Master’s Thesis of Engineering

Parameter Estimation of Unknown Building Properties Using Transfer Learning

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Department of Architecture and Architectural Engineering
College of Engineering
Seoul National University

Yundam Ko

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Advised by Prof. Cheol-Soo Park

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Department of Architecture and Architectural Engineering
College of Engineering
Seoul National University

Yundam Ko

Confirming the master's thesis written by
Yundam Ko

August 2021

Chair	Myoungsouk Yeo
Vice Chair	Cheol-Soo Park
Examiner	Sun Sook Kim

Abstract

To reduce the performance gap between the predicted and measured energy uses, many studies have focused on estimation of unknown parameters of a building energy model. This study proposes a transfer learning (TL)-based parameter estimation method to identify unknown building properties from measured energy use data. TL is a machine learning method that a model developed for one task is reused as the starting point for a model on another task.

Using TL, this study examines the transferability from virtual (EnergyPlus) to existing buildings, especially for identifying wall U-value, HVAC efficiency, and lighting power density (LPD). For this purpose, synthetic data was generated from simulation results of sampled EnergyPlus models, and then we developed artificial neural network (ANN) models using this data. By adopting TL, the ANN models were transferred to the domain of existing buildings and evaluated on 61 existing buildings. As a result, the relative improvements in CVRMSE achieved by the transferred models against the models trained only with existing buildings' data were 8.85%, 10.34%, and 15.73% for nominal cooling COP, wall U-value, and LPD, respectively.

The results indicate that prior knowledge obtained from simulation results of a physics-based model can improve the performance of a data-driven model by adopting TL, leading to reduced data dependency of data-driven methods. Moreover,

it is expected that the use of TL enables the developed model to be reusable for another group of buildings with improved performance and reduced training time.

Keyword: Transfer learning, Parameter estimation, Machine learning, Artificial neural network, Building energy, Calibration

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Chapter 1. Introduction

1.1. Importance of Parameter Estimation in Building Simulation

The built and urban environments comprise a large proportion of energy consumption and greenhouse gas emissions in the world. With the growing concerns to reduce building energy consumption, high performance buildings have attracted attention. Building performance simulation (BPS) tools have been widely used to predict building energy performance and to estimate energy savings from various energy conservation measures (ECMs). However, a significant gap between predicted and measured energy use has been observed, identified as the 'energy performance gap', and this gap has been growing with the increasing availability of high-resolution operational data (de Wilde, 2014). It was reported that measured electricity consumption can be up to 90% higher than that predicted at the design phase (UCL Energy Institute and CarbonBuzz, 2013). The large gap decreases the trust in the design and engineering sectors of the building industry and may result in a distrust of the ambitious targets, such as High Performance Buildings and Net Zero Energy Buildings.

The energy performance gap is mainly caused by inherently uncertain variables that affect building energy performance, such as occupant behavior, thermal properties of building envelope, heating, ventilation and air-conditioning

(HVAC) efficiency, lighting and plug loads, and etc. It is difficult to determine such variables for BPS, because data collection would be too costly or data may not exist due to loss of original drawings and specifications, and some variables may be impossible to be measured (e.g. effective leakage area). In addition, efficiencies of building envelopes and systems can degrade over time, thus might be different to those in drawings. Therefore, many variables are assumed by the judgement of modelers, which may lead to energy performance gap. In this regard, many studies have focused on model calibration and validation to reduce the performance gap (Heo, Choudhary, and Augenbroe, 2012; Sun, 2014). For this purpose, many parameter estimation (inverse modeling) methods have been introduced in the building simulation domain to estimate unknown inputs (e.g. building thermal properties and HVAC efficiencies) using outputs (e.g. measured building energy consumption).

1.2. Current Methods for Parameter Estimation

Existing parameter estimation methods in the building simulation domain can be categorized into physics-based vs. data-driven, and deterministic vs. stochastic, as depicted in Figure 1.1 (Ahn et al., 2019). Physics-based deterministic approaches usually combine first-principle models (e.g. EnergyPlus) with measured data. Manual approach, i.e., trial-and-error, finds unknown parameters by repeated attempts until success. This would work for a simple model requiring only a few inputs but would be an exhaustive procedure for the model of an existing building with a large number of inputs. The least-squares, one of the most widely used approaches for optimization, are to minimize the squared deviation between measured and predicted outputs (Reddy and Andersen, 2002). Yoon et al. (2011) adopted a deterministic optimization to estimate unknown parameters in the lumped model of a double-skin façade system. Many studies have attempted to automatize this optimization process to reduce the manual effort (New et al., 2012; Robertson et al., 2013; Yang et al., 2016). However, most of these require significant computation even for a single building and thus may not suitable for large-scale implementation.

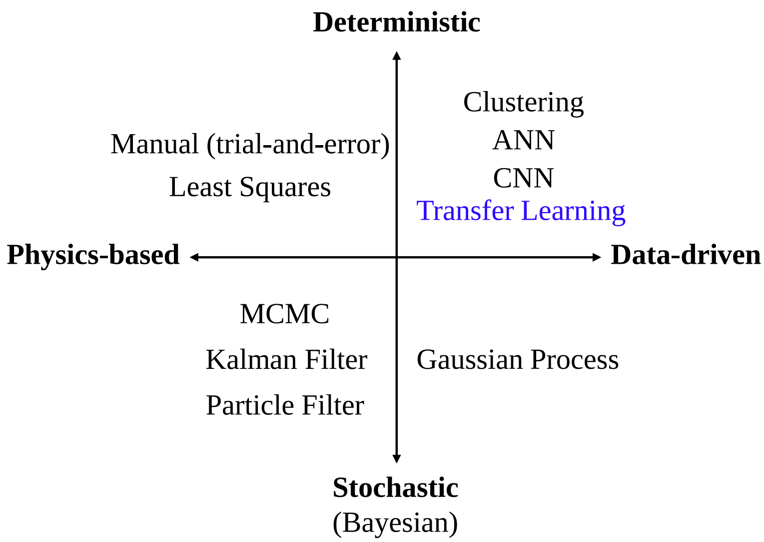


Figure 1.1 Parameter estimation approaches used in the building energy modeling process (scope of this thesis in blue) [modified from Ahn et al. (2019)]

Data-driven deterministic approaches use measured data and can alleviate computational burdens of physics-based models, enabling large-scale applications.

Clustering techniques have been applied to capture building properties (i.e., unknown parameters) from available data. An et al. (2012) clustered buildings based on similarity to estimate thermal parameters. Westermann et al. (2020) identified energy signatures of buildings to estimate heating systems and building use type from smart meter data using K-means and hierarchical clustering. Artificial neural networks (ANN) have been adopted to develop a surrogate model as well as to reduce computational cost. Nagpal et al. (2018) developed surrogate models of ANN to rapidly estimate unknown parameters through optimization routines. Nutkiewicz et al. (2019) applied residual networks (ResNet), one of the deepest convolutional neural network (CNN) architectures, to automatically calibrate urban building energy models.

Because deterministic approaches cannot consider stochastic characteristics of unknown parameters, many stochastic approaches for both physics-based [e.g., Bayesian inference (BI)] and data-driven [e.g., Gaussian process (GP)] have been introduced. Bayesian inference (BI) has attracted attention due to its capability to estimate probability distribution of uncertain input parameters using domain knowledge (i.e. prior distribution) and observed data (i.e. likelihood) (Tian et al., 2018). The Bayesian approach has been widely applied not only to an individual building (Heo et al., 2012; Chong et al., 2017), but recently also to buildings at a large scale (Sokol et al., 2017; Tardioli et al., 2020). Heo et al. (2012) applied Markov chain Monte Carlo (MCMC) to estimate unknown parameters in a normative building energy model. Chong et al. (2017) proposed the improved framework using the No-U-Turn Sampler for BI of building energy models. While the MCMC is used for a one-time estimation, Kalman filter (KF) and particle filter (PF) are used for iterative estimation, meaning that posterior distributions of uncertain parameters are updated at each time step. Kim and Park (2017) applied KF to estimate a time-varying heat sources of a building. Li and Liu (2017) used PF to estimate room cooling load in real time.

Bayesian approaches have been also adopted for urban building energy models. Sokol et al. (2017) first classified buildings into archetypes using available information, and then estimated probability distributions of high-uncertainty parameters by Bayesian calibration. Tardioli et al. (2020) used clustering to identify representative buildings and developed surrogate models for Bayesian calibration of building energy models at district scale.

