An Energy Consumption Prediction Model for Smart Factory Using Data Mining Algorithms

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ABSTRACT

Energy Consumption Predictions for Industries has a prominent role to play in the energy management and control system as dynamic and seasonal changes are occurring in energy demand and supply. This paper introduces and explores the steel industry's predictive models of energy consumption. The data used includes lagging and leading reactive power lagging and leading current variable, emission of carbon dioxide (tCO2) and load type. Four statistical models are trained and tested in the test set: (a) Linear Regression (LR), (b) Radial Kernel Support Vector Machine (SVM RBF), (c) Gradient Boosting Machine (GBM), and (d) Random Forest (RF). Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are used for calculating regression model predictive performance. When using all the predictors, the best model RF can provide RMSE value 7.33 in the test set.

Keywords : Energy Consumption, Data Mining, Random Forest, Linear Regression, Gradient Boosting Machine, Support Vector Machine

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요 약

산업용 에너지 소비 예측은 에너지 수요와 공급에 동적이고 계절적인 변화가 있기 때문에 에너지 관리 및 제어 시스템에서 중요한 위치를 차지한다. 본 논문은 철강 산업의 에너지 소비 예측 모델을 제시하고 논의한다. 사용되는 데이터에는 후행 및 선도적인 전류 반응 전력, 후행 및 선도적인 전류 동력 계수, 이산화탄소(TCO2) 배출 및 부하 유형이 포함된다. 테스트 세트에서는 (a) 선형 회귀(LR), (b) 방사형 커널(SVM RBF), (c) Gradient Boosting Machine (GBM), (d) 무작위 포리스트(RF). 평균 제곱 오차(RMSE), 평균 절대 오차(MAE) 및 평균 절대 백분율 오차(ME)의 네 가지 통계 모델을 사용하여 예측하고 평가한다. 회귀 설계의 효율성 모든 예측 변수를 사용할 때 최상의 모델 RF는 테스트 세트에서 RMSE 값 7.33을 제공할 수 있다.

키워드 : 에너지 소모량, 데이터 마이닝, 램던 포레스트, 선형회귀, 점진적 부스팅 머신, 서포트 벡터 머신

1. Introduction

Due to the advancement of industrialization on a global scale and development of industry, the energy demand is elevated and is considered to be a major concern in national policy [1]. Furthermore, economic growth and human development also add to the rapid growth of energy consumption [2]. The Unregulated use of energy like over-consumption, poor infrastructure, and energy waste are the causes of such an outcome [3]. Among the demanders of different sources of energy, Streimikiene forecasts a significant proportion of residential energy usage by 2030 [4]. As seen by Zuo, Energy consumptions in buildings cover 39 per cent of the total energy consumption of the United States [5].

In South Korea, production industry has begun to evolve at an elevated pace since the 1990s and has become the primary pushing power with the fast

economic development continuing in South Korea. In the 1990s, primary power usage grew at an annualized pace of 7.5%, which in the same era was greater than the annualized financial development level of 6.5%. This is due to strong development in energy-intensive sectors, including petrochemical sectors. The strong increase in industrial electricity consumption helped to boost the reduction of energy conversion, which further subverted energy intensity. The increase in energy production after 2009 significantly buffered the country against the global financial crisis but adversely affected the overall energy efficiency of the country [6]. The energy consumption of the industries is impacted by several unstable variables, like industrial structure, level of technology, cost of energy, financial scale and national policy.

Research and industrial practice draw primary concern in forecasts related to energy resource and planning issues, which is resulted due to the increasing issues of oil and coal shortages. Making fair use of by-product gasses in the steel industry demands scheduling operators to be aware of the quantity of real-time generation, usage and storage. The accurate prediction of these units of energy flow provides a useful guide for their planning and distribution. The iron and steel industries are always energy-intensive, covering 10% of the full industry's energy consumption. Recently, with the rising energy resource shortage, the energy supply condition in the iron and steel industries has become highly challenging. Establishing an energy-saving plan is a common task that can be achieved in areas such as technological development, refurbishing of equipment and improving management. When oil prices increase, the cost of consuming energy is 10-20 times higher than that of the total production of the iron and steel industries. High energy consumption results in higher prices for the iron and steel products which lead to increased pollution and emissions. To this end, several steps, such as improving the production framework and accelerating the improvement and advancement of power saving and discharge reducing techniques, are required to ensure efficient energy supply in the manufacturing industry in South Korea.

