Grey-box models supported by transfer learning for improving the prediction of ongoing commissioning of water-cooled electric chillers

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ABSTRACT

This paper presents the application of transfer learning strategies to two grey-box models for the prediction of chiller performance, when measurements data at 15-minute time intervals from the building automation system (BAS) are used. The two grey-box models hold comparable performance with the classical Gorden-Ng (GN) chiller model.

This paper confirms the hypothesis that the grey-box models of the source chiller, which are pre-trained with the dataset of measurements of July 2013 (called source dataset, D_s), predict well the operation variables of another chiller over the cooling season of 2016 (called target chiller, D_t), after the models are re-trained with the combined dataset, which is composed of 1) the training dataset of D_s and 2) the training dataset of D_t.

The two pre-trained grey-box models are transferred to the target chiller by using three strategies: SelfL, TLS0, and TLS1. SelfL strategy trains and tests the proposed grey-box models only with the target data (D_t). TLS0 strategy directly transfers the two pre-rained grey-box models, which are pre-trained with the source data (D_s), to the target chiller, and the model performance is evaluated with the testing dataset of D_t. TLS1 strategy transfers the two grey-box models, which are pre-trained with an extended dataset, composed of D_s and one set of training dataset D_t, and finally are tested with another set of testing data (D_t).

When the grey-box models are only trained over the target data (SelfL strategy), without having the benefit of previous knowledge from the source chiller, the predictions are generally less accurate. The models trained only with the source dataset (TLS0 strategy) do not perform well. The results reveal that the TLS1 strategy gives the best results, even when the grey-box models are re-trained with only three days of data.

INTRODUCTION

Background of transfer learning

Chillers usually takes a large proportion of energy use of heating, ventilation, and air-conditioning (HVAC) systems, which serve modern buildings and are indispensable. Saidur et al. (2011) reported that chillers consume more than 40% of the total energy usage in the commercial and industrial buildings. Building automation system (BAS) are usually installed in these buildings to record the building operation data for control or monitoring purpose. Moreover, BAS plays a crucial role in improving the energy efficiency as it facilitates multiple functions, such as automated control, and energy management (Qiang et al., 2023).

The data extracted from BAS is useful for the study of building energy efficiency based on data-driven models (Qiang et al., 2023). However, BAS may collect only necessary data that is within the scope for the control purpose. Under some circumstances, for instance when a new system or equipment starts operating, the recorded data is not enough for guaranteeing the exact control or deriving a model with high performance. Some approaches have been proposed to solve this problem, such as integrating data extracted from simulation results to augment the datasets (Dowling and Zhang, 2020) or relying on expert knowledge to reduce the need for large-amount data (Christophe and Geert, 2019).

Another promising solution, the transfer learning (TL), provides an alternative approach to solve the above issue. To start with, let us introduce some basic concepts of TL (Yang et al., 2020):

(1) Domain - a domain consists of two components including a feature space and a marginal space. A source domain (D_s) and a target domain (D_t) are two common domains of a TL case. If the feature spaces or marginal spaces of two domains are different, the two domains are reported to be different.
(2) Task – a task consists of two components, and they are a label space and a function. The function is a predictive function that can be 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.

Given a source domain D_s and learning task T_s, and a target domain D_t and learning task T_t, the transfer learning aims to help improve the learning of the target predictive function $f_t(\cdot)$ for the target domain using the knowledge in D_s and T_s, where $D_s \neq D_t$ or $T_s \neq T_t$. 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 (Yang et al., 2020).

TL has the advantages of transferring knowledge from one domain to another, which allows a model to extrapolate the range beyond their original creation. Hence, a definition of TL is described as a paradigm in which an algorithm extracts knowledge from one or more application scenarios to help boost the learning performance in a target scenario (Yang et al., 2020). TL has been widely applied to various fields, such as improving the deep learning model accuracy and stability of photovoltaic power system (Tang et al., 2022), the fault diagnosis of oil-gas treatment station (Liu et al., 2023), and medicine sensitivity analysis (Dhruba et al., 2018).

This paper explores the application of TL to grey-box models for the performance prediction of large capacity chillers. The cooling plant system of a large institutional building are used as a case study to validate the proposed TL approach.

TRANSFER LEARNING AND GREY-BOX MODELS

TL has various versions of definitions, and a formal one is defined by Pan and Yang (2009):

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 size, qualities, time steps, etc. However, in the practical applications, high-quality datasets are not easy to obtain. Yang et al. (2020) summarizes some scenarios to explain why a TL approach should be deployed.