Despite many advantages of Bayesian approaches, the several issues remain unsolved including prior selection, data quality and quantity, large computational cost, and parameter identifiability (Yi et al., 2019; Yi et al., 2020).

In contrast to ANN, CNN, and clustering algorithms, GP can reflect the stochastic relationship between inputs and outputs of a model. Ahn et al. (2019) used GP to estimate the stochastic heat removal rate and efficiencies of eight parallel heat pumps in a hospital building.

Although many rigorous approaches have been introduced, many of them require a large amount of data. In other words, at least a similar amount of data used for case studies may be required to apply the methods to new target buildings. This hinders previous models to be reused for other buildings.

1.3. Research Hypothesis and New Parameter Estimation Method

To overcome the lack of detailed building data and the reusability issue, this study proposes a transfer learning (TL)-based inverse approach. Figure 1.2 depicts the hypothesis of this study investigating the feasibility of the TL approach. This can maximize the utility of limited data available by transferring the prior knowledge obtained from other existing buildings or even from virtual buildings, e.g. EnergyPlus models, leading to less data dependency than conventional machine learning approaches. In addition, the developed data-driven models can be easily re-used by adopting TL that re-trains the models with a new dataset (i.e., a new target building) while maintaining useful fundamental knowledge obtained from previous data, leading to the performance improvement and computational efficiency.

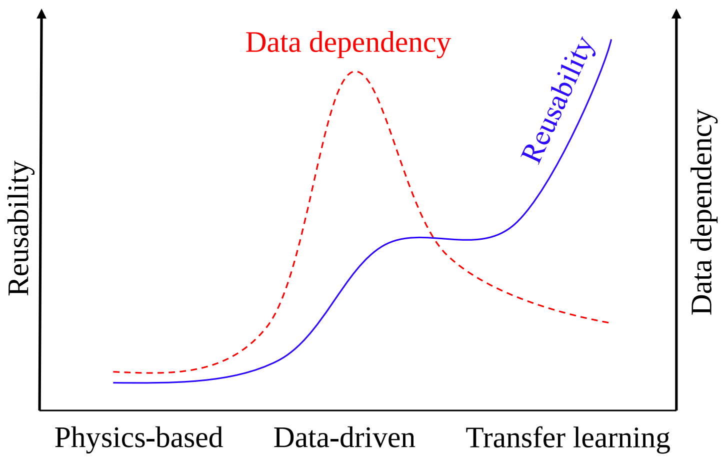
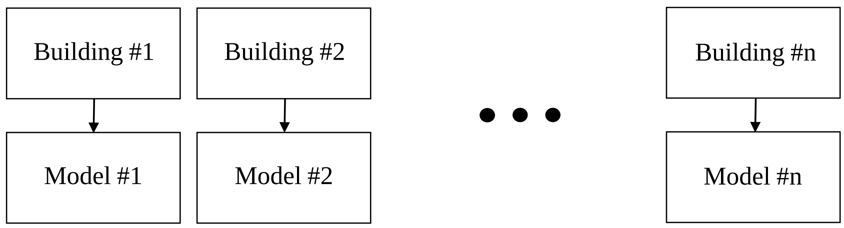
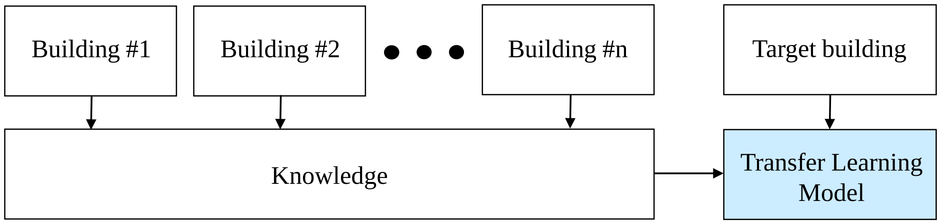


Figure 1.2 Hypothesis of this study: reusability vs. data dependency for three different modeling approaches (Ko and Park, 2022)

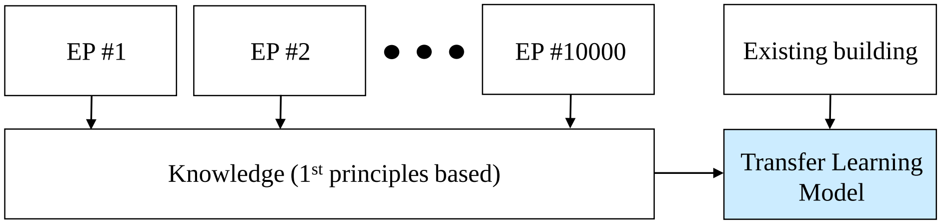
Figure 1.3 compares conventional data-driven approaches and transfer learning for building simulation. While the conventional approach requires a separate model for each building (Figure 1.3(a)), transfer learning uses the knowledge extracted from multiple buildings to improve the model performance for a target building (Figure 1.3(b)). However, this cannot be employed when data of other buildings are not accessible. In this regard, as depicted in Figure 1.3(c), this study proposes transfer learning from virtual buildings (i.e., EnergyPlus models) to existing buildings for the identification of unknown building properties. For this purpose, an ANN (artificial neural network) model is pre-trained with simulation results of 10,000 EnergyPlus models generated by Latin Hypercube Sampling and then is transferred to real data of 61 existing buildings by fine-tuning the model, one of the TL strategies. The proposed approach can rapidly identify building properties, such as U-value of building envelopes, COP (coefficient of performance) of heat pumps, and lighting power density (LPD), given aggregated monthly electricity use data. It is noteworthy that the data generated from simulation runs can improve the performance of the data-driven models through TL.



(a) Conventional data-driven approach



(b) Transfer learning from existing buildings to an existing target building



(c) Transfer learning from virtual buildings (EnergyPlus models) to an existing target building (proposed in this study)

Figure 1.3 Comparison of conventional data-driven approach and transfer learning for building simulation [modified from Ribeiro et al. (2018)]

1.4. Organization of the Thesis

This thesis is outlined as follows:

- Chapter 1 presents motivations for parameter estimation in BPS, followed by the literature reviews on current parameter estimation methods, and proposed a new method using transfer learning from virtual to existing buildings.
- Chapter 2 describes the technical background of artificial neural network (ANN) and transfer learning (TL) that are machine learning

techniques applied in this thesis and provides a review of related works.

- Chapter 3 provides the detailed overview of the TL-based proposed method in three steps as well as the description of the data collected and used in this study.
- Chapter 4 shows the estimation performance of the proposed method for the properties of the existing buildings, compared to the baseline methods.
- Chapter 5 concludes the remarks to understand the overall results of the thesis including the benefits and limitations of the proposed method and suggests the future directions to pursue.

Chapter 2. Background and Related Works

2.1. Artificial Neural Network (ANN)

Artificial neural network (ANN) is one of the supervised machine learning methods that consists of input layers, hidden layers, and output layers as shown in Figure 2.1**,** where w_{ij} is the weight of the ith input neuron to the jth hidden neuron and w_{jk} is the weight of the jth hidden neuron to the kth output neuron. The number of input and output neurons is equal to the number of input and output variables, and each neuron in the network is connected by a weight. The neurons in the hidden layers perform the summation of the values obtained from the input layer, and then it processes the summations with its activation function, such as the sigmoid function, tangent-hyperbolic function, linear function, or ReLU (Rectified Linear Unit), that converts the neuron values into meaningful response values (Biswas, Robinson, and Fumo 2016). The output of ANN is calculated by the input values propagated through all layers and weights.

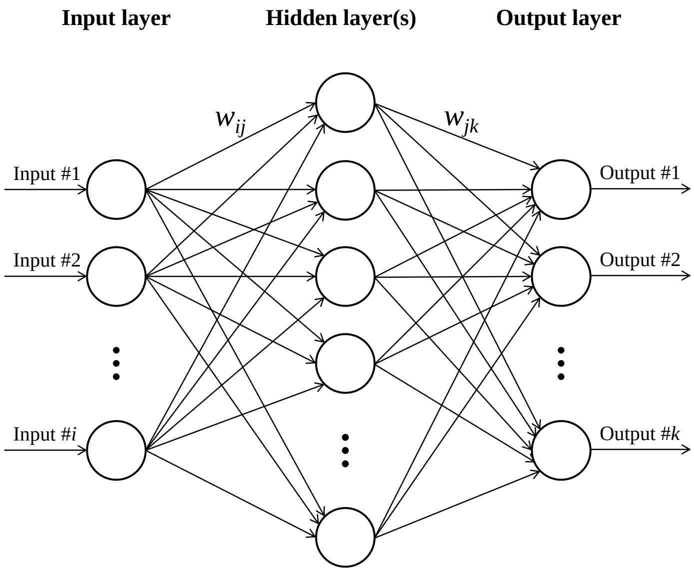


Figure 2.1 Structure of multi-layer perceptron artificial neural network [modified from Ahn et al. (2020)]

The training process of ANN uses a back propagation learning algorithm to update the weights started from random initial values to map the input and output relationship. The error between the output of ANN and the training dataset is back propagated, and the weights are updated based on the back propagated error using a gradient descent method until a desired output is achieved (Raza and Khosravi 2015).

