on its performance compared to the other two. In a real implementation, the model yielded a MAPE value of 14.79% and an RMSE value of 7.48 kWh when predicting weekly electricity consumption. Therefore, the Type 1 data-based model could satisfactorily forecast building electricity consumption.

Keywords: *building electricity consumption prediction; consumption patterns; data driven modeling; historical database; support vector regression.*

Received July 2nd, 2020, 1st Revision August 13th, 2020, 2nd Revision September 18th, 2020, 3rd Revision October 15th, 2020, Accepted for publication 19 November 2020.
 ISSN: 2337-5779,
DOI: 10.5614/j.eng.technol.sci.2021.53.3.13

1 Introduction

The fourth industrial revolution will increase energy consumption, especially in the form of electricity that powers computers and production machinery. Electricity demand prediction is useful for short-term load allocation and long-term planning for the new generation of transmission infrastructures. An accurate prediction allows better decisions in terms of cost and energy efficiency [1]. In Indonesia, electricity consumption data is only used for increasing the awareness of energy usage in offices, public buildings, or universities. However, energy usage can give some other indications, such as the cost of utilities, CO_2 emission equivalent (when electricity is produced from fossil sources), building energy consumption index, and energy efficiency labeling. A further benefit of using electricity consumption data is it enables energy management systems that can improve the efficiency of buildings or conserve energy. According to the Indonesian energy policy, the government encourages to reduce energy consumption through efficient energy management systems. Building energy consumption accounts for 39% of total global energy consumption and 38% of total global CO_2 emissions [2]. Managing electricity used in buildings could contribute significantly to CO_2 emission reduction, which will ultimately have a positive impact on the environment.

On the production side, renewable energy is an effort to reduce mankind's carbon footprint on our planet. However, renewable energy has its problems, such as intermittent energy generation and high initial investment. Therefore, an accurate electricity consumption model may aid in achieving a successful renewable energy project.

According to Zhong, *et al.* in [2] and Wang & Srinivasan in [3], building energy consumption models can be classified into three types: physical models, data-driven models, and hybrid models. Among these, the data-driven models have become the most popular approach owing to their low time consumption and good performance, as data mining is revolutionizing many industries. Various methods of data-driven model development can be found in the literature. In [4], Ma, *et al.* utilized a support vector regression (SVR) method to forecast building energy consumption in southern China. Biswas, *et al.* [5] have proposed an artificial neural network (ANN) method to model energy consumption in residential buildings. A short-term electrical load forecasting using a support vector regression (SVR) model for office buildings is reported by Chen *et al.* in [6].

Chammas, *et al.* in [7] present a report on the development of building electricity consumption prediction models that are supported by advancements in smart home and smart city technologies. Wireless energy sensors installed in smart homes can give insight into the electricity consumption profile of a building, including making a contribution to the reduction of the electrical energy consumption that is needed for energy- and cost-efficiency. The method proposed in the paper is multi-layer perceptron (MLP). The MLP training data features the electricity consumption from appliances and lighting, room temperature and humidity, weather station visibility, temperature, humidity, wind speed, dew point temperature, and atmospheric pressure data. The research object was a two-story building in Lebanon. Day of the week (Monday to Sunday) and week status (weekday or weekend) were also included in the data set. This method was compared with other machine-learning algorithms such as support vector machine (SVM), gradient boosting machine (GBM), and random forest (RF). The mean absolute percentage error (MAPE) performance metric achieved by this method was 27.09%.

An investigation was carried by Fayaz, *et al.* [8] on 4 multi-story (33 floors) residential buildings to predict electricity consumption using a feed-forward back propagation artificial neural network. The buildings were located in Seoul, South Korea. This energy prediction method is aimed at energy-efficiency improvement on the production (supply) side as well as by using a building energy management system (energy conservation). The problem and challenge in this prediction model development were to get an accurate result based on weather data, geographical location, occupancy level of the residential household, time, etc., in addition to smart meter data. As the inputs of the neural network machine learning were kWh, outdoor air temperature (OAT), humidity, occupancy (to differentiate between busy and vacant conditions). Data collection was performed on each floor. The reported average of MAPE for this method and case was 11.96%.

