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Transfer Learning for the Prediction of Energy Performance of Water-Cooled Electric Chillers: Grey-Box Models Versus Deep Neural Network (DNN) Models †

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Abstract: The development of data-driven prediction models of energy performance of HVAC equipment, such as chillers, depends on the quality and quantity of measurement data for the model training. The practical applications always struggle with the credibility of results when the training dataset of an existing chiller is relatively small. Moreover, when the energy analyst needs to develop a reliable predictive model of a new chiller, the manufacturer's proprietary data are not always available. The transfer learning method can soften these constraints and can help in the development of a predictive model that captures the knowledge from the available chiller, called the source chiller, using a small dataset, and apply it to a new chiller, called the target chiller. The paper presents the successful application of transfer learning strategies by using grey-box models and DNN models for the prediction of chillers performance, when measurement data are recorded at 15 min time intervals by the building automation system (BAS) and used for training and testing. The paper confirms the initial hypothesis that both the grey-box models and DNN models of the source chiller from July 2013 predict well the energy performance of the target chiller with measurement datasets from 2016. The DNN models perform slightly better than the grey-box models. The pre-trained grey-box models and DNN models, respectively, are transferred to the target chiller using three strategies: SelfL, TLS0, and TLS1, and the results are compared. SelfL strategy trains and tests the models only with the target data. TLS0 strategy directly transfers the models from the source chiller to the target chiller. TLS1 strategy transfers the models, pre-trained with an extended dataset that is composed of training dataset of D_s and training dataset of D_t. Finally, the models are tested with another set of testing data. The difference in computation times of these two types of models is not significant for preventing the use of DNN models for the applications within the BAS, when compared with grey-box models.

Keywords: chiller; performance; transfer learning; measurements; grey-box; neural network

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1. Introduction

Chillers consume more than 40% of the total energy usage of heating, ventilation, and air-conditioning (HVAC) systems in commercial and industrial buildings [1]. Building automation systems (BASs) are usually installed in these buildings to record the building operation data for control purposes. However, they could play an important role in energy efficiency through automated control and energy management using data-driven models [2]. In many circumstances, there are not enough recorded measurements of HVAC systems to derive a reliable data-driven model of the equipment performance. This is the case of a recently installed new equipment (e.g., chiller and boiler), when the dataset is quite small. Some approaches have been proposed to solve this problem, such as integrating data extracted from simulation results to augment the datasets [3].

A new approach consists of the use of transfer learning strategies, which were applied successfully in other domains, as shortly discussed in Section 2.1. However, there are only a few examples of TL applications in HVAC systems. If such TL applications are proven to be successful, they can increase the performance of BAS, especially for the continuous commissioning of existing buildings and energy systems.

2. Literature Review

This section presents the background of transfer learning, a few examples of applications of TL strategies, and a short presentation of grey-box and deep neural network, which are compared in this paper. This section ends with the proposed objective of the paper which is the hypothesis testing that the grey-box models and DNN models can be successfully applied in the transfer learning strategies for HVAC systems.

2.1. Background of Transfer Learning

The transfer learning (TL) method is an alternative approach to solving the above issues. This section introduces some definitions and basic concepts of TL for a better understanding of the presentation and calculation method.

A transfer learning case has two common domains, a source domain (D_s) and a target domain (D_t). A task consists of two components, a label space and a predictive function. The predictive function is used for the evaluation of unseen instances. A learning task within D_s is marked as T_s, and a learning task within D_t is marked as T_t.

TL can be classified based on the similarity of feature spaces and target spaces of D_s and D_t. If both the features and labels in D_s and D_t are the same, it is the case of homogeneous transfer learning; if either the features or labels in D_s and D_t are different, it falls into the class of heterogeneous transfer learning [4].

TL has the advantage of transferring knowledge from the source domain to a target domain, which allows a predictive model to extrapolate the range of applications beyond their original source of data [4]. TL has various other versions of definitions, and a formal definition was given by [5].

TL has been widely applied to various fields, such as improving the deep learning model accuracy and stability of photovoltaic power systems [6], the fault diagnosis of oil–gas treatment station [7], and medicine sensitivity analysis [8].