Due to the hiking population and economic growth, over the past decades, energy consumption has increased significantly around the world. Energy is viewed as a significant factor in the social and economic development of a nation, and thus in prosperity of the individuals [7]. Long time energy utilization predictions are noteworthy and are required for capacity extension studies, capital consumption in energy supply systems, income examination and revenue analysis. Still, the enormous number of vulnerabilities that portray long term forecasts regularly extending as long as 30 years ahead of time, bringing about the healthy interest of researchers and the steady rise of new strategies for exact and reliable predictions.

Rest of the paper is structured as follows. Section 2 describes the previous energy consumption studies in different sectors. Section 3 displays the data description used in the paper. Section 4 discusses the suggested energy consumption prediction models. The results of the comparison test for the performance of the suggested models are mentioned in Section 5. Section 6 gives the conclusion.

2. Related Works

Multiple studies are carried out for the prediction of energy demand referred to in Section 1. Statistical techniques are used in the past primarily to predict demand for energy. Munz et al. used clustering of k-means to predict the irregular pattern in time series [8]. To predict energy consumption, Kandananond used different methods, which are autoregressive integrated moving average (ARIMA), artificial neural network (ANN) and multiple linear regression (MLR). Cauwer et al. proposed to use a statistical model and the physical concepts behind it to estimate energy consumption [9, 10]. Statistical techniques have limited efficiency owing to unusual patterns of energy demand, and many prediction models are investigated through machine learning methods, level of technology, cost of energy, financial scale and national policy.

Dong et al. implemented SVM with consumption and weather data to predict the energy requirements for buildings [11]. Gonzalez and Zamarreno forecast the upcoming temperature from the current temperature using a feedforward neural network (NN), and with their difference predicted the necessity [12]. Ekici and Aksoy predict the building energy requirements, with building properties excluding environmental conditions [13]. Li et al. used SVM to estimate the

yearly energy demand using the building's transfer coefficient[14]. However, these works only developed models to predict the correct value corresponding to the input, leaving no basis for the input characteristics to influence. Using a fuzzy c- means clustering and predicted demand with fuzzy SVM[15], Xuemei et al. set the condition for estimating energy consumption to fix this issue. Ma predicted energy consumption using the inputs of MLR model with particular population behaviors, unforeseen events and weather condition [16]. Technology degree, energy prices, the financial scale and national policies.

While the aforementioned studies identified the state and predicted future use based on it, classification of the state was lacking in the system. A long-term energy consumption prediction is suggested in by using a granular computing approach integrating industrial-driven semantics and granulating initial data based on the specificity of manufacturing processes [17]. The authors used real-world industrial energy data from a Chinese steel plant to assess the efficiency of the proposed method. The findings reveal that the method proposed is better compared to some other data-driven methods. Also, it can fulfil the needs of the practically viable prediction. Support vector machine (SVM) classifier is intended to predict the ironmaking process energy consumption level in [18]. To boost the precision of optimizing SVM parameters, particle swarm optimization (PSO) was implemented. Through the examination for the energy consuming framework in ironmaking process to accurately model the prediction problem, the improved SVM algorithm was suggested. And, the experimental study was carried out on the basis of practical information from a Chinese Iron & Steel company. The proposed method can predict the energy consumption of the ironmaking process with adequate precision. On the basis of the Gray system theory, a homologous gray prediction model with one parameter and one first order equation (HGEM (1,1)) is proposed to estimate total Chinese production energy consumption [19]. Using this model, they forecast China's manufacturing industry's complete energy utilization over the years 2018-2024. The findings indicate that Chinese manufacturing's complete energy consumption slows down but is still too massive.

A prediction of energy consumption and green-house emissions for India's pig iron manufacturing organization are discussed, as executives are charged with understanding the present and future trends of these smarter environmental policy measures [20]. The Autoregressive Integrated Moving Average (ARIMA) reveals, for predictive purposes, that ARIMA $(1,0,0) \times (0,1,1)$ is the optimum energy consumption predictor. ARIMA $(0,1,4)(0,1,1)$ is the finest equipped configuration of greenhouse emissions. For both cases the predictions are comparable to those of the seasonal random trend model, yet appear clearer as the seasonal trend and pattern d for both energy consumption and GHG emissions is essentially averaged. [21] discusses the generic model for the power-consuming device specification. A tree-based compositional approach encourages arbitrary levels dependent on machine structure, or external factors such as company policies. This technique is very extensible because the models are embedded in ontology. Secondly, for each structural level a methodology is proposed for static and dynamic modeling of the power consumption. You can make the prediction based on the model. Furthermore, an instance is given for implementing and predicting a continuous casting machine process.

