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Transfer-Learnt Models for Predicting Electricity Consumption in Buildings with Limited and Sparse Field Data

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Abstract— **Buildings are a primary consumer of electricity in the United States and are also increasingly being perceived as providers of grid services such as load shifting, shedding and modulation. High fidelity models of building electricity consumption are needed to set appropriate baselines for measurement and verification (M&V) of controllers designed for energy efficient operation of buildings and to enable buildings to provide grid services via. participation in demand response programs. State-of-the-art modeling techniques for building electricity consumption either rely on physics-based models, or extensive instrumentation of the building envelope to gather "big" data to train machine learning based models such as deep neural networks. While physics-based models are often limited by their accuracy, it is not always feasible to gather a significant amount of field data required to train machine learning based models with sufficient accuracy. In this paper, we explore the use of transfer learning-based strategies to address unsatisfactory accuracy of models for estimating building electricity consumption when available field data for training is sparse or of unacceptable quality. In particular, we transfer knowledge in the form of data and parameters, from physics-based simulation frameworks to the field to improve the model accuracy, thus resulting in a physics-informed machine learning framework. We evaluated the efficacy of our approach on field data collected from six commercial buildings and our results indicate that the proposed transfer learning-based models provide comparative (and in some cases better) accuracy than state-of-the-art machine learning and deep learning solutions, with just one month of field data.**

I. Introduction

The building sector is responsible for more than 40% of the total energy consumption worldwide [1]. Therefore, energy efficient buildings have the potential for a large sustainability impact at a global scale. Also, buildings consume 75% of all U.S. electricity and drive 80% of peak demand. Hence, they have a significant potential to be utilized in grid planning and operation through demand-side management and are being increasingly viewed as providers of grid services beyond energy efficiency such as load shedding, load shifting and modulation [2]. In addition, an average American individual spends about 93% of their time indoors [3], which enforces providing a comfortable environment for occupants as an important goal in building electricity management. Hence, efficient control of buildings that balances economic, environmental, grid service and occupant comfort goals is an important problem [4].

In the last couple of decades, researchers have identified, demonstrated, and advocated several control solutions to achieve these goals within buildings. Some of these solutions include demand response (DR) [5], pre-cooling or pre-heating [6], optimal supervisory control [7] and model predictive control [8]. However, the assessment of the success of these techniques requires checking if the underlying goals such as energy savings targets have been met, and this process is called Measurement and Verification (M&V). A specific technical challenge associated with M&V is obtaining an accurate estimation of the *baseline* consumption, or in simple terms, the electricity consumption that is likely to occur without the advanced control technique being implemented. In addition, knowing the baseline consumption accurately for short-term, medium-term, and long-term prediction horizons for buildings is also important for the electric utility to plan their demand response programs.

The accurate modeling of building electricity consumption relies on various static and dynamic parameters, which includes outside weather conditions, stochastic schedule of the occupants, and appliance usage patterns. While one can easily monitor the building level electricity consumption and the weather conditions surrounding the building, it is often expensive to sense granular-level building-specific information such as, occupants' schedule and usage patterns of electric fixtures. Limited access to such critical information often restricts the deployment of white-box or grey-box models for modeling building electricity consumption. However, recent studies have shown promising results with various black-box models applied on easy-to-collect data [1], [9].

For instance, Wang et al. [10] used climatic conditions, room occupancy, and static features (such as week of the day, hour of the day) as input features to train a Random Forest that can predict electricity consumption with an accuracy of 88%. Likewise, Fan et al. [11] proposed a combination of unsupervised autoencoder and generative adversarial network to estimate building electricity consumption, while using time variables, outdoor variables, and operating parameters, such as the temperatures and flow-rates of the chilled water in the feature set. Though their studies indicate good accuracy numbers with these black box models, the authors had to collect data for one complete year to train their models.

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In the real-world, for a new building one cannot wait for one whole year to get the data and then train the model to estimate the building electricity consumption in *near* real time. For practical applications, users prefer a plug-n-play solution that can accurately predict from day one. Also, even if field data is available for a year, it might have quality issues such as data gaps and anomalies. Moreover, accuracy is subjective and depends on the requirements of an application. Therefore, if a model trained over data corresponding to a few days, can achieve accuracy numbers comparable to a model trained on a year-long data set, users would typically prefer a quicker solution than the delayed one. In this paper, we propose one such plug-n-play building electricity consumption modeling technique, which is powered by the concepts of transfer learning and has the ability to estimate building electricity consumption even with the "limited" and "sparse" field data. Our results indicate that the model can estimate building electricity consumption with an accuracy of 68% with just four days of field data (where the baseline accuracy is 57%) and 83% with three weeks of data (the baseline accuracy is 71%). Here, the baseline model represents a machine learning model trained just on the field data.

