EFNet: Attention based CNN-LSTM Networks for Energy Usage Forecasting with External Factors

Hyangsuk Min
hs_min@kaist.ac.kr
Graduate school of Knowledge Service Engineering, KAIST
Daejeon, South Korea

Yongshin Kim
ys.k@kaist.ac.kr
Graduate school of Knowledge Service Engineering, KAIST
Daejeon, South Korea

Youngeun Kim
jadekim@kaist.ac.kr
Graduate school of Knowledge Service Engineering, KAIST
Daejeon, South Korea

Abstract

Recently, deep learning methods have been used to predict energy usage. It is important to use appropriate factors for the accuracy of the prediction. Factors that affect energy usage include not only weather, date factors but also social and economic factors. Social and economic factors are expected to affect energy usage significantly due to the recent COVID-19 trend. We propose EFNet(Energy usage Forecasting Network) which forecast energy usage by using attention based CNN-LSTM networks. EFNet is a sequential prediction model that reflects the characteristics of variables such as weather, calendar, oil price, and COVID-19 confirmed cases. We conduct experiments on the real-world data in South Korea and we demonstrate that the proposed model can effectively predict the energy usage and significantly outperform other baseline models. Furthermore, since the model reflecting the number of COVID-19 confirmed cases have higher predictive power than the model that do not, external variables such as COVID-19 can be seen as important factors in predicting energy usage.

CCS Concepts: **• Computer methodologies → Artificial intelligence; Neural Networks**; **• Applied computing** → *Forecasting;*.

Keywords: neural networks, DNN, LSTM, time series analysis, load forecasting, energy usage forecasting

ACM Reference Format:
Hyangsuk Min, Yongshin Kim, and Youngeun Kim. 2020. EFNet: Attention based CNN-LSTM Networks for Energy Usage Forecasting with External Factors. In *Proceedings of ACM Conference (KSE526'20).* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

KSE526'20, Dec 2020, Daejeon, South Korea

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM...$15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 Introduction

Energy usage has been changing rapidly over the past few decades due to rapid changes in industry and economy.[14]. Since energy has traditionally been produced using fossil fuels, which is a major cause of the greenhouse effect, policies are changing in the direction of producing renewable energy such as wind power, hydropower, geothermal heat, and biomass in many countries[16]. It is desirable to use as little fossil fuel as possible due to environmental issues[2]. Renewable energy is difficult to produce in a stable manner compared to fossil fuels, so energy storage facilities are required, but there is a problem that it is expensive[7]. Therefore, it must be consumed at the same time as it is generated in the power plant, and it is essential to predict power demand. Excessive forecasting of energy usage results in unnecessary excess energy capacity, and underestimation can lead to energy supply disruption in extreme situations. As energy usage forecasting becomes more sophisticated, it is helpful for energy production planning, and thus, research on energy usage forecasting is being actively conducted[15].

Variables correlated with the prediction of energy usage can be divided into three categories: weather, time, and economic factors[10, 19]. Weather is the most influential factor for short-term changes in energy usage, including temperature, humidity, dew point, wind speed, and sunlight. In the prediction of energy usage in regions where summer and winter changes are significant, it is necessary to take into account that the energy usage patterns in summer and winter have clearly different patterns. The time factor is that the pattern of electricity demand varies by day on holidays and weekdays. Economic factors are influenced by economic stimulus policies or electricity rate price management policies, and are used for mid- to long-term forecasts over a yearly or seasonal basis.

Energy usage forecasts can be divided into long-term, medium-term and short-term forecasts according to the forecast period[1, 17]. Long-term forecasts are closely related in the long run from the perspective of economic policies such as the degree of economic revitalization of various industrial facilities and service industries, population growth rate, and warming regulation. Mid-term forecasting is used for fuel planning, power transmission management, and peak power planning in summer or winter. Short-term prediction is generally used for optimizing power generation supply and managing power transaction schedules, and predicts power flow in advance to prevent excessive supply of power. Time-based prediction prevents power generation equipment from overloading or power outages.