A detailed overview of the works carried out in the area of energy consumption is given in the above studies. Data mining approaches have easy and precise methodology of learning among the methods used in the energy consumption field. Four data mining algorithms such as Linear Regression (LR), Vector Support System with Radial Base Kernel (SVM), Gradient Boosting System (GBM) and Random Forest (RF) are used to estimate energy usage in the industry.

3. Data Description for Energy Consumption Analysis

The data is gathered from DAEWOO steel company in Gwangyang city, South Korea. The Industry produces several kinds of the coil, steel sheets and iron plates. The data on energy consumption is filed on the website of the Korea Electric Power Corporation (pccs.kepco.go.kr).

This analysis focuses on energy usage (Kwh) information recorded for the industry every 1 hour. The data period is 365 days (2018, 12 months). Table 1 provides the load type and timing of each month.

Table 1. Load Type and Its Timings

Load Type	June-August	March-May, September-October	November-February
Light Load	23:00-09:00	23:00-09:00	23:00-09:00
Medium Load	09:00-10:00 12:00-01:00 17:00-23:00	09:00-10:00 12:00-01:00 17:00-23:00	09:00-10:00 12:00-07:00 20:00-22:00
Maximum Load	10:00-12:00 01:00-17:00	10:00-12:00 01:00-17:00	10:00-12:00 17:00-20:00 22:00-23:00

Since the steel industry in open space and has no heaters or cooling facilities, the temperature variables have no impact on energy consumption. The overview of the full dataset is shown in Table 2.

Table 2. Data Variables and Description

Data Variables	Type	Measurement
Industry Energy Consumption	Continuous	KWh
Hour of the Day	Continuous	Hour
Lagging Current Reactive Power	Continuous	KVarh
Leading Current Reactive Power	Continuous	KVarh
Lagging Current power Factor	Continuous	%
Leading Current Power Factor	Continuous	%
tCO2 (CO^2)	Continuous	Ppm
Week Status	Categorical	(Weekend (0) or a Weekday (1))
Day of Week (Monday Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday)	Categorical	Sunday, Monday …. Saturday
Load Type	Categorical	Light Load, Medium Load, Maximum Load

Certain added features are created from the date/time factor, which consists of dNumber of seconds each day from midnight(NSM), weekend or week day status, and day of the week. Fig. 1 displays the energy consumption profile over the interval, and displays elevated variability.

For five consecutive weeks, an hourly heat map is produced to identify any time trends, and shown in Fig. 2. This shows that the steel industry's energy consumption trend has a powerful time component.
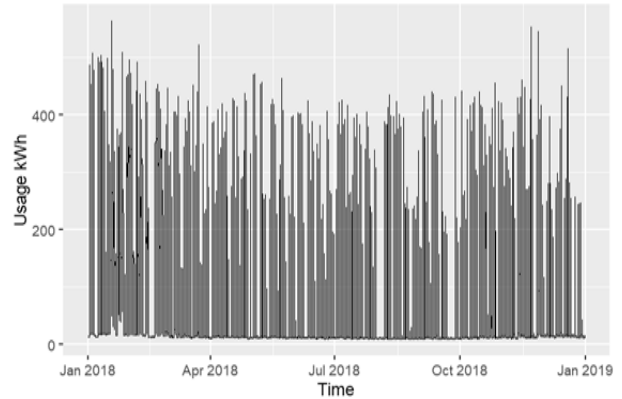

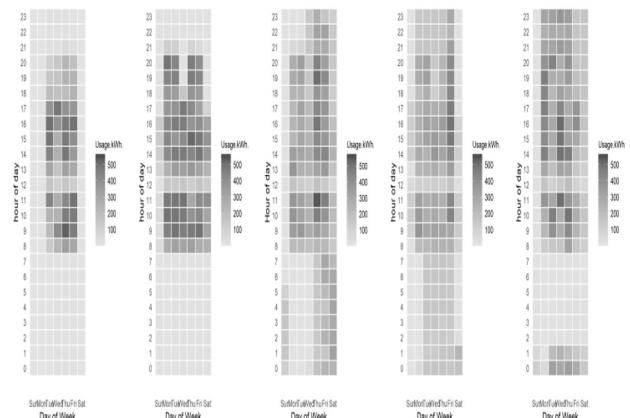Fig. 1. Steel Industry Energy Consumption Measurement for 1 Year

Fig. 2. First Five Weeks Hourly Steel Industry Energy Consumption Heat-map

During the weekend, energy usage is lower than at the other days. Energy usage continues to grow from 8 a.m. Then holds it up until 8 p.m.