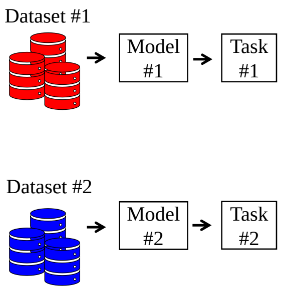
The performance of ANN may significantly vary according to hyperparameters which determine the network structure including the number of network layers, the number of nodes in each layer, and the type of activation functions and determine how the network is trained including learning rate, batch size, and the number of epochs. To improve the performance of ANN by tuning such hyperparameters, manual search, grid search and random sampling search can be used (Bengio, 2013).

Artificial neural networks (ANN) have been widely employed in many research fields including building simulation due to its ability to describe non-linear dynamics (Zhao and Magoulès, 2012; Kumar, Aggarwal, and Sharma, 2013). Major applications of ANN in the building simulation domain are as follows:

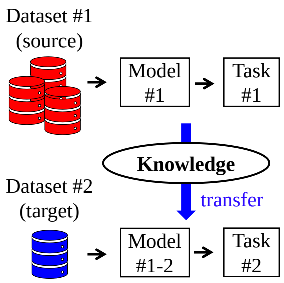
- Prediction of heating and cooling loads (Olofsson and Andersson, 2001; Ben-Nakhi and Mahmoud, 2004; Yokoyama, Wakui, and Satake, 2009; Wang, Lee, and Yuen, 2018)
- Prediction of energy consumption (Roldán-Blay et al., 2013; Biswas, Robinson, and Fumo, 2016; Jovanovic, Sretenovic, and Zivkovic, 2016)
- Prediction of building thermal responses (e.g. solar radiation and indoor air temperature) (Mechaqrane and Zouak, 2004; Argiriou et al., 2004; Moon, Yoon, and Kim, 2013; Chen et al., 2020)
- Model predictive control (MPC) and optimization of a building system (Afram et al. 2017; Ahn et al., 2020)

2.2. Transfer Learning (TL)

The lack of detailed data for training is a main challenge to develop a new data-driven model. In addition, training a model with a large dataset often takes a long time. To overcome these issues, transfer learning (TL) was introduced and has been applied to many tasks in various fields including image classification and natural language processing. The aim of TL is to transfer knowledge acquired from ‘source’ domain to ‘target’ domain in order to improve performance of models with reduced training time. In this study, the author used TL for identifying unknown factors because TL can inherit knowledge learned from ‘source’ data as exemplified from Figure 2.2. While conventional machine learning approach requires a separate model for each task, TL approach can use one model for many tasks by rapid fine-tuning (Figure 2.2). In other words, a data-driven model trained with ‘source’data, i.e. a pre-trained model, can be re-used after fine-tuning with target data which may be not sufficient for a training dataset.



(a) Conventional machine learning modeling approach



(b) Transfer learning modeling approach

Figure 2.2 (a) conventional machine learning (ML) vs. (b) transfer learning (TL) (Ko and Park, 2022)

Three possible benefits of TL are illustrated in Figure 2.3: higher start (higher initial performance), higher slope (faster training), and higher asymptote (higher final performance). However, TL can also result in lower performance, which is referred to as negative transfer (Torrey and Shavlik, 2009). To avoid this, a source dataset that related with a target task should be carefully selected (Weiss et al., 2016).

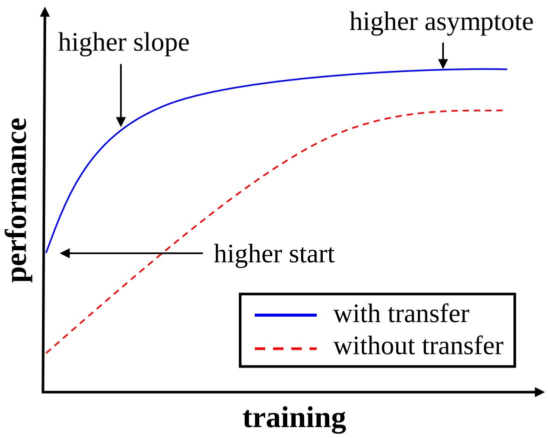


Figure 2.3 Three possible benefits when using transfer learning [modified from Torrey and Shavlik (2009)]

Fine-tuning is one of the widely used transfer learning approaches. Major fine-tuning strategies for neural network-based models are depicted in Figure 2.4. If the target dataset is large enough and not similar to the source dataset, we can develop a new model, needless to fine-tune the pre-trained model (Quadrant 2 in Figure 2.4). On the other hand, if the target dataset is large and similar to the source dataset, we should consider fine-tuning the model pre-trained on the source dataset rather than training a model from scratch (Quadrant 1 in Figure 2.4). This is because starting from pre-trained weights to train a model may result in better performance than from initial random weights, even if the target task is different to the source task (Yosinski et al., 2014). If the target dataset is small and different to the source dataset, which may be the most difficult case, we should fine-tune the weights in the last layers of the pre-trained model on target data (Quadrant 3 in Figure 2.4). For fine-tuning, usually earlier layers are frozen and only later layers are unfrozen to be retrained with target data. This is because earlier layers contain more generic information that can be applicable to many datasets and tasks, while later layers include more specific information (Yosinski et al., 2014). If the target dataset is small and similar to the source dataset, we could replace only the output layer of the pre-trained model and retrain a new output layer on target data (Quadrant 4 in Figure 2.4).

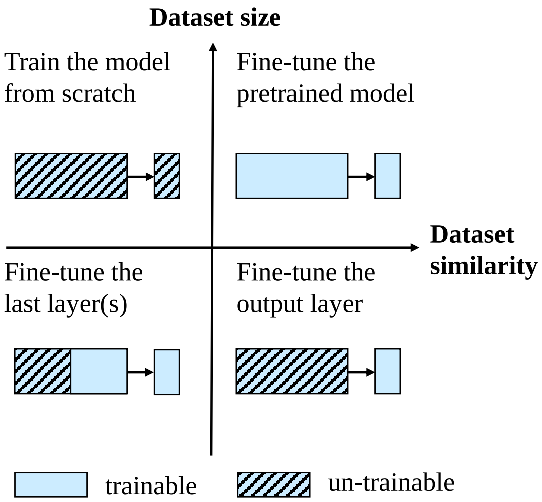


Figure 2.4 Fine-tuning strategies for transfer learning of neural network-based models [modified from Gao et al. (2020)]

Recently, several studies have applied TL to building simulation domain. Grubinger et al. (2017) presented an online TL framework to predict indoor temperature in residential buildings, and the performance improvement of TL was proved by experiments on a simulation environment. Ribeiro et al. (2018) developed a data-driven model to predict electricity consumption of a school building by using data of the four other school buildings as source data. Fan et al. (2020) showed that a TL-based methodology can reduce the prediction error of electricity consumption from 15% up to 78%. Chen et al. (2020) experimented the transferability of deep neural network models for indoor temperature and relative humidity prediction of two buildings located in different climate zones using EnergyPlus. Xu et al. (2020) tested whether a deep reinforcement learning-based HVAC controller developed for an individual building can be transferred to another building. The result showed that transfer learning can significantly reduce training time, energy cost, and temperature violations.

Depending on tasks, data-driven prediction models can be transferred even without any calibration process. Markovic et al. (2021) developed a long-short-term memory (LSTM) model for electric load prediction using data collected from a research building located in Abu Dhabi, United Arab Emirates (UAE). Without any calibration, the model showed competitive accuracy evaluated using data from two additional buildings located in different climates. Ward et al. (2021) explored the transferability of models for occupant-related electricity load prediction by training ML models on data from one building in UK and using these models for the other building in Singapore. The result showed that the models can be transferable from one building to the other building, and vice versa.

