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A reinforcing transfer learning approach to predict buildings energy performance

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Abstract

Purpose – The purpose of this paper is to propose a novel data-driven approach for predicting energy performance of buildings that can address the scarcity of quality data, and consider the dynamic nature of building systems.

Design/methodology/approach – This paper proposes a reinforcing machine learning (ML) approach based on transfer learning (TL) to address these challenges. The proposed approach dynamically incorporates the data captured by the building management systems into the model to improve its accuracy.

Findings – It was shown that the proposed approach could improve the accuracy of the energy performance prediction compared to the conventional TL (non-reinforcing) approach by 19 percentage points in mean absolute percentage error.

Research limitations/implications – The case study results confirm the practicality of the proposed approach and show that it outperforms the standard ML approach (with no transferred knowledge) when little data is available.

Originality/value – This approach contributes to the body of knowledge by addressing the limited data availability in the building sector using TL; and accounting for the dynamics of buildings' energy performance by the reinforcing architecture. The proposed approach is implemented in a case study project based in London, UK.

Keywords Innovation, Neural networks, Artificial intelligence

Paper type Research paper

1. Introduction

Energy consumption (EC) in buildings accounts for approximately one-third of global EC and is one of the key contributors to global carbon dioxide emissions and climate change

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(CZ Li *et al.*, 2020). Thus, building energy performance is paramount in attaining a low-carbon or carbon-neutral society. In addition, due to the growing global energy demands and ever-increasing energy prices, improving buildings' energy efficiency has gained popularity in residential, commercial and public sectors.

Over the past few years, many researchers have focused on reducing buildings' EC (Seyedzadeh *et al.*, 2018), developing optimal control strategies (Zhang *et al.*, 2019) and using renewable energies in buildings and formulating novel energy-saving measures (Zhao *et al.*, 2019). However, predicting buildings' EC, as the initial step for improving their environmental performance, is challenged by the complexity of their energy performance, dynamics and nonlinearity (Zhang *et al.*, 2021). There are three categories of building energy prediction models in the literature:

(1) White-box models account for buildings' envelope parameters and surrounding environment to calculate their EC using the fundamental laws of mass, energy and momentum (Harish *et al.*, 2021). The development and implementation of white-box models are time-consuming due to their complexity and high computational costs.

(2) Black-box models map the different features of a building (i.e. input space) to its EC (i.e. output space) based on empirical data (Guidotti *et al.*, 2018). These models use different inputs for prediction purposes, such as past EC data, outside weather conditions and occupancy schedules to predict building EC.

(3) Grey-box models mix the capabilities of the white- and black-box models by first developing simplified versions of white-box models and then predicting some of the building's features using black-box models (Pintelas *et al.*, 2020). This approach improves the computational efficiency and prediction accuracy of grey-box models compared to white- and black-box models.

Data-driven approaches for energy prediction are more practical than the conventional white-box models as data-driven approaches are computationally cheaper and are influenced by actual historical data. However, the effectiveness of the data-driven methods is strongly influenced by both the volume and quality of training data, and the suitability of the machine learning (ML) algorithms that are used. Yan *et al.* (2019) emphasized that the EC patterns for individual households can be extremely irregular, which can reduce reliability of using pure data-driven methods on EC prediction. To address these drawbacks, predicting buildings' EC with data-driven methods often requires a significant volume of historical data. However, in practice, sufficient high-quality, labelled data for training data-driven models may not be available, either due to the short life of buildings (i.e. new buildings with no data) or the lack of proper building management systems to capture the data. In these conditions, transfer learning (TL) methods can be used to build predictive data-driven approaches.

In TL, the knowledge acquired from a given task in one domain (i.e. source domain) is applied to accomplish the same task in a different domain (i.e. target domain) or to improve the prediction accuracy for a different task in the target domain (Liu *et al.*, 2022). TL methods improve the scalability of ML techniques (Pan and Yang, 2009) and provide a promising perspective for developing advanced and reliable predictive models when ML models require a large amount of training data, either unavailable or expensive to collect. With TL, data required for training the models do not need to come from the same feature space or have the same characteristics.