(1) High quality data is insufficient to derive an accurate and reliable model.
(2) The general assumption, that both the training and test data are drawn from the same distribution, is hard to hold for machine learning models. TL contributes to covering as many data distribution characteristics as possible.
(3) General purpose of machine learning models is hard to be adapted to a specific situation, as the personal data from an individual user is usually not accessible in real world.
(4) The user privacy and data security prevent the acquisition of some specific and proprietary data.

TL provides a solution to reduce 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 model. A few examples of application of TL method are listed here, such as the forecasting of building energy demand (Qian et al., 2020; Yuan et al., 2023; Zhou et al., 2023), fault detection and diagnosis of HVAC systems (Miyata et al., 2023; Zhu et al., 2021), and control of building systems.

In a study of forecasting daily and monthly cooling loads of a building (Qian et al., 2020), TL is proven to be an effective way to improve the model performance. The data of cooling load derived from EnergyPlus program ("EnergyPlus," 2011) were used for the case study, where only six days data (July 15-21, 2009) were available as D_s and five months data (May to October, 2010) were used as D_t. The effectiveness of TL was verified by improving the forecasting accuracy.

Yuan et al. (2023) used four machine learning models (e.g., convolutional neural network model, and long and short-term memory model) to forecast the building energy demand with the method of TL. The parameters of the pre-trained model were transferred to the target model to initialize its parameters. The hourly measurements data, extracted from four large shopping malls of four cities of China, was collected for the case study. Datasets with different lengths (2 months, 4 months, etc.) of 2018 were used for the model training, and the whole data of following year (2019) were used for the model testing. A significant improvement of model accuracy was observed by using TL strategy, especially when the training dataset is insufficient. This paper also concluded that the minimum dataset for model training should cover at least one cooling season in order to derive an accurate model.

A domain adaption heterogenous TL strategy was used to transfer the prior knowledge of an information-rich chiller to a target chiller, where only easy-to-collect normal operation data are available (Zhu et al., 2021). This paper contributed to a framework for the chiller fault diagnosis, which integrated an adversarial neural network model. Results indicated that the proposed TL strategy achieved the diagnose accuracy of 81.27%. By comparison, the conventional machine learning models (e.g., long and short-term memory model) only reached the accuracy below 55%.

Miyata et al. (2023) applied the homogenous TL strategy to convolutional neural networks (CNN) to detect and diagnose the electric power faults of chillers. 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 using the dataset of 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 1 to 200. 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, and using 10 epochs achieved the high-accuracy of proposed models, compared with the cases where TL were not applied.

METHODOLOGY

Transfer learning strategies

The homogeneous transductive transfer learning is one of the three transfer learning scenarios (Weiss et al., 2016). Such transfer learning features are useful for the case of different source and target domains, and for the same tasks. This paper applied the homogeneous transductive transfer learning. The information between two domains is staged as (1) from the source domain or source chiller (D_s), that has measurements data used for the pre-training and testing of grey-box models, and (2) to the target domain or target chiller (D_t), that has measurements data used for the updating of grey-box models, and for testing of updated models.

Two transfer leaning strategies are used in this paper:

1. **TLS0**: The grey-box models are pre-trained and tested with the dataset of D_s, and then used directly with the dataset of D_t, without changes of model parameters. TLS0 is also called direct TL. The performance of grey-box model is evaluated with the testing dataset of D_t.

2. **TLS1**: The grey-box models are first pre-trained and tested with the dataset of D_s, and then they are updated by using the dataset of D_t. The parameters of grey-box models are updated with the combined dataset, which is composed of 1) the training dataset of D_s and 2) the training dataset of D_t. Finally, the updated grey-box models are evaluated with the testing dataset of D_t.

In addition to the above two transfer learning strategies, the self-learning (**SelfL**) strategy is used in this paper, which trains and tests grey-box models only with the dataset of D_t.

Grey-box models

A grey-box model is a data-driven model that starts with a physical model, and then identifies important parameters representative of certain key or aggregated physical parameters by statistical analysis (ASHRAE, 2017). The model parameters are usually identified using experimental or operational data (Sarran et al., 2022). As a result, grey-box modelling inherits the advantages of 1) physical modelling approaches that are computationally efficient, and 2) data-driven models that describe the system operation data (Coakley et al., 2014; Shamsi et al., 2021).