In the recent global coronavirus pandemic, governments of each country are implementing strong social control policies, which are expected to have a great impact on energy usage[6]. As factories operate less, usage may be drastically reduced, or energy usage may increase as the use of electronic devices increases because people stay only at home.

We propose a novel deep learning based energy usage forecasting model called EFNet(Energy usage Forecasting Network). This study focuses on predicting energy usage as accurately as possible for the near future (i.e. 1, 2 weeks). Energy usage can be predicted using weather, day of the week, oil price, and COVID-19 confirmed cases as external factors. These are time series data that change every day. Therefore, it is essential that the predictive model contains the complex temporal relationship of these many factors. The contributions of this study are as follows.

- A number of external factors are used to predict energy usage in the specific situation of the COVID-19 epidemic. For this, CNN and LSTM are integrated to improve prediction accuracy.
- Using real-world data, our model's RMSE and MAPE are showing higher accuracy than conventional models.
- Evaluating the influence of external factors on energy usage prediction through Ablation study.
- The results predicted using 2020 data after the COVID-19 outbreak can be used for power supply policy in the COVID-19 situation.

The rest of this paper is organized as follows. Section 2 reviews relevant studies for energy use prediction. Section 3 summarizes the data sets used for the assessment. Section 4 proposes structure and methodology. Section 5 presents the evaluation results. Finally, section 6 concludes the paper.

2 Related Work

Many studies are being conducted to extract features from electrical energy usage data and predict energy usage. Three categories are used for energy usage prediction: statistical modeling, machine learning based modeling, and deep learning based modeling.

2.1 Statistical method

Traditionally, automatic regression integrated moving average (ARIMA) models and linear regression models are widely used to predict power demand. X. Lu reported the result of predicting energy usage through ARIMA using only the target variable without a set of independent variables[12]. Zakarya predicted Kuwait's power consumption as independent variables based on economic factors such as weather temperature and humidity, average salary, gross domestic price, oil price, population, residence, and currency return (total import/export USD)[18]. The weather parameters were more important than average salary, domestic gross and oil prices.

N. Fume predicted the residential energy used in the home using multiple linear regression and confirmed that the temporal resolution of the observed data affects the performance of the predictive model[8]. K. P. Amber applied genetic programming to multiple linear regression to predict by integrating five important independent variables[3] Linear regression models can cause multiple collinearity problems due to correlations between independent variables used for prediction. Energy usage forecasts include several time series variables. These variables may exhibit various irregular patterns and contain complex nonlinear patterns between the collected variables. Therefore, in predicting electrical energy usage, a machine learning-based technique capable of mapping nonlinear functions is more useful than using the classical prediction method based on the linearity assumption.

2.2 Machine learning method

Y. Chen used support vector regression to predict the electricity consumption of a building, and improved performance by adding ambient temperature as a variable to the basic electricity consumption[5]. A. Bogomolov used human dynamics analysis to predict energy usage after 1 week using the random forest regression method, and generated complex decision boundaries even if the data had few features[4]. This machine learning method can perform nonlinear mapping in a high-dimensional space, but it is difficult to predict long-term consumption because overfitting occurs when a complex correlation of variables becomes complicated or the number of data increases.

2.3 Deep learning method

Recently, convolutional neural network with long short-term memory units (CNN-LSTM) is used as a basic model for energy usage prediction. CNN is used to remove noise and consider correlations between multivariate variables. LSTM models temporal information and maps time series to separable spaces to generate predictions. Energy usage is a multivariate time series recorded over time, including spatial information between variables and irregular patterns of time information. Using the CNN-LSTM model, it can be used as information to properly adjust supply through the estimated consumption derived by learning the spatiotemporal characteristics of electric energy usage. T. Kim predicted the energy usage of buildings using a data set including time and usage patterns of electronic devices used in buildings and a CNN-LSTM model, showing more accurate predictive power than linear regression, decision trees, and random forests[9]. Y. Li showed that it is possible to predict the change in the annual energy generation method using the CNN-LSTM model and a data set that includes the change in China's total energy usage and annual energy generation method[11].

