The University of Hong Kong

# ELEC7021 Dissertation

## Deep Reinforcement Learning on Energy Management for Buildings in Hong Kong

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# Contents

# 1. Project Plan and Domain

The whole idea centers on the Energy Management in Hong Kong University Residential Halls. I will propose several artificial intelligence learning methods to predict the energy consumption pattern in certain buildings either in short terms (in priority) and long-terms, which can be promoted to other similar buildings even the whole cities. The inherent mechanism of electricity generation and the supply-demand relationship between the producer and consumer decides the importance of knowing the accurate consumption trend of electricity. In total, the power production and the consumer demand must be balanced to maintain the robustness of the whole system.

In Hong Kong, there are two main grid companies, the CLP and HK Electric. Being informed that the CLP have formed the league with CSG (China Southern Power Grid Company Limited), we know that they can mutually achieve power transmission in order to keep the whole demand balanced whenever situation meet, i.e., if in special days/period the consumption of electricity in Hong Kong goes high, CSG can transmit the power to the CLP, in converse, the CLP can sell the redundant power to make profit. Otherwise, we can use the prediction value to evaluate the load of whole system, which will enhance the performance of automatic generation control (AGC) in grid.

However, we cannot make prediction just by human experience, so I plan to design a reliable method using several machine learning algorithms to achieve a high accuracy estimation of building electricity consumption pattern by day-ahead, and then several days ahead and compare the result of different methods, form a solid algorithm to maintain the robustness and balance of the system.

On the other hand, how to keep the models robust is another issue needed to be done.

# 2. Dataset Selection and Feature Engineering

I decide to use the historical electricity/energy consumption data sampled from HKU residential hall by BlueSky (Released by Benny via GPU server).

**First**, we should implement the primary preprocess of the dataset: cleaning the data, make up the missing value and delete the no-need value (low scale of dataset, or have too many blank values).

**Second**, normalization is needed. Since normalization can be of help to the training process and generally get better performance, we may control the scale of data into [0,1] and N (0,1). After finishing the training process, we should de-normalization of the data and then evaluate the accuracy of the result.

**Second**, dividing the dataset into appropriate situations is necessary. Since Hong Kong located in tropical region, so we can divide the round year into two parts rather than four seasons: the relatively cold weather (from Dec. to Feb. of the next year) and the warm weather (the left days), or we can simply add a feature to express it.

**Third**, the Feature Engineering. There is no doubt that the potential elements which can affect the behavior of electricity consumption are various, from the temperature, humidity, the heating degree days and cooling degree days, the holiday days to the different functions of buildings, and maybe even the economic trend may have impact on the whole performance. Besides, in this case, I extract the other features from HKO, and try to use the needed ones among them.

**Finally**, to achieve the better performance, in this process, we should analyze these elements and the label (true value), then select the suitable features, which can be used to prohibit the underfitting and overfitting, even take up the less computing resources. I will form an Auto-Encoder to encode and decode the datasets, which will help me to re-construct the whole data.

# 3. Implementation Method

Since the datasets are time-series, I plan to select Linear Regression, SVR, Random Forest, Long-Short-Term Memory, One-Dimension Residual Network and Reinforcement Learning. Even though all of them are good, I will select some of them that match the situation better.

**For example**, I can use the *dummy prediction* (e.g. roughly use the last day value as the prediction value) as the benchmark and make the LR or SVR and Neural Network groups for comparison.

After the training process, I plan to compare the accuracy expressed by these models, and ensemble the algorithms by distribute the different weights to achieve the higher performance, or just draw the conclusion about the suitable method we can use.

### 3.1 Extra idea here:

The above-mentioned machine learning algorithms are only used appropriate for **small steps** prediction, while predicting the **long steps** value, based on my own experience and some past papers, the bad results were gained and thus the new method need to be applied.

In this case, some papers from 2014 pointed out that the Encoder-Decoder structure-based LSTM algorithm, or we can call it **Sequence to Sequence Architecture,** are much suitable for this situation. Hence, in my plan, we can compare the result between the small-step and long-step prediction use the S2S as well in the applied dataset.