Usually, a model only trained/derived with one system (System A) might not work well on another system (System B). Due to the model training with System A, the model inherits some operation characteristics of System A, which might be different from the operation characteristics of System B.

However, there exists a possibility that System A can provide some basic information to a data-driven model if System A and System B share some characteristics. This paper demonstrates this hypothesis by applying the transfer learning approach to grey-box models, using measurement data of a cooling plant in a real building. First, the paper presents and validates two grey-box models of the chiller performance. Second, the grey-box models that are pre-trained for one chiller (called source chiller) with a small dataset of measurements of 14 days of 2013 are applied for the prediction of operation variables of another chiller (called target chiller). For this purpose, the pre-trained model is updated with another small dataset of the target chiller, which was recorded three years later, in 2016.

The operation data of a cooling plant is extracted from BAS with a time step of 15 minutes, which show a larger variation compared to the hourly or daily measurements data. In terms of the data type, in contrast with synthetic data or experimental data, measurements data from a real building usually comes with more noise, missing data, and errors. Hence, training a grey-box model with high performance using transfer learning in this study is more challenging.

This paper presents two grey-box models of chiller coefficient of performance (*COP*) and electric power input (*E*) (Dou and Zmeureanu, 2022), as described by Equation 1 and Equation 2, respectively. The models use as regressors some selected operational variable with an important impact the performance targets, *COP* and *E*.

$$COP_b = a_1\, T_{chwl} + a_2\, V_{chw} + a_3\, PLR + a_4 m_{ev,refr} + a_0 \quad (1)$$

$$E_b = b_1(T_{chwl} - \overline{T_{chwl}}) + b_2\, V_{chw} + b_3\, m_{ev,refr} + b_0 \quad (2)$$

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

$$PLR = Q_{ev}/Q_{ev,des} \quad (3)$$

Where Q_{ev} is the evaporator cooling load defined in

Equation 4.

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

Here T_{chwr} is 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; $Q_{ev,des}$ is the cooling capacity at design condition (i.e., 3,165kW).

The derived COP_m value is calculated as:

$$COP_m = Q_{ev}/E \quad (5)$$

Gorden – Ng chiller models

For comparison purpose, a well-known model is used to estimate the chiller *COP* (Gordon and Ng, 1994), which is also presented by ASHRAE Guideline 14, 2014 (Equation 6):

$$1/COP = c_1\, 1/Q_{ev} + c_0 \quad (6)$$

Where the parameters c_0 and c_1 are identified during the training phase, using the least-squared algorithm. Equation 6 is modified to predict the electric power input of the chiller (E_{GN}), as described by Equation 7:

$$E_{GN} = c_0 Q_{ev} + c_1 \quad (7)$$

The main difference between the two grey-box models (Equations 1-2) and Gordon&Ng (GN) chiller models (Equations 6-7) lies in the independent variables that are used to predict the chiller *COP* or *E*. The two grey-box models consider *PLR* and $m_{ev,refr}$, while GN chiller models select Q_{ev} as the sole regressor. Though T_{chwl} is almost constant in the case study, it is however used in the two grey-box models, considering the models' potential application in fault detection and diagnosis. We expect that the two grey-box models can well predict chiller *COP* and *E*, as the independent regressors are selected from the analysis of chiller operation characteristics.

This paper uses three performance metrics, (1) root-mean-square-error (*RMSE*), (2) coefficient of variation of the *RMSE* (*CV*), and (3) the mean absolute deviation (*MAD*) to compare the measurements and model predictions. They are defined in Equations 8-10.

$$RMSE = \sqrt{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2/n} \quad (8)$$

$$CV = \sqrt{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2/n}\,/\bar{y} \times 100\% \quad (9)$$

$$MAD = \sum_{i=1}^{n}|\hat{y}_i - y_i|/n \quad (10)$$

According to ASHRAE Guideline 14 (ASHRAE, 2014), the calibration of a computer model for a single building is acceptable if the *CV* between the measurements and predictions of the whole-building energy use is smaller than 30% when using hourly data, or smaller than 15% when using monthly data. This paper calculated the *CV* values from the difference between measurements of target chiller and predicted values of models.

Preprocessing of data

The raw measurements are preprocessed by the following three sequential steps: (1) samples with missing data and variables with abnormal values (e.g., negative values of V_{chw}) were removed, when the cooling plant was in normal operation conditions; (2) measurements under transient conditions (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 (Guideline 2-2010). In addition, measurements during weekends and holidays were removed.