This study focuses on predicting Korea's enery usage after the COVID-19 situation. COVID-19 is expected to last at least one year in the future, and its effects are difficult to predict. Previous work has focused primarily on improving the prediction accuracy of models using datasets provided for research purposes, but our work is the first attempt to predict the impact of unprecedented pandemic situations on energy usage in Korea.

3 Data Description

In this section, we describe the data used to train our models. The data comprises Power usage, COVID-19 confirmed cases, Meteorology and Oil price. All datasets are publicly available on the Internet. Data from January 1st to November 24th, 2020 were used.

- **Energy Usage**: This dataset was collected from Korea Power Exchange. It consists of last & this year's daily maximum energy usage and this year's daily energy reserves. We used last year's maximum power data and this year's energy reserves data for model training and this year's maximum power data was used for both model training and testing. We thought that last year's data from the same period of this year helped explain energy usage patterns of this year.
- **COVID-19**: COVID-19 has changed the paradigm of energy usage so we used COVID-19 data as an external factor. This dataset was provided by Korea Statistical Information Service. It indicates the number of confirmed cases per day. The daily increase in the number of confirmed cases was added.
- **Meteorology**: The use of products with high-energy consumption, such as heating, ventilation, and air conditioning systems, is directly related to weather conditions. Therefore, input variables derived from meteorological data are commonly used in energy prediction models.[13] This dataset was collected by Korea Meteorological Administration. It contains average, minimum, maximum temperature of each days, maximum precipitation for 1 hour a day, average dew point a day, daily sunshine and average land temperature for every region in South Korea.
- **Oil Price**: Oil prices are an economic factor that affects energy usage. This dataset was collected by Korea National Oil Corporation. It shows the amount of change compared to the previous day of gasoline and diesel price.
- **Calendar**: Since time series data represents trends in energy usage, we consider weekday and holiday, which are input variables that can display calendar data.

4 Methodology

4.1 Overview

Figure 1 overviews the architecture of our proposed model. The model is composed of three components. (a) energy usage inference network; (b) external feature extraction network; (c) prior information network. For (a) energy usage inference network, the network consists of CNN, LSTM, and Attention layer. CNN and LSTM are capable to capture nonlinear complex temporal dependency among features, and Attention layer is able to concentrate on the important information at prediction time t. Since EFNet forecasts the upcoming 7 days, considering useful information becomes an important problem. For (b) external feature extraction network, we use COVID-19 daily confirmed cases, and oil price dataset. Since these features don't have an impact on energy usage directly, we consider them as mediators and construct a separate model from (a). To capture correlations between features, 1D-CNN is capable of capturing correlations between input features and learning the salient features, and LSTM train temporal dependency through time steps. For (c) prior information network, weekday and whether holiday or not on target day are included as inputs. Energy usage patterns are repetitive weekly, and holidays such as Thanksgiving Day, make an abnormal pattern which is hard to be captured using historical data only. The prior information is incorporated into the model using a simple fully connected layer. Finally, energy usages for 7 days are predicted by (d) energy usage prediction network. Concatenated representations extracted from three components forecast the energy usage through a fully connected layer. In the following section, our model is described in detail.

4.2 Energy Usage Inference Network

One of the important challenges of energy usage forecasting is how to capture the informative temporal correlations and establish an inherent relationship between various time series data. Since energy usage has repetitive patterns, capturing temporal trends is most important. Towards this, we design an energy usage inference network based on Attention-based CNN-LSTM network, to learn complex relationships among features and temporal trends.

