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Utilization of MLP and Linear Regression Methods to Build a Reliable Energy Baseline for Self-benchmarking Evaluation

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Abstract

This paper presents a reliable energy baseline model for self-benchmarking evaluation of energy saving potential by using multilayer perceptron (MLP) method. The measured energy data and product quantities of the sample plant in daily period dating back since 2011 to 2016 are used as variables and then normalized to represent the energy baseline (EnB) of the manufacturing plant. A comparison of MLP and linear regression (LR) methods for creating the baseline model is investigated during the factory expansion capacity. For LR method, we use the ASHRAE Guideline 14-2002 as a reference in recommended values for modeling uncertainty. As the uncertainty problem, the LR method is more sensitivity to the outliners, because the nature of plant variables has more complexity and nonlinearity. So we introduce the MLP method to solve or reduce the effect of nonlinearity by supervised learning in the short-term and long-term period of the production. For simulation results, in short-term period the LR method demonstrates some better results of uncertainty parameters. However, the proposed MLP with LR method can build a reliable baseline showing in better R-square values than LR method. This is useful for energy evaluation when the plant is expanding capacity to protect misleading interpretation occurring during the year. For long-term period, the MLP method can overcome the LR method in all uncertainty parameters. Therefore, the MLP method may be able to the alternative choice for creating the EnB in nonlinearity circumstances of the plants for short-term and long-term period.

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Keywords: energy conservation; uncertainty; energy baseline; multilayer perceptron; linear regression

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1. Introduction

Energy conservation in manufacturing plant is the energy-awareness management of modern industries. In many countries, the factories have to be controlled and operated under the energy conservation act or energy conservation standard such as ISO 50001:2011 [1]. The major procedure in this standard is to propose the energy saving measures to minimize the energy consumption by setting priority on the maximum load to be done first.

Furthermore, ISO 50006:2014 standard [2] indicates that we must create energy baseline (EnB) and choose a suitable energy performance index (EnPI) for comparison the saving between pre-retrofit and post-retrofit. Usually, we use the specific energy consumption index (SEC) to determine the energy efficiency. In addition, the baseline duration can range from less than one year to multiple years based on business condition information together with statistical method such as regression analysis.

In energy saving potential, energy service companies (ESCOs) need to evaluate the feasible energy saving of the factories or buildings by using the measurement and verification (M&V) procedures [3] and ASHRAE Guideline 14-2002 [4]. The limitation of ASHRAE Guideline 14-2002 is the use of least square regression in approximation of energy baseline and seems to be sensitive to outliners and nonlinear relationships.

Mostly reviewed papers, the research tasks are done in short-term (duration $\leqslant$ 12 months). There is an attempt as in [5] proposed a comparison of Gaussian process regression and change-point regression for the baseline model in industrial facilities. In uncertainty analysis, the application of Gaussian mixture models [6] is used to model the baseline and localize adaptive uncertainty quantification. For weather season changing, there is a study of baseline model using linear regression for office building energy consumption in hot summer and cold winter region [7] by using monthly energy-bill. The application of multilayer feedforward artificial neural network is used for short duration [8] with 15-minute aggregate energy data and shows the performance with more accurate results than a baseline thin plate spline model.

At this point, the confusion of the duration used and the amount of information data for creating the baseline is arisen on how we could apply these to the suitable method. So, we propose the MLP approach for approximation on the reliable baseline, which rarely use in short-term and long-term analysis. Then, we can use this reliable baseline to develop the EnPI for self-benchmarking evaluation for the factory that hardly to find the companies to benchmark with or they have a big difference in technologies used in the process or machine.

2. Energy baseline approaches

In the case study, Mahasawat water treatment plant located in Nontaburi province, Thailand is chosen for investigation the baseline. The energy consumption data of the plant equipment and facilities is measured from local recordable power meters and complied into a daily report.

We can formulate the input-output variables of the system as independent variable vector of DDTF (Daily distribution and transmission flow) and dependent variable vector of DPEC (Daily plant energy consumption) for linear regression approach. For MLP approach, we use DRF (Daily raw water flow) as the independent variable to predict DPEC and DDTF as shown in Fig.1.