DATASET OF CASE STUDY

The BAS trend data from a central cooling plant of a university campus (Monfet and Zmeureanu, 2011) is selected as the case study. This cooling plant is composed of two water-cooling centrifugal chillers at design conditions and serves, with chilled and hot water, several AHUs and fan coils installed in a university campus, Montreal, Canada. The two water-cooled centrifugal chillers use low-pressure R-123 refrigerant, and are identical at design conditions. The chillers are named CH#1 and CH#2 in this paper, and cooled down by two cross-flow cooling towers, having a capacity of 4,540 kW (1,290 tons) each at design conditions (Table 1).

The two chillers start first by rotation to balance the number of operating hours over the life span for each chiller, or for maintenance reasons. When the first chiller starts, the corresponding chilled-water and condenser-water pumps start too. The second chiller starts only if the first chiller cannot meet the chilled-water demand. Details about the operation performance of these two chillers are available in (Dou and Zmeureanu, 2021).

The two grey-box models and GN models are first trained and tested with D_s. The measurements collected from the first seven days (326 data points), starting at 23:00 on July 11, 2013, and ending at 19:15 on July 24, 2013, are used for the model training. Measurements collected during the last two days (119 data points), starting at 10:30 on July 25, 2013, and ending at 23:45 on July 26, 2013, are used for the model testing. The time interval of the measurements is 15 minutes. The information of the training dataset and the testing dataset over D_s and D_t is listed in Table 1.

In this paper, the data in D_s is composed of measurements

over July 2013 when the chiller CH#2 worked alone; the data in D_t is composed of measurements of 2016 when the chiller CH#1 worked alone. Data of D_s are used for the pre-training and testing of grey-box models. The knowledge extracted from the source chiller (D_s) is transferred to the target chiller CH#1 (D_t).

Table 1. Datasets of source domain and target domain for testing with type #1 datasets.

Datasets		D_s (CH#2)	D_t (CH#1)
Training dataset	Period	7/1, 2013 - 7/24, 2013	6/22, 2016 - 6/24, 2016
	Dataset size	326	138
Testing dataset	Period	7/25, 2013 - 7/26, 2013	7/11, 2016 - 8/12, 2016
	Dataset size	119	1,040

The grey-box models are (1) trained using the training dataset of D_s of 14 days of July, 2013 (Table 1), and then (2) tested with testing dataset of D_s of two of July 25 2013 (Table 1).

Over D_t, the data of three days (from June 22 to June 24, 2013) are available for model retraining, while a large amount of data (from July 11 to August 12, 2016) are used for model testing. This division of training dataset and testing dataset over D_t provides the condition when only very limited data are available for model re-training, which is used for validating the effectiveness of TL.

RESULTS

Measurement uncertainty

Although the two chillers were identical at design conditions, their operation conditions showed different states, which is represented by the characteristics of the training datasets of CH#2 (2013) and CH#1 (2016) (Table 2). The measurement uncertainty in Table 2 was calculated according to ASHRAE Guideline 2-2010 (ASHRAE Guideline 2-2010). The values in Table 2 are presented in the format of "mean value ± measurement uncertainty" over the corresponding training dataset.

The different operation states of two chillers are noticed from Table 2. For instance, the E of target chiller CH#1 is smaller than the value of source chiller CH#2, while COP and T_{ev} values of chiller CH#1 are greater than the values of chiller CH#2. The refrigerant temperature at the condenser T_{cd} of CH#1 is smaller by up to 5°C than the value of CH#2.

Results of models training and testing over D_s

The two grey-box models and GN models are trained and tested over Ds. The corresponding predicted and measured values of the COP and E over the testing dataset of Ds are displayed in Figures 1-4.

Table 2. Comparison of average values and uncertainty of directly measured and derived variables of the training datasets of the source domain and target domain.