Previous studies effectively showed the adaptation capability of TL from virtual buildings (i.e., buildings in simulation environments) to virtual buildings or from existing buildings to existing buildings. However, it might be more difficult to collect data of many other existing buildings than that of a target building. In this regard, this study examines the transferability from virtual to existing buildings, especially for identifying unknown factors in existing buildings. This transferability may overcome not only the lack of data but also the model's non-reusability issue in the building simulation domain.

Chapter 3. New Parameter Estimation Method Using Transfer Learning

This chapter describes the data collected for this study and the methodology in three steps:

- Step 1: the author generates synthetic data composed of 10,000 EnergyPlus models of a virtual building [i.e., U.S. DoE (Department of Energy) reference building] through Latin Hypercube Sampling (LHS). Please note that this is a single building with 10,000 combinations of varying parameters.
- Step 2: the author pre-trains an artificial neural networks (ANN) model on the generated synthetic data out of Step 1.
- Step 3: the author fine-tunes (re-train) the ANN model fit to 49 existing buildings out of 61 existing buildings and then apply it to estimating the properties of the remained 12 buildings.

Figure 3.1 provides an overview of the proposed TL-based parameter estimation method. The details of each step are described in the following subchapters.

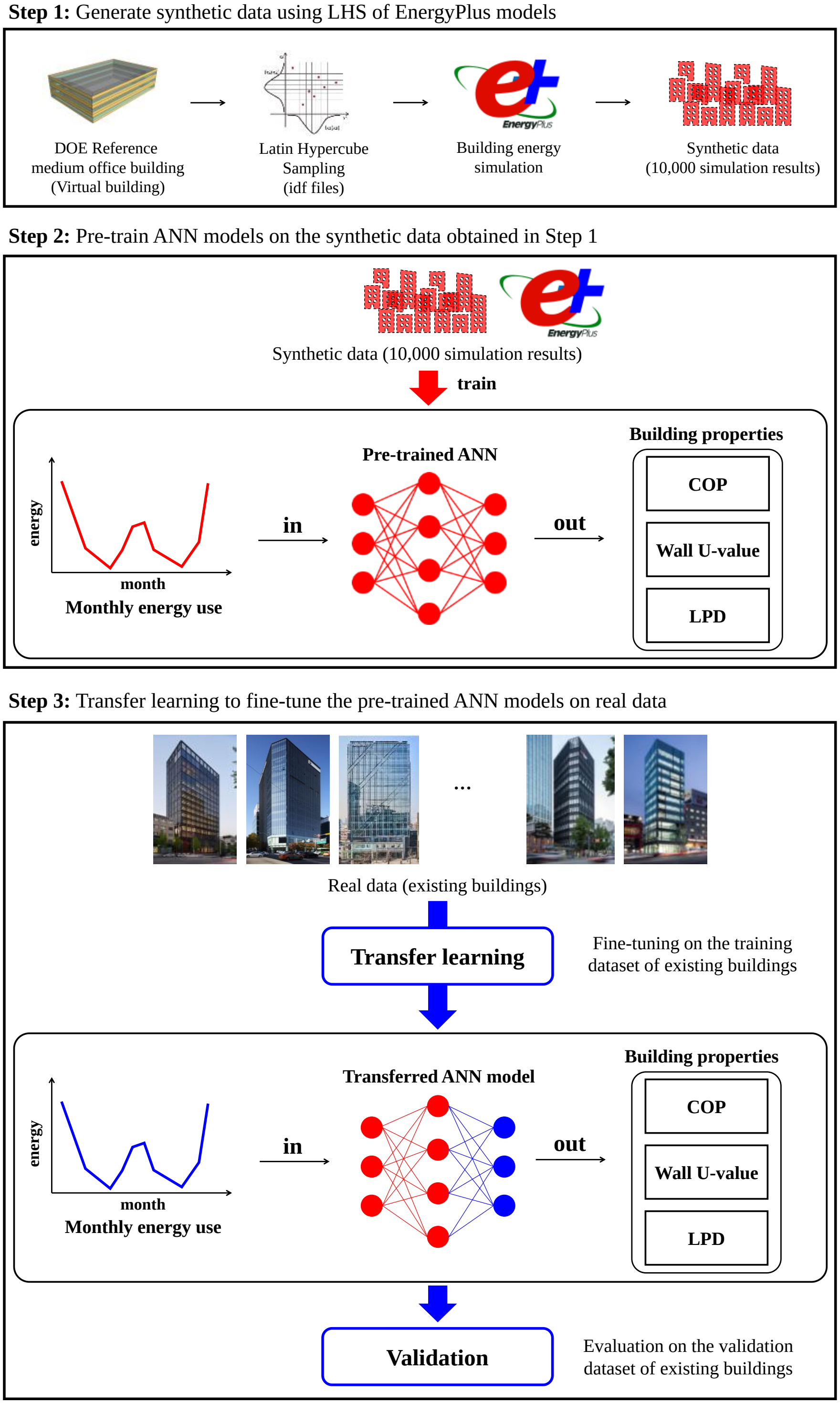


Figure 3.1 Procedure of the proposed transfer learning-based inverse modeling approach (Ko and Park, 2022)

3.1. Data Description

Data of 61 existing office buildings located in South Korea was collected from the building energy certificate database managed by the Korean government's energy agency (KEA). These buildings are equipped with electric heat pumps (EHP). The data is obligatorily collected from the audits conducted by certified energy inspectors and submitted for issuing a certificate. This includes date of construction, gross floor area, the number of floors, nominal cooling and heating COP of EHP from the manufacturers' data sheets, thermal properties of envelopes (U-values of wall, roof, floor, and window) calculated based on construction drawings and documents, lighting power density (LPD) (W/m^2) based on the total power of installed lights divided by the gross floor area of a building. Monthly electricity consumptions of these buildings are collected from a public open database of building energy provided by a Korean government agency (MOLIT, 2021). Fig. 3.2 shows five selected buildings out of 61 existing office buildings, and Fig. 3.3 shows the distributions of building characteristics. Monthly EUI (electricity) of these 61 buildings are plotted in Fig. 3.4.

