Integration of IoT and Enhanced LSTM framework for water-cooled chiller COP forecasting

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***Abstract*— The water-cooled chiller is one of the indispensable equipment in each building. Due to long-term use or improper operation, it is easy to cause components of the equipment to be wore out, generating additional energy consumption, and even causing malfunction. In this study, we used technology of IoT (Internet of Things) to upload the operating parameters and data in each period of every water-cooled chiller to the cloud, and presented the visualized result. Managers were able to understand the current status of each water-cooled chiller much easier with the visualized results, and at the same time we conducted predictive analysis on the collected water-cooled chiller data. If we can predict the COP value trend accurately, managers can effectively arrange personnel to carry out the maintenance work of each water-cooled chiller to reduce unnecessary energy and cost losses.**

Keywords—Water-cooled, IoT, COP, Forecast, Enthalpy

I. Introduction

The Coefficient of Performance of a water-cooled chiller represents its ability of refrigeration and operating condition. Through the performance, it can be decided whether the water-cooled chiller needs to maintain or clean. COP of every water-cooled chiller is in a certain range according to the locating environment or types of compressor, however, the function of the chiller decrease due to long-term use, equipment worn out, improper operation and maintenance or other factors. In Breuker's[1] research about how machinery breakdown affect the refrigerating ability and function of an air conditioner, when the leakage of the refrigerant reach 14%, the ability of refrigeration decrease 8% while COP decrease 4.6%, and when the fouling of the condenser reaches 28%, the ability of refrigeration decrease 4.8% while COP decrease 4.4%. Once the function decline severely, lots of energy can be wasted, life of the water-cooled chiller become shorter, and malfunction occurs more which means the need of maintenance gets higher as well. Therefore, we installed sensor accordingly to every water-cooled chiller and uploaded the results to the cloud through IoT, then we predicted the COP value trend of every chiller by analyzing the information which is collected by Seq2Seq with thermodynamics and theories of different scholars. Manager can arrange the maintain schedule efficiently with our prediction. Attention mechanism is added in our COP prediction, using the temperature of overheated gaseous refrigerant from the compressor discharge(T_{hg}), saturated evaporate pressure(P_{ev}) and saturated condensate pressure(P_{cd}) to calculated the Enthalpy value. The Enthalpy value, discharge temperature of condenser and evaporator can be used as a reference parameter for training model, which helped to increase the accuracy of the prediction.

II. Research Method

In this chapter we are introducing the structure of our experiment system and research method, they are mainly separated into two parts, model training and water-cooled chiller cloud platform. Model training can be divided into three section which are data cleaning model, COP calculation, and Seq2Seq LSTM model in this research. As for cloud platform, we are going to explain how we visualized the collected data and present the COP value trend prediction on cloud platform through the trained model.

1) Model Training

a) Data Cleaning: As Fig. 1 shows, we installed sensors in water-cooled chillers and uploaded these data to cloud server. Table 1 is the original data, including the information of operating and closing status, uploaded from the chillers. The power consumptions are 0 in the last two data on the table, therefore they should be filtered out since they are not in operation status. In addition, some data were lost which shows "Null" on the table and because every data has high relevance, we determined to discard the data to assure the completeness rather than padding the data by square numbers.

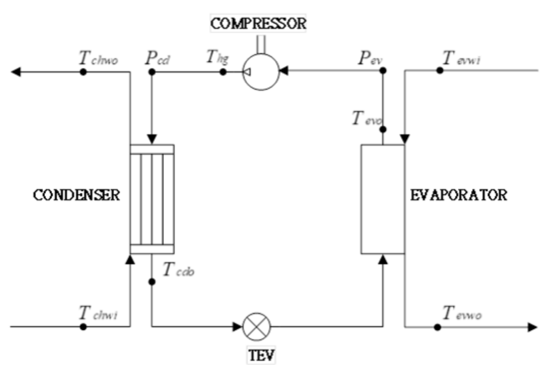

Fig. 1 Sensor locations in water-cooled chiller

TABLE I. DATA OF WATER-COOLED CHILLER

	Data 1	Data 2	Data 3	Data 4	Data 5
Unix time	1588262429	1588262612	1588262797	1588263155	1588263338
Ice Water Outlet Temperature	11..8	12.1	12.2	11.9	11.8
Ice Water Inlet	9.4	9.7	9.6	9.3	9.6

