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Sharing Is Caring: An extensive analysis of parameter-based transfer learning for the prediction of building thermal dynamics

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Abstract

In recent years deep neural networks have been proposed as a lightweight data-driven model to capture high-dimensional, nonlinear physical processes to predict building thermal responses. However, the need of a large amount of data for the training process of deep neural networks clashes with the potential limited data availability in most existing or new buildings. Transfer learning aims to enhance the performance of a target learner exploiting knowledge from related and similar environments. This study conducted a suite of experiments that leveraged 250 data-driven models based on a synthetic dataset of a building archetype to study the influence of data availability, energy efficiency level, occupancy and climate for the transfer process of thermal dynamics. The performance of the transfer learning process was compared against a classical machine learning approach. The results suggest that building thermal dynamics can be effectively transferred under the same climatic conditions, increasing performance when dealing with different occupancy schedules, efficiency levels and low data availability. Furthermore, the paper compares the performance of both transfer learning and machine learning approaches in an online fashion, to support the implementation in real-world deployment.

Keywords: Transfer Learning, Building Thermal Dynamics, Deep Neural Network, Data-driven Models, Grid-interactive Buildings

1. Introduction

The current energy transition is deeply changing the way energy is used and generated. The need of a further decarbonisation of the building sector [1] has fostered the use of distributed renewable energy resources. In this framework, Grid-interactive Efficient Buildings (GEB) [2] are crucial in the energy transition process, exploiting advanced control strategies, identified as a way to increase energy savings up to 28% [3] while providing benefits for the

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32 electric grid [4]. However, the main bottleneck for their widespread implementation is that
33 these control strategies often rely on predictive-based optimization [5], which requires the
34 development of a fast and accurate building thermal dynamic model [6]. A thermal dynamic
35 model of a building (usually built at the resolution of a thermal zone or room/space) pre-
36 dicted how the indoor environmental conditions (e.g., indoor air temperature and humidity)
37 respond to the internal disturbances (e.g., heat gains from occupants, lighting and plug-in
38 equipment), external factors (e.g., outdoor air temperature, humidity, solar irradiance), and
39 HVAC operations (zone temperature setpoint, supplied cooling or heating energy) both in
40 normal and faulty conditions [7]. The thermal dynamics of a building is governed by high-
41 dimensional, nonlinear and discontinuous dynamics, which require effort and expertise to be
42 properly modeled [8].

43 In particular, three main techniques are used to model building thermal dynamics: white-
44 box modeling, gray-box modeling and black-box modeling. White-box models use physical
45 knowledge to describe building dynamics [6] and are based on the concept of heat transfer
46 and energy and mass conservation. The major barrier of white-box modeling is represented
47 by the time and effort necessary to define and collect reliable building features. The gray-
48 box category covers a wide range of models that exploit simplified physical relationships
49 but also require parameter estimation based on measured data. A typical concept in gray-
50 box models consists in the resistor-capacitor analogy with electrical circuits [9], and their
51 development is related to the robust estimation of R-C parameters. Black-box models learn
52 the building thermal dynamics directly from the measured historical data, without assuming
53 prior hypothesis regarding any physical relationships [10]. The main advantages of the black-
54 box models are the lower development cost and the flexibility in using any measured signal
55 as an input or output, due to the absence of physics involved. On the other hand, black-box
56 models require a large amount of training data and cannot extrapolate outside the training
57 domain. Due to the higher complexity of white-box models and the increasing adoption of
58 sensing and metering technologies in buildings that provide a growing amount of building-
59 related data, there is a rising interest towards the use of data-driven methods for advanced
60 control in buildings [11, 12].

61 *1.1. Literature review*

62 The present subsection introduces a literature review on the application of black-box
63 models for the building thermal dynamics prediction, highlighting common practices and
64 limitations while identifying innovative approaches in the field. Among the first applications,
65 Ruano et al. [13] explored the use of a radial basis neural network in the built environment
66 for the prediction of indoor air temperature. Sun et al. [14] proposed a multiple linear re-
67 gression model to predict the supply temperature of a district heating network, adjusting it
68 according to actual indoor temperature deviation. Shi et al. [15] used a back-propagation
69 neural network to predict indoor relative humidity and air temperature with different fore-
70 casting horizon. Kusiak and Xu [16] proposed a dynamic neural network to relate HVAC
71 energy consumption with indoor temperature evolution, optimizing the control strategy of
72 the HVAC system with a data-driven approach. Similarly, nonlinear [17, 18] autoregressive
73 neural networks for the indoor temperature prediction were integrated with controllers to

74 optimize the HVAC systems. More recently, Huang et al. [19] coupled a neural network,
75 used to estimate the temperature evolution of a multi-zone building, with a predictive con-
76 troller, with the aim to optimize the operation of an HVAC system, while Drgoňa et al. [12]
77 exploited neural networks and regression trees to construct an approximate model predictive
78 controller.

79 To evaluate the effectiveness of the different machine learning (ML) techniques and neural
80 network architecture, Wang et al. [20] applied 12 data-driven models with the aim of predict-
81 ing the heat load of a single building. Results showed Long Short Term Memory (LSTM)
82 and eXtreme Gradient Boosting (XGBoost) to be the best, respectively, for short-term load
83 prediction and long-term load prediction.

84 Recently, much interest has been devoted to the application of LSTM for short-term load
85 and thermal dynamic prediction. Mtibaa et al. [21] used an LSTM to analyse indoor air
86 temperature evolution in a multi-zone building. Xu et al. [22] compared two LSTM models to
87 predict indoor temperature evolution one step ahead and multiple time steps ahead, studying
88 the advantages of using an error correction for multiple time steps ahead. Ellis and Chinde
89 [23] used an Encoder-Decoder LSTM to describe the dynamic of an air-handling unit with
90 variable air volume relating it to the indoor temperature evolution, coupling the information
91 with a model predictive controller (MPC) to reduce energy costs. Fang et al. [24] proposed
92 three LSTM-based sequences to sequence model architectures to perform multi-step ahead
93 indoor air temperature forecasting: an LSTM-Dense model, an LSTM-LSTM model and
94 an LSTM-dense-LSTM model, evaluating the performance under different forecast horizons.
95 The results and analyses showed that the LSTM-dense model performs better for shorter
96 forecast horizons, while the other two are more suitable for longer forecast horizons. Lastly,
97 Pinto et al. [25] proposed LSTM models to predict indoor temperature evolution in multiple
98 buildings, deploying one model per building and coupling them with a deep reinforcement
99 learning (DRL) controller to perform district demand side management, speeding thermal
100 dynamics simulation at the district level. Recently, a new paradigm in neural network was
101 introduced with physics-informed neural networks (PINNs) [26]. These neural networks are
102 trained to solve supervised learning tasks while respecting any given laws of physics described
103 by general nonlinear partial differential equations, combining the advantages of white-box
104 modeling with black-box modeling. However, despite the interest in this field, only a few
105 works explored PINNs in the domain of building energy control. Bünnig et al. [27] compared
106 physics-informed Autoregressive-Moving-Average with Exogenous Inputs (ARMAX) models
107 to Machine Learning models based on Random Forests and Input Convex Neural Networks.
108 In [28] a physics-informed neural network was exploited to forecast temperature evolution in
109 a building, increasing the sample efficiency of neural networks and performances for longer
110 prediction horizons. The authors of [29] introduced a physics-constrained recurrent neural
111 network (RNN) to model the thermal dynamics of buildings, imposing meaningful physics-
112 based boundaries to the learned dynamic with penalties, and constraining model eigenvalues.
113 Di Natale et al. [30] proposed a physics-informed NN that predicts indoor air temperature in
114 response to different control inputs, zone-zone, and outdoor-zone air temperature variations.
115 However, although Gokhale et al. [28] proved a greater sample efficiency of PINNs, they still
116 need a lot of data and physics knowledge. Furthermore, gathering and preparing a significant

117 volume of high-quality data to train ML algorithms is a time consuming procedure not always
118 viable.

119 To overcome these barriers, a turning point is the possibility to transfer ML models
120 from one building to another, a concept called transfer learning (TL) [31]. Pinto et al.
121 [32] reviewed the application of transfer learning in smart buildings, highlighting the role
122 of transfer learning for building thermal dynamics models, the challenges and the future
123 directions. However, the application of TL for building thermal dynamics is still in its
124 infancy, so only a few studies have been conducted. Of those, none have thoroughly analyzed
125 under which circumstances transfer learning performs better than classical machine learning,
126 therefore, a thorough analysis is required. Hossain et al. [33] learned RC model directly
127 training a Bayesian neural network (BNN), rather than estimating its parameters. The
128 results highlighted the reliance of classical ML models on a large quantity of data to achieve
129 satisfactory performance. The paper proposes a methodology to overcome extreme data
130 scarcity (one day of data) by identifying the best RC model based on historical consumption
131 patterns that outperforms time-series methods that were directly built using available data.
132 Jiang and Lee [34] employed a significant amount of data from source buildings to train
133 an LSTM sequence-to-sequence model to analyze building temperature evolution and used
134 this information to fine-tune a model that improved the performance on a target building,
135 while [35] froze neural network hidden layers to transfer the building thermal model. Chen
136 et al. [36] used transfer learning to predict both relative humidity and internal temperature,
137 while Grubinger et al. [37] presented an online transfer learning approach, able to integrate
138 building dynamic prediction with an MPC controller, easing a real-world implementation of
139 these applications.

140 *1.2. Research gaps and contributions*

141 Despite the opportunity to overcome the data availability issue presented for the classical
142 ML problems, the literature review [32] highlighted the following research gaps:

- 143 1. The effectiveness of transfer learning is influenced by similarity between the source
144 and the target building, however it is still unclear how to leverage such similarity to
145 identify the best source building.
- 146 2. Further studies are necessary to quantify the most important features of transfer learn-
147 ing for building dynamics.
- 148 3. Minimum data availability for an effective transfer and the time-horizon applications
149 have not been fully explored.

