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Dynamic performance prediction of vehicle variable speed air conditioner based on LSTM recurrent neural network

Chen Zhijie[1], Xiao Fu[1,*]

1 Department of Building Services Engineering, The Hong Kong Polytechnic University, Hong Kong

ABSTRACT

Accurate prediction of air conditioner's dynamic operation is very important for advanced control and fault diagnosis method. The prediction of vehicle air conditioners' performance faces many challenges like unstable working conditions and frequent "on-off" operation. This research proposes a long short-term memory (LSTM) recurrent neural network-based method to tackle this tricky issue. The proposed model is trained and tested with field operation data to prove its capability.

Keywords: Dynamic performance prediction, Recurrent neural network, Deep learning

1. INTRODUCTION

Public transport in high-density cities like Hong Kong plays an important role in people's daily life. According to Moovit[1], Hong Kong people spend average 73 minutes in public transport every day. Air conditioners (ACs) on vehicles are responsible for creating comfortable and healthy environment for passengers. The efficient control of vehicle ACs can also reduce the power consumption since mechanical power consumed by ACs accounts for 12-17% of the power provided by internal combustion engines [2]. In electric vehicles, ACs could increase the energy consumption up to 32% depending on different working environment, which significantly limits the driving range per charge[3] Efficient control and fault diagnosis of vehicle ACs is of great importance to the operation of public transport.

Accurate prediction of ACs' performance is the basis for many advanced control method and fault diagnosis method. The modelling of vehicle ACs faces many difficulties because it is different from the ones working in buildings. Building ACs usually work under rather stable conditions since buildings have large thermal inertia and relatively slow change of indoor and outdoor environment. While in vehicles, the thermal inertia is not so large and the constant impulse of changing working environment such as frequent door open/close, intermittent shading effect and random number of passengers lead to the unstable operation of vehicle ACs. What's more, the start-up and shut-off cycle in vehicle ACs is much more frequent than building ACs.

A lot of research regarding the simulation of ACs primarily focuses on the steady-state simulation. However, more and more research concerning the dynamic simulation of ACs is emerging during these years. Dynamic simulation of ACs is a challenging work since the complex physical process happening in heat exchangers. Typically, there are two different methods applied in the dynamic simulation of ACs. First approach is based on white-box models. Moving boundary method [4,5] is usually adopted for heat exchanger because of its advantage in model complexity and relatively good accuracy, when compared with finite volume method. These proposed dynamic simulation models comprised high order differential equations and were able to infer nonlinear operation inside ACs. Switch criteria [6] between different form of models were developed to enable model's capability during large transients when the rapid destruction and creation of dynamic states happen. Although these white-box models are capable of simulating ACs' operation under various conditions, there are numerous parameters in the model need to be determined and the tuning process is often tedious. [7]

With the wide application of machine learning, many researchers adopt black box models for the dynamic simulation of ACs. Atuonwu et.al.[8] developed a recurrent neural network to simulate the dynamic behavior of evaporator. Bechtler et.al. [9] used a generalized radial basis neural network to predict chillers' coefficient of performance (COP) and compressor electrical input during dynamic processes. The trained neural network model can simulate system's performance with 5% error. However, the test cases in

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their research only include small portion of dynamic processes. Ng et.al. [10] developed a neural network based on the recurrent manner for dynamic simulation. They conducted a series of experiments with the air conditioner from a real vehicle to test the performance of the neural network. They used compressor frequency to predict the response of cabin temperature. The experiments were conducted under the constant condenser and evaporator air temperature, constant condenser and evaporator air flow rate. Their research neglects the effect of changing indoor and outdoor environment which makes their model less suitable for field use.

Recurrent neural network (RNN) is a prevalent tool in deep learning community. It specializes in various time series problem. The simulation of ACs is a typical time series regression problem since different parameters are correlated and time dependent. LSTM recurrent neural is adopted in this research. Experiments setups and data information will be mentioned in chapter 2. Detailed principle about LSTM neural network will be provided in chapter 3. The results and discussion will be conducted in the last part.

2. SYSTEM CONFIGURATION AND EXPERIMENT SETUP

An AC installed on an electrical city bus is the data source of this research. The city bus works with a fixed route every day in Guang Zhou, China. Data from real-time operation is logged and transmitted to the central monitor center. Fig. 1 depicts system configuration and sensors' location.