TL is a relatively new concept in building energy prediction. In one of the recent applications, Gao *et al.* (2020) proposed two deep learning models: using a 2D convolutional neural network; and a sequence-to-sequence model based on the TL methods. In their study, the TL-based model improved the prediction accuracy of buildings' energy performance using two years of historical data collected from similar buildings (source) and one month of high-quality data from the target building. In an earlier effort, Ribeiro *et al.* (2018) proposed an energy forecasting method based on multi-feature regression with seasonal and trend adjustments based on time series data. Their proposed method could predict the energy performance of a given building using data collected from similar buildings with different distribution and seasonal profiles. Ribeiro *et al.* (2018) managed to improve the energy prediction accuracy of a school building by 11.2%, using additional data acquired from other school buildings. In contrast to the existing methods that often rely on actual data collected from similar buildings, in their proposed approach, Ahn and Kim (2022) used simulation data as the source domain to implement TL and predict the energy performance of a target building.

In a more recent effort, Fang *et al.* (2021) proposed a hybrid deep TL method for short-term cross-building energy prediction using long-short-term memory (LSTM) and domain adaptive neural network (DANN). In their study, they implemented an LSTM-based feature extractor to extract the temporal features (e.g. time) of the source and target buildings; and DANN to find the domain-invariant features of the two buildings through adversarial domain adaptation and domain classifier. Li *et al.* (2021) developed a TL-based artificial neural network (ANN) model to predict building energy demands for 1 h. They found that the building use cases (e.g. office, laboratory, classroom and dormitory) and the industry (e.g. education and government) were the most influential factors affecting the performance of TL-based models. Using multiple source buildings and multi-source TL are other approaches to improve performance of TL-based models. For instance, Lu *et al.* (2023) developed a multi-source TL energy prediction model using different types of source and target buildings. Using this approach, they could improve accuracy of energy predication (i.e. mean absolute percentage error [MAPE]) by 6.88%–15.37%.

Most applications of TL in building EC are focused on selecting relevant source data or developing different model architectures to improve their performance (Fang *et al.*, 2021; Gao *et al.*, 2020; Ahn and Kim, 2022). These studies often focus on short-term energy demand prediction (e.g. hourly predictions; Li *et al.*, 2021) due to the dynamic nature of buildings. In addition, existing TL-based models are limited in terms of scalability as they are not adaptive to the changes that may occur in the target building's characteristics, such as weather conditions and occupants' behaviour. Therefore, a new approach is required to consider the dynamic nature of building systems, and yet it can be scalable by adapting to the changes in buildings. This study bridges the gap by proposing a reinforcing TL that dynamically incorporates the data collected from the target building into the model to improve prediction accuracy. Our proposed approach can reduce the burden of selecting relevant source data by retraining the model over time using data from the target domain (i.e. data from the building being studied). Easing the burden of source data selection extends the application of TL-based methods in this context by allowing modellers to use open-source data repositories for developing their TL-based models. The remainder of the paper is organized as follows. Section 2 explains the preliminary knowledge of TL. Section 3 describes the proposed approach for reinforcing TL, which is followed by a case study project in Section 4. Finally, conclusions and future research directions are discussed in Section 5.

2. Transfer learning

TL helps to reduce the reliance of conventional ML techniques on historical data by allowing cross-domain data utilization and reduces the computational costs of ML techniques by speeding up the training process (Chen *et al.*, 2020). In conventional ML techniques, the data sets used for training and testing purposes consist of domain set (D), which forms the input space of the ML model, and task (T), which forms the output space of the model.

In TL, the learning task consists of two components, as shown in Figure 1:

(1) the output space (Y), which represents data labels; and

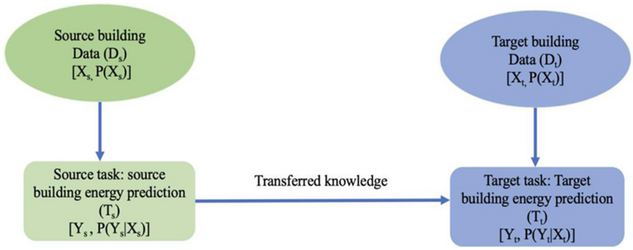
(2) the predictive function, written as P(Y|X), which is learned from training data (from the source domain) $\{(x_i, y_i)|x_i \in X_s \text{ and } y_i \in Y_s\}$.

The TL process uses the domain and learning task of the source domain (D_s and T_s), as well as the domain and learning task of the target domain (D_t and T_t) to improve the predictive function of the target domain $P(Y_t|X_t)$. Specifically for buildings' energy prediction models, the source domain D_s is the data collected from a building from which labelled training data already exists, and T_s is the EC predictions made from a model that is trained using the labelled training data from the source building. In this context, D_t represents the domain set (i.e. the input features and their marginal probability) of the building with insufficient data; the target task T_t is the predictions made for the EC of the target building.