150 In this paper, a synthetic dataset was used to create multiple energy models of a single
151 building in different conditions, changing building features such as efficiency level, occupancy
152 and climate. The dataset was then used to train and compare machine learning and transfer
153 learning models. A machine learning model only leverages data available for the target
154 building, while the transfer learning model reuses knowledge from a source building to
155 reduce implementation costs, speed up the training and increase performance. The aim is
156 to assess their performance, isolating the contribution of specific features and studying the

157 effect of data availability on transfer learning performance. With this in mind, this study
158 aimed to address the literature gaps, with the following contributions:

- 159 1. Isolating and evaluating the contribution of key features in determining machine learn-
160 ing and transfer learning effectiveness, using a synthetic building dataset gathered from
161 a detailed physics-based building energy model.
- 162 2. Performing a statistical investigation by developing approximately 250 models to assess
163 the feature importance and data availability impact.
- 164 3. Conducting a specific analysis of negative transfer to assess the limitations of transfer
165 learning for building thermal dynamics, to identify guidelines for future research.
- 166 4. Assessing the effectiveness of transfer learning in an online deployment setting, sup-
167 porting its real-world implementation

168 2. Methods

169 The following sections describe the methods used within the paper, starting with the
170 theoretical background of transfer learning, followed by a brief description of the neural
171 networks exploited during the analysis.

172 2.1. Transfer learning

173 The transfer learning concept is based on that of “domain” and “task,” whose definitions
174 are reported below according to Pan and Yang [31].

175 **Definition 1.** Domain: a domain \mathcal{D} consists of two components: a feature space \mathcal{X} and a
176 marginal probability distribution $P(X)$, where $X = \{x_1, \dots, x_n\} \in \mathcal{X}$.

177 The prediction of building thermal dynamics can be modelled as a regression task. As
178 a result, \mathcal{X} is the space of all influencing variables, (e.g., external temperature, occupancy,
179 HVAC load), while x_i represents the i^{th} influencing variables and X a specific learning
180 sample.

181 **Definition 2.** Task: a task consists of two components: a label space Y and an objective
182 predictive function $f(\cdot)$ (denoted by $\mathcal{T} = \{Y, f(\cdot)\}$), which is not observed but can be
183 learned from the training data, represented by a pair $\{x_i, y_i\}$, where $x_i \in \mathcal{X}$ and $y_i \in \mathcal{Y}$.
184 The function $f(\cdot)$ is used to approximate the conditional probability $P(y|x)$ and predict the
185 corresponding label of a new instance x .

186 Analyzing the same application, Y is a continuous space with the possible values of the
187 internal (indoor air) temperature.

188 We denote the source domain data as $D_S = \{(x_{S1}, y_{S1}), \dots, (x_{Sn_S}, y_{Sn_S})\}$, where $x_{Si} \in X_S$
189 is the data instance and $y_{Si} \in Y_S$ is the corresponding output. Similarly, the target domain
190 data are denoted as $D_T = \{(x_{T1}, y_{T1}), \dots, (x_{Tn_T}, y_{Tn_T})\}$, where $x_{Ti} \in X_T$ and $y_{Ti} \in Y_T$
191 are the corresponding outputs. In many cases, transfer learning provides advantages where
192 $0 \leq n_T \ll n_S$.

193 **Definition 3.** Transfer Learning: Given a source domain \mathcal{D}_S and learning task \mathcal{T}_S , a target
194 domain \mathcal{D}_T , and a learning task \mathcal{T}_T , transfer learning aims to help improve the learning of
195 the target predictive function $f(\cdot)$ in \mathcal{D}_T using the knowledge in \mathcal{D}_S and \mathcal{T}_S , where $\mathcal{D}_S \neq \mathcal{D}_T$,
196 or $\mathcal{T}_S \neq \mathcal{T}_T$.

197 Transfer learning can be classified according to label availability, domain and task simi-
198 larity and technique used to transfer the knowledge.

199 Looking at label availability, there are three main categories: inductive, transductive and
200 unsupervised transfer learning.

- 201 • In inductive transfer learning, both the source and target domains have labeled data,
202 yet the source and target tasks are different.
- 203 • In transductive transfer learning, the source and target tasks are the same, yet the
204 source and target domains are different. In this setting, the source domain has sufficient
205 labeled data while the target domain has none.
- 206 • In unsupervised transfer learning the settings are similar to that in inductive learning,
207 i.e., the source and target domains are the same with different but related tasks.
208 However, there are no labeled data in both domains, and the aim is to explore the
209 intrinsic data characteristics in different domains.

210 Moving to the domain and task similarity, there are mainly two cases: i.e., heterogeneous
211 and homogeneous transfer learning. In the space classification, if the feature space and
212 the label space of both source and target domain are the same, the scenario is classified as
213 *homogeneous*. Otherwise, if they have a different feature space or label space, the scenario
214 is classified as *heterogeneous*. Lastly, transfer learning can also be categorized according
215 to the strategy that is adopted to share the knowledge, i.e., data instance-based, model
216 parameter-based, feature representation-based, and relational knowledge-based strategies;
217 the classification based on the strategy adopted hereafter will be defined as *solution classi-*
218 *fication*.

- 219 • The instance-based TL exploits data from a source domain in a target domain. The
220 reasoning behind this is that a subset of data from the source domain can be used
221 to improve the task in the target domain. To incorporate source domain data into
222 the target task training process, one common practice is to use re-weighting and im-
223 portance sampling techniques. These techniques are typically used when the domains
224 share the same data variables, increasing the data availability for training purposes
225 without changing the algorithm itself.
- 226 • The feature representation-based TL extracts and exploits features to map instances
227 between the two domains (source and target) to increase the performance of the target
228 model. A popular approach is to identify a latent feature space from the source domain,
229 based on which the marginal distributions between two domains are minimized.

- 230 • Relational knowledge-based TL is based on the assumption that data have similar
231 relations in the two domains. As a result, it is used in multi-relational datasets and
232 the knowledge to be transferred is the relationship between the data.
- 233 • The model parameter-based TL shares some parameters or prior distributions of the
234 hyper-parameters of the models (e.g., neural networks). The latter is built assuming
235 that model parameters or hyper-parameters generated for similar tasks would be simi-
236 lar. In this situation, the information collected from the source task is sent to another
237 task in the form of shared model weights. The increasing advancement in deep learning
238 has inspired a new type of transfer learning — network-based transfer learning [38] —
239 that falls within the parameter-based transfer learning category and may be further
240 categorised based on the approach used to share model parameters:
 - 241 – The first method is to extract the features from the pretrained model. The weights
242 of these layers are fixed in this scenario, with the exception of the input/output
243 layer, which is domain dependent and must be fine-tuned using target data. The
244 key benefit is the acquired ability to deal with limited quantity of data to gener-
245 alize over different domains.
 - 246 – An alternative is to use the source model for initialization purposes. In this
247 scenario, the source model is used as a starting point and further fine-tuned.

248 Figure 1 shows the two parameter-based TL approaches used, henceforth called *feature-*
249 *extraction* and *weight-initialization*. In the feature extraction case, only the hidden layer of
250 the source neural network (in yellow) are shared, and frozen. In the weight initialization
251 case, all layers are transferred and subsequently fine-tuned (highlighted by the yellow and
252 red colors). Considering that in this work different neural networks share the same feature
253 and label space, a homogeneous inductive problem using model parameter-based TL was
254 explored.

255 2.2. Deep Neural networks

256 The study employed both the Multi-Layer Perceptron (MLP) and Long Short-Term
257 Memory networks (LSTM). An MLP is composed of at least three layers of nodes: an input
258 layer, a hidden layer and an output layer. With exception for the input nodes, the other
259 nodes are neurons which activation is regulated by nonlinear functions. MLP utilizes a
260 supervised learning technique called *backpropagation* for training. However, classical MLPs
261 are finite response systems that are unable to capture long-term temporal dependencies.
262 On the other hand, LSTM are able of learning long-term dependencies [39], thanks to the
263 combination of multiple gating mechanisms and two states:

- 264 • Hidden state: able to retain the short-term memory
- 265 • Cell state: able to retain the long-term memory

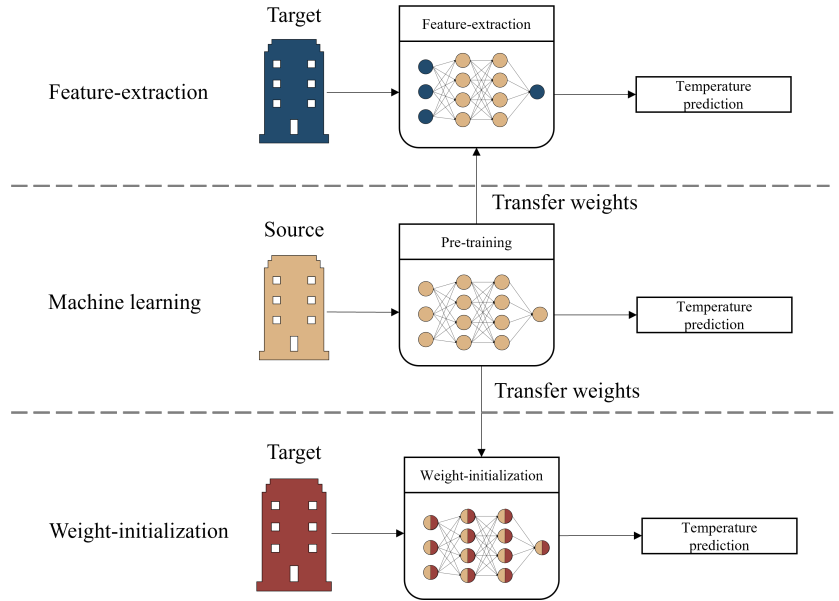


Figure 1: Feature-extraction (top) and weight-initialization (bottom) transfer learning schematization