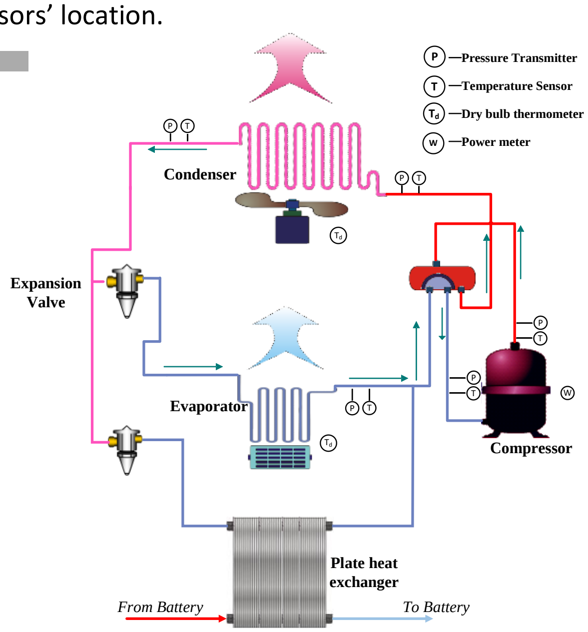


Fig. 1 System configuration and experiment setup

The studied system includes a variable speed rotary compressor with 12.5 kW rated cooling capacity. Refrigerant R407C is charged in the system. Two electrical expansion valves (EEV) are installed at the exit of condenser, corresponding to two cycles. One is for the cooling of cabin by evaporator. Another EEV is connected to a plate heat exchanger, which serves as the cooler for the battery of electrical bus. When battery temperature exceeds certain threshold, the second EEV will open to cool down the battery. During the experiment, the second EEV keeps closed.

Several pressure and temperature sensors are placed at the entrance and exit of major components. Other than the thermal parameters measured during the operation, control signals like compressor frequency, EEV opening, indoor fan speed and outdoor fan speed are also recorded and transmitted to the central control center.

Operation data from 1st July to 8th October 2019 constitutes the training data in this research. Time interval of the recorded data is 10s. Most city buses are controlled manually by bus drivers, which causes a lot of "on-off" cycles during the operation. The original data is preprocessed by separating them into individual sequences representing different "on-off" operation cycles. In total, 1986 sequences are obtained from four months' operation data. These sequences have different size and 139,295 data points are included in these sequences. Fig. 2 shows the volume of training data obtained from each month and these training sequences' corresponding size. It can be inferred from the figure that most "on-off" operation cycles are under 1,500 seconds with few operations last several hours. Frequent "on-off" operations are very common among the operation of vehicle ACs. Operation data from July and August, 2020 is used for the testing of the trained model.

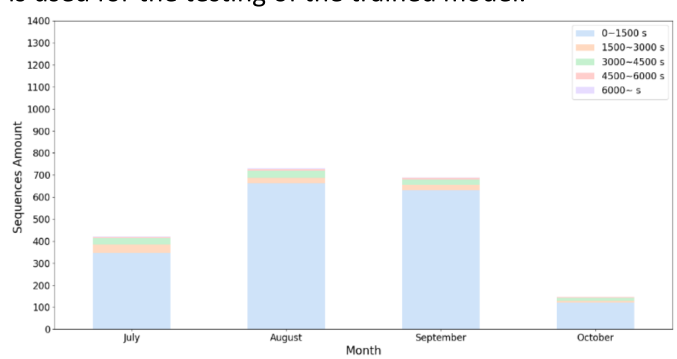


Fig. 2 Sequence amount of training data

3. METHODOLOGY

RNN refers to a special type of neural network that is designed to process sequential data. It origins from the basic idea of sharing parameters of neural network along different time steps. Thus, the neural network can be applied on different length of time series and generalize across them. If network parameters are not shared among different time steps, then the network is useless when applied on a time series whose length is not seen during training.