The task of model development usually highly relies on the collected data. The factors affecting the accuracy and reliability of a model include the data availability, size, quality, and recording time interval. However, in practical applications, high-quality datasets are not easy to obtain. The following three scenarios [4] summarize the need for the deployment of TL:

(a) High quality data are insufficient to derive an accurate and reliable model;
(b) It is usually assumed that the training and test data have TL that contributes to covering as many data distribution characteristics as possible;
(c) The general purpose of machine learning models makes it difficult to adapt to specific situations, as the personal data from an individual user is usually not accessible in the real world;
(d) User privacy and data security prevent the acquisition of some specific and proprietary data.

Transfer learning reduces the strict requirements of data quality and amount by transferring the knowledge learnt from one project to another project. For this reason, it shows great potential in improving the performance of a predictive model.

2.2. Examples of Applications of TL Strategies

A few examples of the TL method are presented in this section: the forecasting of building energy demand [9–11], and the fault detection and diagnosis of HVAC systems [12,13].

In a study of forecasting daily and monthly cooling loads of a building [9], TL proved to be effective in improving the model performance. The data of cooling load derived from the EnergyPlus programme [14] were used for the case study, with only six days of data for training as D_s, and five months of data were used for testing as D_t. The effectiveness of TL was verified by improving the forecasting accuracy.

Four machine learning models were used [10] to forecast the building energy demand with the TL strategy. The parameters of the pre-trained model were transferred to the target model to initialize its parameters. The hourly measured data, extracted from four large shopping malls in four cities in China, were collected for the case study. Datasets with different lengths (e.g., two months and four months) from 2018 were used for the model training, and the whole data of the following year, 2019, were used for the model testing. A significant improvement in model accuracy was observed by using the TL strategy, especially when the training dataset is insufficient. They concluded that the minimum dataset for model training should cover at least one cooling season in order to derive an accurate model.

A heterogenous domain adaptation TL strategy was used to transfer the prior knowledge [12] of an information-rich chiller to a target chiller. The results indicated that the proposed TL strategy achieved a diagnose accuracy of 81.27%. By comparison, the conventional machine learning models only reached an accuracy below 55%.

A homogenous TL strategy using convolutional neural networks (CNNs) was applied to detect and diagnose the electric power faults of chillers [13]. The parameters of layers of pre-trained CNN models, except that of the last layer, were fixed and migrated to CNN models of a target chiller. Then, the parameters of the last layer were re-trained for the target chiller. This study investigated a series of cases, using measurements from a BAS of two cooling plants, where the dataset for model re-training was reduced and the epoch numbers were set from one to two hundred. These cases were studied to identify the minimum training dataset to derive the accurate CNN models. The re-training of TL with 50% dataset of D_t, using 10 epochs achieved the high-accuracy of proposed models, compared with the cases where TL were not applied.

2.3. Grey-Box Models Versus Deep Neural Network Models

A grey-box model is a data-driven model that starts with a physics-based model, and then it is improved by identifying important parameters using statistical analysis [15] of experimental or operational data [16]. As a result, a grey-box model inherits the advantages of physics-based models and data-driven models that describe the system operation data [17,18].

An example of deep learning (DL) model [19], the multilayer perceptron (MLP), relates input values to output values. Different mathematical functions can be used for the representation of the input. DL refers to machine learning models with multiple levels of nonlinear transformation. A few examples of the use of DL are listed in [20].

A DNN model with more hidden layers usually performs better for instance for preventing overfitting.

2.4. Hypothesis Testing

This paper verifies the hypothesis that the grey-box models and DNN models that are pre-trained from the source chiller with a small dataset from July 2013 can predict, using TL strategies, the performance of the target chiller during the cooling season of 2016. This case study uses measurement data from a university campus.

Section 3 presents the TL method applied in this study. Section 4 presents the grey-box models and DNN models developed and applied in this study. The case study is presented in Section 5. The results of the TL method applied with the grey-box models and DNN models, respectively, are compared in Section 6. The conclusions are summarized in Section 7.

3. Method

The homogeneous transductive transfer learning strategy is one of the three transfer learning strategies [21]. This paper applied the homogeneous transductive transfer learning strategy. The information from the source chiller is used for the pre-training and testing of both the grey-box models and DNN models. The information from the target chiller is used for the updating of both the grey-box models and DNN models, respectively, and for the testing of updated models.