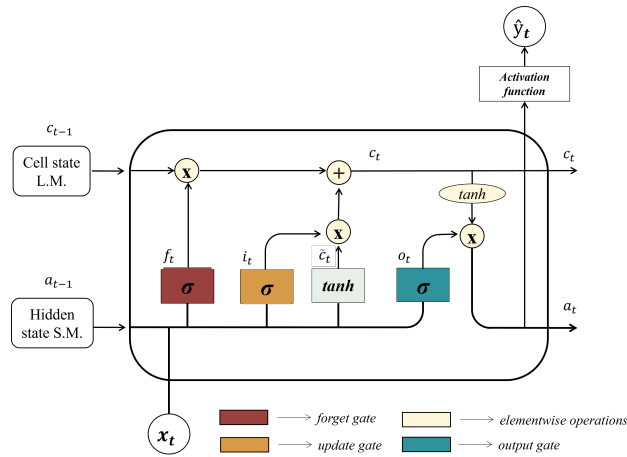


Figure 2: A schematic representation of a Long-Short Term Memory neural network

266 A schematic representation of the LSTM cell is displayed in Figure 2:
 267 The cell state, which is responsible for maintaining long-term dependencies, is the main
 268 feature of LSTMs. With the cell state the information is either deleted or added via three
 269 gates. The *forget* gate determines which information should be erased, the *update* gate
 270 determines which information should be saved, and the *output* gate computes the LSTM
 271 cell's output.

272 **3. Case study**

273 The selected case study is an archetype building energy model developed from the U.S.
 274 Department of Energy (DOE). The model is a medium-sized office building with three floors
 275 and a total floor area of 4,890 square meters [40]. The building consists of 12 space types:
 276 open and enclosed office rooms, conference room, classroom, dining area, lobby, corridor,
 277 stair, storage, restroom, plenum and mechanical room. A schematic representation of a floor
 278 is shown in Figure 3.

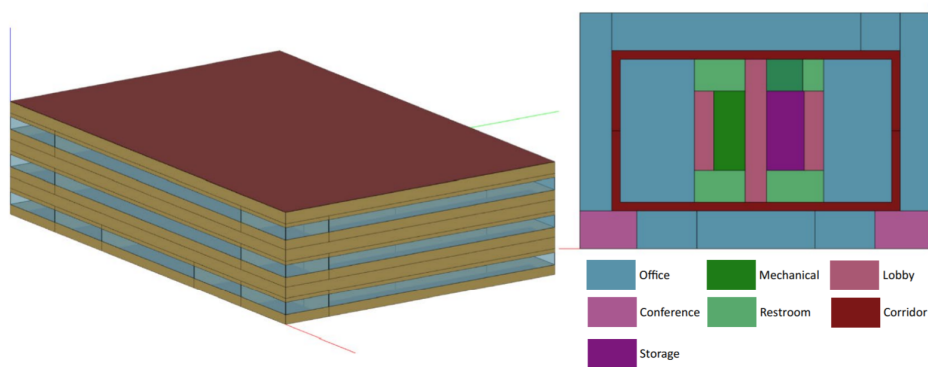


Figure 3: A schematic representation of medium office geometry and thermal zones for a single floor

279 The synthetic dataset includes simulations for the selected building model in different
 280 climates for multiple years, efficiency levels and occupancy patterns. The dataset includes
 281 three energy efficiency levels, obtained by changing building envelope properties, and the effi-
 282 ciencies of lighting, miscellaneous electric loads (MELs) , and HVAC systems. Furthermore,
 283 three sets of schedules for zone-level occupancy, lighting, MELs, and thermostat setpoint,
 284 reflecting realistic building operations from stochastic occupancy simulations, were used [41].
 285 The resulting configuration are reported in Table 1.

Table 1: Parameters and modified features used for the design of experiment

Parameter	Cases	Features involved
Efficiency	Low, Standard, High	Building envelope properties, efficiency of lighting, MELs and HVAC systems
Climate	1A,3C,5A	Outdoor air temperature, solar radiation
Occupancy	1,2,3	Schedule of occupancy, MELs, lighting, setpoints

286 To study the contribution of different weather conditions on model performance, three
 287 typical climate zones were selected: Miami (1A, hot and humid), San Francisco (3C, mod-
 288 erate/mild), and Chicago (5A, cold winter and hot summer). A synthetic dataset [42] was
 289 used with twofold advantages: (i) it can reflect the effects of different influencing variables
 290 on building operation, and (ii) it isolates the contribution of specific features on machine
 291 learning and transfer learning model accuracy.

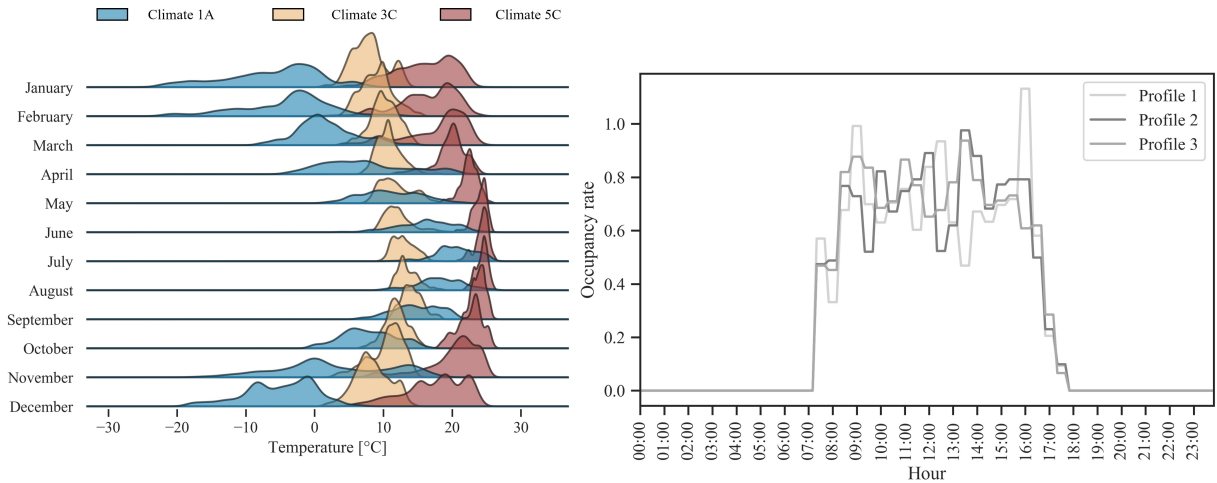


Figure 4: Distribution of the outdoor air temperature for each month and climate considered during the analysis (left) and occupancy profile distribution (right)

292 Figure 4 shows on the left part the outdoor air temperature distributions for the three
 293 climates selected. The selected climatic zones exhibit very different temperature patterns,
 294 with Climate 1A being cooling dominant, Climate 5A being heating dominant, and Climate
 295 3C representing a mild climate. Furthermore, it shows the probability distribution of the
 296 three occupancy profile considered to highlight different users behaviour. For each combina-
 297 tion between efficiency level, occupancy and climate, up to two years of meteorological data
 298 were used for training and testing purposes. The simulations yielded time-series data that
 299 included whole-building and end-use energy metering, indoor and outdoor environmental
 300 variables, and system and component variables (e.g., zone thermostat setpoints, VAV ter-
 301 minal supply air temperature). For a detailed description of how the synthetic dataset was
 302 obtained, refer to Li et al. [42].

303 4. Methodology

304 This section reports the methodological framework adopted, as shown in Figure 5. The
 305 methodology unfolds in four main steps, described below.

306 4.1. Source building selection

307 The first step consists in the identification of the “source building,” used as a starting
 308 point for transfer learning. As pointed out in the previous section, the dataset analyzed
 309 refers to a medium-sized office building simulated in 3 climates, 3 energy efficiency levels, 3
 310 stochastic occupancy schedules, for a total of 27 EnergyPlus models. The source building
 311 was conceived with a standard energy efficiency, the occupancy profile 1 (according to Table
 312 1) and was simulated in Climate 3C. The climate and the energy efficiency level were chosen
 313 to represent an intermediate condition between the other two options, with the aim to
 314 further evaluate the potential of applying transfer learning. The dataset has a 10-minute
 315 granularity, with information related to whole building variables as well as zone variables.