The historical energy usage data and meteorology data pass through 1D-CNN and a pooling network and extract important features. The extracted features are passed to the pooling layer for sampling, and the largest values are chosen. CNN represents the correlation between energy usage and meteorology features and filters noise in features. The extracted features are passed through LSTM layer which is capable of modeling long-term temporal dependency. we use Bahdanau attention method to refer to the information

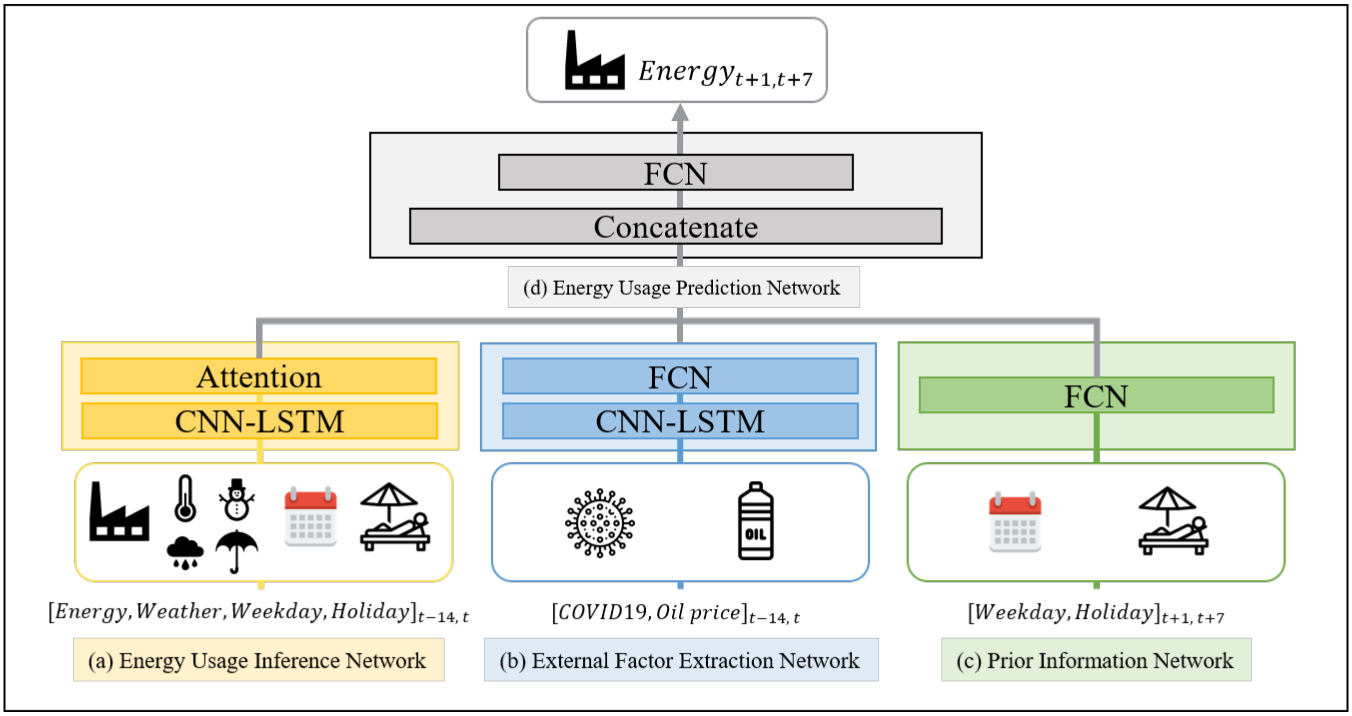

Figure 1. Overall architecture of the proposed EFNet.

that LSTM layer lost after passing time steps and capture important information among hidden states extracted from LSTM layer. Final outputs are extracted from attention layer.

4.3 External Factors Extraction Network

Energy usage is fluctuating depending on external factors such as social and economical events. In order to improve the accuracy of energy usage prediction, we propose 2 different external factors that can present social and economic situations: COVID-19 and, oil price. They don't have an impact on the energy usage directly, but affect energy usage mediately. We mainly focus on representing the multiple correlated information among features and near time steps. Both COVID-19 and oil price on the past 14 days are passed through a 1D-CNN layer to secure multiple nonlinear correlations between factors and extract salient features. LSTM layer gets the features processed from 1D-CNN layer and learn temporal dependency. Finally, fully connected layers pass through outputs extracted from CNN layer for each time step and generate the representation that infuses external factors information.