Three transfer learning strategies are used in this paper:

1. TLS0 (or direct TL) strategy: The grey-box models and DNN models are pre-trained and tested with the source chiller, and then used directly with the target chiller, without changes to model parameters. The performance of grey-box models and DNN models is evaluated with the testing dataset of target chiller;
2. TLS1 strategy: The grey-box models and DNN models are first pre-trained and tested with the source chiller. The parameters of grey-box models and DNN models are then updated with a combined dataset, composed of the training dataset of source chiller and the training dataset of target chiller. Finally, the updated grey-box models and DNN models are evaluated with a sub-set of testing dataset of D_t;
3. SelfL strategy: This is the so-called self-learning strategy, which trains and tests both the grey-box models and DNN models only with the dataset of task domain D_t.

4. Models

4.1. Grey-Box Models

The operation data of a cooling plant are extracted from BAS with a 15 min time interval that shows a larger data variation compared to the hourly or daily data. In contrast with synthetic data or experimental data, measurement data from a real building usually comes with more noise, missing data, and errors. Hence, training a grey-box model using transfer learning is more challenging.

The paper presents two grey-box models, the chiller coefficient of performance (*COP*) and electric power input (*E*) (Equations (1) and (2)) [22]. The models use some selected operational variables with an important impact on the performance targets as regressors, namely, *COP* and *E*.

$$COP = a_1\, T_{chwl} + a_2\, V_{chw} + a_3\, PLR + a_4 m_{ev,refr} + a_0 \tag{1}$$

$$E = b_1\left(T_{chwl} - \overline{T_{chwl}}\right) + b_2 V_{chw} + b_3 m_{ev,refr} + b_0 \tag{2}$$

where a_i and b_i ($i = 0, 1, 2, \ldots$) are the parameters to be estimated in the model training phase, using the least-squared error algorithm; T_{chwl} is the chilled water leaving temperature in °C; V_{chw} is the volumetric flow rate of chilled water in L/s; PLR is the part load ratio at the evaporator (Equation (3)); and $m_{ev,refr}$ is the mass flow rate of refrigerant in kg/s.

$$PLR = Q_{ev}/Q_{ev,des} \tag{3}$$

where Q_{ev} is the evaporator cooling load (Equation (4)):

$$Q_{ev} = c\rho V_{chw}\left(T_{chwr} - \overline{T_{chwl}}\right) \tag{4}$$

where T_{chwr} is the chilled water return temperature in °C; $\overline{T_{chwl}}$ is the mean value of T_{chwl}, as the information for the setpoint temperature of T_{chwl} is not available in this case study; and $Q_{ev,des}$ is the cooling capacity at design condition (i.e., 3165 kW).

The derived COP_m value is calculated as (Equation (5)):

$$COP_m = Q_{ev}/E \tag{5}$$

4.2. DNN Models

Two DNN modes are developed, DNN1 for the prediction of E, and DNN2 for the prediction of COP [20]. For instance, the input variables for the DNN1 model are the chilled water leaving temperature, (T_{chwl}, in °C); the volumetric flow rate of chilled water (V_{chw} in L/s); and the mass flow rate of refrigerant ($m_{ev,refr}$ is in kg/s) (Table 1).

Table 1. Architecture of the DNN1 and DNN2 models.

DNN Model	Input Layer		Hidden Layer (HL)		Output Layer	Target Variable
	Input Variables	Input Neurons	HL1 Neurons	HL2 Neurons	Output Neurons	
DNN1	T_{chwl}, V_{chw}, $m_{ev,refr,}$	3	14	7	1	E
DNN2	T_{chwl}, V_{chw}, PLR, $m_{ev,refr}$	4	18	9	1	COP

The results revealed that the time lag effect is not important for the steady-state DNN models of chillers. Thus, the multiple layer perceptron (MLP) is selected rather than a time-series model.

The optimum hyper-parameters, the activation function, learning rate, and stopping criteria for training, are identified via trial-and-error. The iteration is set for 10,000 epochs, and the selected activation function is ReLU [23] for DNN1 and SeLU [24,25] for DNN2. The optimum learning rate is selected as 0.01 for ReLU = 0.1 and 0.01 for SeLU = 0.01.

The model training stops when one of the two criteria is met: (1) the mean square error of the output variable is smaller than 1.4×10^{-3} for the DNN1 model, and 3.7×10^{-3} for the DNN2 model; or (2) the number of iterations equals 10,000 epochs.

