Predictive Analytic for Estimating Electric Consumption of Smart Grid Platform in Residential Single-Family Building using Support Vector Regression Approach

A B Pangaribuan¹, Andhika Octa², IWW Pradnyana³ and Sarika Afrizal²

¹Department of Informatics, Faculty of Computer Science, University Pembangunan Nasional Veteran, Jl. Rs. Fatmawati, Pondok Labu, South Jakarta, 12450, DKI Jakarta, Indonesia
²Department of Information System, Faculty of Computer Science, University Pembangunan Nasional Veteran, Jl. Rs. Fatmawati, Pondok Labu, South Jakarta, 12450, DKI Jakarta, Indonesia

Email: artambo@upnvj.ac.id

Abstract. This present paper attempts to corroborate the theoretical expert knowledge model-based data with the data-driven method in order to optimize energy efficiency use by high fluctuate occupants’ behavior level in typical residential single-family building at tropical country (i.e. Indonesia). Existing data set gathered from field observation and finished computed with Building Performance Simulation (BPS) software tools. The methodology for data-driven knowledge is using supervised machine learning with support vector regression technique, hence the physical engineering data become training data for learning purpose. Predicting algorithm is done in sequential minimal optimization for regression task (SMOreg), a library for support vector machine integrated in WEKA software with using radial basis functions (RBF) as the kernel. Moreover, electric bills are included to forecast future economic value of using smart grid technology.

1. Introduction
Applying the terminology “smart” into residential building becomes bias since the occupants’ behavior level is very dynamic. Engineering model approach by computational building simulation software most often difficult to accommodate the owner’s expectation for their smart house, therefore the automation installation system at the typical residential buildings are hard to reach satisfaction level from the tenant.

One of the tasks in machine learning that can be used for determining the electricity consumption profile analysis prediction in numeric term is support vector machine. The intention of regression is to analyze the patterns electricity consumption made by tenants numerically. The purpose of analysis electricity consumption data is to help determining in which month the electricity at most and the least used. This information can help identifying consumption behavior patterns of the clients.

The house building is located in Medan, Indonesia, a tropical region and most of the time indoor cooling purpose is the highest electrical demand. The temperature in the area relative constant throughout the year. The building physics condition has been simulated for renovation into green building model using drawing CAD software i.e. Revit 2015.
Table 1 Building Properties [3]

| Name              | Value       |
|-------------------|-------------|
| Location          | Medan, Indonesia |
| Average Temperature | 28 - 29 °C  |
| Space Area        | 1570        |
| Building Surface  | 300         |
| Established       | 1983        |
| Bedroom(s)        | 5           |
| Bathroom(s)       | 3           |
| Hall/Living Room  | 2           |
| Kitchen           | 1           |
| Patio             | 1           |

2. Literature Review

Support vector regression (SVR) is the algorithm of support vector machine (SVM) to solve regression function estimation of arbitrary type from training dataset. The model depends only on a subset of the training data and ignore the training points that lie within a threshold $\varepsilon$, this method proposed in 1997 by Vapnik et al [1].

The SVR is formulated in equation:

\[
\text{Minimize} \quad \frac{1}{2} ||\omega||^2 + C \sum_{i=1}^{l} (\xi_i + \xi_i^*)
\]

Subject to

\[
\begin{align*}
    y_i - (\omega, x_i) - b & \leq \varepsilon + \xi_i \\
    (\omega, x_i) + b - y_i & \leq \varepsilon + \xi_i^*
\end{align*}
\]

$\xi_i, \xi_i^* \geq 0, i=1,...,m$

Fig. 1. The parameters for the support vector regression [6]

2.1. Sequential Minimal Optimization

Sequential Minimal Optimization (SMO) is fast and simple algorithm that solve the SVM Quadratic Programming (QP) optimization case without extra matrix storage and without using any numerical QP optimization stages [2]. There is no matrix algorithm is used in SMO, hence large SVM data training could fit inside of the memory of a normal laptop or desktop computer.