In our framework, we propose knowledge transfer from the simulation data to the field data in two forms - instance-transfer and model-transfer. While simulation data provides a sense of "generic" behavior of the building, the field data captures the stochastic dynamics of the building. We evaluated the efficacy of our approach using the field data collected from six different commercial buildings for an year and our results indicate that transfer-learning based models are much more effective than reference models - random forest and feed-forward network, especially when the data is limited and sparse.

The major contributions of this paper are:

1) Transfer learning-based strategies for modeling building electricity consumption.
2) Comparative evaluation of proposed approaches with the state-of-the-art data-driven modeling techniques.
3) TransBEAM: A python-based library to compare different data-driven modeling techniques for building electricity consumption with transfer-learning based methods.

The rest of the paper is organized as follows. Section II discusses the related work. The overall approach and the baseline strategies are laid out in Section III. Section IV presents the experimental setup and Section V evaluates the proposed approaches on the field data. We then discuss the limitations and future work in Section VI before concluding the paper in Section VII.

II. Related Work

Two categories of literature are most relevant to our work - (1) studies exploring data-driven modeling of building electricity consumption, and (2) studies deploying transfer learning for building-related applications.

A. Modeling Building Electricity Consumption

Modeling building electricity consumption has a long history, and in the past, studies have proposed various white-box, grey-box, and black-box solutions to the problem. In white-box techniques (e.g. EnergyPlus [12]), physics-based equations are used to model building components and sub-systems to predict its electricity consumption, among many other parameters related to building characteristics. With the help of detailed dynamic equations, the aim usually is to capture the building dynamics well. However, white-box models are computationally expensive and demand building information at a granular level for accurate modeling; and thus, are hard to scale and use for practical purposes.

Grey-box models are hybrid models that use simplified lumped-parameter thermal models to simulate the behavior of building energy systems [13], [14]. The simplification reduces the need of building details at a granular level, resulting in faster computation. However, grey-box models are often limited by their prediction accuracy.

Black-box models lie on the other side of the spectrum because they are purely data-driven. The statistical models try to capture correlation between building electricity consumption and the operational data. Since black-box models can find complex patterns in the data, they can often accurately predict the building electricity consumption with easy-to-collect information [1], [9], [15]. For the same reason, the field of electricity consumption modeling is noticing a gradual increase in the number of papers employing machine learning (e.g. Support Vector Machines [16], Random Forest [10], [17]) and other deep learning methods (e.g. LSTM [18], Autoencoders [19], Adversarial Networks [11]), specifically in the context of buildings. However, need of significant amount of data to train the model often leads to the problem of cold-start with the black-box models, and that is where transfer learning can be valuable.

B. Transfer Learning in Building Applications

Transfer learning is the ability to transfer knowledge from one domain (source domain) to another domain (target domain). The knowledge transfer can happen in the form of data (also known as instance-based transfer), feature representation, model parameters, or relational-knowledge [20]. Since transfer learning can enable accurate modeling with limited and sparse data, studies have manifested the efficacy of transfer learning strategies in the field of natural language processing, semantic analysis, and many others. However, the use of knowledge transfer in the building domain has been limited. Most of the existing applications are either limited to residential apartments, small-scale commercial buildings, or to simulation studies [21], [22]. A recent work on commercial buildings is limited to building-to-building transfer only [23]. Since a building's electricity consumption profile relies on dynamic schedule of the occupants, the usage profile of electric fixtures in each building is often distinct. Therefore, it is hard to find an appropriate twin for knowledge transfer. To the best of our knowledge, ours is the first work that explores knowledge transfer from the

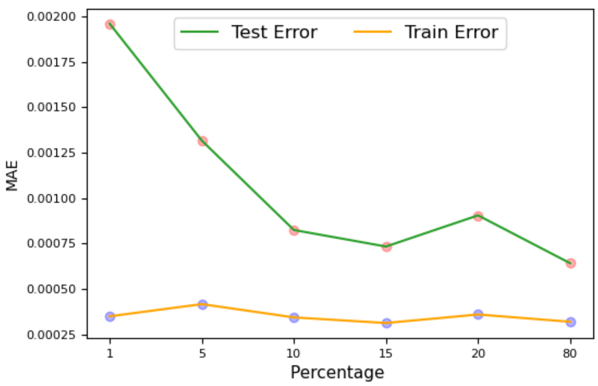

Fig. 1. The plot depicts training and testing errors for different percentages of data. The plots shows big gap between training and testing error for smaller datasets, which is an indicator of overfitting.

simulation data to the field data, especially in the context of modeling building electricity consumption.