4.3. Performance Metrics

Three performance metrics, the root-mean-square-error ($RMSE$), the coefficient of variation in the $RMSE$ (CV), and the mean absolute deviation (MAD) (Equations (6)–(8)) are used to compare the measurement data and model predictions.

$$RMSE = \sqrt{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2 / n} \tag{6}$$

$$CV(RMSE) = \sqrt{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2 / n / \overline{y}} \times 100\% \tag{7}$$

$$MAD = \sum_{i=1}^{n} |\hat{y}_i - y_i| / n \tag{8}$$

According to ASHRAE Guideline 14 [26], the calibrated simulation of the energy use or relevant independent variables of an equipment is acceptable if the $CV(RMSE)$ value between the measurements and predictions is smaller than 30% when using hourly data.

4.4. Data Preprocessing

The raw measurements are preprocessed through three sequential steps: (1) samples with missing data or abnormal values were removed, when the cooling plant was in normal operation; (2) measurement data during the start-up and shut-down periods of a chiller were eliminated; and (3) outliers detected in raw measurements were removed, according to Chauvenet's criterion as recommended by ASHRAE Guideline 2-2010 [27]. In addition, measurements during weekends and holidays were removed. The measurement uncertainty and the propagation of errors through the prediction models of COP and E are calculated according to ASHRAE Guideline 2-2010 [27].

5. Case Study

The two chillers installed in a central cooling plant of a university campus are used as the case study, similar to [28], along with data from the BAS from 2013 to 2016. The two water-cooled centrifugal chillers use R-123 refrigerant and have identical characteristics in design conditions. The chillers are named CH#1 and CH#2. Details about the operation performance of these two chillers are available in [29].

The measurement data of source chiller for the models training are composed of records from July 2013 when only the chiller CH#2 was in operation (Table 2); the measurement data of target chiller for the models training are composed of records from 2016 when only the chiller CH#1 was in operation. The data of D_s are used for the pre-training and testing of grey-box and DNN models. The knowledge extracted from the source chiller (D_s) is transferred to the target chiller CH#1 (D_t). Both models use the same training and testing datasets (Table 2).

Table 2. Datasets of source chiller and target chiller.

Datasets		Source Chiller (CH#2)	Target Chiller (CH#1)
Training dataset	Duration	7/11–7/24, 2013	6/22–6/24, 2016
	Dataset size	326	138
Testing dataset	Duration	7/25–7/26, 2013	7/11–8/12, 2016
	Dataset size	119	1040

First, the two grey-box models and DNN models of *COP* and *E* are trained and tested with the source chiller data, and the results of the two models are compared. The measurement data collected from 11 July 2013 to 24 July 2013 are used for the model training. The measurement data collected from 25 July 2013 to 26 July 2013 are used for the model testing.

Second, the grey-box models and DNN models, which are developed with measurement data from 2016 from chiller CH#2, are used with the proposed transfer learning strategies (Section 2) along with datasets of target domain (D_t) from 2016 from chiller CH#1.

6. Results

6.1. Measurement Uncertainty

Although the two chillers are identical in design conditions, their operation conditions showed different states, which are indicated by the characteristics of the training datasets of CH#2 (2013) and CH#1 (2016). The following direct measurements are available for each chiller: supply and return chilled water temperatures, supply and return condenser water temperatures, electric power input *E*, and chiller operation status (on/off). The following measurements are available at the exit of cooling plant: chilled water volumetric flow rate and supply and return chilled water temperatures. The following derived measurements are calculated from the direct measurements: the cooling load at the evaporator and the coefficient of performance (*COP*) of chillers.

The measurement uncertainty was calculated according to ASHRAE Guideline 2-2010 [27]. The bias errors of sensors are as follows:

(a) $B_T = T_{chw} \cdot 0.005 + 0.3$, for the chilled waters sensor;
(b) $B_U = V_{chw} \cdot 0.05$, for the chilled water volumetric flow rate; and
(c) $B_E = E \cdot 0.05$, for the electric power metre.

The values in Table 3 are presented in the format of "mean value $\pm$ measurement uncertainty" over the corresponding training dataset.

Table 3. Average values and uncertainty of variables of the training datasets of chillers CH#2 and CH#1.