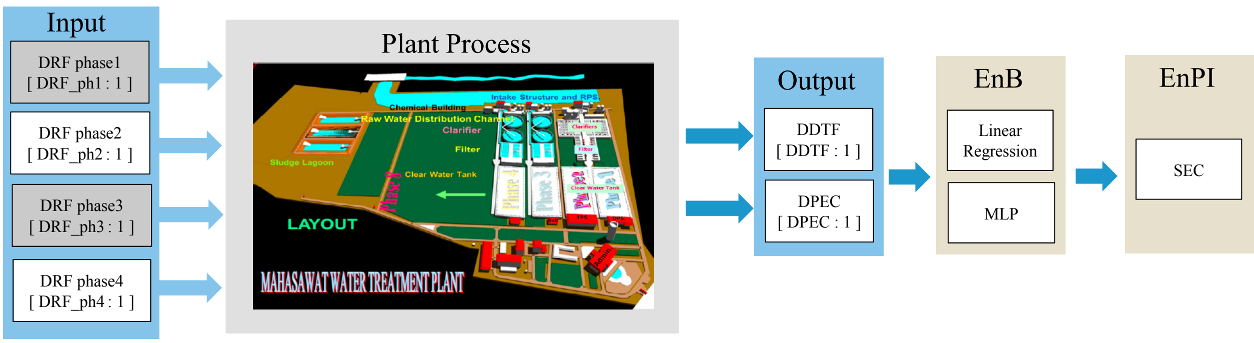

Fig. 1 Mahasawat water treatment plant input-output formulated system

2.1. Linear Regression Techniques

In ASHRAE Guideline 14-2002, denotes that a linear regression is used to build energy baseline within the coefficient of variation of the root mean square error (CV-RMSE) and the normalized mean bias error (NMBE) as shown in Table 1. The linear regression is a combination of independent variables multiplied by constant as shown in equation (1).

Table 1 Recommended values of baseline model uncertainty from ASHRAE Guideline 14

Baseline model uncertainty	Monthly	Hourly
CV-RMSE	15%	30%
NMBE	5%	10%

$$E = C + B_1V_1 + B_2V_2 + B_3V_3 + \ldots \tag{1}$$

Where, E is the estimated energy consumption or demand by least square method, C the constant value in [energy units/day] or [demand units/month], B_n the coefficient of product variable V_n in [energy units/product/day] or [demand units/product/day], and V_n the product variable.

2.2. Multilayer Perceptron

Multilayer Perceptron (MLP) is a feedforward neural network for function approximation. In [9] it has been shown that the MLP ranked best for energy consumption estimation for the Canadian manufacturing industries, followed by radial basis function network and support vector machine. MLP consists of input layer, hidden layers, and output layer. Node *i*, also called a neuron, in an MLP network is shown in Fig. 2. It includes a summer and a nonlinear activation function *g*.

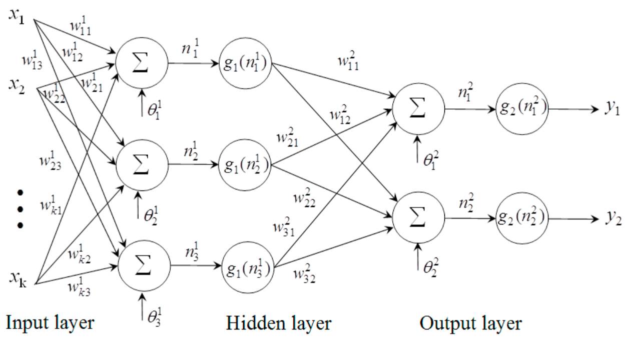

Fig. 2 A multilayer perceptron network

The output y_i, i =1,2, of the MLP network becomes

$$y_i = g_2\left(\sum_{j=1}^{3} w_{ji}^2 g_1(n_j^1) + \theta_j^2\right) = g_2\left(\sum_{j=1}^{3} w_{ji}^2 g_1\left(\sum_{k=1}^{K} w_{kj}^1 x_k + \theta_j^1\right) + \theta_j^2\right) \tag{2}$$

From (2) we know the set of input x_k within the input layer then pass it through neurons or nodes multiplied by weights w_k. Then, sum it with bias θ_j and activate the neurons n_j by activation function g_1 in hidden layer and g_2 in output layer. In this paper we chose g_1 as *tansig* and g_2 as *purelinear* [10] and use Levenberg-Marquardt method for training and gradient descent optimization for learning and estimating the weights and biases of the final outputs y_1 and y_2.

3. Simulation results

We classified the experiments into short-term and long-term period to study the behavior of variables affecting the baseline. In short-term period, the results show that the EnB estimated from LR all years are in range of the ASHRAE Guideline 14-2002. The MLP training results and validation are shown in Table 2 and then we get a better training for MLP2. The CV-RMSE and NMBE values of LR approach are better than the uncertainty values derived from MLP method as shown in Fig.3 and Table 3. However, R^2 results from MLP are shown a superior than LR.