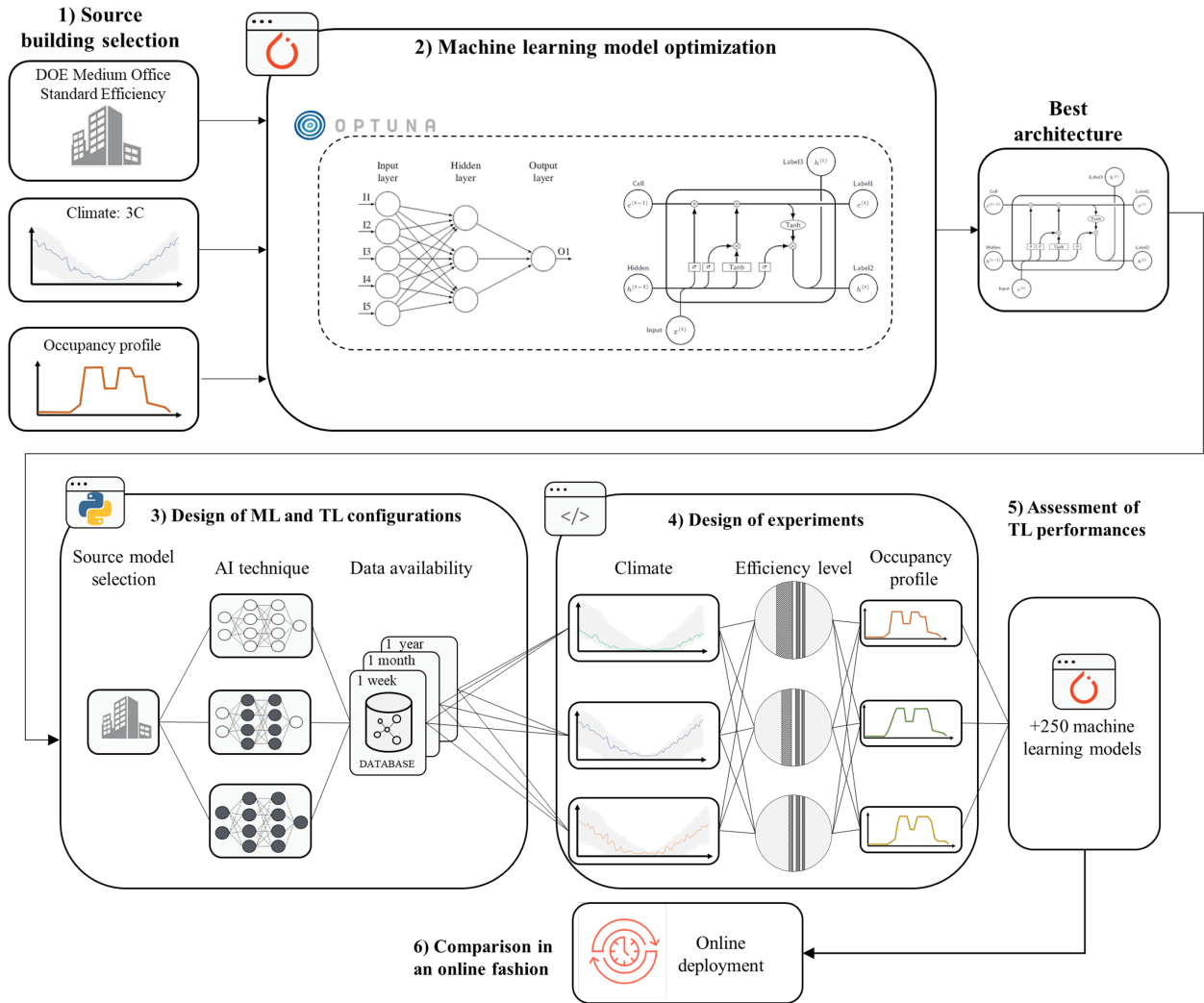


Figure 5: Methodological framework

316 *4.2. Machine learning model optimization*

317 The second step includes the model development, the selection of the architecture and
 318 the optimization of the related hyperparameters. The models aimed to predict the tem-
 319 perature evolution of a single zone (mid-office) one-hour ahead (six time-steps), exploit-
 320 ing information of the specific zone. This was necessary due to the impossibility of aggregat-
 321 ing data at a higher level, since different zones may have different setpoints and occupancy
 322 schedules. The selected inputs for the machine learning models were the zone heating and
 323 cooling temperature setpoints, the outdoor air temperature, the previous internal (zone
 324 air) temperature, solar radiation, and information about hour, day and month. Figure 6
 325 shows the input parameter together with the sliding window approach used to perform the
 326 predictions.

327 The architectures selected were MLP and LSTM. The developed models used 48 time-

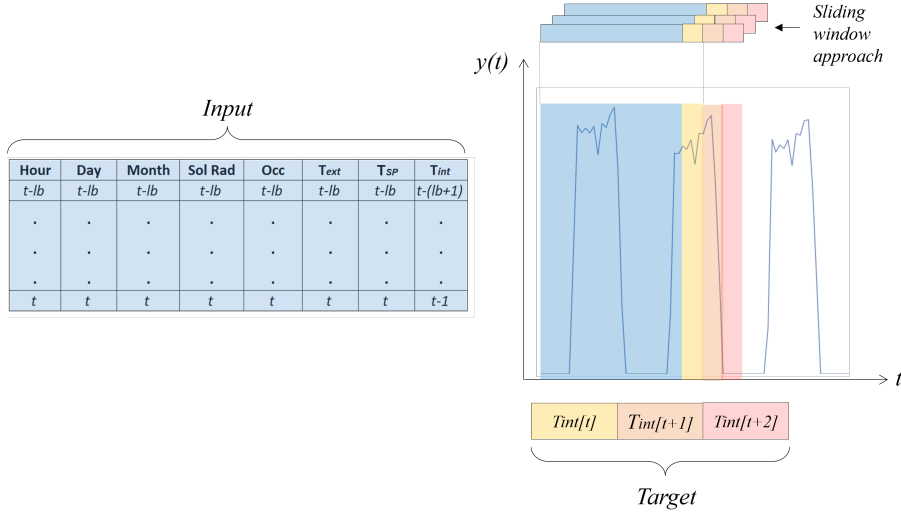


Figure 6: Input of the neural networks and sliding window approach

Table 2: Neural network hyperparameter optimization process

MLP	Range	Optimum	LSTM	Range	Optimum
# Neurons layer 1	[50-200]	100	# LSTM layer	[3-7]	3
# Neurons layer 2	[50-150]	70	# Neurons per layer	[70-300]	175
# Neurons layer 3	[20-90]	70	Epochs	[80-120]	90
# Neurons layer 4	[10-70]	10	Learning rate	$[7-8.5 \cdot 10^{-3}]$	$7.7 \cdot 10^{-3}$
Epochs	[80-200]	120	Batch size	[800-1000]	900
Learning rate	$[7-8.5 \cdot 10^{-3}]$	$7.57 \cdot 10^{-3}$	Optimizer		Adam
Batch size	[800-1000]	900			
Optimizer		Adam			
MAPE		1.096			0.535

328 steps (8 hours) as a lookback period to predict the next 6 time-steps (1 hour). Each architec-
329 ture was characterised by specific hyperparameters, therefore an optimization process was
330 carried out using the Optuna [43] framework. The tool allows the optimal hyperparameter
331 combination to be searched by performing an automatic grid-search. The work performed
332 the grid-search using five values in the specified interval shown in Table 2 with a uniform
333 distribution. The dataset included two years of data: one used for training and validation
334 and the other one used for testing. Table 2 illustrates the hyperparameters subject to the
335 grid-search optimization with their optimized values, as well as the value of the mean ab-
336 solute percentage error (MAPE) evaluated in the testing period. Table 2 highlights the
337 higher accuracy of the LSTM architecture, which was then selected to perform the experi-
338 ments. Consequently, all the transfer learning models further described will share the same
339 architecture, despite changing the learning rate.

340 4.3. Design of ML and TL configurations

341 The third step compares classical ML with two TL techniques to predict indoor air tem-
342 perature evolution. A classical machine learning approach used the optimal hyperparameter
343 identified in step 2 to train LSTM models on data available for the target building. The
344 performance of the LSTM model was then compared with that resulting from the models
345 trained using two transfer learning methods: weight-initialization and feature extraction. In
346 weight-initialization, the whole network is fine-tuned using the data available in the target
347 building and a lower learning rate with respect to the one used to train the source network,
348 while in the feature extraction, the LSTM layers are frozen and only the last dense layer
349 is fine-tuned. For both weight-initialization and feature-extraction, a learning rate equal to
350 $2 * 10^{-3}$ was used to train the LSTM for 80 epochs.

351 Moreover, this step aims to analyse the impact of data availability on model performance.
352 To this purpose, three cases were considered regarding the data availability for the target
353 building: (i) 1 week of data, (ii) 1 month of data, and (iii) 1 year of data. The cases of
354 one week and one month of data were used to represent a data-scarcity context and had
355 the main purpose of highlighting in which conditions TL performs better than ML and the
356 minimum amount of data necessary to develop an effective ML model. On the other hand,
357 an ideal case that considered one year of data available in the target building was used to
358 assess the generalizability of TL over ML, to assess if TL can provide additional advantages
359 even in the presence of an extensive amount of data for the target building.

360 4.4. Design of experiments

361 The fourth step deals with the design of the scenarios resulting from the combination of
362 the different features for the target building as reported in Section 3. Machine learning and
363 the two transfer learning strategies were implemented to consider the combination of three
364 climates, three energy efficiency levels, three occupancy patterns and three data availability
365 periods. This led to 243 different models, including the one related to the source model
366 used for transfer learning. These simulations were used to perform a statistical investigation
367 on the most important features for the application of TL for building thermal dynamic
368 models. All the information on the data, the code and the results produced by the statistical
369 investigation are open-source and available at the following link: [https://github.com/
370 baeda-polito/Transfer_learning_building_dynamics](https://github.com/baeda-polito/Transfer_learning_building_dynamics).

371 4.5. Assessment of TL performance

372 Lastly, model performance is compared using several metrics. In particular, model abso-
373 lute performance was compared using metrics such as MAE , MAPE, and MSE, the defini-
374 tion of which is provided below. Relative performance was quantified using the asymptotic
375 performance and jumpstart.