Variables	Source Chiller (CH#2, 2013)	Target Chiller (CH#1, 2016)
E (kW)	324.67 ± 19.02	328.24 ± 21.81
COP (-)	5.02 ± 0.48	5.96 ± 0.61
	Chilled water loop	
PLR (-)	0.52 ± 0.04	0.62 ± 0.05
T_{chwl} (°C)	7.19 ± 0.34	6.94 ± 0.34
ΔT_{chw} (°C)	4.31 ± 0.52	5.28 ± 0.54
V_{chw} (L/s)	91.15 ± 4.56	88.90 ± 4.46
	Condenser water loop	
ΔT_{cdw} (°C)	4.07 ± 0.66	4.83 ± 0.69
	Refrigerant loop	
T_{ev} (°C)	4.91 ± 0.33	4.78 ± 0.33
T_{cd} (°C)	33.59 ± 0.53	30.20 ± 0.58

The different operation states of two chillers are noticed in Table 3. For instance, the electric power input E, and the coefficient of performance COP of chiller CH#1 (2016) are slightly greater than the values of chiller CH#2 (2013). The chilled water flow rate V_{chw}, and the supply chilled water temperature T_{chwl} of chiller CH#2 are slightly smaller than the values of chiller CH#2.

6.2. Results on the Training Domain (Ds) of the Grey-Box and DNN Models

The grey-box models and DNN models of chiller CH#2 are trained and tested over the source domain D_s. The performance metrics derived from the training and testing datasets, listed in Table 4, show that the grey-box models and DNN models have a good and close performance with the training dataset. Both models have the *CV(RMSE)* values well below the benchmark of 30% recommended by [26], and the *RMSE* values are smaller than the uncertainty. The same good prediction performance of both models is noticed for the testing within the source domain D_s, except for the estimation of E that is slightly greater than the uncertainty.

Table 4. Performance metrics of grey-box models and DNN models for E and COP, using the source chiller data (CH#2, 2013).

Model	Target Variables	Training Dataset				Testing Dataset		
		RMSE	*CV(RMSE)* (%)	*MAD*	U_m	*RMSE*	*CV(RMSE)* (%)	*MAD*
Grey-box	E (kW)	17.85	5.61	12.22	19.02	21.71	6.35	14.76
	COP (-)	0.29	5.77	0.21	0.48	0.34	6.69	0.26
DNN	E (kW)	16.93	5.31	16.39	19.02	23.48	6.89	12.45
	COP (-)	0.21	4.16	0.19	0.48	0.26	5.17	0.15

6.3. Results of Transfer Learning

The grey-box models and DNN models, derived with the source chiller dataset, are applied to the target chiller using three strategies, i.e., TLS0, and TLS1, and SelfL:

(1) TLS0 strategy directly transfers the grey-box models and DNN models, pre-trained with the source chiller data (CH#2, 2013) to the target chiller (CH#1 2016), and the model performance is evaluated with the testing dataset of the target chiller;

(2) TLS1 strategy transfers the grey-box models and DNN models, pre-trained with the source chiller (CH#2, 2013) to the target chiller (CH#1 2016), and the model parameters are updated with the combined training dataset of source chiller and the training

dataset of the target chiller. Finally, the models are tested with the testing dataset of the target chiller;

(3) SelfL strategy trains and tests the grey-box models and DNN models only with the dataset of task domain D_t.

The results of both models tested with different TL strategies over the testing dataset of D_t are listed in Table 5.

Table 5. Performance metrics of DNN and grey-box models for *E* and *COP* across the testing dataset of the target chiller data (CH#1, 2016).

Target Variable	DNN				Grey-Box		
	RMSE	*CV*(*RMSE*) (%)	*MAD*	U_m	*RMSE*	*CV*(*RMSE*) (%)	*MAD*
				TLS0			
E (kW)	15.15	6.43	15.15	21.81	45.80	14.78	43.64
COP (-)	0.41	8.26	0.41	0.61	0.59	10.04	0.52
				TLS1			
E (kW)	9.0	3.5	9.0	21.81	21.00	6.78	16.62
COP (-)	0.22	4.76	0.22	0.61	0.40	6.84	0.32
				SelfL			
E (kW)	26.65	9.39	26.65	21.81	22.80	7.36	14.13
COP (-)	0.16	9.9	0.16	0.61	1.10	18.88	0.66