III. Approach

Typically, any machine learning problem statement consists of a *domain* D and a *task* T. The domain D is the set of feature space χ and the marginal probability distribution $P(X)$, where $X = \{x_1, x_2, ..., x_n\} \in \chi$. For example, in the case of building electricity consumption modeling, at any timestamp t, x_i would depict the feature vector comprising of features like outdoor temperature, week of the day, among others. For a given domain $D = \{\chi, P(X)\}$, the task T consists of a label space γ and an objective predictive function $f_\theta(.)$, where, θ denotes the trained parameters of the model. In this paper, the label space is the electricity predictions at any time, normalized by the area of the building, also known as energy use intensity (EUI). To predict the corresponding label, we learn the predictive function on the training examples, that comprises of pairs $\{x_i, y_i\}$, where $x_i \in \chi$ and $y_i \in \gamma$.

As we discussed earlier, the problem with training a predictive function $f_\theta(.)$ on the field data is that we need a "good" amount of data to train a model that can predict the output labels with an "admissible" accuracy. However, one might have to wait for months, if not years, to gather a "good" number of training samples $\{x_i, y_i\}$. If we train a complex model on the limited and sparse field data (cold start), we might end up with the problem of data overfitting - good accuracy on the training set but poor accuracy on the test set, which means that the model cannot generalize well. For instance, as shown in Figure 1, the testing error is much higher than the training error (indicating overfitting) when we trained a feed-forward network (Figure 2) on the field data collected from one of the six commercial buildings. In other words, the long wait for the data can limit the real-world implementation of the data-driven models, and training on limited and sparse data will make them inaccurate. Therefore, instead of cold start, we need a way to train the model and predict electricity consumption even when we don't have enough data to start. One way to tackle this problem of *cold start* is to train the model on simulation data.

A. Tackle Cold Start: Train on Simulation Data

To tackle the problem of cold start, we can use the simulation data to train the model parameters θ, and then use the trained model to predict the electricity consumption, initially. It is relatively easy and quick to build the simulation model of a building and generate a significant amount of data by incorporating the weather forecast into the simulation model. However, since it is hard to capture the building details perfectly, the models trained on simulation data are often limited by their prediction accuracy. Simulation models usually do not capture the stochastic behavior of occupants and thus perform badly, when tested as is on field data. For example, when we trained a feed-forward neural network on the simulation data and used it to predict the electricity consumption for the field data, on an average, the prediction accuracy dropped by 28% (when compared to the model trained only on the field data) for all six buildings considered in this study. Therefore, we need a way to incorporate knowledge from the field data.

B. Tackle Cold Start: Transfer Learning

In transfer learning, we typically have a *source* and a *target*. *Source* is the problem statement from which we transfer the knowledge, and *target* is the problem statement to which we transfer the knowledge. In this manuscript, the problem of training a machine learning model on simulation data is defined as the *source* problem and training the model on field data as the *target* problem. In the rest of the paper, we will denote source domain and task as $D_s = \{\chi_s, P(X_s)\}$ and $T_s = \{\gamma_s, f_{\theta_s}(.)\}$, respectively, and target domain and task as $D_t = \{\chi_t, P(X_t)\}$ and $T_t = \{\gamma_t, f_{\theta_t}(.)\}$, respectively. As discussed earlier, the problem with the cold start is that $\gamma_s \neq \gamma_t$, and thus $T_s \neq T_t$. In other words, the distribution of output labels y is different for the simulation data and the field data. When no field data is involved in the training stage, the predictive function $f_{\theta_s}(.)$, trained only on the simulation data, predicts inaccurately because it is unaware about the temperature-energy correlation for the field data. To resolve this issue, we incorporated the field data in the training stage through instance-based and model-based transfer learning, which is discussed next in detail.