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (1)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{\hat{y}_i - y_i}{y_i} \right| \quad (2)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i|^2 \quad (3)$$

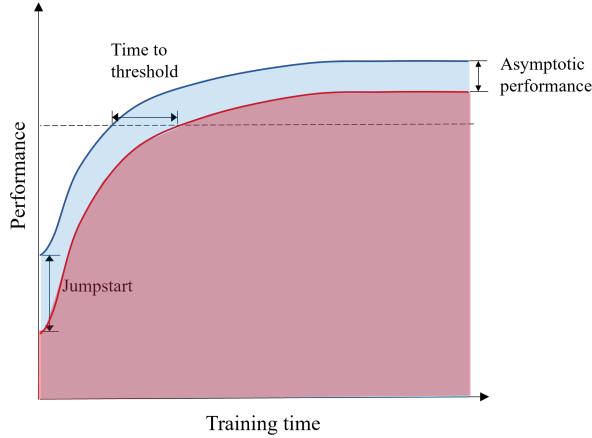


Figure 7: Transfer learning metrics used to quantify the performances of the new model

376 Figure 7 shows three metrics often used to assess the improvements after transfer learning
 377 application.

- 378 1. *Jumpstart*, which reflects the improvement in initial performance in the target task
 379 achieved by utilizing transferred information prior to any further learning.
- 380 2. *Time to threshold*, which compares the time it takes the model to acquire a specific
 381 level of performance in the target task given transferred knowledge to the time it takes
 382 to learn it from scratch.
- 383 3. *Asymptotic performance level*, which quantifies the ultimate performance level of the
 384 agent in the target task when transferred from the source.

385 Regardless of the specific ML task, jumpstart and asymptotic performances for the re-
 386 gression problem are evaluated using MAE, MAPE and MSE. However, in this paper the
 387 metric time to threshold was not analysed due to the necessity to quantify a specific thresh-
 388 old (e.g., MAE = 0.5 °C), which may or may not ever be reached by machine learning
 389 models.

390 4.6. Comparison in an online fashion

391 To further demonstrate the effectiveness of transfer learning in an online fashion, this
 392 study compared an online machine learning approach (updating the weights of the neural
 393 network as new data become available) with an online transfer learning deployment strategy.
 394 Online transfer learning leverages one year of source data and updates the model in an online

395 fashion each week as new data become available, performing a fine-tuning of the model. The
 396 comparison is helpful since real-world application often works with online data and building
 397 thermal dynamic models are used as a part of a model predictive control implementation,
 398 thus requiring it to be robust and fast.

399 5. Results

400 This section describes and analyses the results obtained from the proposed design of
 401 experiments. Section 5.1 describes the results obtained from both ML and TL models,
 402 analysing the performance distribution and identifying the factors that most influence model
 403 performance. Furthermore, statistical analysis was performed to compare absolute and relative
 404 performance of the proposed approaches with respect to the different features. Section
 405 5.2 focuses on negative transfer, describing the boundary conditions in which it occurs and
 406 assessing benefits and limitations. Lastly, Section 5.3 describes computational advantages
 407 related to the application of TL, analysing jumpstart and training asymptotic performance.

408 5.1. Machine learning and transfer learning performance

409 Figure 8 shows the average performance over the entire design of experiments of ML
 410 and TL models using one month of data to assess the previously introduced metrics (MAE,
 411 MSE, MAPE) over all the six time-steps. As can be seen, the ML algorithm error is almost
 412 constant over the time-steps, while both transfer learning techniques show a lower error for
 413 the first prediction time-step, reaching about the same accuracy at the last time-step (one
 414 hour). On average, both feature extraction and weight initialization techniques perform
 415 better than machine learning. The analysis of MAE, expressed in $^{\circ}\text{C}$ shows that for the first
 416 time-step the two TL techniques have a value of 0.17°C smaller compared to standard ML,
 417 achieving a performance improvement of 50%. Similar considerations can be made for the
 418 other two metrics, that show substantial improvement with respect to ML performance for
 419 the first time-step and a better average performance.

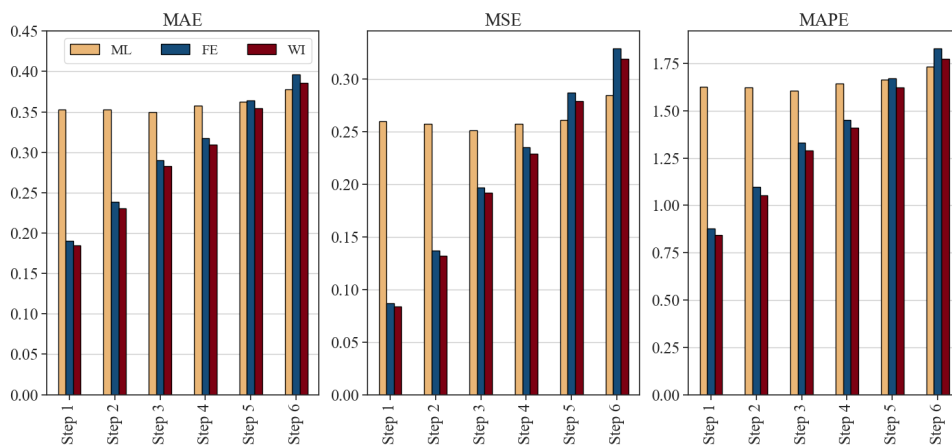


Figure 8: Performance of the different techniques over the control horizon

420 For the sake of simplicity, the following analysis considers only the average performance
 421 of the mean absolute error over the entire prediction horizon, since it can be interpreted
 422 easily.

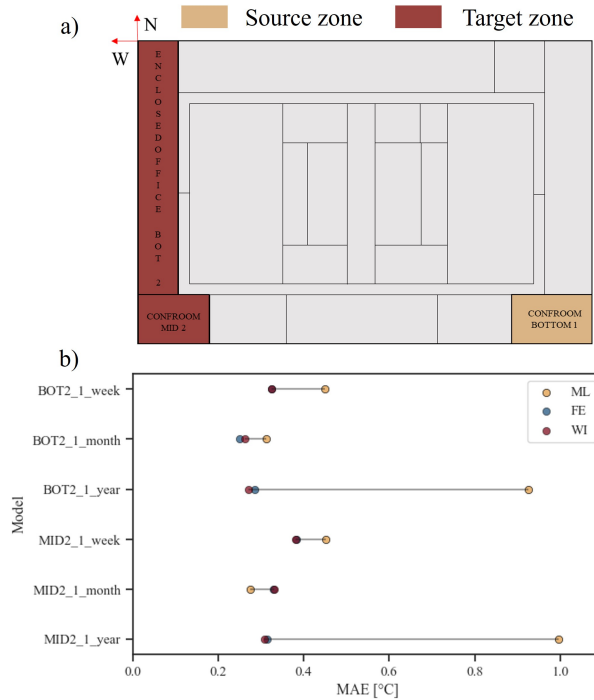


Figure 9: Performance of the different techniques over different zones

423 The first step aimed to assess the effectiveness of transfer learning between different
 424 zones of the building. To prove the effectiveness of TL in different zones, two target zones
 425 (highlighted in red in Figure 9a) were selected: a conference room on the second floor and an
 426 enclosed office on the second floor. The rationale behind zone selection was to test the neural
 427 networks with different orientation, area and floor, that represents the heterogeneity in terms
 428 of size, shape, and orientation of different buildings. The conference room on the second floor
 429 (MID_2) was selected to test the influence of a different exposure on the model (changing
 430 it from east to west), while the enclosed office on the second floor (BOT_2) was selected
 431 to test both a different area and a different exposure. Once the zones were identified, the
 432 analysis was performed, considering different data availability (from one week to one year).
 433 Then several tests were performed that considered different data availability and compared
 434 the results of ML and TL models analysing the mean absolute error. Figure 9b shows
 435 that despite the different characteristics, TL was able to obtain better performance than
 436 standard ML independently from the data availability. Indeed, the ML model performance
 437 was heavily influenced by the amount of training data for the target building, while the TL
 438 model presented robust results over different data availability. After having assessed the
 439 ability of TL in different thermal zones, to isolate the effect of other variables, the following
 440 analysis was performed using the same thermal zone as a source.

441 Then, to analyse the average performance of the three techniques on the whole design of
 442 the experiments, mean absolute error was used to aggregate results over different climate,
 443 data availability, efficiency and occupancy profiles. As a result, Figure 10 shows the average
 444 MAE distribution for the three proposed approaches over all the simulations performed. The
 445 analysis of the distributions showed that ML trained over a period of one year in Climate
 446 5A had in many cases unacceptable errors. A specific analysis will be conducted later to
 447 understand the main factors related to the lower ML model performance. Furthermore,
 448 Figure 10a highlights the larger error distribution of the ML technique, which reaches values
 449 of more than 1 °C, while the TL maximum errors are below 0.7 °C. To better understand
 450 how the ML error is distributed, details for different data availability are shown in Figure
 451 10b. The figure displays how one year of data led the ML model to a large error distribution,
 452 while one month of data showed the best performance, with an average error of 0.35 °C. As
 453 a result, the focus was shifted toward a one month training period. Figure 10c compares the
 454 error for each technique, assessing a slight performance improvement for both TL techniques
 455 over ML, with no particular differences between feature extraction and weight initialization.