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Temperature					
Cooling Water Inlet Temperature	25.1	25.5	25.4	25.5	25.4
Cooling Water Outlet Temperature	26.3	26.8	26.8	27	26.9
Right Saturated Condensation Temperature	35.7	null	37.1	37.9	37.5
Right Saturated Evaporation Temperature	5.2	null	5	4.3	4.1
Left Saturated Condensation Temperature	12.2	11.7	12.4	11.3	10.7
Left Saturated Evaporation Temperature	27.8	27.2	27.6	27.9	27
Right Machine Low Pressure	2.39	2.51	2.41	2.41	2.47
Right Machine High Pressure	52	52.4	54.7	56.3	59.1
Left Machine Low Pressure	3.27	3.31	3.37	3.47	3.49
Left Machine High Pressure	7.95	8.04	7.94	8.08	7.99
Power Consumption	63.2	63.1	64.5	0	0

b) eature data result: In our research we found out feature data which affected COP for training perdition model, the data are three-point temperature of refrigerant circulation (Enthalpy value h1, h2, h3), evaporator discharge temperature(T_{evo}), and condenser discharge temperature(T_{cdo}). The way of calculating COP is based on the formula (1) that Industrial Technology Research Institute[2] proposed. The enthalpy value h1、h2、h3 were obtained respectively by finding out the corresponding points in the Mollier diagram[3] with compressor discharge pressure(T_{hg}), saturated evaporate pressure(P_{ev}) and saturated condensate pressure(P_{cd}), shows as Fig. 2.

$$\mathrm{COP} = \frac{(\int_{t_1}^{t_2} h_1\, dt - \int_{t_1}^{t_2} h_3\, dt)}{(\int_{t_1}^{t_2} h_2\, dt - \int_{t_1}^{t_2} h_1\, dt)} \tag{1}$$

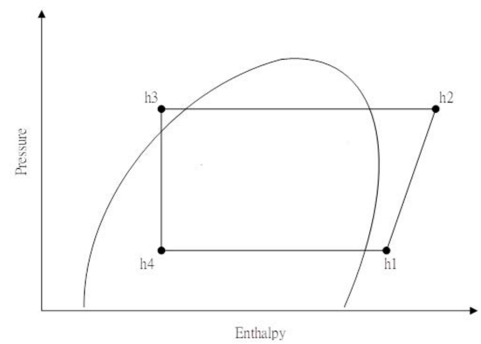

Fig. 2 Corresponding points of enthalpy value in Mollier diagram

c) Model structure: We used Seq2Seq(Sequence to Sequence) network framework for model training. The Encoder and Decoder concept in the framework could assure the unity of different length data inputted from water-cooled chillers and added different attention mechanism individually, they have better prediction result compare to regular LSTM model. The description of Encoder and Decoder concept from the LSTM model improved by our research are as below:

i) Encoder with soft attention: Fig. 3 is the first part of the model, which we inputted our feature data as Encoder module. In the module, Enthalpy value of evaporator discharge represents as h1, Enthalpy value of compressor discharge represents as h2, Enthalpy value of condenser discharge represents as h3, cold water charge temperature represents as Tevwi, and cooling water temperature represents as Tcdwi. As the input sequence data St, we added Soft attention mechanism that gave different weights value at according to the enthalpy value, cold water charge and discharge temperature and cooling water charge and discharge temperature in each time sequence data. Multiplying the input number sequences St and weights value at, xt was obtained to be the input data for LSTM model, and the hidden status when outputting will be decided by the hidden layer states inputted in the last moment, as formula (2) to (6).

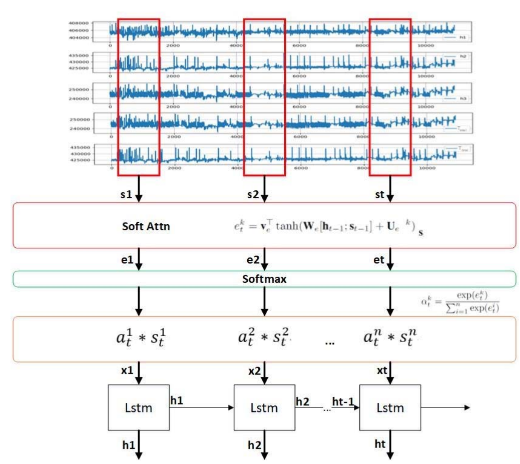

Fig. 3 Encoder structure in this research

$$s_t = [h1_t; h2_t; h3_t; T_{evwi_t}; T_{cdwi_t}] \tag{2}$$
$$e_t^k = v_e^T \tanh(W_e \cdot [h_{t-1}, s_{t-1}] + U_e s^k) \tag{3}$$
$$a_t^k = \frac{\exp(e_t^k)}{\sum_{i=1}^{n} \exp(e_t^i)} \tag{4}$$
$$x_t = (a_t^1 \cdot s_t^1 + a_t^2 \cdot s_t^2 + \cdots + a_t^n \cdot s_t^n)^T \tag{5}$$
$$h_t = LSTM(h_{t-1}, x_t) \tag{6}$$