Table 5 indicates that the pre-training of models is essential, as proved by the better prediction results of the TLS1 strategy. The dataset of D_s endows the models with some chiller operation characteristics, reducing the need for a large training dataset of D_t for model re-training. Overall, the DNN models [20], which are used for the comparison in this paper, perform slightly better than the grey-box models, when they are applied for transfer learning from the source domain (chiller CH#2) to the target domain (chiller CH#1). For instance, for the case of the TLS1 strategy, RMSE = 0.22 for the *COP* prediction (DNN model), while RMSE = 0.40 (grey-box model), compared with the estimation uncertainty of 0.61. The DNN models also perform slightly better when the other two performance indicators, i.e., CV and MAD, are compared, except in the case of SelfL strategy for the prediction of *E*. However, such differences are not significant for preventing the use of grey-box models against the DNN models.

When both the grey-box models and DNN models of the target chiller are trained using the SelfL strategy, the predictions are generally less accurate. This strategy does not have previous knowledge of the source chiller. Thus, the models trained only with the data from a target chiller do not give good results on the same target chiller.

6.4. Comparison of Computation Cost

The comparison shows that the grey-box models are faster on the same computer than the DNN models (Table 6). The simulation with the DNN models is carried out several times with different initial randomly selected weights, and the best solution is finally selected. This iterative phase can partially explain the longer computation time taken by the DNN models. However, such a difference is not significant for preventing the use of DNN models against grey-box models.

Python (Version 3.9.12) [30], with open libraries like TensorFlow [31], was used for the development of grey-box and DNN models. The calculations were executed on a computer equipped with an Intel® Core(TM) i7-14700 processor and 64 GB of RAM.

Table 6. Computation cost of DNN versus grey-box models.

Dataset	Target Variable	Computation Time, s		Scenario
		DNN	Grey-Box	
Source domain	E	179.33	4.12×10^{-4}	Model training of TLS0. Model pre-training of TLS1.
	COP	91.78	4.28×10^{-4}	
Target domain	E	0.23	2.08×10^{-3}	Model re-training of TLS1.
	COP	0.24	2.01×10^{-3}	
	E	1.32	2.13×10^{-4}	Model training of SelfL.
	COP	2.03	2.10×10^{-4}	

7. Conclusions

The development of data-driven prediction models of energy performance of HVAC equipment, such as chillers, depends on the quality and quantity of measurement data for the model training. The practical applications always struggle with credibility of results when the training dataset of an existing chiller is relatively small. Moreover, when the energy analyst needs to develop a reliable predictive model of a new chiller, the manufacturer's proprietary data are not always available. The transfer learning method can soften these constraints and help in the development of a predictive model that captures the knowledge from the available chiller, called the source chiller, using a small dataset, and apply it to a new chiller, called the target chiller. Through the initial learning and subsequent re-training with the available data from the new chiller, the performance of predictive model of the energy performance of a new chiller is increased in spite of the limited information available.

This paper confirms (1) the usefulness of application of transfer learning for real engineering applications, and (2) the initial hypothesis that both the grey-box models and DNN models of the source chiller from July 2013, predict well the energy performance of the target chiller with measurements datasets from 2016. For this purpose, the direct and derived measurements were used for the development of DNN and grey-box models, and then the transfer learning method was applied.

The DNN models perform slightly better than the grey-box models, when they are applied for transfer learning from the source domain (chiller CH#2) to the target domain (chiller CH#1).

The results reveal that the models re-training with target data of only three days (22–24 June 2016) and the application of TLS1 strategy shows good predictions over a one summer month period in 2016 (11 July–12 August 2016).

When both the grey-box models and DNN models of the target chiller are trained using the SelfL strategy, the predictions are generally less accurate.

The difference in computation times of these two types of models is not significant for preventing the use of DNN models instead of grey-box models for the applications within the BAS. The grey-box models have a relatively straightforward structure compared with the DNN model. Hence, the grey-box model might be simpler to build.

Future work should focus on the generalization of transfer learning strategies with both the grey-box and DNN models, considering various chiller models, cooling capacities, control strategies, and for the fault detection and diagnosis of HVAC systems. The development of rules for the selection of hyperparameters, activation functions, and learning rates should be addressed in future work. Future study should also explore other methods such as the recurrent neural network (RNN) or long short-term memory (LSTM) models.

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