3. Proposed reinforcing transfer learning approach

Buildings' EC can be envisioned as a dynamic system affected by several parameters, such as environmental conditions (e.g. temperature and precipitation), building characteristics and occupants' behaviour. Given the dynamic nature of these systems, many researchers have focused on predicting their behaviour (i.e. EC) in the short term using stationary building data. As mentioned in Section 1, these predictive models are applicable for short-term decision-making, and inappropriate for long-term, more strategic decision-making (e.g. buildings' design) scenarios. Because domain-specific parameters can significantly affect buildings' energy performance, novel modelling approaches are needed to incorporate the EC data realized through the buildings' life cycle into the training data sets. The proposed reinforcing TL approach in this paper aims to address this gap by continuously collecting data from the target building, incorporating the new data collected into the training data, and re-implement the TL process. Figure 2 presents the architecture of the proposed approach.

As seen in Figure 2, the first step is to build the base model using the source-building data set. To this end, the domain and learning task of the source domain (D_s and T_s) are determined in Period 1 (i.e. t_1). Although our proposed approach reduces the reliance of TL models on the similarity of the source and target domains, selecting the source building from a similar use-case (e.g. office, school and residential) and climate as the target building is still



Source: Authors' own creation

Figure 1. Transfer learning technique

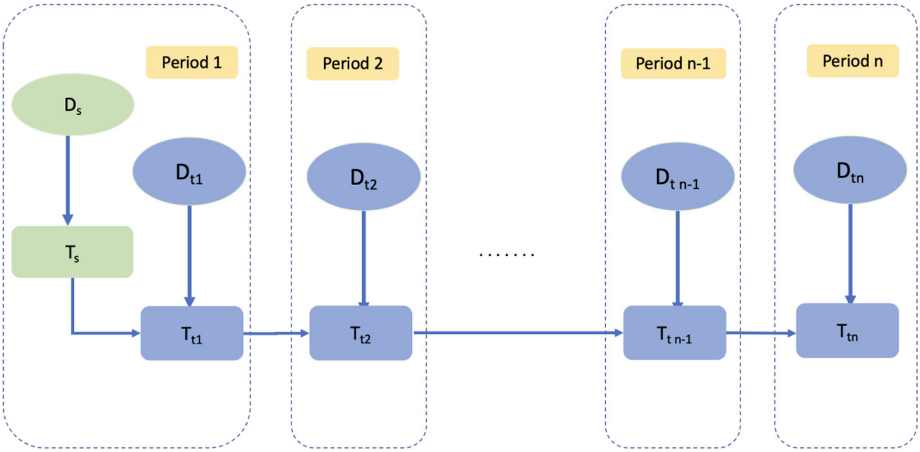


Figure 2.
The proposed reinforcing transfer learning approach

Source: Authors' own creation

essential. Once the source building and its associated data set are selected, appropriate pre-processing tasks will be implemented on the data, including normalization, dimensionality reduction and missing data imputation. Then, the base model is created using the pre-processed source data set.

For creating the base model, any suitable ML technique can be used. This study uses a three-layer LSTM to develop the base model. Section 3.1 describes the detail of LSTM method for developing the base model.

3.1 Developing the base model: long-short-term-memory

LSTM is a class of recurrent neural network (RNN) with the capacity to learn long-term dependencies, particularly in sequential prediction problems. LSTMs have feedback connections, which allow them to process the time-dependency between sequential data rather than treating them as independent singular data points (Hochreiter and Schmidhuber, 1997).

LSTM can address the vanishing gradient problem observed in other types of RNNs (Hochreiter and Schmidhuber, 1997). Because the gradient-based algorithms require error gradients, which vanish as they propagate through the network; hence, gradient-based methods take an extremely long time to train the models. As a result, the first layers of RNNs stop learning once the sequence becomes long enough, and the RNN struggles to propagate information from earlier time steps to later ones. Therefore, due to the vanishing gradient, gradient-based RNNs cannot remember the long-term dependencies (Hochreiter and Schmidhuber, 1997).