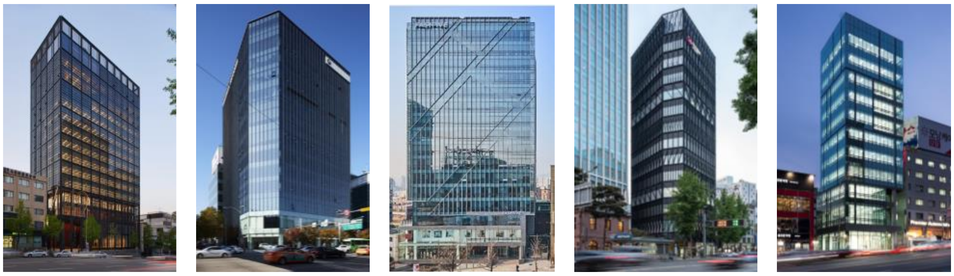


Figure 3.2 Five selected buildings out of 61 existing office buildings

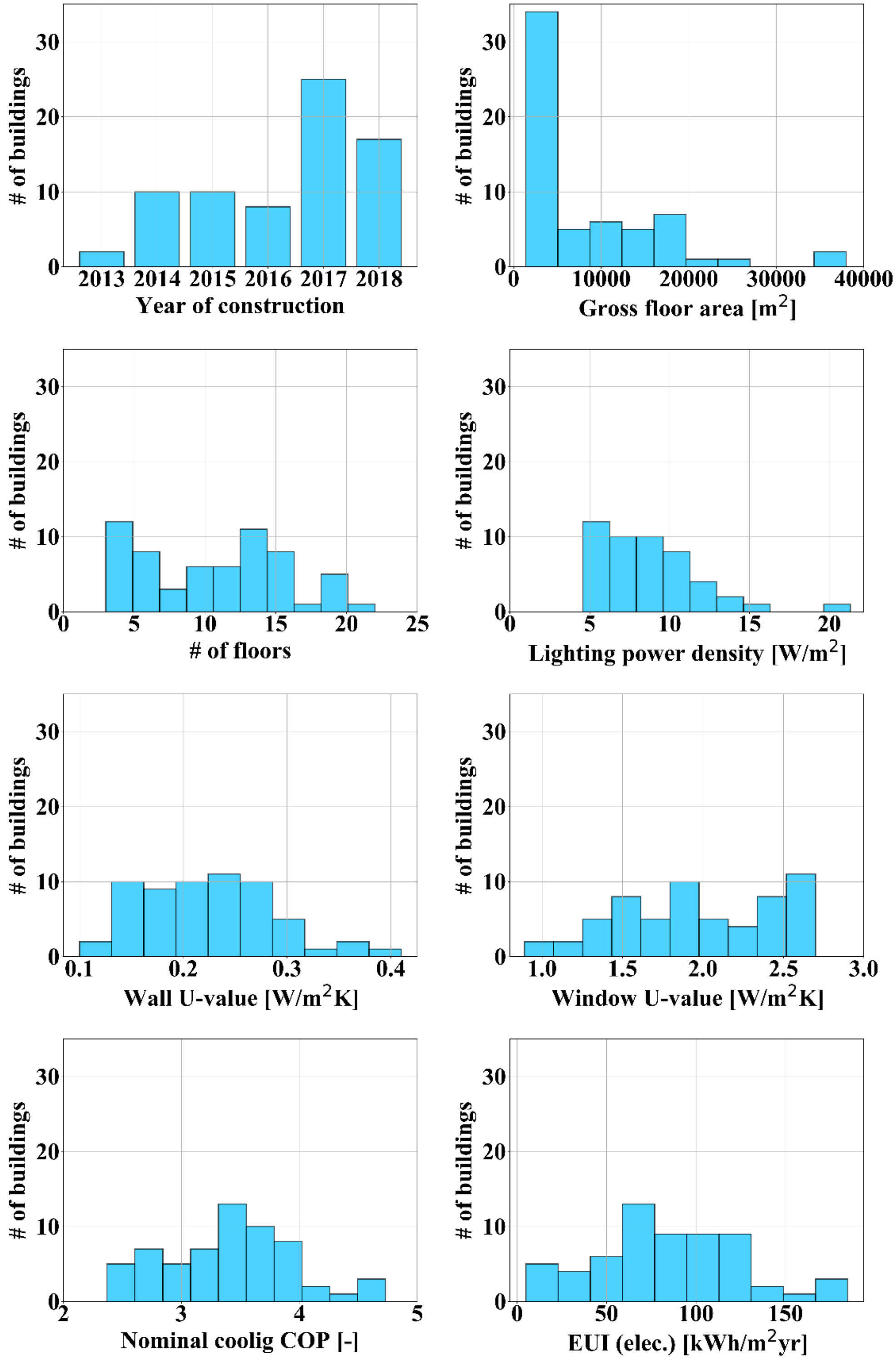


Figure 3.3 Distribution of collected data (61 existing office buildings)

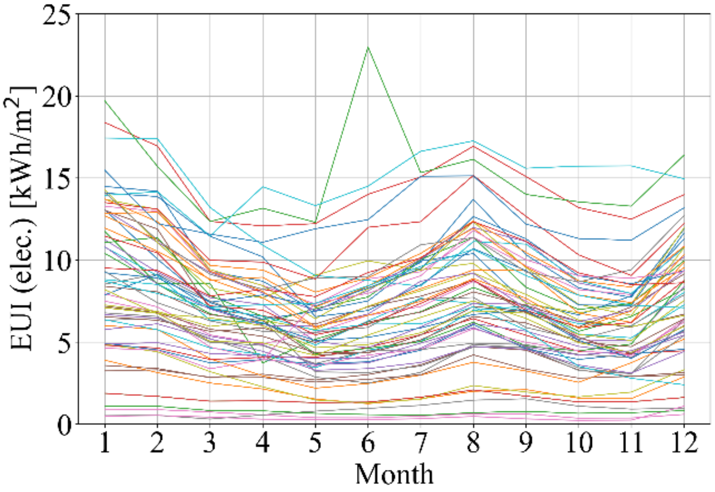


Figure 3.4 Monthly EUI (electricity) of 61 existing buildings

3.2. Generate Synthetic Data Using Latin Hypercube Sampling (LHS) of EnergyPlus Models

To explore the transferability of a data-driven model from virtual buildings (i.e., EnergyPlus models) to existing buildings, the author first generated synthetic data in this chapter to develop an artificial neural network (ANN) model. For this purpose, a medium office of U.S. DoE (Department of Energy) reference commercial buildings was sampled using Latin Hypercube Sampling (LHS) based on Table 1 (U.S. DoE, 2012). The office building has a total floor area of 4,982m^2 with three stories above ground and is equipped with an EHP for heating and cooling and a gas boiler for hot water. The weather data of Seoul, South Korea is used for a one-year simulation (Lawrie and Crawley, 2019).

Table 3.1 Sampling distribution of parameters

Variable	Distribution (uniform)	Variable type	References
U-values (wall, roof, and floor) [W/m^{2}K]	[0.18, 0.5]	continuous	MOLIT (2018)
U-value (window) [W/m^{2}K]	[2.1, 3.8]		
SHGC [-]	[0.4, 0.8]		
Infiltration [ACH]	[0.1,0.7]		Hyun et al. (2008)
Cooling COP [-]	[2, 6]		Collected data from drawings and specifications in this study
Heating COP [-]	[2, 6]		
Occupancy [people/m^2]	[0.04, 0.3]		Li et al. (2016);
Lighting power density [W/m^2]	[6, 35]		Hopfe (2009)
Equip. density [W/m^2]	[6, 30]		
HVAC start [hour]	[6, 9]	discrete (step = 1 hour)	-
HVAC stop [hour]	[19, 22]		-
Cooling set point [˚C]	[24, 27]	discrete (step = 1˚C)	-
Heating set point [˚C]	[17, 21]		-

Uniform distribution was selected for LHS because the purpose of sampling is not to reflect the actual statistics of the variables, but to provide ANN models with balanced dataset that could result in better prediction accuracy. In total, 10,000 EnergyPlus models (i.e., a single building with 10,000 combinations of variable parameters) were generated and simulated to obtain 12-monthly energy use data associated with the parameters in Table 3.1, which will be used for pre-training. Although these models do not represent existing office buildings, an ANN model could acquire prior knowledge, e.g. building thermal dynamics and HVAC dynamics, and could use this knowledge to adapt rapidly to the domain of existing buildings. Moreover, it can be examined whether virtual data obtained from the 1st principles-based models can be utilized to improve the performance of a data-driven model for existing buildings through transfer learning, although synthetic data from a virtual building is not a representative for target existing buildings. Please note that using data of buildings that are similar to target buildings may improve the performance of transfer learning but such approach would not be practical because it is difficult to collect or generate those actual data.

3.3. Pre-train ANN Models on Synthetic Data

Using the synthetic data obtained from 10,000 EnergyPlus simulations in Chapter 3.2, three ANN models were developed to identify (1) nominal cooling COP of EHPs, (2) U-value of walls, and (3) LPD, respectively from aggregated monthly electricity use data. There are many significant parameters such as SHGC, air infiltration rate, and operational parameters other than these three variables, but due to lack of such data, only these three that are available from the buildings' drawings and specifications are selected to evaluate the proposed method. Figure 3.5 shows the structure of the ANN models that has 12 inputs (monthly energy use) and three outputs (cooling COP, wall U-value, LPD). For ANN modeling, Keras, a deep learning library written in Python, was used (Chollet, 2015). The dataset of 10,000 simulation results were split into two subsets: 7,000 for training and 3,000 for validation. The following hyperparameters of ANN models were determined by a trial-and-error method:

- Number of hidden layers: 10
- Number of nodes at each hidden layer: 16
- Epoch: 1,000
- Optimizer: Adam (Adaptive moment estimation)
- Activation function: leaky ReLU (Rectified Linear Unit)

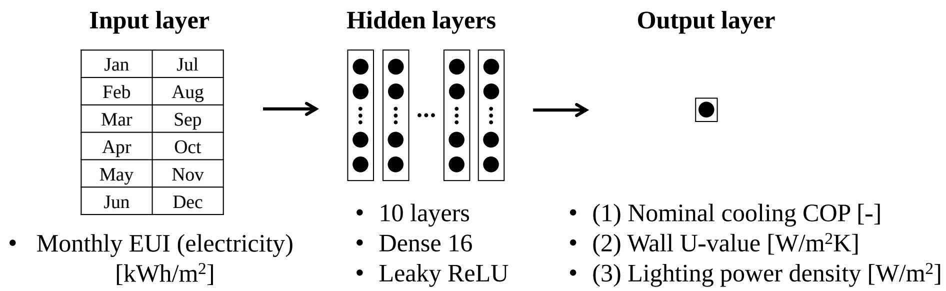


Figure 3.5 Model structure of ANN for identifying three building properties: nominal cooling COP, wall U-value, and lighting power density (Ko and Park, 2022)

3.4. Transfer Learning to Fine-tune Pre-trained ANN Models on Real Data (Existing Buildings)

In this chapter, the ANN models pre-trained in Chpater 3.3 were fine-tuned to be used for existing buildings by adopting transfer learning. After fine-tuning (re-training) the pre-trained models on 49 out of 61 existing buildings (for LPD, 38 out of 48 buildings due to missing data), the estimation models were evaluated on the remained 12 buildings (for LPD, 10 buildings).