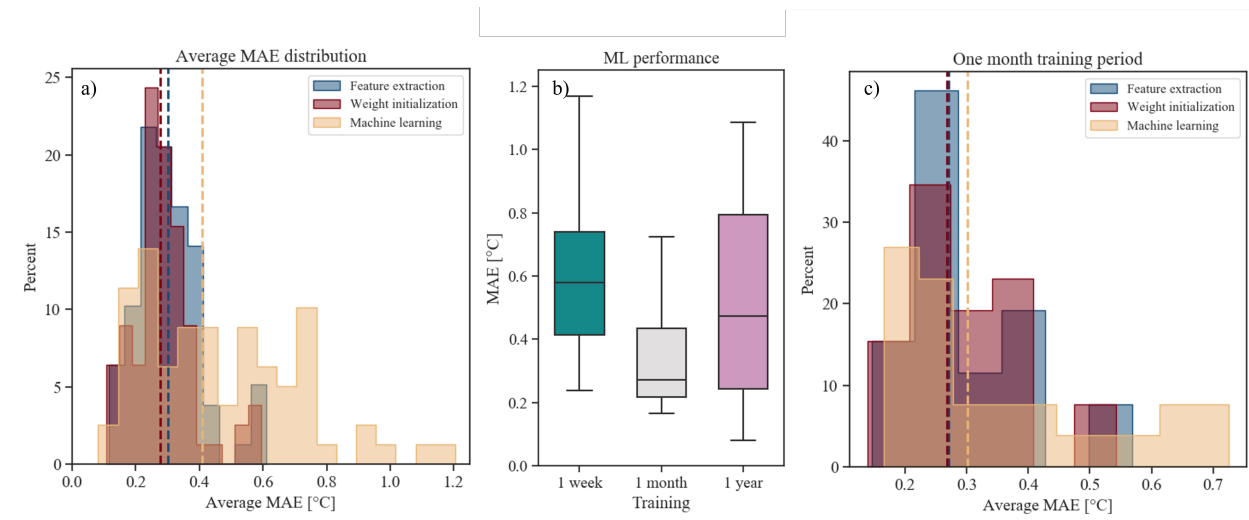


Figure 10: MAE distribution over different periods and techniques

456 To further study the effectiveness of transfer learning, average MAE distributions were
 457 divided in three ranges: low error ($MAE < 0.4$ °C), medium error (0.4 °C $< MAE < 0.7$ °C),
 458 and high error ($MAE > 0.7$ °C).

459 Figure 11 shows the error distribution by technique over all the influencing factors using a
 460 categorical plot. The ML technique is the only one with a high error, which mainly occurred
 461 with one week and one year of data. Furthermore, it shows how high errors are predominant
 462 in Climate 5A but are evenly distributed over the efficiency levels and occupancy runs. On
 463 the other hand, both feature extraction and weight initialization showed better performance;
 464 almost evenly distributed over different data availability, with lower error for Climate 3C,
 465 the same climate as that of the source building.

466 Due to the co-occurrence of different features on the model (e.g, different climate, occu-

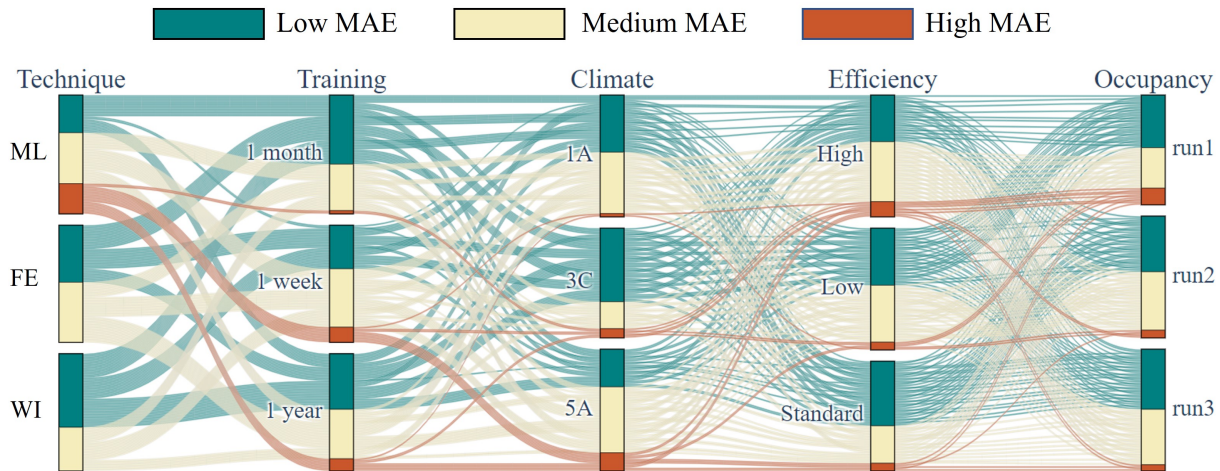


Figure 11: Methodological framework

467 pancy and efficiency levels), a specific analysis was performed by changing only one feature
 468 at a time, with the goal of isolating their effect on model performance. Figure 12 shows
 469 the MAE for different techniques for several cases. Furthermore, it shows how by chang-
 470 ing only the efficiency level (same climate and same occupancy profile), transfer learning
 471 outperforms machine learning for every data availability, while negative transfer can occur
 472 when buildings across different climates are analysed, with very different results according to
 473 data availability. Looking at results with various occupancy profiles, a narrow performance
 474 improvement can be seen, with a negligible case of negative transfer learning, since both ML
 475 and TL techniques have an average error below $0.2\text{ }^{\circ}\text{C}$ and very similar performance.

476 Therefore, to assess the influence of climate and data availability on model performance,
 477 a specific analysis was conducted, as shown in Figure 13. In particular, Figure 13a shows
 478 the distribution of the mean absolute error for one week, one month and one year of data
 479 availability over the three different climates. For the sake of clarity, the error bar related
 480 to one year and Climate 5A, which exceeded $1.5\text{ }^{\circ}\text{C}$, has not been shown, while its lower
 481 outliers have been included in the figure. Note that often an MAE of $0.5\text{ }^{\circ}\text{C}$ is seen as
 482 threshold for the deployment of a model that predicts the internal air temperature. As a
 483 result, the figure highlights the inadequacy of ML models to be deployed for the specific
 484 combination of climate and time horizon. With increasing data availability, the median
 485 value of the ML models decreases. In general, TL approaches are more robust compared
 486 to ML approaches. Furthermore, the analysis showed how almost every TL model had an
 487 error below $0.5\text{ }^{\circ}\text{C}$, while ML often exceeded this threshold. Figure 13b uses the asymptotic
 488 performance improvement to compare the simulation point by point. It can be seen how,
 489 on average, the best performance improvements are achieved in Climate 3C (i.e., the climate
 490 selected for the source building). Note that performance improvements for climate 5A are
 491 highly influenced by the poor performance of ML models, increasing the advantages of using
 492 TL. The main reason may be related to the high temperature variation of Climate 5A, which
 493 makes it hard for the model to generalize over the entire year. However, Figure 13b also

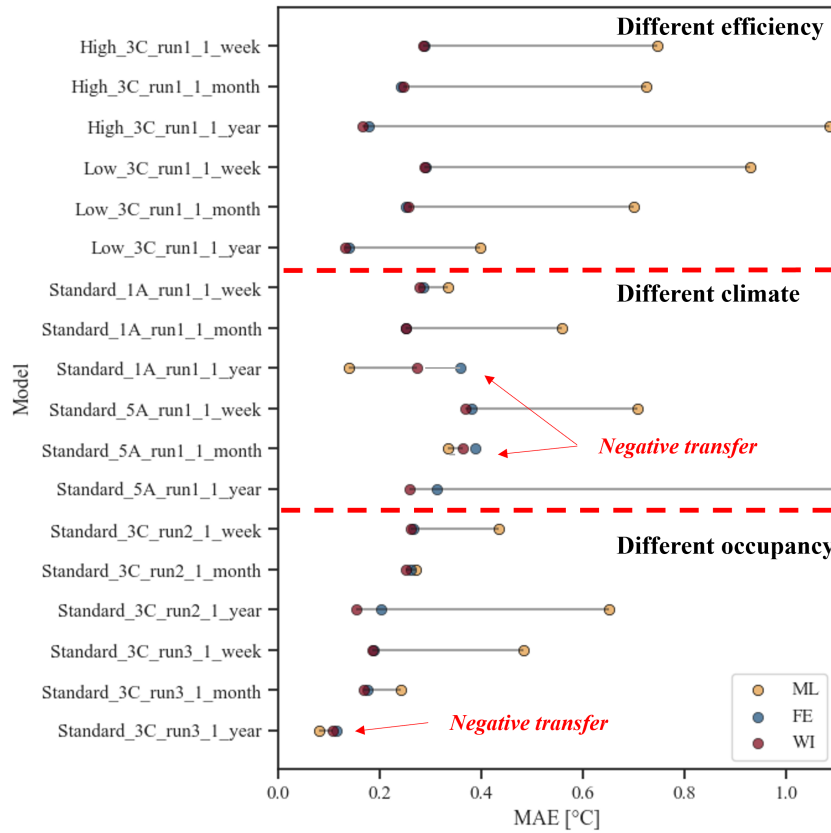


Figure 12: Performance comparison with isolated effects of features

494 highlights the presence of negative transfer, especially with one month of data, a period in
 495 which ML already has good performance. As a result, a further analysis was conducted to
 496 identify the main driver of negative TL.