An explicit aim of LSTMs is to address long-term dependency, which is accomplished in three parts using a cell state as a central component to maintaining its state over time. Each cell's state is recorded for the previous (C_{t-1}) and current (C_t) timestamps. The first part makes a decision about remembering the previous timestamp information or ignoring it. In the second part, each active cell learns new information from the inputs, and in the third part, it passes the updated information from the current timestamp to the next. These three parts are called gates, regulating how information is added to or removed from the cell state, namely "forget gate", "input gate" and "output gate", respectively.

The hidden state is also present in an LSTM, which is H_{t-1} for the previous and H_t for the current timestamp. Hidden memory is known as short-term memory, and long-term memory is known as cell memory. The first step in the LSTM network is deciding whether the LSTM cell should keep the previous timestamp information. To this end, the input gate quantifies the significance of new information carried by an input. A hidden state at timestamp t−1 (H_{t-1}) and the input at the current timestamp t (X_t) determine what information needs to be passed to the cell state.

In equation (1), a sigmoid function evaluates the forget gate at the current timestamp (F_t), between 0 and 1:

$$F_t = \sigma\left(X_t \,.\, U_f + H_{t-1} \,.\, W_f\right) \tag{1}$$

where for $F_t = 0$, the network forgets everything; for $F_t = 1$ the network does not forget anything. X_t is input data at timestamp t, and H_{t-1} is the hidden state at timestamp $(t-1)$. U_f and W_f are the weights associated with the input and hidden states, respectively. Next, as presented in equation (2), a sigmoid function determines the value of the input gate at the current timestamp (I_t), between 0 and 1:

$$I_{t=} \quad \sigma(X_t \,.\, U_i + H_{t-1} \,.\, W_i) \tag{2}$$

Next, in equation (3), the new information to be passed to the cell state (N_t) is determined using a hyperbolic tangent activation based on the hidden state at the previous timestamp (H_{t-1}) and the input at the current timestamp (X_t). As a result of the *tanh* function, the result will be a value between −1 and 1. A negative value subtracts information from the cell state, and a positive value adds information to the cell state:

$$N_t = tanh(X_t \,.\, U_c + H_{t-1} \,.\, W_c) \tag{3}$$

The new information value (N_t) will be added to the cell state after being updated based on the cell state at the previous timestamp (C_{t-1}) and the forget gate and input gate at the current timestamp (F_t and I_t, respectively), as shown in equation (4):

$$C_t = f_t \,.\, C_{t-1} + I_t \,.\, N_t \tag{4}$$

In equation (5), the output gate is evaluated using a sigmoid function, similar to the forget and input gates:

$$O_t = \sigma(X_t \,.\, U_0 + H_{t-1} \,.\, W_0) \tag{5}$$

Using the output gate at the current timestamp (O_t) and the updated cell state, the hidden state at the current timestamp is calculated, as shown in equation (6). The output of the current timestamp can be calculated by applying the SoftMax activation on hidden state H_t:

$$H_t = O_t \,.\, tanh(C_t) \tag{6}$$

The number of nodes used for modelling purposes is one critical parameter affecting the accuracy of LSTM models. However, despite some general suggestions in the literature, there is no generic formulation to identify the optimum number of nodes for these models. In this paper, we will use Bayesian Optimization to identify the optimum number of nodes for each layer of our LSTM model. Bayesian Optimization is commonly used for tuning hyper-parameters in ML approaches as its capability to consider previous decisions' makes it significantly more efficient than the random and grid search methods (Turner *et al.*, 2021).

3.2 Developing reinforcing transfer learning models

Once the base model is developed, the proposed reinforcing TL approach will be implemented. In this stage, first, the data collected from the target building in Period 1 (i.e. D_{t1}) will be used to develop the initial TL model (T_{t1}). The detail of developing TL models was provided in Section 2. As shown in Figure 2, T_{t1} predicts the buildings' energy performance in Period 2 (i.e. t_2). Afterwards, once the EC in Period 2 is realized, the new data collected from the target building in this period (i.e. D_{t2}) will be used to reinforce the model by retraining it and developing T_{t2}. T_{t2} is generally expected to outperform T_{t2} in accuracy for predicting the building's energy performance in the third period (t_3) as it uses more data for training.

The cycle of collecting data from the building, and incorporating it into the TL models for updating them are repeated in the next periods as shown in Figure 2. When sufficient data from the target building becomes available and the reinforcing TL approach is no longer needed, this process can be stopped.

4. Case study

The proposed reinforcing TL approach is used to predict the EC of a building in London, UK. The EC data from this building exists only for four months, which is insufficient for developing an accurate ML model using historical data (called in this paper "conventional ML approach"). Therefore, TL can be used by considering this building as a target building.