1) Instance-Based Transfer: In instance-based transfer, the source domain and the target domain data use same set of features and labels, but the data distribution in two domains are different. Since both the distributions are different and not all the samples from the source domain are useful, we first optimally sub-sample the training set of the source domain (X_s) and then append it to the training instances of the target domains (X_t) to reconstruct the training set.

Equation 1 depicts the formal representation of this, where $X_s^{'}$ is the optimally sub-sampled training set from the source domain, θ_t° is the set of untrained parameters, and θ_t is the

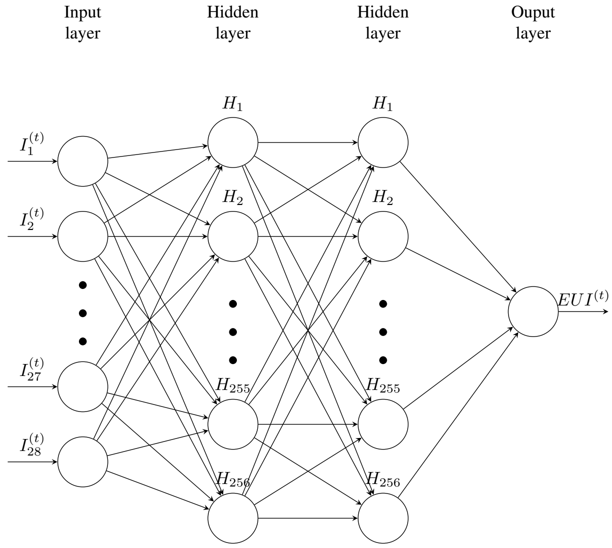

Fig. 2. Feed Forward Network: The network consist of an input layer which takes 28 features as the input, two hidden layer with 256 nodes, and an output layer predicting the EUI.

set of trained parameters for the target problem statement.

$$opt(X_s) \rightarrow X_s^{'}, f_{\theta_t^{\circ}} \xrightarrow{\{X_s^{'}, X_t\}} f_{\theta_t} \tag{1}$$

We implemented TrAdaBoost [24] for instance-based transfer. TrAdaBoost, iteratively re-weights the source domain data to reduce the impact of the "bad" source samples and rather focus on the "good" samples.

2) Model-Based Transfer: Earlier, to tackle the problem of cold start, we trained the ML models on the simulation data to predict electricity consumption for the field data. In model-based transfer, we will retrain the last two layers of the pretrained (from the simulation data) model using the field data. We will retrain only the last two layer to keep the internal representation intact while training the model for the new task, which is electricity prediction using the field data. Equation 2 depicts a formal representation of the model-based transfer.

$$f_{\theta_s} \xrightarrow{X_t} f_{\theta_t} \tag{2}$$

Here, f_{θ_s} is the pretrained model and f_{θ_t} is the pretrained model with last two layers fine-tuned with the field data.

C. Baseline Approaches

For the baseline comparison, we implemented two commonly used machine learning and deep learning models - Random Forest and Feed-Forward Network.

1) Random Forest: Random forest [17] in an ensemble learning method that fits a number of decision trees on various sub-samples of the dataset and averages over them to avoid overfitting and improve the prediction accuracy. We implemented Random Forest through *scikit-learn* package in python and performed *randomized search* for the hyperparameter tuning.

2) Feed Forward Network: Feed Forward Network, also known as multi-layer perceptron [25], is typically used for supervised machine learning tasks where the target labels are known. Formally, the model architecture (as shown in Figure 2) can be defined as -

$$u^i = relu(W^{n\times h}x^i) \tag{3}$$

$$f_1^i = relu(W^{h\times h}u^i) \tag{4}$$

$$d^i = dropout(f_1^i) \tag{5}$$

$$f_2^i = relu(W^{h\times h}d^i) \tag{6}$$

$$v^i = W^{h\times 1}f_2^i \tag{7}$$

where for the ith input x^i, $relu$ is the non-linearity function, f_1^i and f_2^i are the two hidden layers, $W^{n\times h}$ is the weight matrix with respect to input layer, $W^{h\times h}$ is the weight matrix respective to two hidden layers, $W^{h\times 1}$ is the weight matrix respective to output layer, n and h depict the total number of input variables and hidden nodes, respectively.

We implemented the feed forward network using *PyTorch*. The network is compiled using the *adam* optimizer with mean squared error (MSE) as the loss function. The total number of nodes (h) in both the hidden layers is 256.