4. Evaluation Indices

The performance of the regression model is evaluated using different assessment parameters. Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are the performance measurement indices used here. Root mean squared error (RMSE) is the standard deviation of the sample between the observed value and the predicted one. Using these metrics, large errors can be identified and variability of the model response can be assessed with respect to variance. RMSE is a scale-dependent calculation which results in the same unit measurement values. RMSE is determined using Equation (1).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n}} \qquad (1)$$

Mean absolute error (MAE) is used to evaluate the acuteness of the prediction. MAE is a scale-dependent metric which effectively represents prediction error by minimizing the offset between positive and negative errors. We can calculate MAE using the equation below.

$$MAE = \frac{\sum_{i=1}^{n}[Y_i - \hat{Y}_i]}{n} \qquad (2)$$

The mean absolute percentage error (MAPE) is the mean or average of forecast errors in the absolute percentage. Error is defined as the actual or observed value without the forecast value. Percentage errors are summed up irrespective of signing for MAPE estimation. Since it gives an error in terms of percentages, this measure is fairly easy to grasp Furthermore, since absolute percentage errors are used, the issue of equally cancelling positive and negative errors is prevented. MAPE, therefore, has a managerial appeal and is a measure that is generally used in forecasting. If MAPE is smaller, it indicates a better forecast.

$$MAPE = \frac{1}{n}\sum_{1=1}^{n}\frac{|Y_{i_i} - \hat{Y}_i|}{Y_i} \qquad (3)$$

Here, Y_i is the actual measurement value, $\hat{Y}_i$ is the value predicted, $\bar{y}$ is the sample average, and n is the sample size.

5. Model Selection

The entire one-year data set is divided into training and test validation. In model training, 75% of the data is utilized and 25% in testing purposes. The figures are shown in Table 3.

It is essential to find optimal tuning parameters for each of the regression algorithms for finding and reducing error values while designing a model. LR

Table 3. Training and Testing Set

Dataset	Number of Observations
Training	6572 and 10 Variables
Testing	2188 and 10 Variables

has no tuning parameters and the grid search is not performed for LR. The outcomes of the grid search for RF, SVM and GBM are presented in Fig. 3, Fig. 4, Fig. 5 respectively.
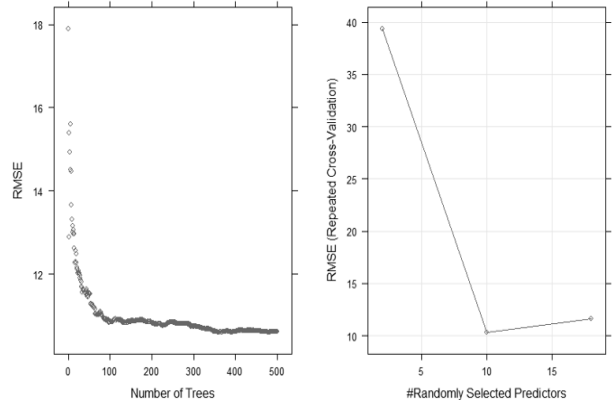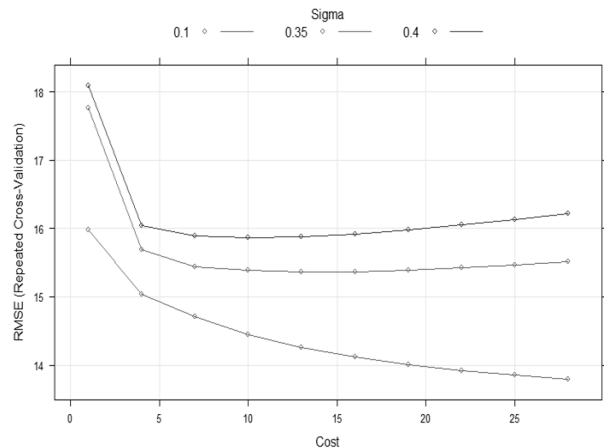

Fig. 3. RF with all the Parameters

Fig. 4. Grid Search Outcomes for Optimal Values of Sigma and Cost Values for the SVM−Radial Model

The grid quest suggests setting parameters by putting all configurable grids within the parameter space [22]. Each axis of the grid is an algorithm parameter, and at each point in the grid is a particular combination of parameters. The role needs to be optimized at every level. In this paper one of the most common validation methods, such as k-fold CV, is used during the hyperparameter tuning process to remove bias in data collection. K-fold CV is a common sort of cv which is generally used in data mining. Even though there is no definite / strict rule for determining the value of K, in the field of data mining a value of K = 5 (or 10) is very common.