As discussed in Section 2, a relevant source building is selected for creating the base model. In this case study, the source building is selected from Genome project data sets (Miller *et al.*, 2020). Genome is a rich online data set that contains two years' worth of data for 3,053 energy meters from 1,636 non-residential buildings in 19 sites across North America and Europe. The Genome data sets contain one or more types of meter data per building measuring electrical, heating and cooling water, steam and solar energy, as well as water and irrigation data (Miller *et al.*, 2020). Table 1 shows the main features of the source building selected from the Genome data set and the target buildings in London, UK.

Once the source and target buildings are selected, the base model is created using a three-layer LSTM model. In the developed LSTM model, the optimum number of nodes was determined as 64, using Bayesian Optimization. For the other developed models developed in the case study, 64 was the optimum number of nodes, or the difference between the performance of the models with the optimum number of nodes (which was larger than 64), and with 64 nodes was insignificant. As a larger number of nodes increases the complexity of the models and leads to more computational burden, 64 nodes were used for the other

Table 1. Source and target building features

	Building type	Building size	Building location
Target building	Office	82,548 sq ft	London
Source building	Office	81,881 sq ft	London

Source: Authors' own creation

models to maintain the balance between the performance of the models and the computational burden. The base model was created using Robin_office_Zelma data from Genome project data sets (Miller *et al.*, 2020). The models were developed using Python programming language. Some of the main libraries used for developing the models are: keras.preprocessing.sequence.TimeseriesGenerator, keras.layers.LSTM, keras.layers.Dense, keras.layers.Dropout and sklearn.preprocessing.MinMaxScaler.

In this case study, three sets of experiments were conducted to demonstrate the performance of the proposed reinforcing TL technique compared to the conventional ML approaches, for which LSTM models were developed based on only the target/source building data, and a conventional TL (non-reinforcing) model developed based on the source data and one month worth of data from the target building.

The first experiment is to show the effectiveness of using TL over conventional ML approaches (LSTM in this case) when limited data (one month of data in this case) is available.

Three scenarios were considered in this experiment:

(1) *Scenario 1-1. Conventional ML with Insufficient Data (one month of data) from the Target Building*: An LSTM model is developed using insufficient data from the target building (it is assumed that only one month of data from the target building is available, and no source-building data set is used).

(2) *Scenario 1-2. Conventional ML with Sufficient Data (two years of data) from the Source Building*: An LSTM model is developed using the source-building data set from Gnome. No historical data from the target building is used in this scenario.

(3) *Scenario 1-3: TL-Based ML with the Source and Target Buildings' Data*: An LSTM model is developed using the source building's data from Gnome, and then it is fine-tuned using one month of data from the target building. In the retraining process, the weights at different layers of the LSTM model are modified to improve its prediction accuracy in the target domain. Fine-tuning does not have a set rule for how many frozen layers to use. Hence, this paper determined the optimum number of frozen layers with trial and error.

In the second experiment, the performance of the conventional TL approach is compared to the proposed reinforcing TL technique. As discussed in Section 3, the proposed reinforcing TL technique uses the realized data from the building to further improve its prediction accuracy. The conventional TL, though, relies only on one session of the retraining process. For this experiment, three scenarios were considered:

(1) *Scenario 2-1. Conventional TL approach*: An LSTM model is trained using the source building's data and retrained with one month's data from the target building. Then the model is used to predict the target building's EC in the fourth month.

(2) *Scenario 2-1. The Proposed TL approach with Two Retraining Cycles*: In two retraining cycles, the LSTM model is fine-tuned by the data from the target building. Then, the model is used to predict the target building's EC in the fourth month.

(3) *Scenario 2-1. The Proposed TL approach with Three Retraining Cycles*: In three retraining cycles, the LSTM model is fine-tuned by the data from the target building. Then, the model is used to predict the target building's EC in the fourth month.

The third experiment is to implement the proposed reinforcing TL approach and examine its practicality and performance. To this end, the model is repeatedly retrained and updated monthly, using the new data realized from the target building.