Table 2 MLP training results and validation

Methods	No. of inputs	No. of hidden layers and neurons	No. of outputs	R^2 of training vs target & validation vs target	Mean square error and epoch
MLP1	[1×2,071]	5 neurons	[2×2,071]	Training: 0.97026 Validation: 0.975501	0.008570 epoch =3
MLP2	[1×2,071]	10 neurons	[2×2,071]	Training: 0.975920 Validation: 982402	0.006346 epoch =6

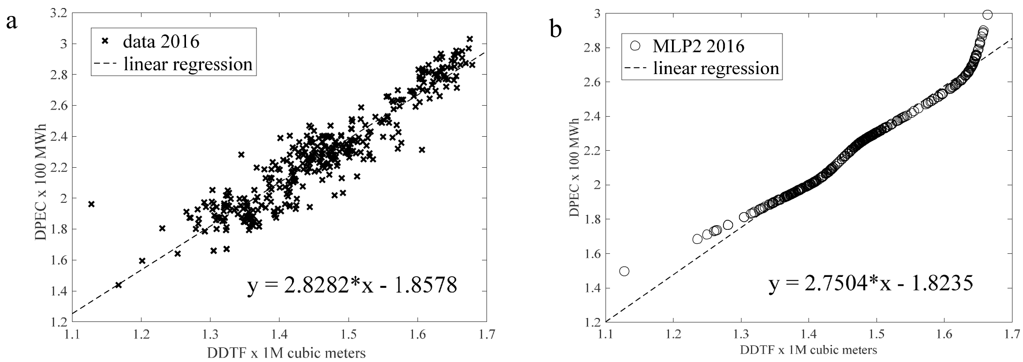

Fig. 3 Example of Short-term EnB : (a) LR; (b) MLP

Table 3 Short-term modeling uncertainty values (used daily data)

Methods	Year	R^2	CV-RMSE (%)	NMBE (%)
Linear regression	2011	0.7161	5.5139	0.0027
(Energy baseline, $y=ax+b$)	2012	0.9253	4.0762	-0.0011
x: Actual-DDTF	2013	0.8800	5.9141	0.0002
y: Actual-DPEC	2014	0.3157	8.7786	0.0032
	2015	0.7972	5.9513	-0.0003
	2016	0.8727	5.1585	-0.0019
MLP2 (best result)	2011	0.9634	6.0324	-0.0257
(Energy baseline, $y=ax+b$)	2012	0.9950	4.5843	0.1294
x: Training-DDTF	2013	0.9688	6.2420	-0.0533
y: Training-DPEC	2014	0.9342	9.2554	0.6159
	2015	0.9311	6.6499	0.1472
	2016	0.9453	4.4450	0.0154

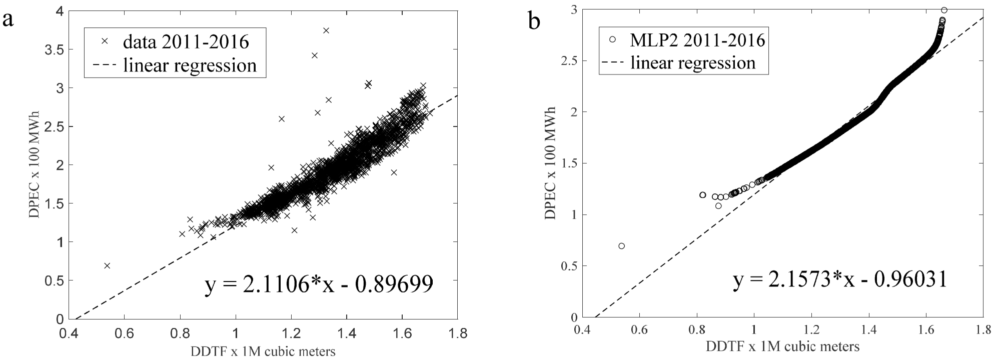

Fig. 4 Long-term EnB : (a) LR; (b) MLP

Table 4 Long-term modeling uncertainty values (used daily data)

Methods	Year	R^2	CV-RMSE (%)	NMBE (%)
Linear regression	2011-2016	0.8726	7.2080	0.0039
MLP2	2011-2016	0.9775	6.7533	-0.0008

For long-term period, we use the data from 2011 to 2016 as a training data for MLP approach. The results shown in Fig.4 and Table 4 clearly demonstrate that MLP is a superior in all parameters of uncertainty. If we see the result in the year of 2014 from Table 3, R^2 value is lowest as 0.3157 and NMBE value is largest as 0.0032. This is because the plant has a big variation in distribution pressures and has structural changes in energy use. Hence, the MLP may be the suitable method for this situation if we use the short-term or long-term model to create a reliable baseline.

4. Conclusion and discussion

MLP approach for approximation on the reliable energy baseline gives the better result of uncertainty than the LR when considered by the ASHRAE Guideline 14-2002 in long-term period. CV-RMSE value of the MLP is less than the LR's by 6.31% and NMBE value of MLP is also less than the LR's by 79.49%. In short-term, the R^2 values of the MLP data are shown a very significant relationship between DDTF and DPEC showing the reliable baseline.

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