Because the generated synthetic data may not be representative for the existing buildings, the fine-tuning strategy that re-trains the last layer(s) of a pre-trained model is selected (Quadrant 3 in Fig. 2.4). This strategy can be adopted when the target dataset is not similar to the source dataset and is not large enough for training a model from scratch. In addition, it is known that starting from pre-trained weights to train a model could lead to better performance than from initial random weights, even if the target task is not similar to the source task (Yosinski et al., 2014).

To re-train only the last layer(s) of the pre-trained model, while keeping the pre-trained weights of the other remaining layers, the layers to be fine-tuned should be unfrozen. The number of unfrozen layers should be selected depending on how large the target dataset is and how different it is to the source dataset. The more data is, the fewer layers should be unfrozen, while the more different data is to source data, the more layers should be unfrozen. To unfreeze or freeze the layers, the weight attributes of Keras were used (Chollet, 2015). In this study, only the last layer was unfrozen and re-trained on the dataset of the existing buildings for 1,000 epochs with the learning rate of 0.001. After un-freezing the last layer, the number of trainable parameters for the ANN models are only 17, while 2,673 parameters are required to train a new ANN model. This indicates that TL can significantly reduce computational cost, i.e., easily scalable to many other buildings. For example, the TL process for the ANN model of COP took only 16.2 seconds in the hardware environment as follows: AMD Ryzen 7 2700X eight-core processor for CPU, 32GB RAM, and NVIDIA GeForce GTX 1060 6GB for GPU.

In this study, estimation results were evaluated with CVRMSE (coefficient of variation of the root mean square error), MBE (mean bias error), and MAPE (mean absolute percentage error). These are computed as follows:

$$CVRMSE\ (\%) = \frac{1}{\bar{m}}\sqrt{\frac{\sum_{i=1}^{n}(m_i - s_i)^2}{n}} \times 100 \quad (1)$$

$$MBE\ (\%) = \frac{\sum_{i=1}^{n}(m_i - s_i)}{\sum_{i=1}^{n} m_i} \times 100 \quad (2)$$

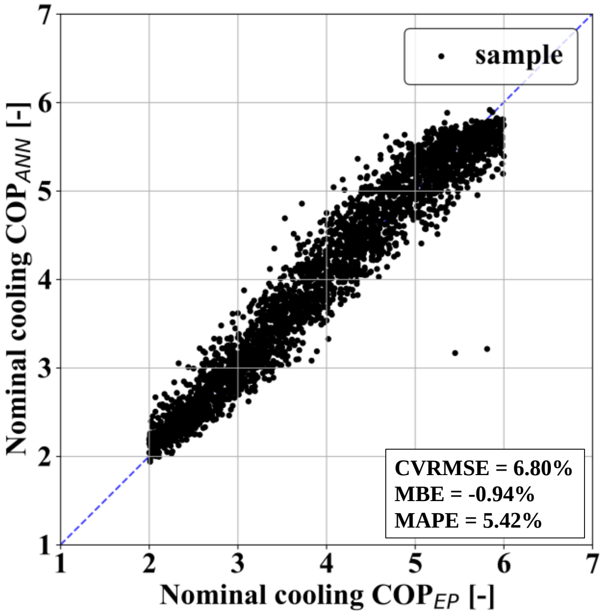
$$MAPE\ (\%) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{m_i - s_i}{m_i}\right| \times 100 \quad (3)$$

where m = measured value, s = simulated (estimated) value, and $\bar{m}$ = mean of measured values.

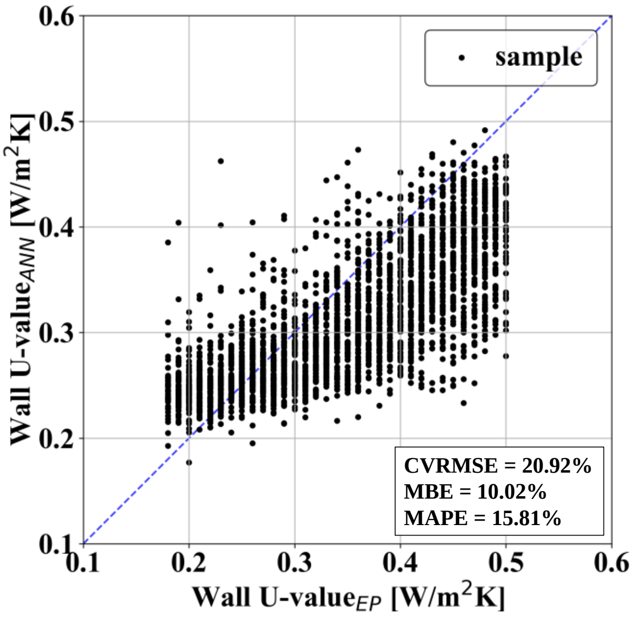
Chapter 4. Transfer Learning from Virtual to Existing Buildings for Parameter Estimation

4.1. Estimation Accuracy of ANN Models Pre-trained on Synthetic Data

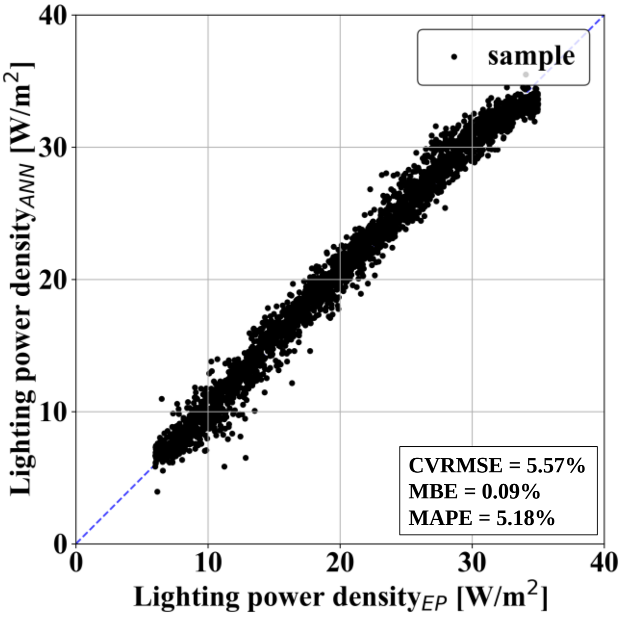
The author generated the synthetic data (i.e., the simulation results of 10,000 EnergyPlus models) in Chapter 3.2, pre-trained the ANN models using this virtual data in Chapter 3.3, and transferred these pre-trained models to the data of 61 existing buildings in Chapter 3.4. In this chapter, the estimation performance of the pre-trained models was evaluated on the validation dataset (3,000 out of 10,000 samples). Figure 4.1 shows the validation results of the pre-trained models. The estimation errors (CVRMSE) of the ANN models are 6.80%, 20.92%, and 5.57% for nominal cooling COP, wall U-value, and lighting power density (LPD), respectively. It can be said that the pre-trained ANN models can well capture the relationship between the input (monthly EUI) and the outputs (cooling COP, wall U-value, and LPD). It is notable that the error of wall U-value is larger than that of COP and LPD. This could be explained by that thermal insulation in building envelope has relatively low impact on energy use of internal-load dominated buildings as which office buildings are usually categorized, while this may significantly influence energy use of skin-load dominated buildings such as residential buildings (Al-Homoud, 2005).



(a) Nominal cooling COP



(b) Wall U-value



(c) Lighting power density

Figure 4.1 Validation results of pre-trained ANN models on 3,000 samples of the DOE reference medium office building

4.2. Improvement of Estimation Performance by Transfer Learning

In order to evaluate the performance improvement by transfer learning, two baseline cases were made: (a) source to target (S2T) and (b) target to target (T2T). S2T represents that the ANN models pre-trained with the synthetic data are directly used to predict real data (i.e., 61 existing buildings), while T2T, a conventional machine learning modeling approach, uses only real data for training and validation. We compared the results of these two baselines with those of (c) our proposed transfer learning (TL) approach.