The big trend of growing smart electricity meter usage in residential households in Canada is presented by Zhang, *et al.* in [9]. The installation of smart meters along with Internet of Things supports the collection of electricity consumption data along with weather data and time-of-usage (TOU) electricity prices. Furthermore, this collected data enables a data-driven based building electricity consumption prediction that can create a residential demand-response scenario. Support vector regression was used for 15 households and the performance metric of the electricity consumption prediction was expressed in MAPE for an hourly prediction model as well as an daily prediction model. The MAPE ranges for the hourly and daily individual household electricity consumption prediction models were 23.31% to 69.17% and 12.78% to 34.95%, respectively.

An accurate prediction of electricity demand can improve the energy performance of a building. This is a complex problem that is highly dependent on the specific building [10]. Variables or features to be included in the prediction model are usually chosen based on expert knowledge and not through formal procedures based on the features of the model. This can lead to a gap between the predictions and the actual values [11]. The feature selection process can be used to find key features in a way that has been formalized and is reproducible. It is important to design minimally adapted prediction algorithms that can be widely applied to different types of buildings and allow scalability [12]. While it is clear that many research papers use machine learning with different features as input for electricity demand, there are still gaps in the existing research that need to be addressed, especially about the scalability and simplicity of the prediction algorithms. The present study focused on using easily obtainable features, such as date and time, to be used as input for electricity consumption prediction.

This paper uses support vector regression (SVR) to model the electricity consumption of a building based on 5-year data collected in a historical database. The object of study was one of the university buildings (Labtek VI, Institut Teknologi Bandung, Bandung, Indonesia; latitude -6.890213; longitude 107.609961), which was already equipped with a measurement system to collect electricity consumption data. The SVR method has proven to have the ability to transform the high nonlinearity between input and output into linearity for improving the prediction accuracy of models and simultaneously ensuring their robustness and generalization ability [13-15]. SVR machine learning methods are utilized to extend the horizon of observed electricity consumption data to give predictive data trends or patterns. The rest of this paper is organized as follows. Section 2 highlights the steps that were undertaken to develop the electricity consumption model. Section 3 describes the experimental setup and tools used to obtain the electricity consumption data. Section 4 discusses the development of the electricity consumption model from raw data, which includes preprocessing, training, and validation phases. In the last section, the accuracy of the model for predicting future electricity consumption is discussed.

2 Methodology

The building energy consumption model was developed using the SVR method. The SVR modeling principle is to find a model (a function $f(\boldsymbol{x})$) that has deviations ε from the actual target value y_i for the training data $\boldsymbol{x}_i$. Consider a dataset $D = \{(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2), \ldots, (\boldsymbol{x}_k, y_k\}$, $\boldsymbol{x}_i \in R^n$, $y_i \in R$, then the SVR function can be written in Eq. (1) as follows [6]:

$$f(\boldsymbol{x}) = \langle \boldsymbol{w}, \boldsymbol{x} \rangle + b. \tag{1}$$

The optimal regression function is given by

$$min \frac{1}{2} \|\boldsymbol{w}\|^2 + C \sum_{i=1}^{k} (\xi_i^+ + \xi_i^-), \tag{2}$$

subject to

$$y_i - \langle \boldsymbol{w}, \boldsymbol{x} \rangle - b \leq \varepsilon + \xi_i^+,$$
$$\langle \boldsymbol{w}, \boldsymbol{x} \rangle + b - y_i \leq \varepsilon + \xi_i^-,$$
$$\xi_i^+, \xi_i^- \leq 0, \tag{3}$$

where the constant $C > 0$ determines the trade-off between the flatness of f and data deviations, and (ξ_i^+, ξ_i^-) are slack variables to cope with otherwise infeasible constraints on the optimization problem of Eq. (2) subject to Eq. (3). In some cases, a nonlinear regression function may be required to adequately model the data. In SVR, this can be achieved using a selected kernel function. A nonlinear mapping can be used to map the data into a high dimensional feature space where linear regression is performed. Different kernels, such as polynomials, sigmoid or Gaussian radial basis functions, can be chosen depending on the problem.

The first step of building an SVR model that can predict electricity consumption is to obtain electricity data from the database, which can be on a local or a cloud server. Afterward, the raw electricity data are going through the preprocessing phase before being used as training data. Preprocessing improves the training data quality by removing outliers while maintaining its consistency. The preprocessing can ultimately improve prediction accuracy. After the preprocessing phase comes the features-selection phase. This phase aims to investigate which features relate the most to electrical energy consumption. In this paper, the data set is divided by the number of days, i.e. Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday. A test was conducted to find the most relevant features for each data set.