497 5.2. Negative transfer learning

498 Figure 14 shows the asymptotic performance of all the simulations, highlighting three
 499 particular areas: negative transfer learning, neutral transfer and effective transfer. Negative
 500 transfer occurs when the MAE is greater than 0.05 °C compared to ML models, neutral
 501 transfer is when it is smaller than 0.1 °C, and effective transfer reduces the MAE at least
 502 0.1°C. As can be seen, about 20% of cases have negative transfer, 20% have neutral transfer
 503 and 60% of cases show effective transfer. Figure 14b displays a detail of negative transfer,
 504 using different shapes and colors to highlight data availability and climate. The figure
 505 highlights how negative transfer occurred only 4 times out of 52 simulations, when one week
 506 of data was used (turquoise color), suggesting an effectiveness of TL in over 90% of the
 507 cases when one week of data is considered. It also can be noticed how negative transfer
 508 occurred only 4 times out of 52 simulations (diamond shape), with a performance increase
 509 in about 90% of the cases when the target building had the same climate as the source

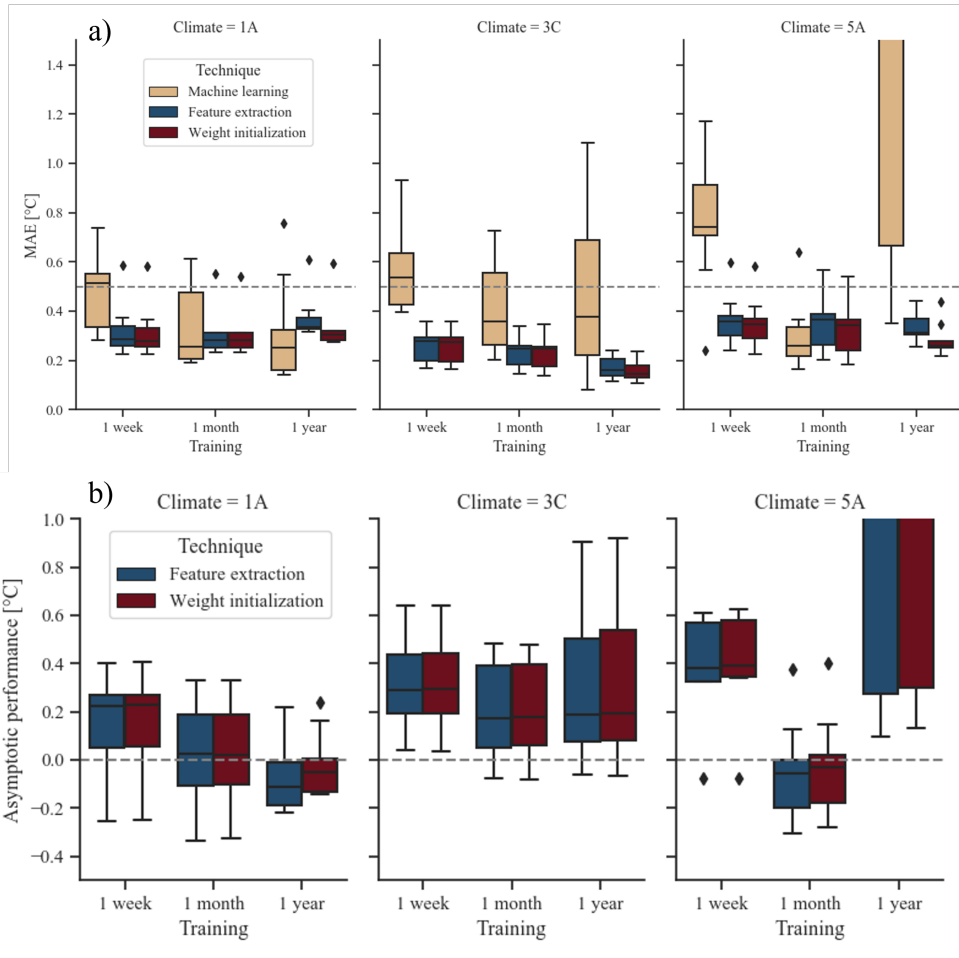


Figure 13: Methodological framework

510 building. The figure shows that the highest amount of negative TL happened with one
 511 month of data availability, identifying this amount of data as enough to obtain a good ML
 512 model performance.

513 Lastly, to provide a comparison of the model performance with effective and negative
 514 transfer, Figure 15 displays temperature evolution for the first predicted time-step over a
 515 random day for real values using ML and TL models. The figure on the left highlights how
 516 in this case ML was not able to properly describe the building dynamics, while both TL
 517 techniques follow the trend of the real value (green). On the other hand, the right figure
 518 shows a case of a negative TL, in which the performance of TL was still able to capture the
 519 building dynamic but perform worse than the classical ML approach.

520 5.3. Jumpstart performance

521 Figure 16 shows jumpstart performance with different data availability. As shown, the
 522 highest jumpstart occurred for one month and one week, reducing the MAE of the first epoch
 523 about 8°C. Despite this reduction, the final performance during training was comparable to

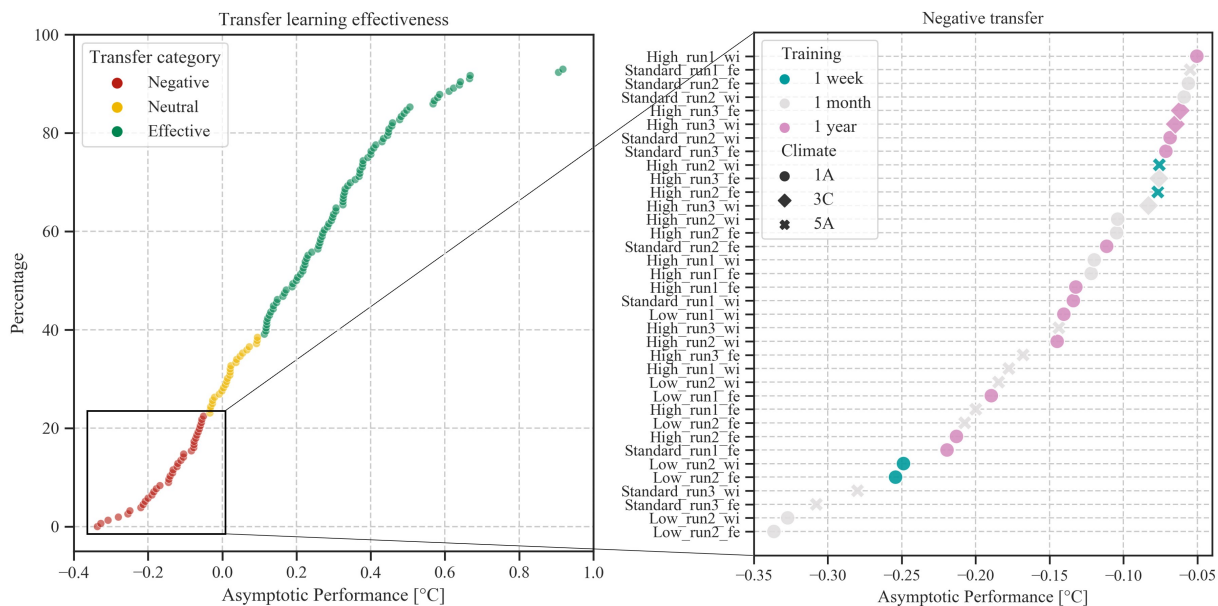


Figure 14: Categorization of transfer learning effectiveness and negative transfer analysis

524 an ML model. Moreover, the figure shows how the performance of transfer learning is almost
 525 constant, thus highlighting the possibility of great computational cost reduction when using
 526 transfer learning. Transfer learning also provided a computational advantage; however, the
 527 model complexity and the time required to train such models in this kind of problem is little.
 528 These advantages are usually more important when dealing with different applications, such
 529 as in computer vision. As a result, the jumpstart performance is a less reliable metric
 530 compared to the asymptotic performance, which is better suited to quantify the goodness
 531 of a model.

532 5.4. Online deployment

533 Figure 17 shows the MAE error distribution over each week of the year for the two
 534 techniques (ML and TL) deployed online. The configuration selected for the target building
 535 was characterized by Climate 3C (the same of the source building), occupancy pattern 2
 536 and a high efficiency level. This configuration was selected on the basis of the outcome of
 537 the previous analysis. The transfer learning model (already trained on one year of source
 538 building data) was updated for the target building each week as new data became available
 539 following an anchored deployment configuration that employed existing data and a new
 540 week’s data using the same learning rate of transfer learning configuration ($2 \cdot 10^{-3}$).
 541 The machine learning model used the same deployment strategy without leveraging pre-training
 542 data from the source building. To highlight both relative and absolute performance, Figure
 543 17 reports a candlestick visualization. The green color of the box highlights the cases when
 544 the TL showed higher performance against ML, while the red box represents the opposite
 545 occurrence. The height of the box measures the difference in terms of performance between

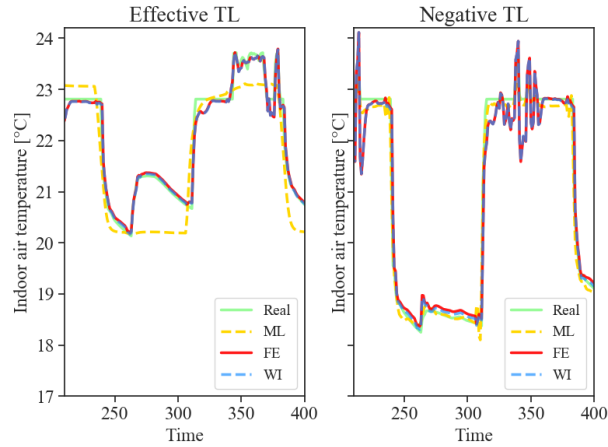


Figure 15: Prediction evolution for the first time-step with different techniques for effective and negative TL

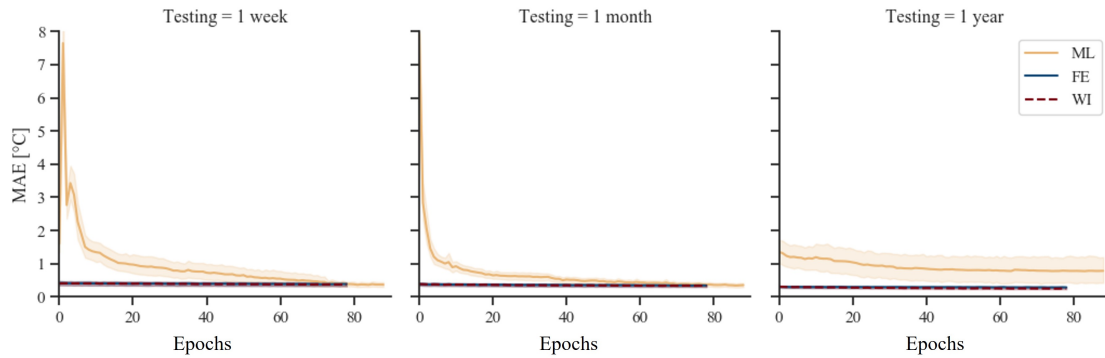


Figure 16: Jumpstart comparison over different training time

546 the two models, while the two extremes indicate the absolute value of MAE. The figure shows
 547 that especially during the first weeks of deployment, the ML had very poor performance when
 548 compared with TL. However, as training data became available for the ML, the performance
 549 difference between the two models tended to decrease, and after week 40, the performance
 550 of the two models were comparable.