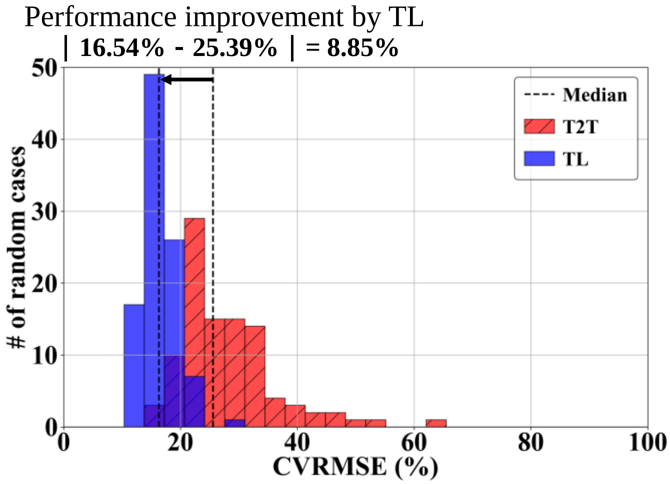
As shown in Table 4.1, the S2T models have poor performance for all three outputs. The estimation errors (CVRMSE) of the S2T models are 106.16%, 70.69%, and 153.19% for nominal cooling COP, wall U-value, and LPD, respectively. Not only large variance in estimation is observed, but also the results contain physically unrealistic values, e.g., negative values of COP, U-value, and LPD were observed. It can be said that that the S2T models cannot be directly used for target data prediction.

To compare T2T with TL, we repeated the evaluation procedure 100 times with randomly shuffling training (80%) and validation (20%) dataset, because which of 61 buildings are included in training or validation set may have huge impact on comparison results. Fig. 4.2 shows the validation results of 100 random cases for T2T and TL. Although TL outperforms T2T in the most of 100 random cases, T2T is comparable to TL or even surpasses TL in several cases. This result may be explained as negative transfer, resulting in lower prediction accuracy of TL than that of T2T. Negative transfers were observed in 1, 18, and 23 out of 100 cases for cooling COP, wall U-value, and LPD, respectively.

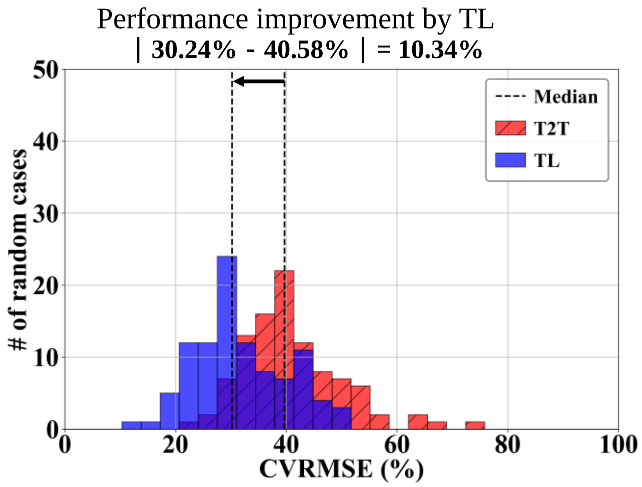
The median values of the estimation results of the 100 random cases for T2T and TL are summarized in Table 4.1. The relative improvements (the difference in the median values of CVRMSE in Fig. 4.2) achieved by TL against T2T were 8.85%, 10.34%, and 15.73% for nominal cooling COP, wall U-value, and LPD, respectively. One of the improvement cases (the lowest CVRMSE of TL) for each output were scattered in Fig. 4.3. The significant gaps between T2T and TL demonstrate that the TL models were properly adapted to the target domain (i.e., existing buildings) by integrating the prior knowledge acquired from virtual buildings.

Table 4.1 Validation results of S2T, T2T, and TL (proposed)

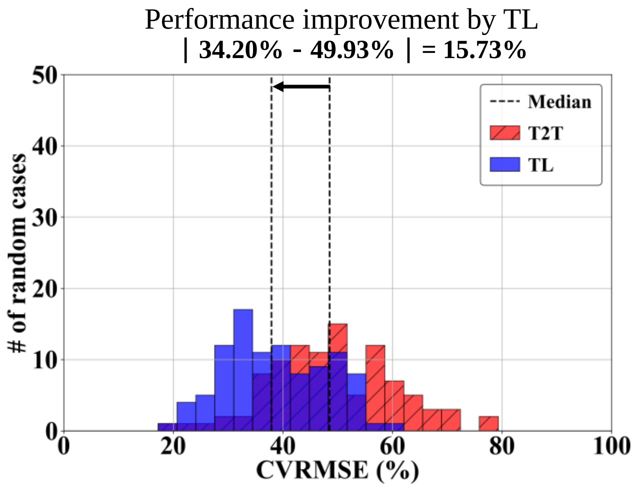
Variable	Case	CVRMSE	MBE	MAPE
Nominal cooling COP	S2T	106.16%	-54.84%	92.48%
	T2T	25.39%	2.82%	20.35%
	TL	**16.54%**	**-0.83%**	**13.27%**
Wall U-value	S2T	70.69%	52.44%	147.04%
	T2T	40.58%	1.09%	36.79%
	TL	**30.24%**	**0.03%**	**24.53%**
Lighting power density	S2T	153.19%	130.61%	59.69%
	T2T	49.93%	-4.93%	40.07%
	TL	**34.20%**	**1.29%**	**29.40%**



(a) Nominal cooling COP

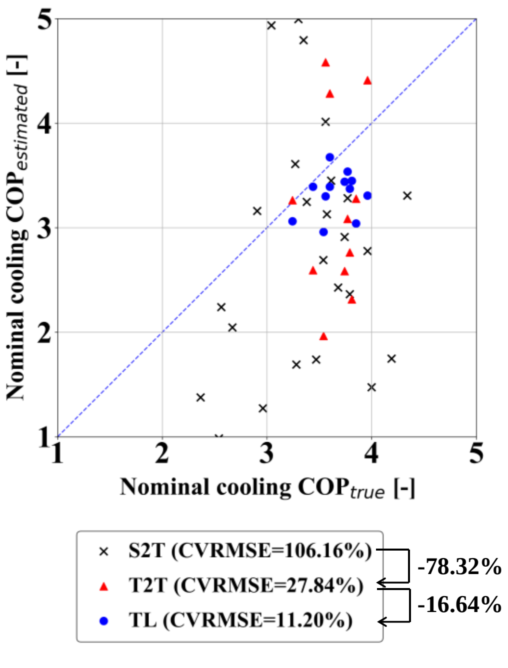


(b) Wall U-value

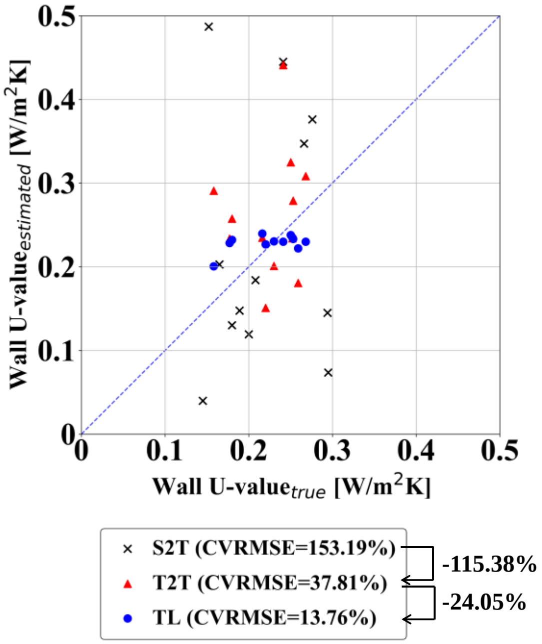


(c) Lighting power density

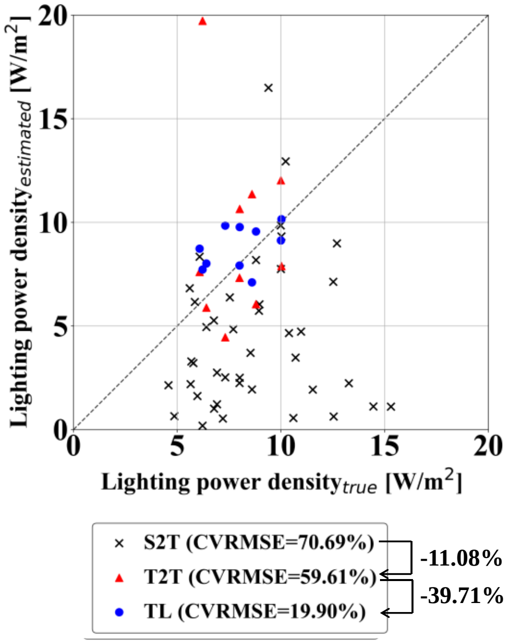
Figure 4.2 Validation results of 100 random cases: T2T vs. TL