Variables	Source domain (CH#2, 2013)	Target domains (CH1, 2016)
E (kW)	324.67±19.02	253.41±16.50
COP (-)	5.02±0.48	5.54±0.57
Chilled water loop		
PLR (-)	0.52±0.04	0.45±0.04
T_{chwl} (°C)	7.19±0.34	6.82±0.33
ΔT_{chw} (°C)	4.31±0.52	3.99±0.54
V_{chw} (L/s)	91.15±4.56	86.31±4.33
Condenser water loop		
T_{cdwr} (°C)	28.62±0.44	23.52±0.42
T_{cdwl} (°C)	32.70±0.49	27.13±0.48
Refrigerant loop		
T_{ev} (°C)	4.91±0.33	5.06±0.44
T_{cd} (°C)	33.59±0.53	27.99±0.51

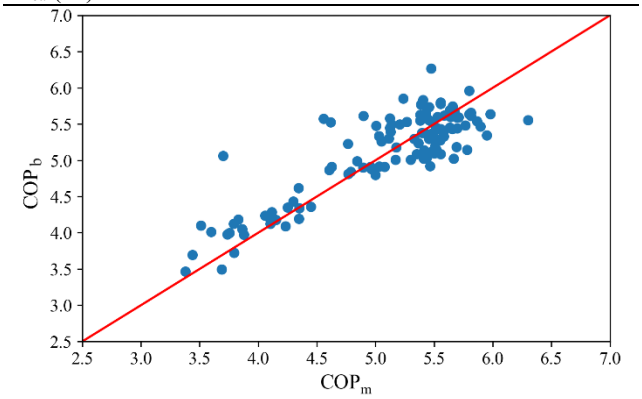

Figure 1. Predicted values of COP_b versus measured COP_m over testing dataset under normal operation conditions of 2013.

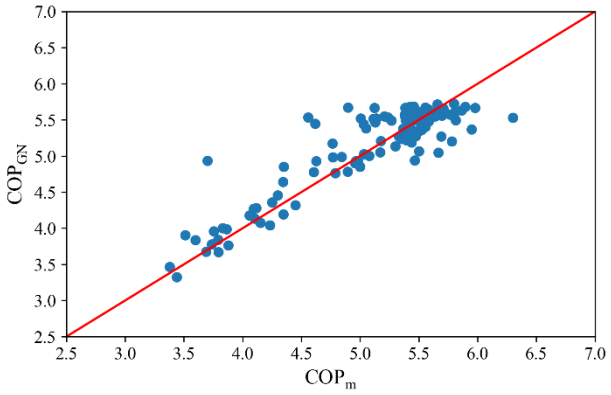

Figure 2. Predicted values of COP_{GN} versus measured COP_m over testing dataset under normal operation conditions of 2013.

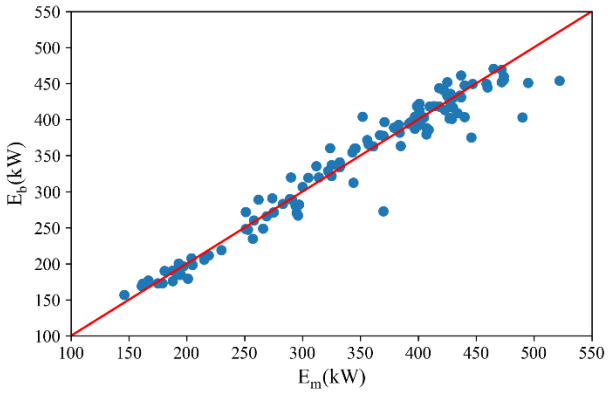

Figure 3. Predicted values of E_b versus measured E_m the over testing dataset under normal operation conditions of 2013.

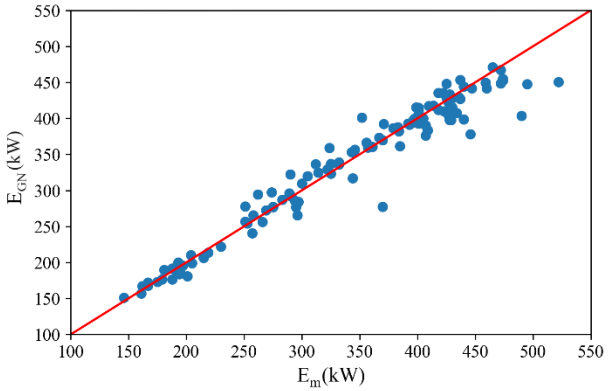

Figure 4. Predicted values of E_{GN} versus measured E_m over testing dataset under normal operation conditions of 2013.

The model performance metrics derived over both the training and testing datasets are listed in Table 3. The *RMSE* values of COP_b (Equation 1) and COP_{GN} (Equation 6) over the testing dataset are smaller than the measurement uncertainty U_m of *COP* (Table 3). The *RMSE* values of E_b (Equation 2) and E_{GN} (Equation 7) over the testing dataset are smaller than the measurement uncertainty U_m of *E* (Table 3). Thus, one can conclude that the four prediction models (Equations 1-2 and Equations 6-7) provide good estimates when compared with the measurements. Performance metrics of two prediction models of COP_b and COP_{GN} indicate they are almost equal, and the same characteristic is noticed for E_{GN} and E_b (Table 3).