4.4 Prior Information Network

Energy usage has a weekly trend, thus, energy usage has the same patterns for each day of the week. Whether a holiday or not is important information because people's behavior is changed. On a national holiday, most people don't go to work or some industry takes a break, it causes the energy trend different from the normal days. Even holidays such as Thanksgiving and New year, people take a break and people move to relative's house, people gather in one area, it usually drops the energy usage significantly. Therefore, weekdays and whether holidays or not can be useful for forecasting energy usage. These two types of features are included as inputs, not only features on training day but also features on target days since weekday and whether holiday or not is an undeniable fact. Using a fully connected layer, the features which are collected on the target day are incorporated into the networks.

4.5 Energy Usage Prediction Network

Lastly, we forecast energy usage for the upcoming 7 days. we firstly combine outputs extracted by (a) energy usage inference network, (b) external factor extraction network, and (c) prior information network for prediction. Finally, the concatenated representations are fed into a simple fully connected layer to forecast the final energy usage prediction. **Objective:** In this work, we aim to predict energy usage at time t with the proposed model. We use Root Mean Squared Error(RMSE) as a loss function, by minimizing the error between prediction value and actual value. Therefore, the loss function is defined as:

$$Loss = \sqrt{\sum_{i=1}^{M} (\hat{y_t} - y_t)^2} \tag{1}$$

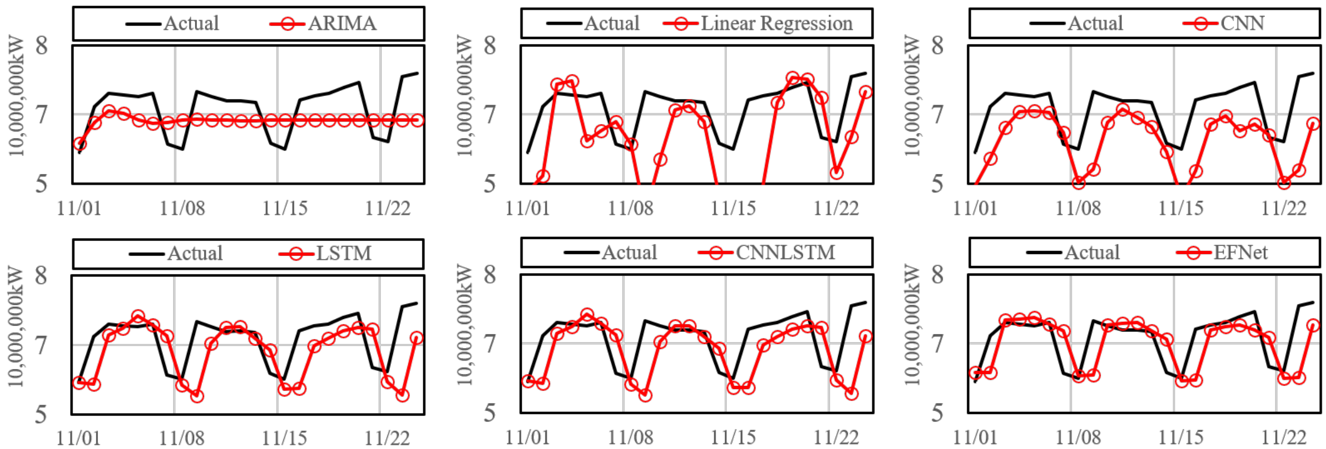

Figure 2. Predicted energy usage and actual energy usage of baseline models and proposed EFNet.

5 Experiments

In experiments, we present the promising results against several baselines on time series forecasting, to show the superiority in terms of prediction performance. We also explore the effectiveness of each component in EFNet and external factors.