(a) Nominal cooling COP



(b) Wall U-value



(c) Lighting power density (LPD)

Figure 4.3 Estimation results of S2T, T2T, and TL: the lowest CVRMSE case of TL

It is noteworthy that the CVRMSE of wall U-value for the target existing buildings is larger than that of COP, as in the domain of EnergyPlus. This may be due to relatively lower impact of wall U-value on energy use of internal-load dominated buildings generally including office buildings, as described in Chapter 4.1. In addition, it is interesting that the LPD were relatively poorly estimated by both T2T and TL, while these were well captured in the domain of EnergyPlus (CVRMSE=5.57%, Fig. 4.2). This might be because LPD would change dramatically in existing buildings as influenced by occupant behaviors and operational schedules, while U-values and COP would change relatively less than lights over time. In other words, LPD in existing buildings may be different from the LPD documented in drawings and specifications, thus it may be difficult to estimate from monthly energy data only.

As a result, it was found that TL can improve the performance of a data-driven model despite the use of virtual data out of a building that is not similar to target buildings. In other words, the proposed approach can be adopted for other existing buildings without collecting actual data of existing buildings. Moreover, it can be expected that the TL models will be further improved by re-transferring those to another group of buildings while keeping fundamental knowledge obtained from the virtual and existing buildings used in this study.

Chapter 5. Conclusion and Future Work

This study presents a transfer learning (TL)-based inverse modeling (i.e., parameter estimation) approach. The proposed approach consists of three steps: Step 1 generates synthetic data including 10,000 EnergyPlus models of a virtual building through Latin Hypercube Sampling, Step 2 pre-trains an ANN model on the generated data, and Step 3 fine-tunes the ANN on 49 existing buildings for TL and then applies it to estimating the properties of 12 buildings. This approach can rapidly identify unknown building properties (nominal cooling COP of EHP, wall U-value, and lighting power density) from aggregated monthly energy (electricity) use data by maximizing the utility of available data through TL.

The results show that the data-driven model trained only with virtual data cannot be directly used for existing buildings, as we expected. On the other hand, the models that are pre-trained with a virtual building and then fine-tuned on existing buildings through TL significantly outperform the models trained only with data of existing buildings in terms of accuracy (CVRMSE) in estimating unknown properties by about 10% on average. It is noteworthy that synthetic data collected from the physics-based models of a virtual building can be used through TL to improve the performance of a data-driven model, even if the virtual building used to generate synthetic data does not exactly represent the existing buildings of our interest. This makes the proposed approach more practical, because no effort is required to collect or generate data of buildings that are similar to target buildings. Moreover, the TL procedure can be conducted in a computationally efficient manner (about 16 seconds in this study), because only a few parameters (17 parameters in this study) are re-trained, i.e., easily scalable to a large group of buildings.

In addition, the performance achieved in this study can be further improved by re-transferring the developed model to other buildings. In other words, the developed TL models in this study can be re-used as a pre-trained model and transferred to another group of buildings, while maintaining useful knowledge captured from virtual and existing buildings used in this study. Such expected improvement potential is shown schematically in Fig. 5.1.

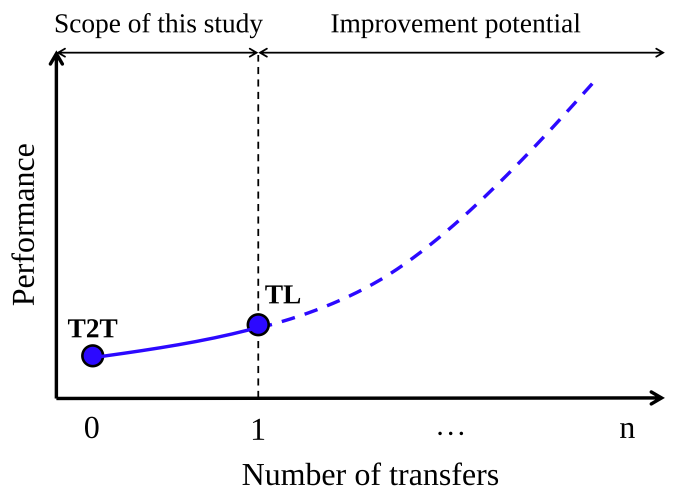


Figure 5.1 Expected performance improvement of transfer learning according to number of transfers (Ko and Park, 2022)

The proposed method can be a good alternative for large-scale collection (or estimation) of building properties when detailed data is not available, and potential applications, which could be future works of this study, may be as follows:

- Building energy benchmarking: Due to the lack of detailed building data, many existing building energy benchmarking systems have to rely on EUI per use type (office, school, hospital, etc). However, it could lead to a false comparison when two buildings consume same EUI but have different thermal characteristics, such as thermal properties of building envelopes and efficiencies of HVAC systems. By using charateristics identified by the proposed method, buildings can be categorized into peer groups by ‘similar’ performance charateristics and then compared for ‘objective energy performance benchmarking’ rather than ‘EUI-based benchmarking’.
- (Urban) building energy modeling and calibration: Identified parameters can be used for simulation inputs of (urban) building energy models when data is not available and on-site data collection is not possible or too costly.

In spite of the merits in the proposed approach, some limitations still exist. While this study showed the transferability of the ANN models from virtual to existing buildings, the transferability to different building use types, climates, HVAC types, or periods of construction should be examined for larger applicability of the proposed method. It should be also figured out whether the proposed method can be used for other relevant parameters not conducted in this study due to lack of data for validation, such as thermal mass, infiltration, operational information (e.g., set-point temperature, HVAC operation schedules, and occupancy). These will be future works of this study.

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국문초록

전이학습 기반 건물 미지 변수의 파라미터 추정

고윤담

건축학과 건축공학전공

서울대학교 대학원

건물 에너지 시뮬레이션 모델의 예측 값과 실제 측정 값의 차이(Performance Gap)를 줄이기 위해 모델 보정 및 검증 (model calibration and validation)에 관한 연구가 활발히 진행되고 있다. 이를 위해, 측정된 건물 에너지 사용량에서 미지 변수를 추정하는 파라미터 추정 (Parameter estimation) 방법이 널리 사용되고 있다. 본 연구는 전이학습(Transfer learning) 기반 파라미터 추정 방법을 제안한다. 전이학습은 딥러닝 분야의 대표적인 모델인 심층 인공 신경망 학습에 필요한 데이터가 적을 때, 유사하거나 전혀 다른 분야에 학습된 신경망 모델을 활용하는 접근이다.

본 연구는 물리 법칙 기반(physics-based) 모델(EnergyPlus)의 시뮬레이션을 통해 생성된 가상 건물의 데이터를 활용하여 미지 변수 추정을 위한 인공 신경망 모델을 사전 훈련시켰다. 사전 훈련된 모델을 전이학습을 통해 실제 사무소 건물 데이터에 미세 조정(fine-tuning)하여 월별 에너지 사용량에서 미지 변수(벽체 열관류율, 히트펌프의 정격 냉방 COP, 조명 밀도)를 추정하였다.

추정 결과, 기존의 실제 건물의 데이터만으로 추정하는 방법 대비 본 연구에서 제안한 가상 건물 데이터로부터 전이 학습하는 방법의 오차(CVRMSE)가 벽체 열관류율, 정격 냉방 COP, 조명 밀도의 추정에서

각각 8.85%, 10.34%, 15.73% 감소하였다. 이는 전이학습을 통해 물리 법칙 기반 모델의 시뮬레이션 결과를 활용하여 데이터 기반(data-driven) 모델 성능을 개선할 수 있음을 보인다. 또한, 본 연구에서 개발한 전이 학습 기반 파라미터 추정 모델을 추가 데이터 수집을 통해 재전이하여 성능을 개선하거나, 새로운 대상 건물 집단으로 전이하여 재사용할 수 있다.

주요어 : 건물 에너지, 전이학습, 파라미터 추정, 기계학습, 인공신경망, 보정

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