LSTM based Analysis of Sequential Usage Pattern for Electrical Appliance

Joa Hyoung Lee, YoonMee Doh, and Tae-Wook Heo
Electronics and Telecommunications Research Institute
Daejeon, Korea, Republic of
jinnie4u@etri.re.kr, ydoh@etri.re.kr, htw398@etri.re.kr

***Abstract*—Electrical appliances used at home are sometimes used independently, but there are also many cases where they are sequentially used in connection with other home appliances. Home appliances used sequentially and continuously have a characteristic that consumes a lot of energy and takes a long time compared to devices used alone. In this paper, we seek a way to find the correlation between home appliances that are used sequentially in succession by using LSTM, a kind of machine learning technique. Since the LSTM has the characteristic of maintaining the past value for a long period by transferring the cell value, it is possible to determine the correlation between the data used by providing a certain interval. Using these characteristics, we tried to analyze the correlation between home appliances, which correlates with the order of use in time. To verify the method, we analyzed the electric usage record in the UK with the LSTM algorithm.**

Keywords—home appliance, electric energy, usage pattern, LSTM algorithm

I. Introduction

Global warming requires efforts to reduce greenhouse gas emissions and reduce energy consumption is urgently needed around the world. These efforts are mainly made in many industries of energy consumption, and general households do not feel the severity as much as in the industry. However, with the recent increase in the amount of energy consumed at home, there is a growing need to improve the perception of energy consumption in the home as well.

However, due to Russia's recent invasion of Ukraine, the prices of underground resources such as oil and LNG, which are raw materials for electricity production, have risen rapidly around the world, and the cost of electricity production has also increased significantly. Electricity rates are also rising steeply and are expected to rise significantly in the future. . Reducing energy consumption at home not only reduces energy costs, but can also contribute to solving the global warming problem by reducing carbon emissions for energy production.

Recently, one of the reasons for the increase in energy consumption in the home is the prolonged summer season and prolonged heat waves, leading to extreme use of the air conditioner for long periods of time all day for several months for cooling, or using the boiler for long periods of time due to the extreme cold in winter. One example is climate change. As the climate changes dramatically, summers are getting longer and hotter, which increases energy consumption and increases carbon emissions due to energy consumption, repeating a vicious cycle that causes climate change. As air conditioners are turned on at full blast for cooling in the summer afternoons and boilers are turned on for heating in the winter evenings at almost the same time across the country, the possibility that electricity use during peak hours approaches or exceeds supply is increasing. If electricity demand exceeds electricity supply during peak hours, when demand for cooling and heating overlaps with production activities, a large-scale power outage may occur.

To reduce energy consumption, it is necessary to understand the characteristics and usage types of home appliances that consume energy. Home appliances used at home have very diverse characteristics such as size, usage time, and energy used. Various home appliances are used at home, from small appliances such as hair dryers and coffee pots to large appliances such as refrigerators and washing machines. In the case of a dryer, it is used for a short time within a few minutes, but in the case of a refrigerator, it has the characteristic of being operated for 24 hours. It is necessary to properly manage energy use by organizing data such as the amount of energy used by each of these various home appliances, operation cycle, and time of use so that energy use is not concentrated[1][2][3][4].

Various home appliances are used in the home. Some products are used individually, but some products are used together with other products or used after one product is used. In some cases, the user resides around the home appliance while the appliance is being used, but some products only are accessed at the start and endpoints of use. It is necessary to analyze home appliances in consideration of these characteristics[5][6][7][8].

In the case of a dishwasher, it has the characteristic of using a very large amount of energy through processes such as high-temperature washing, steam sterilization, and high-temperature drying for sterilization. In the case of a dryer, a lot of electrical energy is required because it maintains a high temperature for drying laundry. In particular, since a dishwasher or dryer is used in succession to other home appliances rather than being used alone, it has the characteristic of consuming energy for a long time. The dishwasher is used after cooking, such as induction or electric rice cooker, and dryer is used after washing machine[9][10].