5.1 Experimental Settings

5.1.1 Datasets. To prove the effectiveness of our model and compare the performance of different methods, we conduct experiments on datasets described in section 3. Datasets are split into train and test sets. Train set is from *2020.01.01* to *2020.10.31*, while test set is from *2020.11.01* to *2020.11.24*. The previous 14 days are as inputs and the next 7 days are as targets. Weekday and whether holiday or not on target days are included in input datasets. Since weekday and whether holiday or not is a self-evident fact, we use them to provide to the model as prior information.

5.1.2 Baselines. We compare EFNet and the following 5 baselines that are typically used for time series forecasting.

- **ARIMA** is well-known time series model that combines autoregressive(AR) and moving average(MA) for prediction. [12]
- **Linear Regression** is a simple linear model that can usually be used for forecasting problem. we use previous 14 days as inputs and next 7 days as outputs.
- **CNN** is convolutional neural networks, which is usually used with image data. But, 1D-CNN is capable of reading across sequence input and automatically learning the salient features.
- **LSTM** is RNN-based model, capturing information of long-short term dependency, which has been commonly used for time series forecasting in the literature.
- **CNN-LSTM** is an encoder-decoder based model, which means that CNN is a encoder and LSTM is interpreted as an decoder. [11]

5.1.3 Variants. Our model consists of energy usage inference network, external factor extraction network, and prior information network. We prove the effectiveness of each component, thus we define the variant models of EFNet and conduct experiments. The results are in section 5.2.2.

- **EFNet-(a)** is composed of only energy usage inference network.
- **EFNet-(a)(b)** consists of energy usage inference network and external factors extraction network to present the effectiveness of the component compared to EFNet-(a).
- **EFNet-(a)(c)** removes external factor extraction network from EFNet to see the performance of prior information network.

5.1.4 Metrics. We evaluate all methods with two widely used metrics for energy usage forecasting: Root Mean Squared Error(RMSE), and Mean Absolute Percentage Error(MAPE), defined as eq (2) and eq (3), where $\hat{y}_t$ and y_t are predicted and ground-truth energy usage value at day t, and N is the number of testing samples.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{M}(\hat{y}_t - y_t)^2} \tag{2}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{3}$$

5.2 Experimental Results

5.2.1 Performance comparison. Table 1 presents the performance of all methods which are mentioned in 5.1.2 baselines. First, machine learning methods such as ARIMA and

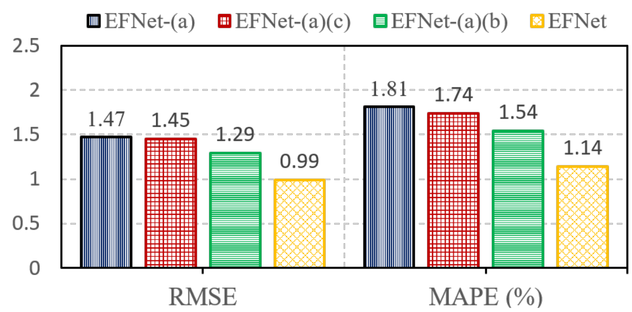

Figure 3. The ablation studies about the proposed methods.

Linear Regression, perform poorly since it cannot capture nonlinear temporal dependencies among multivariate variables. Second, simple deep learning methods such as CNN, LSTM, and CNN-LSTM, give better prediction performance than ARIMA and Linear Regression, but still poor than EFNet since they are incapable of considering correlations within other external mediated factors. Third, EFNet significantly outperforms all baselines on both metrics, which demonstrates the effectiveness of three components in EFNet. For example, EFNet yields 42.66% and 48.65% improvement over the second best approach in terms of RMSE and MAPE.