IV. Experimental Setup

We next carried out a detailed evaluation to compare proposed transfer-learning based methods with the baseline techniques by using data from six commercial buildings.

A. Buildings and Dataset

For the year 2017, we collected electricity consumption and outside weather conditions data from six different commercial buildings. All the six buildings are low-rise with an average occupancy around 200-300 people during the work hours. The work hours in these buildings typically starts at 9 AM and ends at 6 PM. The area of the buildings may vary from 10,000 sq ft to 30,000 sq ft. The data was collected using the building management systems at a time resolution of 15 minutes.

1) Simulation Data: The FEDS building energy simulation software tool [26] was chosen based on its ability to generate hourly thermal, electricity, and electric demand profiles of buildings. FEDS uses the input building data and TMY3 weather data to simulate an 8,760 hour model of building system energy use. Specifically, FEDS can take in detailed user input data on building parameters or estimate unspecified or unknown building details from a minimum set of user inputs for analysis that extends from a single building to a large campus. These characteristics include building function, age, location, occupancy, geometry, envelope, lighting, HVAC systems and distribution, plug load, process loads, and marginal utility rates for the energy resources consumed. Hourly load profiles were generated from FEDS models of the same six buildings mentioned above.

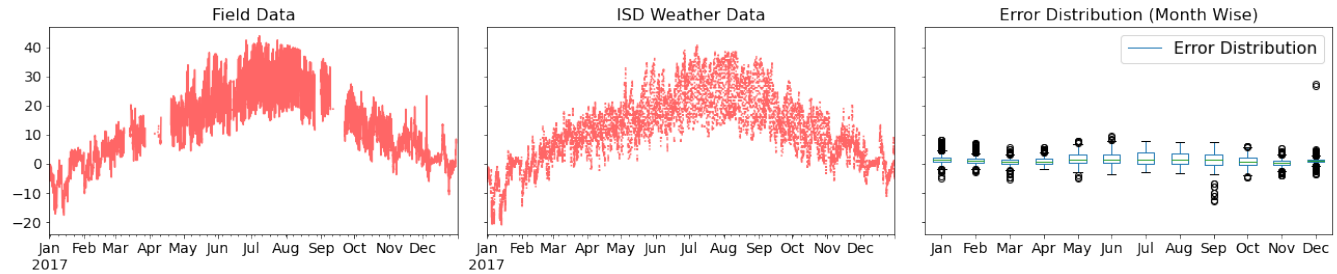

Fig. 3. Data Preprocessing: [Left] We had missing values in the temperature collected from the field. [Middle] To interpolate the missing values for that period, we used weather data from Integrated Surface Dataset of National Centers for Environmental Information (NCEI) of National Oceanic and Atmosphere Administration (NOAA). [Right] Between the two temperature streams, we noticed a mean absolute error of 2°C, across all the buildings.