Nine features that could be obtained from the existing energy consumption characteristics were: date, month, year, hour, days, weeks, holidays, office hours, and occupancy denoted as $[x_1, \dots, x_9]$. Each of these nine features were tested using a mutual information (MI) regression module, which belongs to the scikit module of Python support vector regression library. The next phase was to select the optimal kernel function. Based on the selected kernel function, the optimal values of the function parameters can be found either by trial/error [16] or by using the GridSearch module in the Python library [17].

The final step was selection of the prediction model. The model was selected based on the resulting accuracy by the criteria of mean absolute percentage error (MAPE), as expressed in Eq. (4), and root mean square error (RMSE), as expressed in Eq. (5). The validation was acquired by calculation of the corresponding RMSE value between the SVR estimate and its reference:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f(x) - y_i)^2} \tag{4}$$

where n is the amount of data used in this investigation, $f(x)$ is the output of SVR, and y_i denotes the corresponding target/reference value.

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{f(x) - y_i}{y_i} \right| \tag{5}$$

Furthermore, the MAPE and RMSE values of the three types of data were compared in order to see the effect of data preprocessing, which can help to decide the best training data. If the MAPE value <20% and the value of RMSE <10 kWh, then the prediction model is acceptable to be deployed [18]. If the error value is above the minimum standard, then the parameter search will be repeated to find a better kernel function. The steps of this approach are represented in Figure 1.

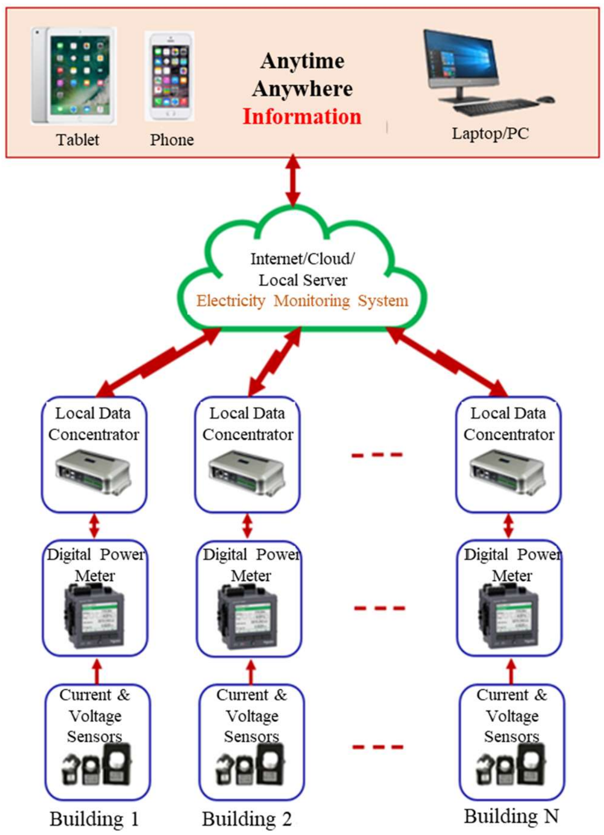

Figure 1 SiElis electricity information system.

3 Experiment Setup

The experiment began with data collection by the edge devices integrated into a system called SiElis (*Sistem Informasi Energi Listrik*, Electricity Information System). The measurement device sends real-time electricity consumption data to a historical database installed on an Internet of Things (IoT) cloud server. This system is an implementation of the advanced metering infrastructure concept as reported by Cecati, *et al.* in [19]. It has the same IoT concept as used by Haq, *et al.* [20] and Friansa, *et al.* [21], however, in this case it is used to measure the electricity consumption of the building. The applications as well as the communication of SiElis are implemented in an embedded system as local data concentrators, as depicted in Figure 2.