In this paper, one of the machine learning techniques, LSTM (Long Short-Term Memory Models), was used to analyze the home appliance usage data to figure out the correlation between devices. Since the LSTM has a memory, the past values can be reflected in the calculation of the current values. Therefore, if the current values are affected by the past values, it can be considered that there is a temporal correlation between the two data. Using these features, we analyzed the home appliance usage data with the LSTM and analyzed whether the correlation between the home appliance data appeared in the learning results of the LSTM. Through data analysis published online, it was possible to derive correlations between data using LSTM.

TABLE I. HOME APPLIANCE PENETRATION AND POWER

Item	Penetration Rate	Power Consumption [kWh]
TV	1.13	312.3
Air Cleaner	0.27	176.2
Refrigerator	1.01	364.2
Electric Kettle	0.46	122.2
Electric Fan	1.53	34.5
Washing Machine	0.99	281.5
Air Conditioner	0.97	689.7
Air Fryer	0.21	160.6
Hot Water Mat	0.17	290.4
Vacuum Cleaner	0.56	146.4
Clothes Dryer	0.07	504.7
Electric Iron	0.51	100
Electric Mixer	0.46	44.1
Electric Rice Cooker	0.9	377.3
Electric Mat	0.71	167.2
Electric Hitter	0.04	442.7
Microwave	0.75	97.9
Dehumidifier	0.13	182.3

II. LSTM AND DATA

A. LSTM

The LSTM technique, a type of RNN (Recurrent Neural Network), is one of the machine learning techniques and is a machine learning technique that has the ability to remember previous data for a long time to solve the long-term dependency problem of basic RNN. LSTM has the state of the previous cell and various gates (input gate, output gate, forget gate).

The input gate is a gate for storing current information. The input value at the current time is multiplied by the weight input to the input gate, and the hidden state at the previous time is multiplied by the weight value transmitted to the input gate. is entered. The value obtained by multiplying the input value at the current time by the weight value transmitted to the input gate and the value obtained by multiplying the hidden state at the previous time by the weight transmitted to the input gate are added to the hyperbolic tangent function. The amount of information to be remembered is determined using the value passed through the sigmoid function and the value passed through the hyperbolic tangent function.

The delete gate is a gate that determines whether or not to delete a memory. It inputs the current input value and the previous hidden state as a sigmoid function and outputs the amount of information that has gone through the deletion process. The closer the output value is to 0, the more it has been deleted, and the closer it is to 1, the more it has been remembered. This is used to calculate the state of the cell. The output gate determines the hidden state at the current time based on the input value at the current time and the value of the hidden state at the previous time passing the sigmoid function. As the cell state value passes through the hyperbolic tangent function and is calculated with the value of the output gate, the value is filtered and becomes hidden.

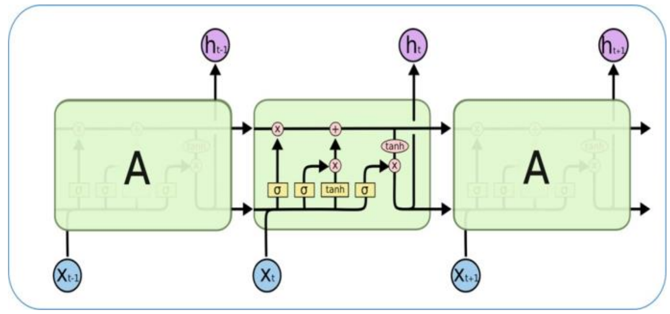

Fig. 1. Basic concept of LSTM

It has the characteristic of determining whether to maintain current information and propagate it to the future through a gate, or to stop propagation by deleting it, and then pass the result to the next cell so that the value of the cell can be propagated. Through this propagation, past values can affect present values and present values can affect future values. If you interpret this in reverse, it can be seen as referring to the past value when determining the current value, and referring to the current value when determining the future value. By checking how much influence past values have when determining current values, you can determine whether there is a correlation in time between the two data. By utilizing the characteristic of LSTM to remember the past and reflect it in the present, we believed that past home appliances that affect currently used home appliances could be found in the usage patterns of home appliances, and actual data was entered and analyzed.

B. Data

UK Domestic Appliance Level Electricity (UK-DALE-2017) dataset was used to analyze the energy use patterns of home appliances in this study. The dataset are records of the energy consumed by 50 British households from 2012 to 2017. The whole house main power demand and power demand from individual appliances in the house were recorded in every six seconds [12][13].