Figure 2 shows that EFNet actually follows the trend better than baseline models. First, ARIMA and Linear Regression fail to capture the weekly trends and learn temporal dependency, thus they are incapable of forecast energy usage. Secondly, deep learning methods are aware of weekly trends but fail to capture the impact on the external factors. Finally, EFNet shows astonishing results following the trend and succeed to predict energy usage close to actual energy usage. It is worthwhile to mention that our method has impressive performance which is incomparable to baseline models.

Table 1. Performance comparisons on collected datasets. Each value in both RMSE and MAPE indicates the amount of error of each day.

Method	RMSE	MAPE
ARIMA	23.7246	0.3354
Linear Regression	5.9963	0.0712
CNN	2.6027	0.0360
LSTM	1.9671	0.0257
CNN LSTM	1.7336	0.0222
EFNet	0.9941	0.0114

5.2.2 Ablation study.

Figure 3 shows the effectiveness of building blocks of EFNet. First, the performance of EFNet-(a) still have better performance than baseline models about 17.12% and 18.47% in terms of RMSE and MAPE. Second, EFNet-(b) proves that external factor extraction network plays an important role on energy usage prediction, which is verified by the significant drop of performance of EFNet-(a). It indicates that energy usage are affected by social and economical events, which proves the importance of external factors. Thirdly, the results of EFNet-(c) doesn't give significant drop, but combining with external factor extraction networks makes good performance. This reveals that each component plays an important role and complements each other in the model.

Table 2. Influence of external factors

External factors	RMSE(%)	MAPE(%)
COVID-19	16.62	19.16
Oil price	5.76	6.77

5.2.3 Influence of external factors.

We conduct experiments to figure out the influence of external factors by individually removing them from EFNet. Table 2 shows information gain if the corresponding factor is incorporated in EFNet. Information gain is calculated as a percentage of reduced error in terms of RMSE and MAPE.

First, we investigated the effect of oil price which reflects the current economic condition. Energy usage is affected by economical events since South Korea has a trade-oriented industry. According to economical conditions, each industry determines how much they operate their manufacturing, or how long they operate their stores. Table 2 shows the effectiveness of oil price, decreasing errors about 5.76% and 6.77% in both RMSE and MAPE.

Second, We investigated the effect of COVID-19 as abnormal situation comparing to last years. COVID-19 has changed a lot in terms of lifestyle and industry. For example, We didn't have outdoor activities comparing to the last year, also lots of companies let workers work at home. Additionally, since the pandemic of COVID-19 is serious all over the world and the industries in South Korea highly depends on trade, obviously, energy usage of industry gets affected by the severity of COVID-19. Therefore, COVID-19 causes unpredictable energy usage trend comparing to our lives without COVID-19. In Table 2, training model with COVID-19 significantly decrease the error rate about 16.62% compared to training without COVID-19. It indicates that considering the social events is crucial to predict energy usage and the factors such as COVID-19 should be considered if we are under this kind of situation.

6 Conclusion

In this paper, we proposed a novel approach by including economic and social external factors in the model. Using CNN, LSTM and attention mechanism, energy usage could be predicted with higher accuracy than conventional models in a situation where the energy usage fluctuates rapidly due to COVID-19. Furthermore, the longer energy supply plan is made possible by predicting energy usage on a weekly basis, rather than by a traditional daily basis models. We showed the practicality and effectiveness of our model through a case study in Korea. By separating weather, calendar data which directly related to energy usage from COVID-19, oil price data which indirectly affect energy usage, we were able to forecast energy usage predictions much more accurately than baseline models.

References

[1] Ahmad S Ahmad, Mohammad Y Hassan, Md P Abdullah, Hasimah A Rahman, F Hussin, Hayati Abdullah, and Rahman Saidur. 2014. A review on applications of ANN and SVM for building electrical energy consumption forecasting. *Renewable and Sustainable Energy Reviews* 33 (2014), 102–109.

[2] Kingsley Akom, Thokozani Shongwe, Meera K Joseph, and Sanjeevikumar Padmanaban. 2020. Energy Framework and Policy Direction Guidelines: Ghana 2017–2050 Perspectives. *IEEE Access* 8 (2020), 152851–152869.