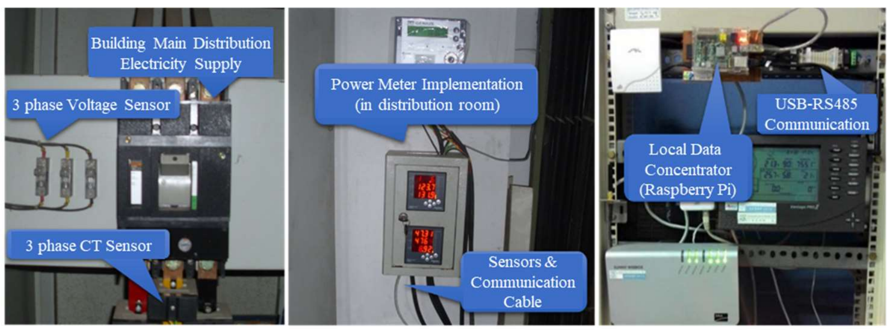

Figure 2 SiElis implementation in Labtek VI building: (a) CT & VT sensors; (b) power meter implementation; (c) local data concentrator.

Electric current measurement is done by current transformers (CT). The voltage and current measurements are done at the electricity main distribution panel of the building, as shown in Figure 3. A power meter is located on every measuring point to process the measurement data into several electrical parameters, such as the average of three-phase current, current of each phase, line to line voltage, line to neutral voltage, the voltage between phases, voltage of each phase, average power factor, power factor of each phase, and frequency. The measurement data from the power meter are sent to a Raspberry Pi 3 with the RS485 communication protocol. Then, the Raspberry Pi 3 sends the collected data to a cloud database via the internet. The online cloud database is in MySQL format. The Raspberry Pi 3 accesses the MySQL database using the TCP/IP protocol. All the mentioned routines are programmed to send the data every minute to the cloud database server. For downloading and preparation purposes the users can access the data through a PHPMyAdmin interface.

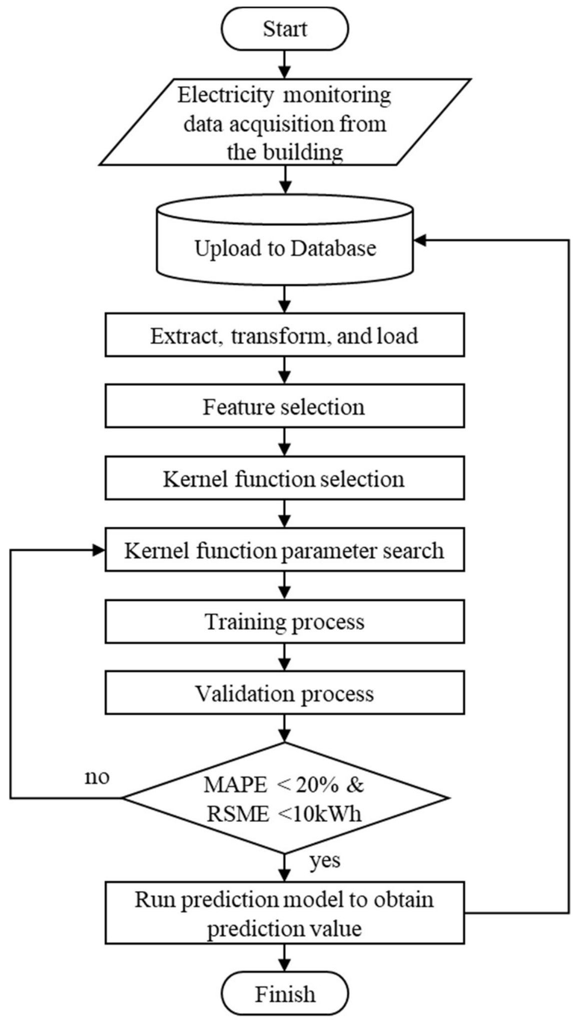

Figure 3 Workflow of the data driven building electricity consumption model.

4 Results and Discussion

From a thorough investigation of the data in the MySQL database, an unexpectedly large amount of anomalous data were found. Therefore, to avoid anomalies, top and bottom limits were set based on average daily electricity consumption from 2013 to 2018. Furthermore, data from holidays, which have relatively low electricity consumption compared to normal weekdays, were also separated. To handle the problem of holidays, they are calculated separately based on the average consumption of each hour on each day.

The data were grouped based on the name of day, e.g. Monday Training Data contained electrical data taken on Mondays. Various tolerance limits were defined for the data; the data sets were called Type 1, Type 2, and Type 0. The tolerance limit for Type 1 data was 15%, Type 2 data is 30%, and lastly Type 0 was without tolerance limit. The effect of data set type on the model's prediction accuracy was studied. Overall, there were 21 data sets for the development of the prediction model as shown in Figure 4.