4.1 Results and model validation

In the first experiment, three models were created for Scenarios #1-1, #1-2 and #1-3 to predict the target building's EC in May 2022. The results of this experiment are shown in Figure 3. In this figure, the x-axis represents the day of the month, and the y-axis shows the EC. The prediction error of the model, as shown in Table 2, was calculated using the MAPE, as formulated in equation (7):

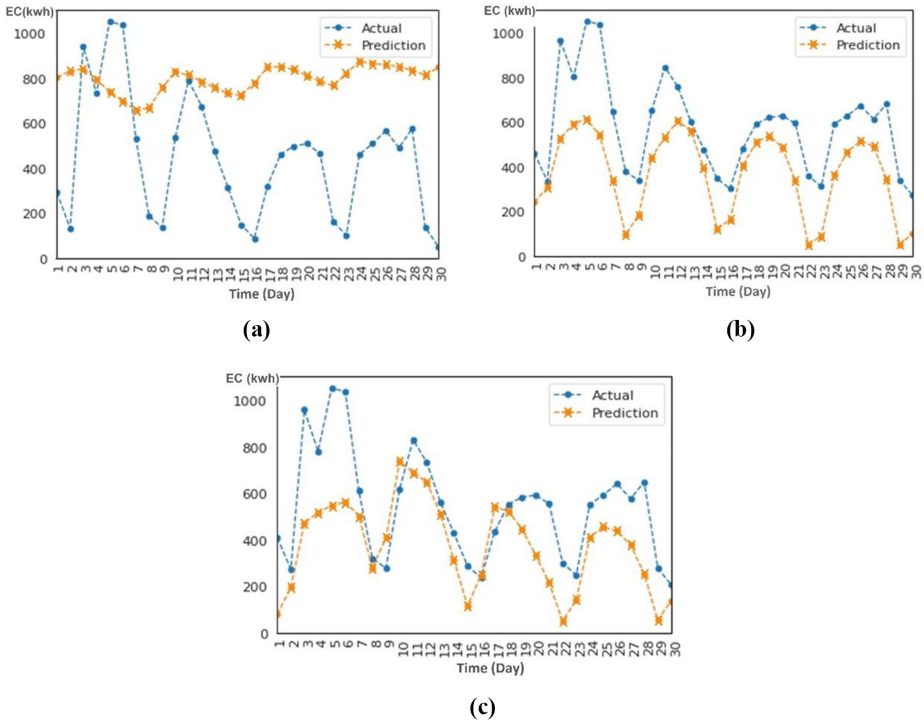


Figure 3. Actual data vs model outputs

Notes: (a) Scenario #1-1; (b) Scenario #1-2; (c) Scenario #1-3
Source: Authors' own creation

Table 2. Errors of experiment #1

Scenarios	MAPE
#1-1 ML with insufficient target-building data	0.46
#1-2 ML with sufficient source-building data	0.27
#1-3 Transfer learning	0.20

Source: Authors' own creation

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{7}$$

As shown in Table 2, the TL approach (Scenario #1-3) has the highest prediction accuracy for predicting the target buildings' EC. Hence, the results confirm the effectiveness of TL approaches in improving the performance of ML algorithms when limited data is available. Interestingly, the results reveal that training an ML model for the target building using TL when there is sufficient data from a relevant source building (i.e. Scenario 1-2) outperforms a model that is trained with limited data from the target building itself (i.e. Scenario 1-1).

In the second experiment, an LSTM model was developed using the source-building data set. Three TL models were subsequently developed using the data collected in March (for Scenario #2-1); March and April (for Scenario #2-2); and March, April and May for Scenario #2-3. The results of the three scenarios in predicting EC for June are shown in Figure 4, and the errors are presented in Table 3. As seen in Table 3, Scenario 2-3 has the lowest error (19 percentage points of MAPE less than Scenario 2-1), which confirms the superiority of our proposed reinforcing TL approach over the conventional TL.