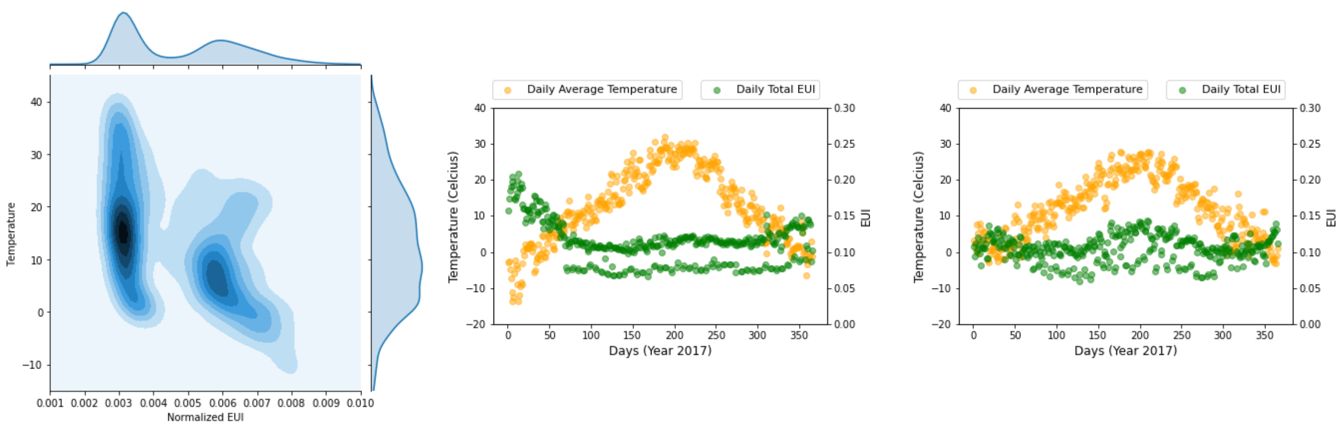

Fig. 4. Data Exploration to Generate Feature Map: [Left] Joint Distribution of EUI (x-axis in kWh/m^2) and Outside Temperature (y-axis in °C) for the Field Data: The two modalities differentiate non-working hours (left contour) from the working hours (right contour). [Middle] Correlation between temperature and EUI for the field data. [Right] Correlation between outside temperature and EUI for the simulation data.

2) Data Preprocessing: For comparison across buildings, we normalized the electricity consumption of the building by its total area, to compute EUI expressed as energy per square foot. For some time periods, the outside temperature data was missing. To interpolate the missing values in the sensor data, we used weather data from Integrated Surface Database (ISD) from National Centers for Environmental Information (NCEI) of National Oceanic and Atmosphere Administration (NOAA) [27]. Figure 3 depicts the actual temperature data from one of the buildings on the left, temperature data from ISD in the middle, and distribution of mean absolute error in the right-most plot. We noticed a mean absolute error of 2°C between field data and ISD data.

B. Feature and Label Spaces

At any time, electricity consumption of a building mainly relies on occupants' schedule and the outside weather conditions. Figure 4 [left] shows correlation between EUI (on x-axis) and outside temperature (on y-axis) for the field data. The two modalities in the EUI distribution (top x-axis) differentiates the non-working hours (left contour) from the working hours (right contour). One interesting point to note here is the correlation between building electricity consumption and outside temperature during the working hours (right contour). The upper half of that contour represents the hot time period of the year and the bottom half of the contour depicts the cold season. The electricity consumption is higher when temperature conditions are extreme for both the seasons. For a typical day, Figure 4 [middle and right] depicts the average EUI and outside temperature for all the six buildings. The plot validates the correlation between building electricity consumption and hour of the day.

On the basis of this exploratory analysis, we derived 28 features from the raw data, which are current and previous outside temperature, hour of the day, weekday/weekend, and working/non-working hours. We used one-hot encoding to represent hour of the day - one binary feature vector for each hour. Weekday/weekend and working/non-working hour are represented by a binary vector. On any working day, 9 AM-6 PM are considered working hours and hours outside this window are considered non-working hours.

C. Performance Evaluation Criteria

We use mean absolute error (MAE: Equation 8), mean absolute percentage error (MAPE: Equation 9), and accuracy (Equation 10) as the metrics to compare the estimation accuracy of the models.

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|y - y'| \tag{8}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{y-y'}{y}\right| * 100 \quad (9)$$

$$Accuracy = 100 - MAPE \quad (10)$$

Here, y and y′ denote the actual and the predicted EUIs, respectively, and N depicts the total number of data instances.

V. Evaluation

Given the experimental setup discussed above, we next evaluate the performance of proposed transfer learning strategies and compare the results with baseline strategies.

A. Training on Whole Year

We did an 80:20 split of the data - 80% for the training and 20% for the testing. We trained two models - Random Forest (RF), Feed-Forward Network (FF) - on the 80% random samples of data (approx. 10 months) and evaluated the performance on remaining 20% data (approx. 2 months) for both simulated and field dataset for the six buildings. Our results (as shown in Figure 5) indicate that the prediction accuracy of both feed-forward neural networks and random forest is comparable across all the buildings. Therefore, for the rest of the analysis, we will only use feed-forward neural network for the baseline comparison.

B. Training on Limited and Sparse Field Data

The value of transfer learning lies in getting good accuracy with the limited and sparse data. We noticed in Figure 1 that the validation accuracy for random forest and feed-forward network drops as we reduce the size of the training data. The drop in accuracy was the indication of data overfitting. However, we noticed an average improvement of 9% in the prediction accuracy with the transfer learning models. As shown in Figure 6, both, instance-based and model-based transfer learning models are mostly accurate and consistent, when compared to the baseline strategies. Our analysis, across all the buildings, indicates that transfer learning based models trained on approx. one week and three weeks of data can predict with better or comparable accuracy than the baseline models.