2.2. Kernel Radial Basis Functions

Radial Basis Functions (RBF) is chosen among the other kernel types (i.e. linear, polynomial, and sigmoid) because of its finite responses across the entire range of the real x-axis and most useful in
high-dimensional spaces (i.e. for a 2D space only use table lookup and interpolation) [7]. This kernel purpose is to approximate multivariate variable via linear combination based on single univariate function. The RBF kernel formulated as:

$$K(x, y) = \exp(-\gamma^2 (x - y)^2) \quad \text{for} \quad \gamma > 0$$  \hspace{1cm} (3)

3. Data Description

The data source is obtained from previous study that has been published as conference proceeding in International Conference on Computing and Applied Informatics (ICCAI, 2016) [3], it contains electric load each room part of the house building, monthly electric demand, monthly electric consumption in 2015 and photovoltaic panel installation as additional power supply in hybrid grid system, meanwhile the national electricity tariff being used is recent policy (April-June, 2018) [4].

3.1. Consumption Distribution

The number of occupants whom occupy at one zone in 1 (one) hour at the same time is assumed to be maximum quantity that the room capacity could reach standard human thermal comfort define by ASHRAE [5]. Electrical loads are divided into two part as lighting and other electronic devices, whilst the electrical cost per zone calculated as total of both loads.

Table 2 Electrical Load Distribution [3]

| Area     | Lighting Load (W) | Appliances Load (W) | Electric Cost (Rp) | Occupants |
|----------|-------------------|---------------------|--------------------|-----------|
| Hall     | 350               | 1506                | 2723.27            | 20        |
| Bathroom 1 | 35                | 66                  | 148.2              | 2         |
| Bathroom 2 | 35                | 51                  | 126.19             | 2         |
| Bathroom 3 | 35                | 84                  | 174.61             | 2         |
| Bedroom 1 | 75                | 200                 | 403.5              | 2         |
| Bedroom 2 | 75                | 400                 | 696.96             | 4         |
| Bedroom 3 | 75                | 153                 | 334.54             | 2         |
| Bedroom 4 | 75                | 500                 | 843.69             | 5         |
| Bedroom 5 | 75                | 100                 | 256.77             | 2         |
| Living Room | 135              | 50                  | 271.45             | 8         |
| Kitchen  | 75                | 340                 | 608.92             | 8         |
| Patio    | 30                | 0                   | 44.02              | 8         |

4. Results and Discussion

Table 3 Actual vs Predicted Electric Consumption, 2015

| Month | Electric Consumption (kWh) | Actual | Prediction | Error (e) |
|-------|-----------------------------|--------|------------|-----------|
| Jan   | 3100                        | 3196.247 | 96.247    |
| Feb   | 2820                        | 3173.27 | 353.27    |
| Mar   | 3295                        | 3161.568 | -133.432 |
| Apr   | 3205                        | 3158.509 | -46.491  |
| May   | 3320                        | 3155.838 | -164.162 |
| Jun   | 3180                        | 3215.268 | 35.268    |
| Jul   | 3315                        | 3187.168 | -127.832 |
| Aug   | 3225                        | 3169.94  | -55.06    |
| Sep   | 3085                        | 3182.305 | 102.305   |
| Oct   | 3220                        | 3163.74  | -56.26    |
| Nov   | 3080                        | 3182.305 | 102.305   |
| Dec   | 3090                        | 3184.201 | 94.201    |
Correlation Coefficient: -0.2447.
Mean Absolute Error: 113.5875.
Root Mean Squared Error: 113.5845.

4.1. Data validation
Electric consumption represents the amount of electricity that has been consumed over a certain time period (kWh), whereas power demand is the rate at which electricity is consumed (Kw). Based on 2015 electric data consumption, we made comparison between actual data and prediction data in order to validate the accuracy of the algorithm. The model validation using 10 (ten) folds cross-validation. The result can be seen on table 3.

| Month | Power Peak Demand (kW) | Actual | Prediction | Error (ε) |
|-------|------------------------|--------|------------|-----------|
| Jan   | 6.68                   | 6.895  | 0.215      |
| Feb   | 6.87                   | 6.826  | -0.044     |
| Mar   | 7.02                   | 6.891  | -0.129     |
| Apr   | 7.11                   | 6.858  | -0.252     |
| May   | 7                      | 6.86   | -0.14      |
| Jun   | 7.08                   | 6.9    | -0.18      |
| Jul   | 7.1                    | 6.892  | -0.208     |
| Aug   | 6.91                   | 6.89   | -0.02      |
| Sep   | 6.73                   | 6.901  | 0.171      |
| Oct   | 6.84                   | 6.91   | 0.07       |
| Nov   | 6.68                   | 6.9    | 0.22       |
| Dec   | 6.75                   | 6.901  | 0.151      |

Correlation Coefficient: -0.3061.
Mean Absolute Error: 0.1499.
Root Mean Squared Error: 0.1656.