[3] KP Amber, MW Aslam, and SK Hussain. 2015. Electricity consumption forecasting models for administration buildings of the UK higher education sector. *Energy and Buildings* 90 (2015), 127–136.

[4] Andrey Bogomolov, Bruno Lepri, Roberto Larcher, Fabrizio Antonelli, Fabio Pianesi, and Alex Pentland. 2016. Energy consumption prediction using people dynamics derived from cellular network data. *EPJ Data Science* 5, 1 (2016), 13.

[5] Yongbao Chen, Peng Xu, Yiyi Chu, Weilin Li, Yuntao Wu, Lizhou Ni, Yi Bao, and Kun Wang. 2017. Short-term electrical load forecasting using the Support Vector Regression (SVR) model to calculate the demand response baseline for office buildings. *Applied Energy* 195 (2017), 659–670.

[6] Steve Cicala. 2020. *Early Economic Impacts of COVID-19 in Europe: A View from the Grid.* Technical Report. Tech. rep. Online, last accessed: May 6, 2020. University of Chicago.

[7] Søren Djørup, Jakob Zinck Thellufsen, and Peter Sorknæs. 2018. The electricity market in a renewable energy system. *Energy* 162 (2018), 148–157.

[8] Nelson Fumo and MA Rafe Biswas. 2015. Regression analysis for prediction of residential energy consumption. *Renewable and sustainable energy reviews* 47 (2015), 332–343.

[9] Tae-Young Kim and Sung-Bae Cho. 2019. Predicting residential energy consumption using CNN-LSTM neural networks. *Energy* 182 (2019), 72–81.

[10] Kangji Li, Chenglei Hu, Guohai Liu, and Wenping Xue. 2015. Building's electricity consumption prediction using optimized artificial neural networks and principal component analysis. *Energy and Buildings* 108 (2015), 106–113.

[11] Yan Li, Yaoyu He, and Meizhen Zhang. 2020. Prediction of Chinese energy structure based on Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM). *Energy Science & Engineering* (2020).

[12] Xiaoshu Lü, Tao Lu, Charles J Kibert, and Martti Viljanen. 2015. Modeling and forecasting energy consumption for heterogeneous buildings using a physical–statistical approach. *Applied Energy* 144 (2015), 261–275.

[13] Jihoon Moon, Sungwoo Park, Seungmin Rho, and Eenjun Hwang. 2019. A comparative analysis of artificial neural network architectures for building energy consumption forecasting. *International Journal of Distributed Sensor Networks* 15, 9 (2019), 1550147719877616.

[14] Richard G Newell and Daniel Raimi. 2020. Global Energy Outlook Comparison Methods: 2020 Update. (2020).

[15] Isaac Kofi Nti, Moses Teimeh, Owusu Nyarko-Boateng, and Adebayo Felix Adekoya. 2020. Electricity load forecasting: a systematic review. *Journal of Electrical Systems and Information Technology* 7, 1 (2020), 1–19.

[16] Poul Alberg Østergaard, Rasmus Magni Johannsen, and Neven Duic. 2020. Sustainable development using renewable energy systems. *International Journal of Sustainable Energy Planning and Management* 29 (2020), 1–6.

[17] Kody M Powell, Akshay Sripprasad, Wesley J Cole, and Thomas F Edgar. 2014. Heating, cooling, and electrical load forecasting for a large-scale district energy system. *Energy* 74 (2014), 877–885.

[18] Salman Zakaraya, Hala Abbas, and Mohammed Belal. 2017. Long-term deep learning load forecasting based on social and economic factors in the Kuwait region. *Journal of Theoretical & Applied Information Technology* 95, 7 (2017).

[19] Yu-Rong Zeng, Yi Zeng, Beomjin Choi, and Lin Wang. 2017. Multifactor-influenced energy consumption forecasting using enhanced back-propagation neural network. *Energy* 127 (2017), 381–396.