In this study, we analyzed the energy usage details of each home appliance in 5 out of 5 households. Household number 5 has a TV, Electric Iron, Toaster, PC, Electric Kettle, Oven, Electric hob, Dishwasher, washer dryer, and vacuum cleaner. Hourly energy consumption history data for 25 home appliances, including vacuum cleaners, are recorded.

TABLE II. HOME APPLIANCE LIST

0	aggregate	5	24 inch lcd bedroom	10	ps4	15	home theatre amp	20	electric hob
1	stereo speakers bed	6	treadmill	11	steam iron	16	sky hd box	21	dishwasher
2	i7 desktop	7	network attached sto	12	nespresso pixie	17	kettle	22	mircowave
3	hairdryer	8	core2 server	13	atom pc	18	fridge freezer	23	washer dryer
4	primary tv	9	24 inch lcd	14	toaster	19	oven	24	vacuum cleaner

C. Data Processing

In this study, the energy consumption history of household 5 out of 5 households by home appliance was analyzed. In household No. 5, energy use records for 25 household appliances such as TV, iron, toaster, pc, kettle oven, electric hob, dishwasher, washer-dryer, and vacuum cleaner are recorded. The data usage was recorded every 6 seconds. For analysis, the data were accumulated in 10-minute units and used. Figure 2 shows the data processing process.

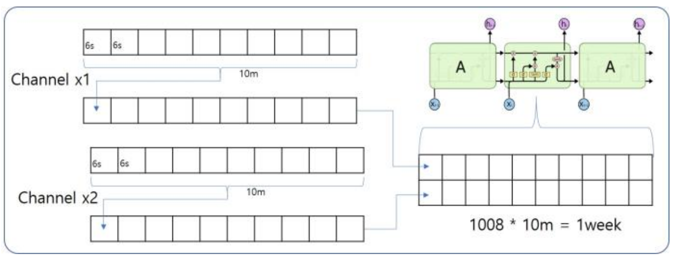

Fig. 2. Data Processing

Since normal family life has a characteristic that repeats every week, the learning model was constructed to predict one future value based on the data for one week. The input/output of the model was set as the input (dataset_x1, dataset_x2) of two home appliance usage history and the output (dataset_y1) of the usage history of one home appliance. Figure 3 shows the LSTM test code briefly.

```
n_past = 1008
n_future = 1
nx_features = 2
ny_features = 1

readcol_x1 = ['datetime', 'electric_hob' ]
readcol_x2 = ['datetime', 'dishwasher']
readcol_y1 = ['datetime', 'dishwasher']

dataset_x1 = read_csv('house_5/channel_all.csv', header=0, infer_datetime_format=True, parse_dates=['datetime'], index_col=['datetime'], usecols=readcol_x1, encoding = "utf-8")
dataset_x2 = read_csv('house_5/channel_all.csv', header=0, infer_datetime_format=True, parse_dates=['datetime'], index_col=['datetime'], usecols=readcol_x2, encoding = "utf-8")
dataset_y1 = read_csv('house_5/channel_all.csv', header=0, infer_datetime_format=True, parse_dates=['datetime'], index_col=['datetime'], usecols=readcol_y1, encoding = "utf-8")

dataset_x1 = dataset_x1.values.reshape(len(dataset_x1), 1)
dataset_x2 = dataset_x2.values.reshape(len(dataset_x2), 1)
dataset_y1 = dataset_y1.values.reshape(len(dataset_y1), 1)
dataset = pd.DataFrame(np.hstack((dataset_x1, dataset_x2, dataset_y1)))

encoder_inputs = tf.keras.layers.Input(shape=(n_past, nx_features))
encoder = tf.keras.layers.LSTM(1, return_state=True)
encoder_outputs= encoder(encoder_inputs)
encoder_states = encoder_outputs[1:]

decoder_inputs = tf.keras.layers.RepeatVector(n_future)(encoder_outputs[0])
decoder = tf.keras.layers.Dense(nx_features)(decoder_inputs)
decoder_outputs = tf.keras.layers.TimeDistributed(tf.keras.layers.Dense(nx_features))(decoder)
model = tf.keras.models.Model(encoder_inputs,outputs=decoder_outputs)

reduce_lr = tf.keras.callbacks.LearningRateScheduler(lambda x: 1e-3 * 0.90 ** x)

model.compile(optimizer=tf.keras.optimizers.Adam(), loss=tf.keras.losses.Huber())
history=model.fit(X_train,y_train,epochs=10,validation_data=(X_test,y_test),batch_size=156,verbose=1)
```