Typical dynamic systems like air conditioners usually can be expressed in the form of:

$$s^{(t)} = f(s^{(t-1)}, x^{(t)}, \theta) \tag{1}$$

Where $s^{(t)}$ refers to the state of system at time t. $x^{(t)}$ is system inputs, ϑ is disturbance of system. Fig. 3 shows the structure of basic RNN cell and long short-term memory (LSTM) cell. The RNN network is established by a series of basic RNN cell sharing the same weights and biases. The state value at one time step is passed on to the next step for the update of state value at next time step. Detailed forward propagation process in RNN cell can be expressed in the following equations:

$$a^t = b + Wh^{t-1} + Ux^t \tag{2}$$

$$h^t = \tanh(a^t) \tag{3}$$

h^t and x^t refer to the hidden state and input of the cell at time t, while W and U are the corresponding weights. The cell structure resembles the expression of dynamic system which makes it suitable for handling time series problems. Regardless of the sequence length, the learned model repeatedly adopts the same transition function and same size of inputs which enables RNN model's capability to operate on different lengths of time series.

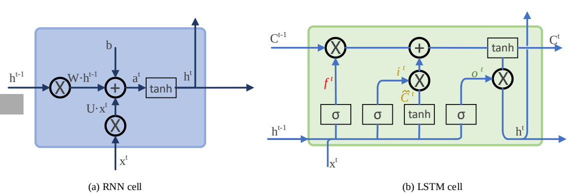


Fig. 3 Structure of basic RNN and LSTM cell

However, the problem of gradient vanishing and exploding [11] makes the application of basic RNN on long time series very difficult. The LSTM cell introduces the concept of cell state, which runs straight down the entire chain. The structure enables the gradient information about error to propagate further back along the time series. LSTM cell adopts the idea of gate control. Several sigmoid functions are deployed to selectively let the signal pass through. The output of sigmoid function is either 0 or 1. Typical LSTM cell contains the following parts: forget gate determines whether to assimilate the state information from the previous state; input gate decides how to upgrade the cell state; output gate controls the outputs provided to the output layer and next state.

$$f^t = \sigma(W_f \cdot [h^{t-1}, x^t] + b_f) \tag{4}$$

$$i^t = \sigma(W_i \cdot [h^{t-1}, x^t] + b_i) \tag{5}$$

$$\tilde{C}^t = \tanh(W_C \cdot [h^{t-1}, x^t] + b_C) \tag{6}$$

$$C^t = f^t * C^{t-1} + i^t * \tilde{C}^t \tag{7}$$

$$o^t = \sigma(W_o \cdot [h^{t-1}, x^t] + b_o) \tag{8}$$

$$h_t = o_t * \tanh(C^t) \tag{9}$$

LSTM cell overcomes the shortcomings of gradient vanishing and exploding. In this research, a neural network architecture based on LSTM cell is built to predict vehicle AC's performance under highly dynamic operation. The architecture can be adopted to build different neural networks for prediction of AC's different operation parameters like power consumption and evaporating, condensing temperature. Fig. 4 presents details of the proposed neural net architecture.

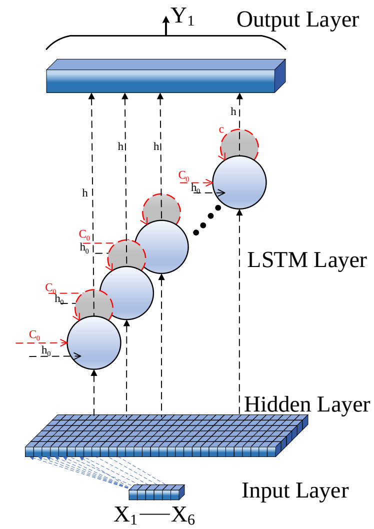


Fig. 4 LSTM cell-based prediction model architecture

The whole neural network architecture is comprised of four layers: input layer, hidden layer, LSTM layer and output layer. Six system operation parameters are chosen as the inputs of the neural network: compressor frequency, EEV opening, indoor fan speed and outdoor fan speed, indoor and outdoor temperature. These parameters are control signals provided to the system during operation. More importantly, these are the key external factors influencing the performance of vapor compression cycle. The whole neural network architecture can be adopted for the prediction of variable operation parameters, like compressor power consumption, evaporating pressure and condensing pressure. Before the neural network training, raw data needs to be preprocessed which includes data segmentation as mentioned in last chapter and data normalization. RMSE (root-mean-square error) of each time series is taken as the accuracy index of each sequence during training and validation, which can be expressed as:

$$RMSE_{sequence} = \frac{1}{len(sequence)} \sum_{start-up}^{shut-down} \sqrt{(Predicted(t) - Measured(t))^2} \quad (10)$$