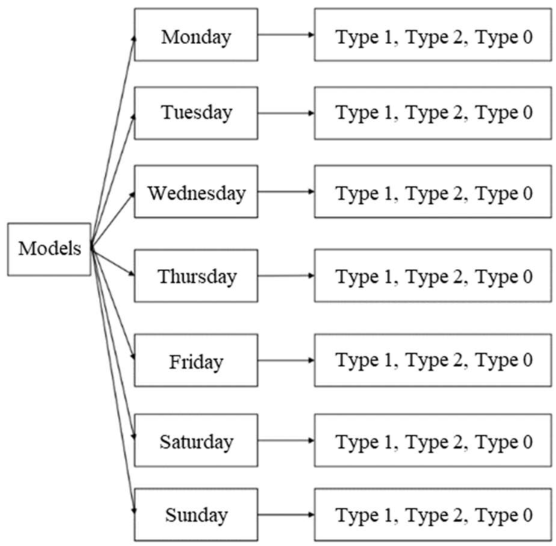

Figure 4 Tested data sets.

In machine learning, the training phase is a teaching stage to discover any specific patterns in the available training data. One kind of machine learning is support vector regression. This is a method based on a supervised learning system, which learns the relationship between features in the training stage. It aims to find specific patterns. The recognized patterns can be used to predict the target or output of the test data.

Each data set was processed with the mutual information (MI) method. A higher MI value corresponds to a closer correlation between features and targets. In this study, 0.1 was chosen as the lower limit for the MI value; this value determines the selected features. The results are shown in Table 1.

Table 1 Feature selection by mutual information.

Features	Variables	MI
Date	x1	0.00
Office hours	x2	0.08
Month	x3	0.12
Year	x4	0.05
Time	x5	1.00
Week	x6	0.60
Holiday	x7	0.08
Day	x8	0.85

Based on the literature, the radial basis function (RBF) kernel has been proven to perform better compared to other kernels [22]. Therefore, the RBF kernel was selected and used in the model development of the electricity consumption prediction. The RBF kernel is the most popular choice of kernel type used in SVR because of its localized and finite responses across the entire range of the real x *axis* [16].

$$\emptyset(x, x_i) = \exp(-\gamma||x - x_i||^2) \tag{6}$$

where σ is the parameter defining the behavior of the kernel.

Suitable values for the SVR parameters C, ε, can be found with Eq. (2) and for γ with Eq. (6). The parameters are determined by utilizing the GridSearch module. The two parameters C and γ found for the RBF kernel are listed in Tables 2 and 3 respectively.

In the validation phase, the test data output and the corresponding actual measurement data were compared. From the comparison, the deviation and the accuracy of the prediction were obtained.

Table 2 *C* parameter for each data set.

Model	Type 0	Type 1	Type 2
Monday	0.372759	7.196857	5.179475
Tuesday	3.727594	5.179475	1.930698
Wednesday	2.682696	5.179475	3.727594
Thursday	0.517947	1.389495	10.000000
Friday	10.000000	7.196857	10.000000
Saturday	0.138950	0.268270	0.138950
Sunday	0.138950	0.138950	0.268270

Table 3 γ Parameter for each data set.

Model	Type 0	Type 1	Type 2
Monday	0.517947	1.389495	1.930698
Tuesday	0.138950	1.389495	2.682696
Wednesday	1.389495	1.389495	1.389495
Thursday	0.719686	0.517947	1.389495
Friday	0.517947	1.389495	0.517947
Saturday	1.000000	1.389495	1.000000
Sunday	1.000000	1.000000	1.389495

Twenty percent of the data was used as test data in the validation stage. At this stage, the machine 'guesses' the output based on its learning experience from the data in the training process. Figure 5 is a prediction example using Type 0 dataset for electricity consumption on Mondays.