This paper selects the use of explicit models of COP_b (Equation 1 and E_b (Equation 2). Equations 1-2 show a great potential for the task of fault detection and diagnosis. Moreover, results from the augmented and sliding window techniques, not presented in this paper, indicated the two models (Equation 1 and Equation 2) are accurate and robust.

Table 3. Performance metrics of grey-box models and Gordon-Ng models over both the training dataset and testing dataset.

Prediction models	Training dataset				Testing dataset		
	RMSE	*CV (%)*	*MAD*	U_m	*RMSE*	*CV (%)*	*MAD*
COP_b (-)	0.29	5.77	0.21	0.48	0.34	6.69	0.26
COP_{GN} (-)	0.27	5.50	0.20	0.48	0.29	5.77	0.21
E_b (*kW*)	17.85	5.61	12.22	19.02	21.71	6.35	14.76
E_{GN} (*kW*)	18.68	5.87	12.92	19.02	21.35	6.24	13.98

Results of transfer learning

The two grey-box models (Equations 1-2), derived with the training dataset of D_s, are transferred to the target chiller with D_t by using three strategies (SelfL, TLS0, and TLS1). SelfL trains and tests the two grey-box models only with TD. TLS0 directly transfers the two grey-box models, pre-trained on D_s (CH#2, 2013), to the target chiller (CH#1 2016) and, then, the model performance is evaluated with the testing dataset of D_t. TLS1 transfers the two grey-box models, pre-trained on D_s (CH#2, 2013), to the target chiller (CH#1 2016) and, then, the model parameters are updated with the combined training dataset of D_s and D_t, and tested with the testing dataset of D_t. Corresponding results of model testing with different TL strategies over the testing dataset of D_t are listed in Table 4.

Table 4. Performance metrics of grey-box models over testing datasets of TD.

Transfer learning strategy	Grey-box models	*RMSE*	*CV (%)*	*MAD*	U_m
SelfL	*E (kW)*	22.80	7.36	14.13	16.50
	COP (-)	1.10	18.88	0.66	0.57
TLS0	*E (kW)*	45.80	14.78	43.64	16.50
	COP (-)	0.59	10.04	0.52	0.57
TLS1	*E (kW)*	21.00	6.78	16.62	16.50
	COP (-)	0.40	6.84	0.32	0.57

Overall, TLS1 performs better than SelfL and TLS0, as all *RMSE* values (Table 4) corresponding to TLS1 are smaller than those of SelfL and TLS0. The *RMSE* of *COP* from the TLS1 is smaller than the measurement uncertainty of *COP* (Table 4), indicating TLS1 works well. Though *RMSE* of *E* of TLS1 is greater than the measurement uncertainty of *E* (U_E), one can still conclude TLS1 works well since the value of MAD of *E* is very close to that of U_E (Table 4).

Table 4 also indicates the pre-training of grey-box models is essential. The dataset of D_s endows the grey-box models with some chiller operation characteristics, reducing the need for a large-amount training dataset of D_t for model re-training.

CONCLUSIONS

This paper presents the successful application of transfer learning strategies to two grey-box models for the prediction of chiller performance, when measurement data of two chillers from two different years from BAS are used. The two grey-box models hold comparable performance with the classical Gorden-Ng chiller models, as the corresponding *RMSE* values are similar.

This paper confirms the initial hypothesis that the grey-box models of the source chiller, which are pre-trained with the dataset of measurements of July 2013, predict well the operation variables of the target chiller with measurements datasets of 2016. Results with target data sets reveal that by using the measurement data with only 3 days for the model re-training, the TLS1 strategy helps for good predictions over one month of summer of 2016.

When the grey-box models of the target chiller are only trained over the target data (SelfL strategy), without having the benefit of previous knowledge from the source chiller, the predictions are generally less accurate. Results of (Liu et al., 2021) support this conclusion: the models trained only with the data from a particular source chiller cannot be used directly to the target chiller.

Future work should focus on the generalization of transfer learning strategy and grey-box models, considering various chiller models, cooling capacities, and control strategies. The models should also be tested for the application of fault detection and diagnosis of HVAC systems.

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