551 6. Discussion

552 Building dynamics prediction proved to be effective to unlock the potential of advanced
 553 control strategies. However, the main bottleneck is represented by the data availability in
 554 most of the buildings, making the exploitation of data driven models a niche. TL promises to
 555 overcome this problem, but still requires further studies to quantify building similarity. This
 556 research aimed to quantify the feature importance of several variables in a TL setting. In
 557 particular, this study compared two TL techniques and assessed the effect of data availability
 558 and case specific features (e.g., climate, efficiency level, occupancy). To capture the effect of

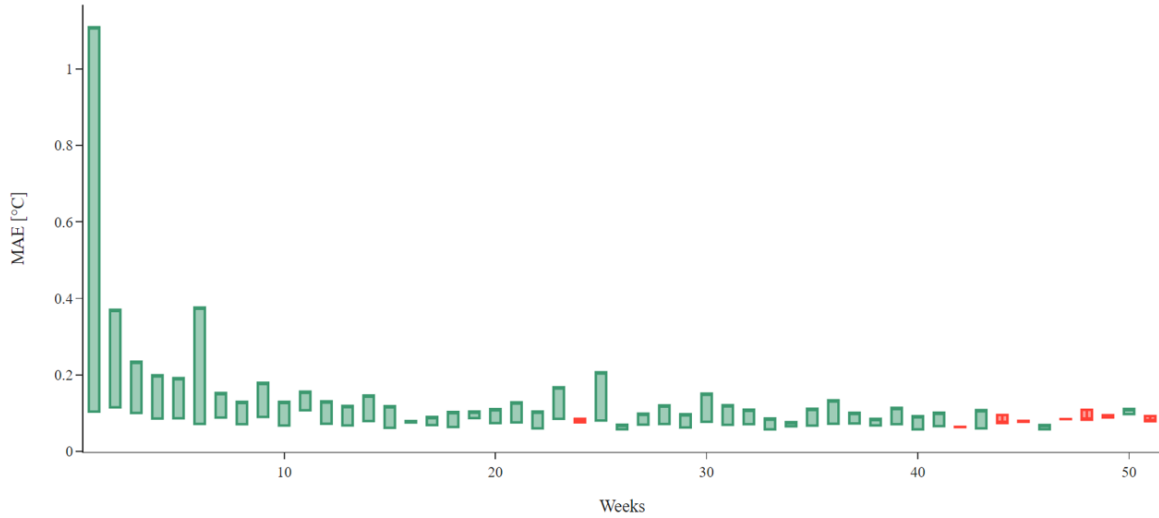


Figure 17: Performance comparison between online ML and online TL

559 the different variables, an experiment design was conceived. Analysis of the results revealed
 560 several insights: first, unlike the ML models, the error performance over multiple time-steps
 561 is very small for the first time-step, increasing more steeply with the following time-steps,
 562 while on average TL showed better performance. This information is particularly helpful for
 563 advanced predictive controllers, where an optimization process can be performed on the basis
 564 of the prediction. In particular, when the control time step is smaller than the prediction
 565 time horizon (e.g., control the energy system every 10 minute, while predicting the internal
 566 temperature for the next hour) the transfer learning approach can ensure higher performance
 567 especially during the first time steps. Additionally, analysis of the data availability aimed
 568 to assess how much data are necessary in TL and ML settings. The analysis showed that
 569 for ML a higher amount of data in the target building may be counterproductive, especially
 570 when the target building is located in climates with a great variation between the different
 571 seasons (Climate 5A). On the other hand, using a large amount of data helps to reduce the
 572 variance of TL models, obtaining more robust results.

573 Furthermore, the analysis confirmed the ability of TL to deal with different efficiency
 574 levels and occupancy, while limitations were observed for its effective applications across
 575 different climates, highlighting the role of external (outdoor air) temperature as the most
 576 important feature. Moreover, the focus on the asymptotic performance and the negative
 577 transfer allowed researchers to identify guidelines and constraints on the application of trans-
 578 fer learning for building dynamics prediction. In particular, the analysis showed how nega-
 579 tive transfer mainly occurs when different climates are considered, identifying data-scarcity
 580 (one week) and the application on the same climate of the source building as the best case
 581 study to deploy TL. Furthermore, performance analysis suggest that for different features
 582 (e.g., climate), when new data are available the optimal solution consists in using online
 583 transfer learning and shifting to online machine learning when a robust dataset in the target
 584 building is available (e.g., one year). On the other hand, when the most important features

585 are the same for the source and target building, transfer learning may achieve performance
586 improvement independently from the amount of data used, highlighting its effectiveness in
587 generalizing machine learning models. Lastly, a specific analysis was carried out on jump-
588 start performance; however, despite the computational advantages introduced by TL, the
589 time needed to train such models is relatively low, due to the small dimension with respect
590 to computer vision domains. This suggests the use of asymptotic performance as a key
591 performance indicator to evaluate the effectiveness of TL.

592 *6.1. Limitations*

593 A key concern about the comparison of the different models is the influence of the testing
594 period on performance. Indeed, a model trained on one year of data and tested on one month
595 may experience different performance based on the month selected for testing (e.g., winter,
596 summer). This can be caused by considering the climate used for training, which can be
597 cooling or heating dominant. However, the purpose of that type of analysis was outside
598 the scope of this study and aimed at evaluating the robustness of ML and TL models.
599 Furthermore, the influence of the thermal zone (e.g., a perimeter zone with more exposure
600 to weather versus an interior zone) has not been fully characterized, since its introduction
601 in the design of experiments would have reduced the output interpretability. Lastly, the
602 limitation of the optimization process lies in the neural network structure, optimized only
603 for the source case with a specific set of features (e.g., climate, efficiency level, occupancy).
604 As a result, other case studies may have sub-optimal DNN architectures, especially for one
605 year of data, that may require a more complex model. However, the methodology avoided
606 the optimization of the DNN for every condition to allow a peer-to-peer comparison between
607 ML and TL.

608 **7. Conclusions**

609 The present work introduced a methodology to assess feature importance in TL settings
610 for building dynamics prediction. The problem involved the development of approximately
611 250 models that were deeply analysed in order to assess their most important features. The
612 error distribution comparison showed that transfer learning reduced error in the first time-
613 steps, suggesting its coupling with advanced control strategies, which rely on short-term
614 predictions. The analysis also demonstrated that climate is the most influential feature,
615 determining the success of the transfer. Another analysis showed that data availability
616 also affects performance, suggesting the coupling of transfer learning with online learning
617 if the features are extremely different, while showing that TL can adapt easily to different
618 building energy efficiency levels and occupancy patterns. The study also compared two TL
619 techniques (weight-initialization and feature extraction), showing a slightly better perfor-
620 mance of weight-initialization. A specific analysis of negative transfer learning identified the
621 strengths and weaknesses of the method. Lastly, this study compared the performances of
622 the algorithm in an online fashion, to support its coupling with an advanced controller in
623 real-world implementations. In conclusion, TL was found to be effective in most of the cases,

624 especially when dealing with changes in building related variables, providing more robust
625 predictions. Future studies will focus on:

- 626 • The application of transfer learning with different input data dimensions. Buildings
627 have different levels of sensing and metering, providing diverse sources of measured
628 data, which may represent a limit for the deployment of transfer learning models. Stud-
629 ies can aim to assess transfer learning’s ability to adapt to different input dimensions
630 without losing the ability to capture building thermal dynamics.
- 631 • The feasibility of developing a database of model archetypes for the most important
632 features. This work aims to create different data-driven archetype models based on
633 climate and building archetypes, which could be used by researchers to test and speed
634 transfer learning applications in both commercial and residential buildings.
- 635 • The deployment of transfer learning techniques in residential buildings based on real
636 data (e.g., the large scale smart thermostat data from ecobee’s Donate Your Data pro-
637 gram). Residential buildings have usually fewer sensors installed and are characterised
638 by high stochasticity (due to occupant use behavior). The analysis can aim to assess
639 the effectiveness of transfer learning on real data at a large scale considering different
640 size, shape, and orientation of the buildings.
- 641 • The implementation of transfer learning to simulate building thermal dynamics in
642 a real building, to support control applications and evaluate its performance when
643 integrated with advanced control strategies like model predictive control, comparing
644 it against a traditional rule-based controller. The main goal of the application would
645 be to study the interaction between neural network prediction and control strategies
646 in a real building.
- 647 • The formulation of a transfer learning framework for control problem. The applica-
648 tion would test the potentialities of transfer learning for advanced control (e.g., model
649 predictive control, reinforcement learning) for performance benchmarking in a stan-
650 dardized test framework such as BOPTEST [44].

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655 05CH11231.

656 **Nomenclature**

657 ARMAX Autoregressive-Moving-Average with Exogenous Inputs

658 BNN Bayesian Neural Network

659 DOE Department of Energy
660 DRL Deep Reinforcement Learning
661 GEB Grid-interactive Efficient Building
662 HVAC Heating, Ventilation and Air Conditioning
663 LSTM Long Short Term Memory
664 MAE Mean Absolute Error
665 MAPE Mean Absolute Percentage Error
666 MEL Miscellaneous Electric Load
667 ML Machine Learning
668 MLP Multy-Layer Perceptron
669 MPC Model Predictive Control
670 MSE Mean Squared Error
671 PINN Physics-Informed Neural Network
672 RNN Recurrent Neural Network
673 TL Transfer Learning
674 VAV Variable Air Volume
675 XGBoost EXtreme Gradient Boosting

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