4. RESULTS AND DISCUSSION

In this research, 50 LSTM cells were implemented in the LSTM layer and batch size is set as 100 during the training. After 100 training epochs, the loss function of the neural network reached an acceptable level. This part will include validation and testing results. First is the validation using the training data to ensure that proposed neural network can successfully study the dynamic relationship of inputs and output. Then, the trained neural network model will be tested by data from July and August 2020 to prove its capability of predicting system's dynamic operation. The prediction results of overall power consumption and evaporating temperature will be presented in this part.

4.1 Training accuracy of the proposed neural network

During the training process, operation data of July and August, 2019 was provided to the LSTM cell based neural network for the prediction of overall power consumption since the overall power consumption data in September and October was missing due to improper data management. Two LSTM RNN models were established for the prediction of AC power consumption and evaporating temperature during dynamic operation. In total, 1150 training sequences were fed to the training process of neural network for overall power consumption prediction and 3936 training sequences were used for the training of evaporating pressure prediction model. Fig. 5 shows training accuracy of these sequences.

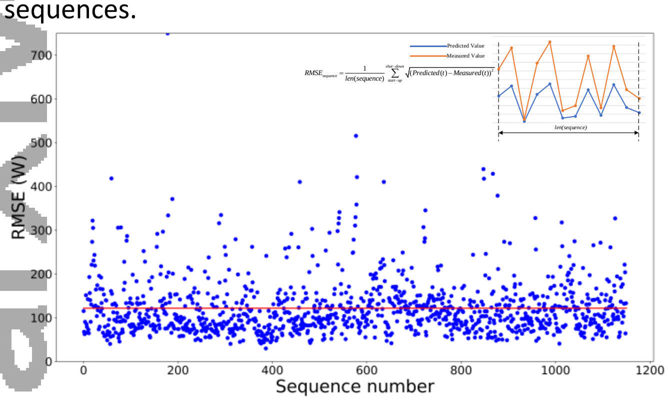
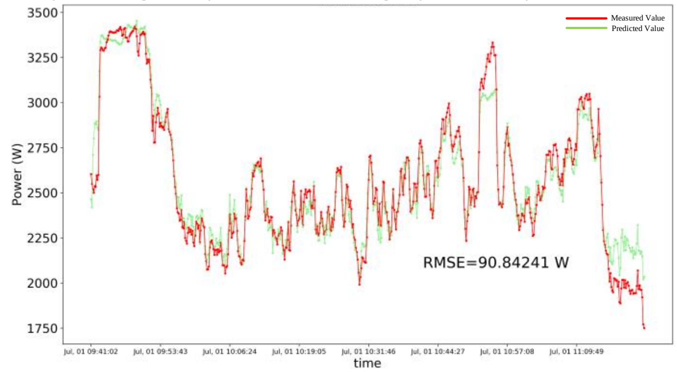
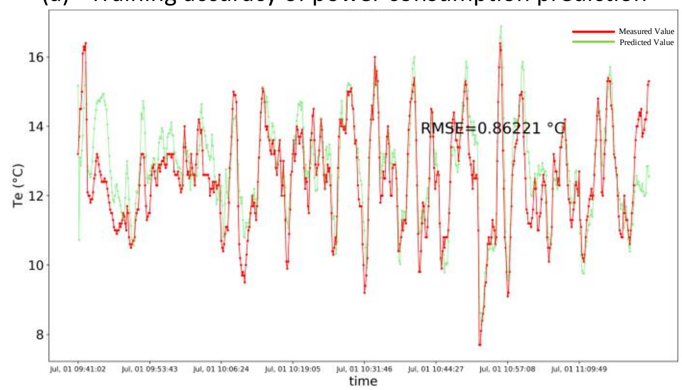


Fig. 5 Training accuracy of the neural network for power consumption prediction

As shown in Fig. 5, the trained neural network is capable of predicting the overall power consumption in most cases. Average RMSE for all the sequences after training is 121 W, marked as red line. Fig. 6 shows a good example where trained neural network successfully predicted AC's overall power consumption and evaporating temperature during dynamic operation.