ii) Decoder with hard attention: Fig. 4 is the second part of the prediction model, the input data in this part is the status of each hidden layer states h1, h2,…, ht that Encoder output. The Hard attention which was imported in this stage was focused on the data in past few days, the prediction point was different in every focusing time. The date which was important comparatively at that moment were labeled as 1 while the other data were labeled as 0. As for the linear layer, ReLu(rect-fied Linear Units) was used to prevent the problem of gradient disappearance, as formula (7) to (10) show. Each moment has different context vector, and finally this sequence Ct was input to LSTM model for prediction.

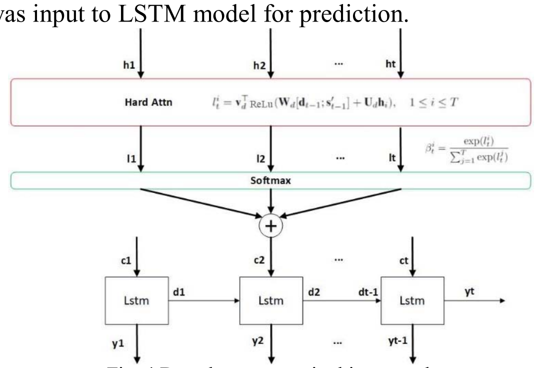

Fig. 4 Decoder structure in this research

$$l_t^k = v_e^T \mathrm{ReLu}(W_e \cdot [h_{t-1}, s_{t-1}] + U_e h_i) \tag{7}$$
$$\beta_t^i = \frac{\exp(l_t^i)}{\sum_{j=1}^{T} \exp(l_t^j)} \tag{8}$$
$$c_t = \sum_{i=1}^{T} \beta_t^i h_i \tag{9}$$
$$y_t = LSTM(y_{t-1}, w^T[y_{t-1}; c_{t-1}] + b) \tag{10}$$

b) Set up cloud platform: We used MVC(Model-view-controller)[4]structure as our cloud platform. The server got data for each water-cooled chillers from cloud database and visualized the received information for the user, meantime, input information into well-trained model, the server predicted COP and presented the result on the website, as Fig. 5. Operation area divided multiple data transmission item into topics, each types of message are sending and receiving in different level, therefore it transmits massage smoothly to the receiving end without conflict. When building network, water-cooled chiller needs to register the specific topic to transmit message, as Fig. 6 shows.

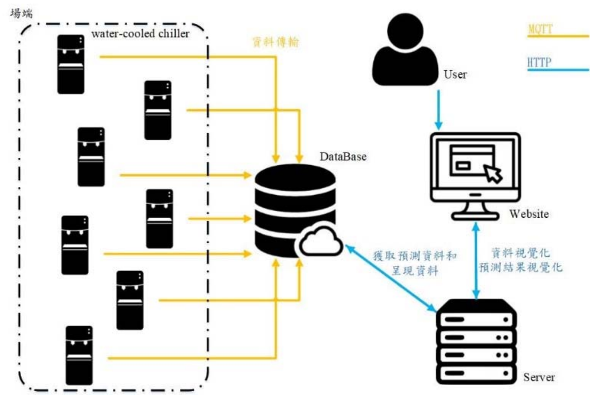

Fig.5 Structure of cloud platform

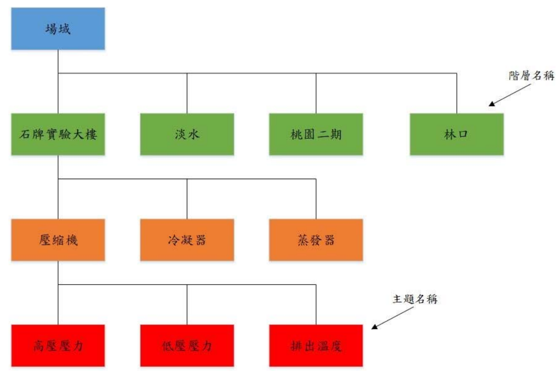

Fig. 6 Message transmission level

Later, connect the water-cooled chiller in each operation area and transform data to MQTT through NB-IoT and LoRa receiver, then transfer the data to cloud.