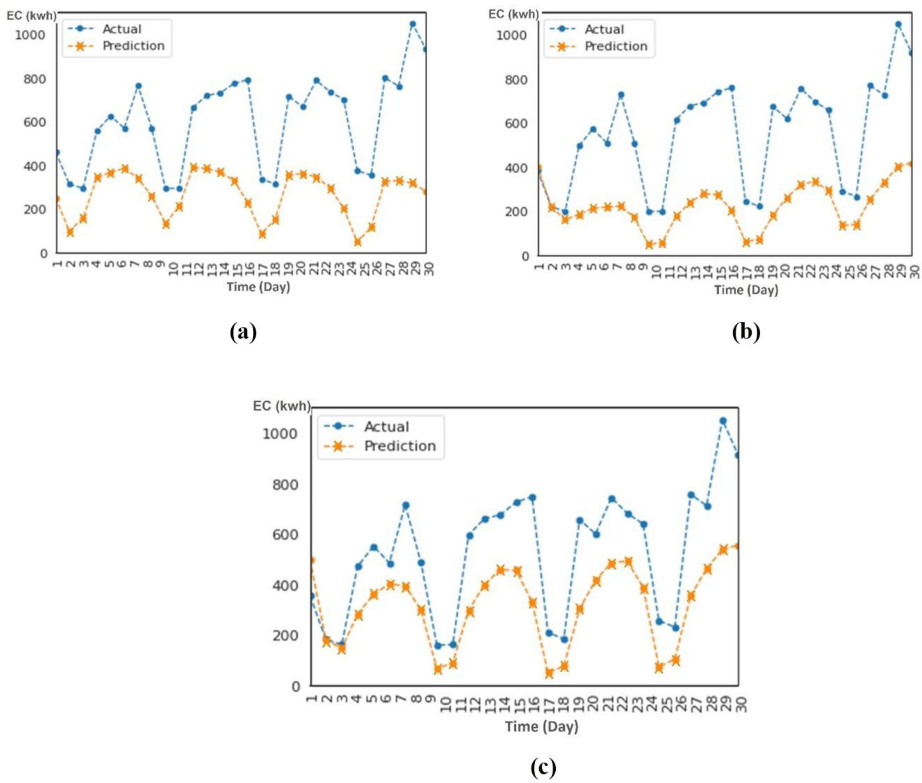


Figure 4. Actual data vs model outputs

Notes: (a) Scenario #2-1; (b) Scenario #2-2; (c) Scenario #2-3
Source: Authors' own creation

4.2 Practical application of reinforcing transfer learning technique

The third experiment tests the practicality of the proposed reinforcing TL approach in predicting buildings' EC in three consecutive months. In Step 1, the data collected in March was used for developing a TL model (i.e. TL_1) to predict the EC in April. Next, the newly realized data in April was used, and TL_1 was retrained, creating a new TL model (i.e. TL_2). In Step 3, the new data from May were used to retrain TL_2 and create a new TL model (TL_3). Figure 5 shows the results of the predictions in these three steps, and their prediction errors are presented in Table 4.

Table 3.
Errors of experiment #2

Scenarios	MAPE
#2-1 TL with one month of data	0.42
#2-2 TL with two months of data	0.35
#2-3 TL with three months of data	0.23

Source: Authors' own creation

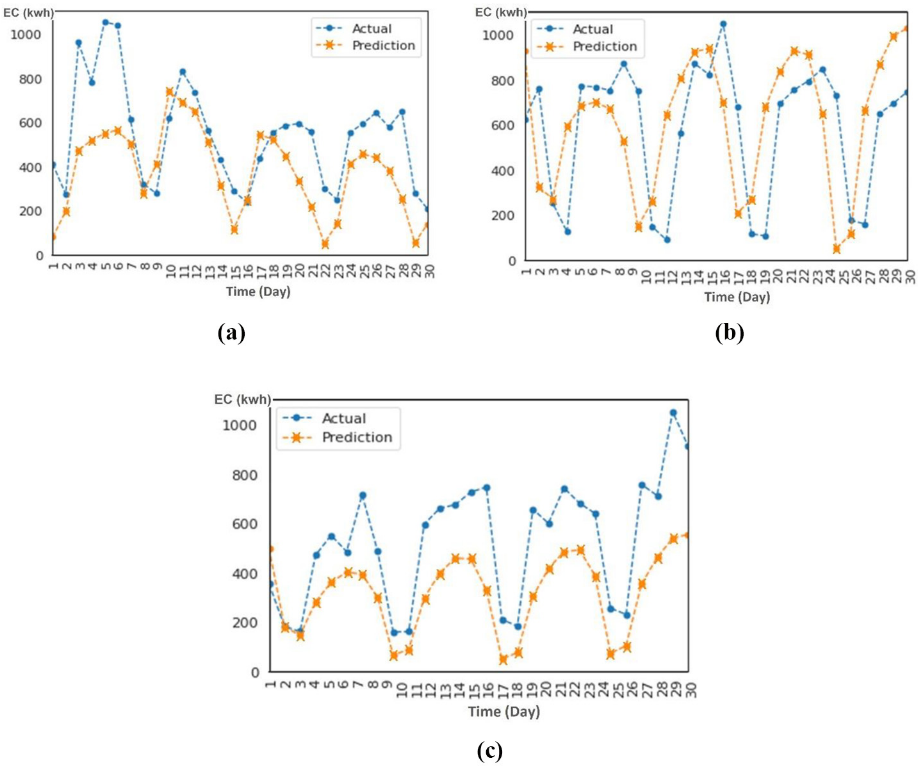


Figure 5.
Actual data vs model outputs

Notes: (a) Scenario #3-1; (b) Scenario #3-2; (c) Scenario #3-3
Source: Authors' own creation