## 4. Loss Function Design/Selection& Model Evaluation

In normal case, we can choose MSE, RMSE etc. to be our loss function and use metric equals accuracy to estimate the overall performance of our algorithm. They are general criterion.

### 4.1 Extra idea here:

However, in energy prediction cases, esp. in the estimation of electricity consumption, we generally would rather predict the higher consumption value than lower prediction value when compared to the true value, because the lower prediction value may result in the false judgement and estimation of the producer, which would be a potential hazard and result in the insufficient electricity supply, while higher prediction may just lead to the wastage.

In short, the loss of higher prediction is smaller than the lower prediction, so we may use a discriminatory way, by means of different loss function from the general version like MSE and RMSE, when we are training the model.

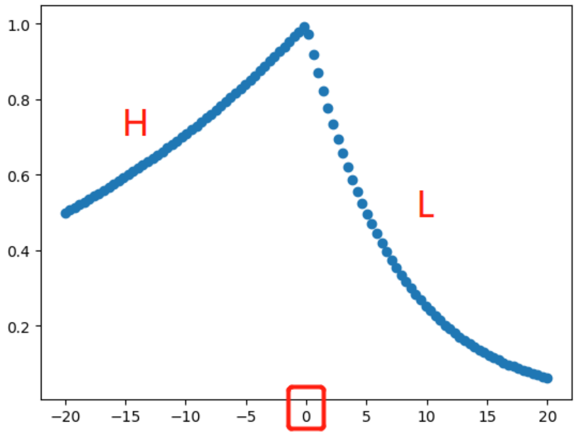

Figure 1 The "score" Achieved by Predicted Value

Figure 1 shows the **score** function which indicate the evaluation of performance when compare the prediction and true value: The '**H**' means the prediction value higher than the true one, and '**L**' means the prediction value lower than the true value. The higher accuracy we achieve, the higher score we may get, and the score decays faster in '**L**' case than the '**H**' case due to the practical significance in real world like mentioned before. Conversely, the score function can be transformed to the loss function if we use 1 minus the score function.

The code of loss function is in the attachment file (Use TensorFlow).

## 5. What is the Result and Impact?

The plan divides the buildings into different function units, divides the all-round year into two parts (warm and cold). I will try to dig out the implicit regulations of consumption values from the consumer side, aiming at knowing the trend of consumption behavior, such that:

1. The administrator of the building can detect the abnormal consume behavior to eliminate the potential risk ahead.
2. The controller of the grid can get ready for the coming peak or trough demand for the electricity, which will prohibit the wrong load distribution to cause the wastage or insufficient power supply.
3. Provide convenience to the maintenance of the grid system, since it can maintain the machines in off-peak season and spare no effort in peak season.

## 6. Still need to know:

In my plan, I try to emphasis the importance of predict the consumption of electricity accurately in certain buildings in Hong Kong, but until now it is just a **qualitative** evaluation but not a **quantitative** analysis.

Hence, I think we should figure out the way to calculate the differences between the accurate prediction model and the normal/unpredicted power distribution by mathematic functions or numerical conclusions, either from methods proposed in the existing literature or empirically design a function, which means by this algorithm can make it avoid the source wastage and bad experience of the consumer.

## 7. Further Idea (If enough time)

Based on the energy consumption prediction result, I would like to make a Feedback system design involved with Wind Power. The idea comes from that Hong Kong Electric& HKO& Government deployed the Wind Engines in Lamma Island, HKO Station and Shek Kwu Chau, and also introduced some policies to encourage common people install the micro wind engine to sell the redundant electricity to the HK Electric, the price of which is much higher than the consumption side of the normal electricity.

Hence, maybe we can do something related to this. The needed data can be gained from the HKO, based on the function of wind-power generation, we can also calculate the output of the wind power engine. Even though it is a virtual assumption, I believe it has its own mean, because all the dataset is real, and practical significance cannot be totally ignored.

Figure 2 Wind-powered generator

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