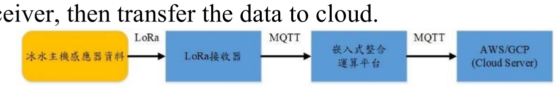

Fig. 7 Transmission flow chart for our research

Fig. 7 is a transmission flow chart for our research, sensing information was released as the frequency of once in two minutes. These data were transmitted by NB-IoT or LoRa, after arranged initially, the data will be transmitted through MQTT to a small embedded calculating platform nearby for temporary storage. When transmitted by MQTT, we used AES to secure and raise the reliability of the data, also, when embedded calculating platform received signal from NB-IoT or LoRa modal as MQTT format, it checked whether the data is correct or not and save the correct data, afterwards, it released the data once in two minutes to cloud platform for synchronize and save through MQTT, the transmitting process is also protected by AES. We used the cloud service that Amazon Web Service(AWS) provide and save the data in the MpngDB cloud database.

III. Experimental Data

In this research we used the data of five water-cooled chillers during January to May, 202 and filtered out the incomplete data. We separated the training data into three parts for deep learning as below:

1) Training set: Data used for training model

2) Validation set: Used for verify the correctness of the model to prevent overfitting

3) Testing set: Data for testing finished training model and calculated the quality of the model

Training and Validation sets contain the data of the whole year of 2019, and testing set contains the data during March and April, 2020. Table 2 and 3 are the detail information of model training and testing.

TABLE II. TABLE 2 EXPERIMENT TRAINING DATA

Data Set	Number of Data	Number of Columns	Time per Unit
Water-cooled chiller (one per year)	63204	9	2 min

TABLE III. TABLE 3 EXPERIMENT TESTING DATA

Data Set	Number of Data	Number of Columns	Time per Unit
Water-cooled chiller (two per two months)	5500	9	2 min

Model COP trend prediction: In this research we took advantage of the processed featured information to predict future COP trend. Different observe length of data can be inputted to prediction model for long-term prediction, and the prediction result of error rate was presented per unit, the value difference between prediction value and actual value were calculated by MAE. We predicted the water-cooled chiller COP by selecting the optimum model from 5000 epoch, by comparing different water-cooled chiller and model, the experiment result could be conspicuous.

i) Different water-cooled chiller: Our observation length is one week as a circulation, we observed the information in first three days and predicted the possible COP trend for the next three days. Sample maps and statistics tables for five testing set during March and April are show as below, Fig. 5 is the COP curve sampling for the first testing set during March, and Fig. 6 is the COP curve sampling for the first testing set during April.

ii) Different model: In this research we inputted the same water-cooled chiller data to models trained by different neural network. Table show as below are the result data, table 3 presents the MAE differences of testing sets using the first water-cooled chiller.

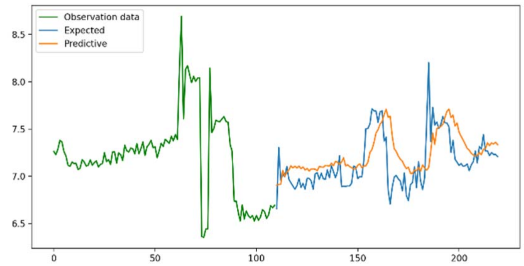

Fig. 5 COP curve sampling for the first testing set during March

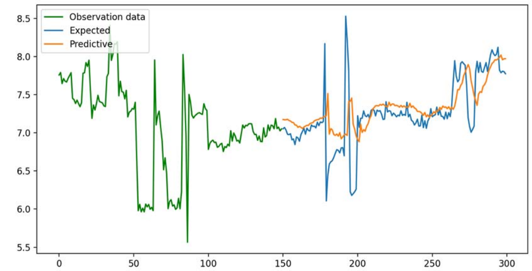

Fig. 6 COP curve sampling for the first testing set during April

TABLE IV. TABLE 3 MAE DIFFERENCES OF TESTING SETS USING THE FIRST WATER-COOLED CHILLER

Metric	Models	Testing set 1	Testing set 2	Testing set 3	Average
MAE (Enthalpy [kg/J])	Ours	0.087	0.121	0.119	**0.109**
	V-LSTM [4]	0.138	0.129	0.130	**0.132**
	RNN	0.112	0.146	0.129	**0.129**
	ResRNN	0.109	0.133	0.122	**0.121**
	LSTM	0.107	0.145	0.151	**0.134**
	GRU	0.106	0.148	0.116	**0.123**

IV. CONCLUSION

We took water-cooled chillers in office buildings as our research experiment samples and proposed an improved LSTM prediction model which could effectively apply in the COP prediction for water-cooled chillers. The average COP differences could be lowered to 0.0311(kg/J) while the highest differences was 0.166(kg/J), this result shows that it is possible to predict the COP trend. Setup of the cloud platform allowed managers to control water-cooled chiller in different areas more easily through visualized data, they could notice mechanical failures at the first moment and arranged maintenance processes effectively. This application can not only be used in the control of water-cooled chillers but widely applied in other field in the future.

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