C. Training of Seasonal Data

In the real-world, timeseries data comes in a sequential order. Therefore, we do not have field data samples for one whole year, but rather a limited data from a particular month or the season. As one might notice in Figure 7 and Figure 8, the accuracy of the baseline models drops by 10%-15% when the models are trained on the data samples from a particular season and tested on the remaining seasons. This happens because the model hasn't seen much seasonal variation during the training. However, lack of seasonal variation in the field data makes an impact of 5%-6% on the transfer learning-based methods - the reason being the knowledge gain from the simulation data.

In instance-based transfer, the model is aware of the seasonal variations through random samples of simulated data. Likewise, in the model-based transfer, the knowledge about seasonal variation is embedded in the weight vectors of the pretrained model. This way, even with the lack of field data for other seasons, the transfer learning based models are doing much better than the baseline models. We did notice some negative transfer in a few cases, especially for the winter season where accuracy dropped by transfer learning for Building-1 and Building-6. This happened because winters were too cold and model never predicted temperature to be so low neither in the simulation, nor in the knowledge we acquired. In Figure 4 [Right], we can notice a bump in the EUI signal in the summer season in the simulation data. The bump doesn't exists for the field data (Figure 4 [Middle]). Therefore, when the knowledge is transferred from the simulation data to a model that is pretrained on the winter data (the other extreme season), the transfer learnt model faced negative transfer and performed poorly, when estimating the electricity consumption for the summer season.

The impact wasn't evident on the estimation of electricity consumption for the fall and the spring, because these seasons are not extreme and there exists some hot and cold days variation. We plan to address these concerns in the future by improving the criteria for transfer learning for both instance-transfer and model-transfer.

VI. Discussion

Our analysis indicates that transfer-learning based models can perform better than the traditional machine learning and deep learning models, especially when the field data is limited and sparse. This is useful to deal with the problem of cold start - when a building or an electricity forecast method has limited data to start with. With transfer learning, models don't need to wait for a long time to gather training data and they can rather make use of the simulation data. Initially, when a data-driven model doesn't have much data to infer about the seasonal variations and its impact on the electricity consumption, the baseline models performed badly. In those cases, our study indicates that knowledge transfer from a model trained from the simulation data to the model that we want to train using the field data can be effective. Since we can generate any number of variations with the help of a simulation model, transfer learning seems to be the way towards modeling building electricity consumption in the future.

Having said that, we believe this work is only the beginning and needs further exploration, which includes but are not limited to, improving the criteria for knowledge transfer to minimize the impact of negative transfer, adding more variations to the simulation data, and implementing advanced techniques of transfer learning. Transfer learning is an active area of research in both machine learning and deep learning. In this paper, we implemented and analyzed two of the most commonly used approaches of transfer learning to solve the problem of cold start and limited and sparse field data. However, this work can easily be extended to address other data-related concerns (such as data labeling, limited

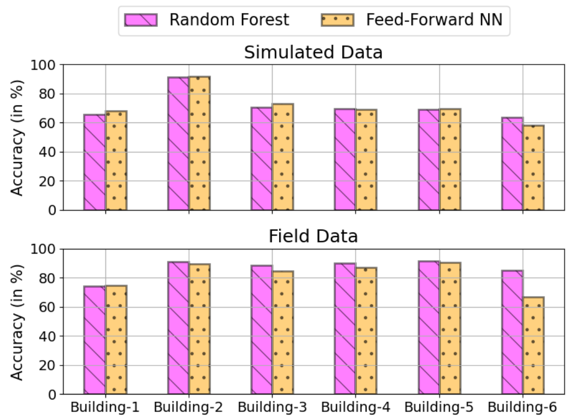

Fig. 5. When trained on one year of data, both the random forest and the feed-forward network had a comparable accuracy in estimating the building electricity consumption.

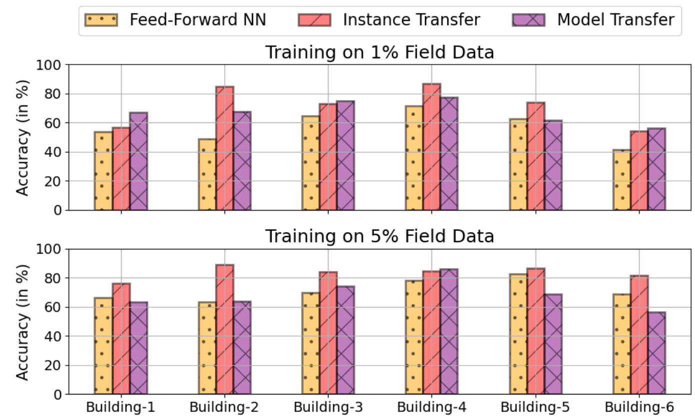

Fig. 6. We implemented both transfer learning strategies for the feed-forward network. Our analysis indicates that, in most scenarios, transfer learning is more effective (in most cases) than the baseline strategy for the smaller datasets.