As Rodriguez stated [23], when the number of folds is either five or ten, the bias of an accurate calculation
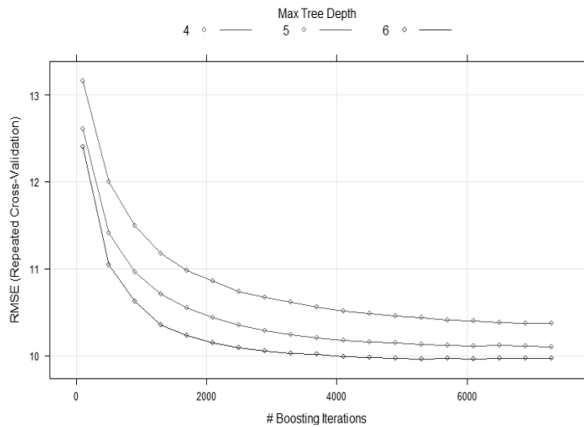
Fig. 5. Grid Search Outcomes for an Optimum Number of Trees (GBM Model Boosting Lterations and Maximum Tree Depth)

would be smaller. In this aspect, as indicated by Kohavi [24] and Wong [25], the number of folds K was set at ten, and correlated with the trade-off between the measurement time and the bias. Ten rounds of training and validation were therefore performed using different partitions, and then the results are summed to reflect the output of LR, SVM, GBM, and RF on the training set. In this study all data processing was done using R software [26].

6. Results and Discussion

LM has no tuning parameters. SVM model has two hyperparameters which is to be fine-tuned. As indicated in Fig. 3, the optimal sigma and cost values for SVM and RBF are 0.1 and 25 respectively. GBM is a tree-based model with two hyperparameters, which are the number of trees and the maximum depth of the tree. The optimal value for the number of trees for GBM is 5300 and the maximum depth of the tree is 6 as shown in Fig. 4. The RF based on an ensemble-based model, has two parameters, which are namely mtry and the number of trees. In Fig. 5, the RMSE value stays constant for RF after 400 and the randomly chosen predictors or mtry value is 10.

Table 4 shows the performance results of each of the models, in which the models producing RMSE, MAE and MAPE are revealed as best. Because it determines the error values processed by the developed models, it is evident that RF and GBM model has less considered to other models, which are RMSE, MAE and MAPE, in the testing set of Table 4. In the result, LM has the worst performance. Out of all 4 models,

the developed RF has fewer error values and considered as the best model in this research. GBM performance is almost close to RF in the test set. But, the performance of GBM is better in case of the test set.

Table 4. Model Performance

Models	Training			Testing		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
LM	16.98	6.98	1.34	9.31	6.12	13.36
SVM	11.09	7.32	2.55	10.66	7.88	27.69
GBM	2.70	1.94	0.75	7.47	4.68	11.57
RF	5.12	2.57	0.63	7.33	4.60	9.89

7. Conclusion

This paper explores the potential for predicting energy consumption by data mining approaches. This study leads to the conclusion that RF is best in predicting the energy and GBM performance also equal to RF. So, RF and GBM are more suitable for predicting steel industry energy consumption prediction. A accurate long-term forecast of energy usage is one among the most critical problems for energy management and optimization in the steel industry. In the exploratory analysis the data analysis reveals thought-provoking results. This work aims to establish the best performing prediction algorithm to predict the hourly consumption of energy in the steel industry. The findings indicate that the RF model improves RMSE, MAE, and MAPE of predictions in consideration to other regression models considered in this research.

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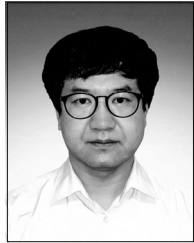
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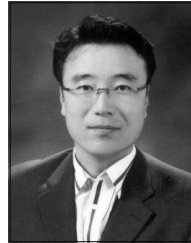
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