Fig. 3. LSTM Source

III. TEST RESULT

To derive home appliances with temporal correlation from the energy use data for each household appliance in the UK, a dishwasher, a kitchen appliance, was selected as the main analysis target. In general, a dishwasher is used after cooking for meal preparation. In household number 5 selected as the analysis target, it was analyzed that toaster, kettle, oven, electric hob, etc. were used together with Dishwasher in the kitchen as related kitchen appliances.

Figure 4 shows some example records that show the usage of general kitchen appliances and dishwashers. In (A), the house owner used the kitchenware such as kettle, oven, and induction for breakfast preparation from around 4 am on July 14, 2014, and used the dishwasher to wash dishes from 5 am. In (B), in the evening of July 19, 2014, It was found that the toaster, kettle, oven, and induction were used from around 22:00, and the dishwasher was used from around 22:30. Through the analysis result, it was confirmed that house owner used the dishwasher after general kitchen equipment such as an oven or induction cooker was used. As a result, it can be seen that there is a correlation in time between the use of the general kitchen electric appliances and the dishwasher. It is the basis for judging that the dishwasher is more likely to be used after general kitchen appliances are used.

datetime	kettle	oven	electric_hob	dishwasher
2014-07-14 3:10	195	0	0	0
2014-07-14 3:20	196	0	0	0
2014-07-14 3:30	198	0	0	0
2014-07-14 3:40	196	0	0	0
2014-07-14 3:50	198	0	0	0
2014-07-14 4:00	200	180698	0	0
2014-07-14 4:10	89030	99063	16098	0
2014-07-14 4:20	200	68349	157037	0
2014-07-14 4:30	204	912	5645	0
2014-07-14 4:40	197	1095	0	0
2014-07-14 4:50	194	517	0	0
2014-07-14 5:00	195	0	0	7919
2014-07-14 5:10	199	0	0	98886
2014-07-14 5:20	198	0	0	156811
2014-07-14 5:30	198	0	0	65935
2014-07-14 5:40	194	0	0	9425
2014-07-14 5:50	197	0	0	7411
2014-07-14 6:00	196	0	0	8011
2014-07-14 6:10	201	0	0	137810
2014-07-14 6:20	199	0	0	106887
2014-07-14 6:30	194	0	0	0
2014-07-14 6:40	199	0	0	269
2014-07-14 6:50	194	0	0	0
2014-07-14 7:00	197	0	0	0

(A)

datetime	toaster	kettle	oven	electric_hob	dishwasher
2014-07-19 21:40	8	198	0	0	0
2014-07-19 21:50	7	200	0	26599	0
2014-07-19 22:00	7	198	0	70072	0
2014-07-19 22:10	22454	63073	148098	28958	0
2014-07-19 22:20	12	203	1273	0	0
2014-07-19 22:30	17	202	1274	0	280
2014-07-19 22:40	13	200	376	0	95191
2014-07-19 22:50	10	200	0	0	19070
2014-07-19 23:00	13	204	0	0	103667
2014-07-19 23:10	17	198	0	0	9603
2014-07-19 23:20	13	201	0	0	115853
2014-07-19 23:30	13	201	0	0	62256
2014-07-19 23:40	13	202	0	0	9552
2014-07-19 23:50	19	198	0	0	9578
2014-07-20 0:00	16	199	0	0	8672
2014-07-20 0:10	13	203	0	0	7804
2014-07-20 0:20	10	201	0	0	132116
2014-07-20 0:30	13	198	0	0	125197
2014-07-20 0:40	7	202	0	0	507
2014-07-20 0:50	15	200	0	0	278

(B)

Fig. 4. Usage records of Kitchen appliances and dishwasher

Figure 5 shows the usage records between general household appliances and dishwashers, not kitchen appliances. As general household appliances, TVs, treadmills, and the like were referred to. Looking at (A) in Figure 5, it can be seen that the dishwasher operates at some times while the TV is on, and the treadmill is not used while the dishwasher is being used through (A) or (B). Based on the analyzed results, it is difficult to see that there is a correlation between the use time between household appliances other than kitchen appliances and dishwashers. Just because a TV or general household appliances are used, it cannot be judged that a dishwasher is likely to be used.