Table 5 Actual vs Predicted Electric Bills, 2015

| Month | Electric Bills (Rp) | Actual | Prediction | Error (ε) |
|-------|---------------------|--------|------------|-----------|
| Jan   | 4,548,568           | 4,689,789.724 | 141,221.925 |
| Feb   | 4,137,729.6         | 4,656,074.946  | 518,345.346 |
| Mar   | 4,834,687.6         | 4,638,906.209  | -195,781.391 |
| Apr   | 4,702,632.4         | 4,634,417.662  | -68,214.738 |
| May   | 4,871,369.6         | 4,630,497.423  | -240,872 |
| Jun   | 4,665,950.4         | 4,717,698.724  | 51,748.324 |
| Jul   | 4,864,033.2         | 4,676,687.16   | -187,565.04 |
| Aug   | 4,731,978           | 4,651,189.126  | -80,788.874 |
| Sep   | 4,526,558.8         | 4,671,117.538  | 144,558.738 |
| Oct   | 4,724,641.6         | 4,642,092.331  | -82,549.269 |
| Nov   | 4,519,222.4         | 4,669,332.868  | 150,110.468 |
| Dec   | 4,533,895.2         | 4,672,114.936  | 138,219.736 |

Correlation Coefficient: -0.2447.
Mean Absolute Error: 166664.6688.
Root Mean Squared Error: 204809.5402.
The electric price in 2015 is Rp 1,524/kWh.
4.2. The Prediction

Forecasting has advantage to show the energy consumption in house building can be managed in the future. If any major additional installation i.e. air-conditioning system or additional renewable energy supply source, the devices specification and parameters should be easily to be determined.

We rule out the electrical supply data, since this paperwork focus on demanding side of the energy need in a single-family house building.

Fig. 2. Electric Consumption Prediction

Fig. 3. Electric Bills Prediction
| Month     | Electric Consumption (kWh) | Maximum Electric Bills (Rp) |
|-----------|----------------------------|-----------------------------|
| January   | 3101.8                     | 4,55,1193.1                 |
| February  | 3093.8                     | 4,539,484.5                 |
| March     | 3084.3                     | 4,525,467.8                 |
| April     | 3068.1                     | 4,501,712.1                 |
| May       | 3061.9                     | 4,492,657.9                 |
| June      | 3052.2                     | 4,478,436.2                 |
| July      | 3045                       | 4,467,899.7                 |
| August    | 3041.3                     | 4,462,455                   |
| September | 3040.9                     | 4,461,961.5                 |
| October   | 3044.3                     | 4,466,900.7                 |
| November  | 3051.3                     | 4,477,055.3                 |
| December  | 3061.8                     | 4,492,558.9                 |

The electric price being used is current tariff (2018) Rp 1,467.28/kWh [4].

In figure 2 and table 6, the forecasted result using train data from year 2015 applied for year 2018 significantly decreased on electric bills because of the decreasing price on national grid tariff. The electric consumption in January 2018 has the high consumptive, whereas in September 2018 is the lowest, as shown in figure 3. The power peak demand relatively same for whole year, hence we do not make the forecast.

5. Conclusion

The study conducted the statistical relationship between physical data that has been measured manually and processed by engineering software with machine learning method to produce the model for aiming estimation energy consumption in residential building. The result shown that SVR approach is applicable to model the analytic prediction. Furthermore, the study could be extending the consumption data exploration into more detail electrical appliances usage with the prediction model and the solar power prediction that supply the house building. Since SVR has strong regression characters and prediction advantages, it is possible to apply the prediction analytic at other region and other type of building i.e. commercial and industrial building as well.

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