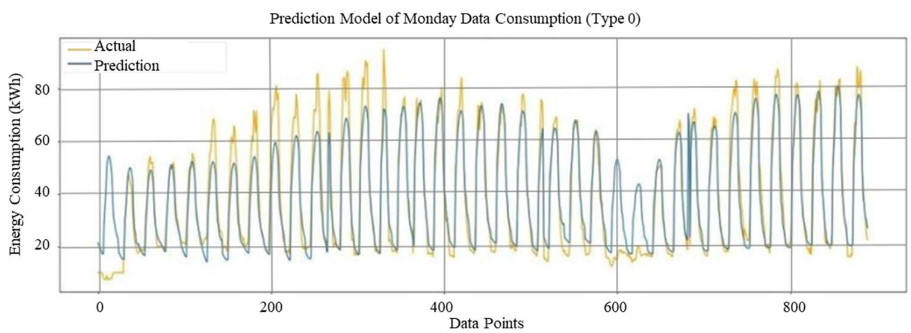

Figure 5 Electricity consumption model for Mondays (Type 0).

The prediction model was selected based on its prediction accuracy, which was quantified by the MAPE and RMSE values. The MAPE and RMSE values of the three dataset types were compared, where the effect of the data preprocessing can be seen from the resulting prediction accuracy. The results will be discussed in the following.

As can be seen in Figure 5, the model can predict the electricity consumption of the building on Mondays in this case. Additionally, it shows the capability of the prediction model to replicate seasonal changes within the year. The model has been provided enough historical electricity consumption data to learn these changes. By providing enough data, the proposed method could potentially be applied to similar buildings in any climate zone.

As can be seen in Figures 6 and 7, the highest MAPE value was shown by the Type 0 data, followed by the Type 2 data, whereas the lowest MAPE value was shown by the Type 1 data. Based on the MAPE and RMSE values for all three data types, the daily model for Type 1 data type gave the lowest MAPE and RMSE compared to the other two types of data.

According to Figures 6 and 7, the Type 1 model could generate a profile of energy consumption with an MAPE error range of 9.65% up to 12.34% and an RMSE error range of 2.42 to 5.29 kWh when compared against the validation set. This model performed better than the other two models (Type 0 and Type 2). Therefore, the prediction model for electricity consumption uses data Type 1 as training data with its related RBF kernels along with their respective features. Compared to the results of similar approaches by Chammas, *et al.* [7], Fayaz, *et al.* [8], and Zhang, *et al.* [9], which also use temporal data to predict electricity use, the proposed prediction method performs within a satisfactory MAPE range.

Once the best model for each day was obtained, the corresponding parameters could be used in the prediction algorithm. They were stored in a file that could be called and used further without any additional training phase.

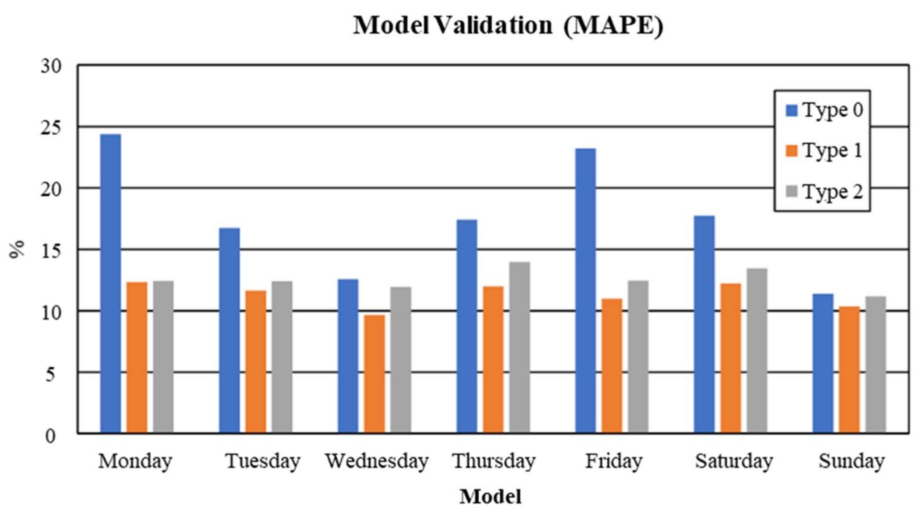

Figure 6 MAPE for the validation of each model.