datetime	primary_tv	24_lcd_bedroom	treadmill	dishwasher
2014-07-14 3:00	10	0	1	0
2014-07-14 3:10	12	0	0	0
2014-07-14 3:20	13	0	1	0
2014-07-14 3:30	19	0	1	0
2014-07-14 3:40	21	0	2	0
2014-07-14 3:50	9	0	1	0
2014-07-14 4:00	5350	0	1	0
2014-07-14 4:10	6790	0	0	0
2014-07-14 4:20	6736	0	1	0
2014-07-14 4:30	6929	0	2	0
2014-07-14 4:40	6712	0	0	0
2014-07-14 4:50	6800	0	3	0
2014-07-14 5:00	6705	0	1	7919
2014-07-14 5:10	6832	0	0	98886
2014-07-14 5:20	6833	0	1	156811
2014-07-14 5:30	6841	0	2	65935
2014-07-14 5:40	6698	0	1	9425
2014-07-14 5:50	6738	0	3	7411
2014-07-14 6:00	6768	0	7	8011
2014-07-14 6:10	6838	0	2	137810
2014-07-14 6:20	6929	0	2	106887
2014-07-14 6:30	6642	0	2	0
2014-07-14 6:40	6378	0	4	269
2014-07-14 6:50	5234	0	4	0
2014-07-14 7:00	485	0	2	0

(A)

datetime	primary_tv	24_inch_lcd_bedroom	treadmill	dishwasher
2014-07-19 21:00	22	0	3	0
2014-07-19 21:10	14	0	0	0
2014-07-19 21:20	19	0	4	0
2014-07-19 21:30	12	0	1	0
2014-07-19 21:40	10	0	0	0
2014-07-19 21:50	13	0	1	0
2014-07-19 22:00	12	0	4	0
2014-07-19 22:10	15	0	0	0
2014-07-19 22:20	22	0	3	0
2014-07-19 22:30	19	0	5	280
2014-07-19 22:40	26	0	2	95191
2014-07-19 22:50	25	0	5	19070
2014-07-19 23:00	15	0	5	103667
2014-07-19 23:10	23	0	4	9603
2014-07-19 23:20	18	0	3	115853
2014-07-19 23:30	12	0	2	62256
2014-07-19 23:40	25	0	3	9552
2014-07-19 23:50	24	0	3	9578
2014-07-20 0:00	21	0	3	8672
2014-07-20 0:10	26	0	1	7804
2014-07-20 0:20	19	0	6	132116
2014-07-20 0:30	26	0	8	125197
2014-07-20 0:40	18	0	5	507
2014-07-20 0:50	22	0	3	278
2014-07-20 1:00	20	0	2	0
2014-07-20 1:10	25	0	5	0
2014-07-20 1:20	18	0	8	0
2014-07-20 1:30	22	0	2	0

(B)

Fig. 5. usage records of general household appliances and dishwashers

Based on the energy use records of home appliances, it was confirmed that there is a correlation between the kitchen equipment and the dishwasher, and it was analyzed whether the correlation could be derived using LSTM, a machine learning technique. As mentioned above, for analysis, data recorded in units of 6 seconds was accumulated and collected in units of 10 minutes, and past data at an interval of 1 week was learned to predict future data 10 minutes later. Through the data learning process, the hidden state value of the cell in the model was finally confirmed. Since a total of 1008 values are received as input, 1008 cells exist in the model, and each cell has a hidden state.

In Figure 6, the energy use records of induction (electric hob) and dishwasher (electric hob) are set as inputs of LSTM, and the use of dishwashers is set as output to predict future use of dishwashers based on induction and dishwasher use records. made to do The results shown in Figure 6 are the hidden state values of the cells of the LSTM that predict whether or not the dishwasher will be used through induction usage records, showing values for 1008 data for a week. From Figure 6, when induction and dishwasher are input, in most cases, it has a value of around -0.6, but it can be seen that the second time has a value of 0.2. This can be analyzed as a pattern in which induction is used at this point and then the dishwasher is used. The cell value of the LSTM is determined by the calculation results of the input gate and the forget gate. If the cell value changes in the opposite direction, it can be determined that the memory state has changed at that point, which indicates that the dishwasher is used after induction. It can be viewed as being recorded in memory.