(a) Training accuracy of power consumption prediction



(b) Training accuracy of evaporating pressure prediction

Fig. 6 Training accuracy of the neural network with data from one sample time series in the morning of 1st July

However, as shown in Fig.6, the accuracy of some sequences is not so satisfactory. After some analyzation, it is found that the start-up process in these sample sequences are different from the majority. In some cases, the control signal for EEV, indoor and outdoor fan have some delay. The operation of vehicle AC is a highly dynamic process, different start-up pattern will lead to very different operation pattern. Since they account for less proportion when compared with other samples, their unique dynamic characteristic may be underestimated during the neural network training.

4.2 Testing accuracy of the proposed neural network

The LSTM RNN trained with the data from July to October 2019 was used to predict the operation performance in 2020. Nearly 100 "on-off" time sequences were obtained from 28th, July to 4th, August. The testing results is presented in Fig. 7 and 8. In most of the testing cases, the trained LSTM RNN neural networks can accurately predict the dynamic change of power consumption and evaporating temperature. The average RMSE for power consumption is 141 W. Considering the power input in vehicle AC usually varies from 1000 W to 4000 W, the prediction accuracy is relatively acceptable. So does the prediction for the evaporating temperature.

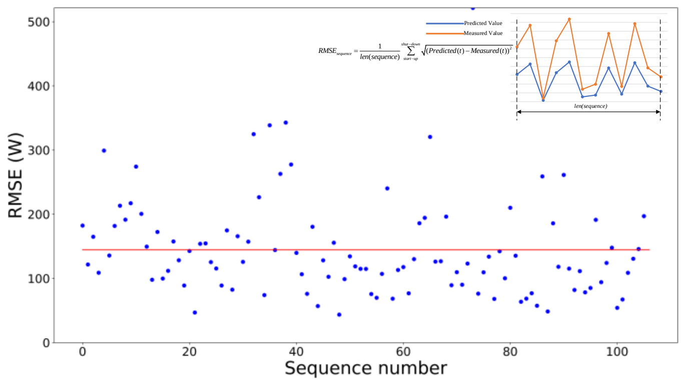


Fig. 7 Testing accuracy of the neural network for power consumption prediction

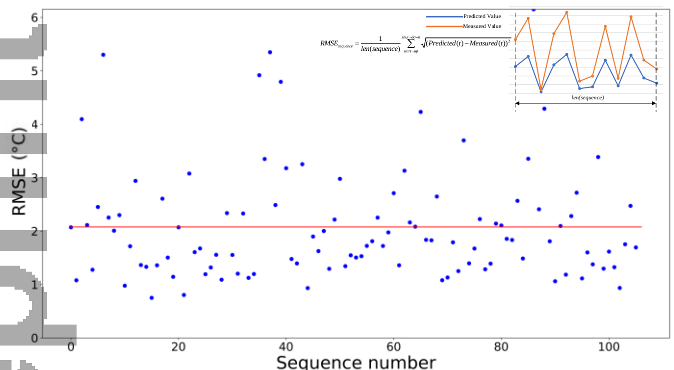


Fig. 8 Testing accuracy of the neural network for evaporating temperature prediction

5. CONCLUSION

The large deployment of IoT devices in the public transportation has created large quantity of operation data. However, these data haven't been analyzed and processed efficiently.

Accurate prediction of the AC operation performance is the key to many advanced control and fault diagnosis methods. Vehicle ACs work under constant shifting outdoor and indoor environment, which makes the prediction of AC operation very difficult. Existing methods in the literature are either too complicated as white-box models or lack of field operation data to test different methods' capability. In this research, a LSTM RNN based prediction model is developed to predict vehicle AC's operation with inputs from EEV, compressor, indoor fan, outdoor fan control signal and indoor, outdoor temperature. The prediction model is trained with data collected from July to October 2019. Both validation and testing results are presented. The average RMSE for power consumption and evaporating temperature prediction is 141 W and 2.1 ℃ respectively. They indicate the great potential of adopting LSTM RNN in the prediction of vehicle AC operation performance.

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