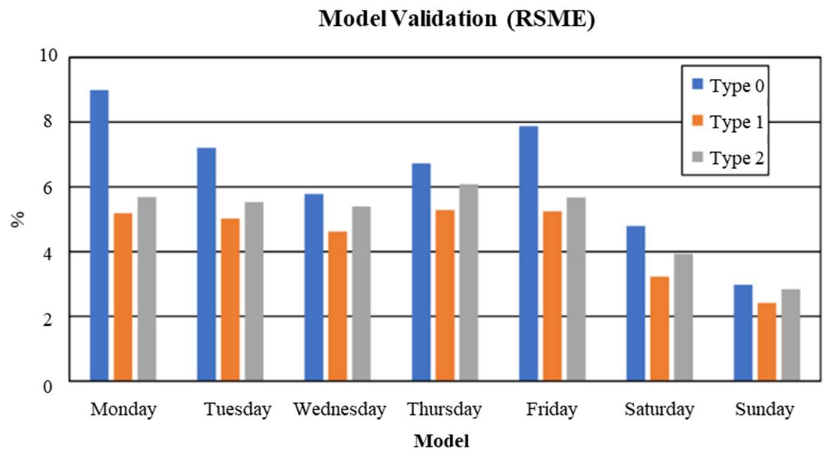

Figure 7 RMSE for the validation of each model.

In the following, the result of the prediction model implementation to an online database is discussed. The model tried to predict the electricity consumption of Monday, May 21, 2018, to Sunday, May 27, 2018. Afterward, the prediction program sent the results to an online MySQL database. Table 4 lists the prediction results that were downloaded from the online database compared to the actual value of electricity consumption obtained from SiElis.

Table 4 Prediction from May 21 to May 27, 2018.

Date	Prediction (kWh)	Actual (kWh)
May 21, 2018	1016,81	829,37
May 22, 2018	1015,75	890,42
May 23, 2018	1008,56	894,08
May 24, 2018	933,59	938,59
May 25, 2018	945,78	917,67
May 26, 2018	568,71	598,53
May 27, 2018	468,14	521,12

Figure 8 shows a comparison of the model prediction output to the actual reading obtained from SiElis. This real-life implementation comparison yielded an MAPE value of 14.79% and an RMSE of 7.48 kWh. After studying the model development results, these prediction results can be useful as an aid for the budget planning process in order to adapt to the electricity tariff during a period, as one example of many potential applications. The predicted results of the weekly electrical energy consumption profile can also be used as a comparison (benchmarking) of the control process and performance of conservation methods that are carried out. The effect of these measures can be seen by comparing the predicted electricity consumption before with electricity consumption after energy-conservation measures.

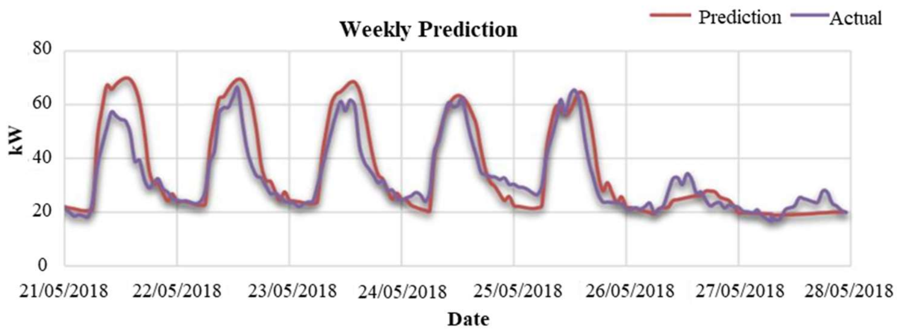

Figure 8 Weekly electricity consumption prediction.

5 Conclusions

A data driven concept was developed to model and predict building electricity consumption using five years from historical data of Labtek VI building, Institut Teknologi Bandung. Three levels of data preprocessing were applied based on anomaly tolerance limits of 15%, 30% and without data preprocessing. The datasets were called Type 1, Type 2, and Type 0, respectively. The highest MAPE value was produced by the Type 0 data, followed by the Type 2 data, and the lowest MAPE value was shown by the Type 1 data. The Type 1 model was fed to the test dataset, with an error range from 9.65% to 12.34% and 2.42 to 5.29 kWh respectively. When the proposed system was applied in a real-life implementation, the model could predict the profile of weekly electricity consumption with a corresponding MAPE value of 14.79% and an RMSE value of 7.48 kWh. With the satisfying performance of the Type 1-based model, the system enables many potential applications, especially in support of electricity budget planning and energy management decisions.

Acknowledgments

This research was partially supported by ITB Research Grant, ITB Center for Research on Energy Policy, and a research grant from the Ministry of Research and Technology/National Research and Innovation Agency of Indonesia.

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