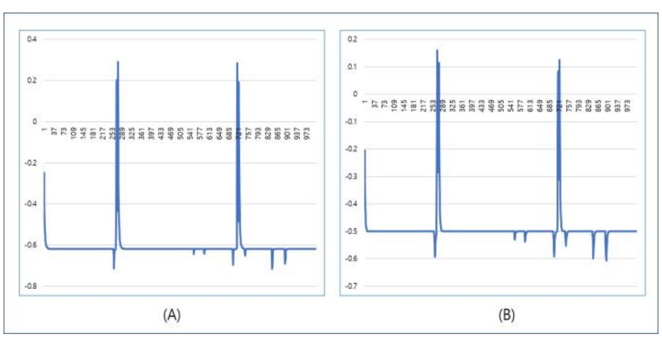

Fig. 6. LSTM Result of induction and dishwasher

Figure 7 shows the TV and dishwasher analysis result, not the kitchen appliance. As in the case of induction, data from the past week was used to determine whether to use it 10 minutes later. In Figure 7, unlike Figure 6, it can be seen that the value changes only in one direction. It can be determined that the TV usage record does not affect the dishwasher usage record. Comparing Figure 6 and Figure 7, in Figure 6, the value changes from minus to minor and then to plus, but in Figure 7, it can be seen that the value changes only in one direction, from plus to minus or from minus to minus. Through this, it is determined that the cell value changes in both directions when there is a correlation in terms of use, but changes only in one direction when there is no correlation. Conversely, when the LSTM results change in only one direction, the correlation between data is small, but when the LSTM results change in both directions, it can be judged that there is a high possibility of correlation.

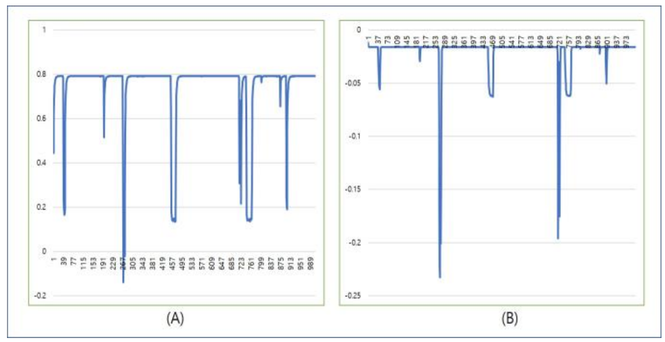

Fig. 7. LSTM result of TV and dishwasher

IV. Conclusion

As population and energy consumption increase dramatically around the world, the Earth's climate is seriously changing. In order to respond to rapid changes, carbon neutrality must be practiced, but this is recognized as only an industry problem. Even ordinary households need to make efforts to save energy in order to respond to climate change, and in order to contribute to reducing carbon emissions at home, it can be used to reduce energy consumption by identifying the characteristics of the usage correlation of home appliances used at home. It must be possible. In this paper, we analyzed public data using LSTM, one of the machine learning techniques, to identify correlations in usage between home appliances. LSTM consists of an input gate, a deletion gate, and an output gate. To overcome the shortcomings of the existing RNN technique, it has a memory cell that determines whether to maintain the value based on the past and present values, so the past value can be reflected in the current value calculation.

In LSTM, if the current input value is influenced by the past input value, there is a correlation in time between the two input data. Based on these characteristics of LSTM, we analyzed energy use record data of home appliances used in British homes published online. We input the usage records of representative home appliances used at home into LSTM and analyzed whether a correlation in usage time between home appliances appears in the learning results of LSTM. By comparing and analyzing general home appliances such as TVs and kitchen appliances such as induction cookers, we were able to derive correlations between data using LSTM. Using this, we can provide a function to select data with correlations between home appliances used at home. It is expected that it can be implemented.

ACKNOWLEDGMENT

This work was supported by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) and the Ministry of Trade, Industry & Energy (MOTIE) of the Republic of Korea (No. 20202020800290, 20192010107290)

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