As seen in Table 4, the performance of the TL model is improved from Step 1 to Step 3, which demonstrates that introducing a new month of target building's data to the base model and retraining the TL models can enhance the performance of the TL approach. This experiment justifies the practicality of our proposed reinforcing TL approach.

Notably, the time gap between the retraining cycles needs to be selected by considering the data generated during the gaps and the computational cost of the retraining process.

4.3 Discussion

The performance of the proposed reinforcing TL approach could vary in different cases, depending on several parameters. First, the selection of the source data set is one of the main parameters. As mentioned earlier, the relevance of the source building can have a significant impact on the results. In this case study, the Genome data set was used to find a relevant source building based on the use case and location of the source and target buildings. The second parameter affecting this approach's performance is the occupants' behaviour. Occupants' behaviour has a significant impact on buildings' EC rates (Delzendeh *et al.*, 2017; Chen *et al.*, 2021; Mahamedi *et al.*, 2022). In some cases, the occupants' behaviour may even outweigh the importance of choosing two similar buildings and cause data drifts. For instance, if a building is not occupied for a period, its EC will reduce significantly, causing a data drift.

If the general trends of the data in the source and target buildings are significantly different, negative TL may occur, which means the learning performance is negatively affected by introducing the source building's data (Zhang *et al.*, 2020). Hence, TL approaches are not effective unless the fundamental assumptions are met, including the relevance of the source and target buildings and the similarity of their occupants' behaviours (Zhang *et al.*, 2020). Therefore, when the proposed reinforcing TL approach is used, it is essential to review the data and identify any significant changes in the data trends.

Another critical parameter affecting the proposed approach's performance is the amount of available data for retraining the model. As shown in Experiment 3, when the amount of data is limited but the data is continuously generated and can be dynamically incorporated into the model, the proposed reinforcing TL technique results in a better prediction performance.

When experimenting different scenarios, it was observed that the computational burden for using reinforcing TL was not significantly changed from the base model. It was due to the fact that the training data set in each cycle was relatively small, and a pre-trained was used for TL. However, preparing newly generated data for retraining the model required extra time and effort.

5. Conclusion

This study proposed a new approach for predicting buildings' EC using a novel TL-based approach, called reinforcing TL. The proposed approach contributes to the body of knowledge by overcoming the following challenges: insufficient data availability for using conventional ML approaches for predicting buildings' energy performance; and static structure of TL approaches despite the dynamic nature of buildings' energy performance.

Scenarios	MAPE
#3-1: TL1 with one cycle of training	0.21
#3-2: TL2 with two cycles of training	0.20
#3-3: TL3 with three cycles of training	0.19

Source: Authors' own creation

Table 4. Errors of experiment #3

Our proposed reinforcing TL approach incorporates the generated data from the target building into the model by retraining the model in pre-determined intervals. The case study presented justifies the validity of the proposed approach and confirms its superiority over the conventional LSTM and TL approaches. Given the reinforcing architecture of the proposed approach, the model's reliance on the source building data is reduced over time. Hence, the relevance of the source and target domains (buildings) is less significant in our proposed approach in comparison to the conventional TL approach. However, the relevance of the source building is still a critical parameter in the model's performance.

Another critical observation in the case study was the impact of data availability on the prediction accuracy of ML approaches. The results confirm that an LSTM model based on the data from a similar building outperforms the model developed using insufficient data collected from the building. In addition, occupants' behaviour was identified as a critical parameter in predicting buildings' energy performance, though investigating its impact is out of the scope of this paper. In future research, the occupants' behaviour will be incorporated into the proposed reinforcing TL approach, and a comprehensive framework for predicting buildings' energy performance will be created. Moreover, several factors (e.g. the time horizon of the decision-making, the amount of generated data and the required accuracy) can impact the selection of the timeframe of each training cycle. The impact of these factors will be investigated in future research.

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