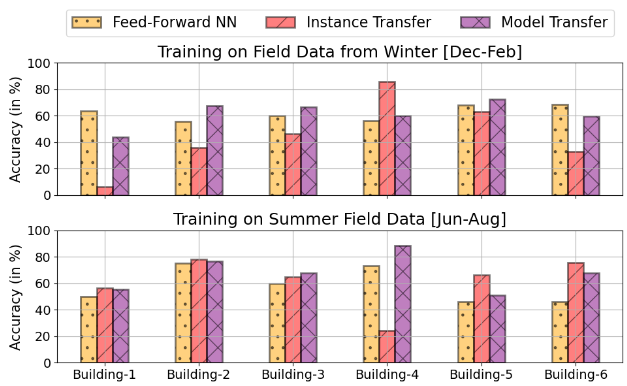

Fig. 7. Training on Winter and Summer Field Data: Knowledge transfer is much more effective when the model is trained on the seasonal data. We did notice performance drop with instance-based transfer for some buildings in the winter season and the reason was negative transfer.

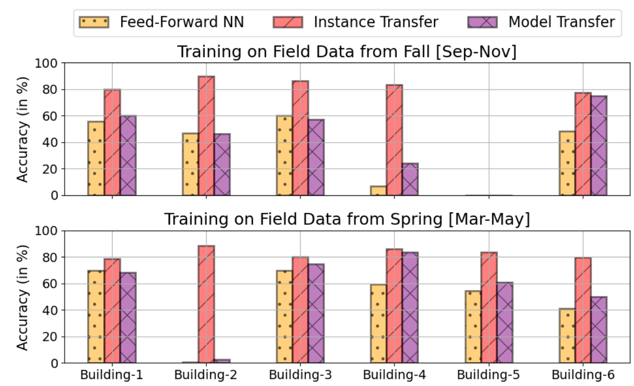

Fig. 8. Training on Fall and Spring Field Data: The transfer learning based methods outperformed the baseline methods with big margins here. The reason is that fall and spring provide enough variation in outside weather conditions to train an accurate model.

sensing, among others) when modeling building electricity consumption. For instance, we can use transfer learning to tackle the problem of limited sensing of the space. We can transfer knowledge from the simulation framework to the field data in case where certain sensors which are not installed in the field, but corresponding data is available in the simulation.

Another way to build on this work is to explore other variations of transfer learning to boost the performance of the proposed techniques. We did notice a few cases of negative transfer learning (especially when the models were pretrained using the winter data), that can be avoided by further strengthening the models, improving the selection criterion, and analyzing what parts of the model are most significant. In addition to this, one can also study other types of information transfer - such as transfer of feature representation and relational knowledge. In the former case, the aim is to find the "good" feature representation to minimize domain divergence. Likewise, in transfer of relational knowledge, we do not assume that the data drawn from each domain is independent and therefore try to transfer the relationship among data from a source domain to a target domain. A detailed evaluation of the possible variants and methods of transfer learning-based modeling can further help us in understanding, what is the most effective way of knowledge transfer for modeling building electricity consumption.

VII. Conclusion

In this paper, we implemented and analyzed two transfer-learning based strategies - instance-based and model-based - for modeling building electricity consumption to tackle the problem of cold-start and limited and sparse field data. The proposed technique is especially useful for developing models to assist building control design, and measurement and verification. For evaluation, we compared the performance of selected approaches with two state-of-the-art baseline approaches - Random Forest and Feed-Forward Network. Our analysis on the field data collected from six different buildings for one year indicates that transfer learning models trained on limited and sparse data can estimate building electricity consumption with a comparable or better accuracy than the baseline models. Furthermore, when the real-world data doesn't contain seasonal variations, the transfer learning models are much more effective than the baseline strategies. In the future, we plan to extend this work by further improving the transfer-learning based methods and applying building-to-building transfers. Besides, we also plan to investigate the use of transfer learnt models to serve as baselines for M&V of advanced control strategies such as MPC for building energy efficiency and participation in grid services.

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