Targeting Buildings for Energy Retrofit Using Recurrent Neural Networks with Multivariate Time Series

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Abstract

The existing building stock accounts for over 30% of global carbon emissions and energy demand [25]. Effective building retrofits are therefore vital in reducing global emissions [17]. Current methods for building energy assessment typically rely on walk-throughs, surveys or the collection of in-situ measurements [19], none of which are scalable or cost effective. Supervised machine learning methods have the potential to overcome these issues, but their application to retrofit analysis has been limited. This paper serves as a novel showcase for how multivariate time series analysis with Gated Recurrent Units can be applied to targeted retrofit analysis via two case studies: (1) classification of building heating system type and (2) prediction of building envelope thermal properties.

1 Introduction

A growing body of research confirms that retrofitting residential buildings provides a net reduction in carbon and energy use, as well as monetary savings [9][18][17][24]. The findings of these studies are reflected in international policies regarding building retrofits [17]. The development of large-scale computational approaches to building performance analysis are essential to the success of such retrofitting programs. Modern techniques for building assessment often involve expensive in-situ measurements and on-site appraisal [19][11][4][2], but researchers have started investigating the use of big data to scale this process [3] [22][23][10][15]. Supervised machine learning methods, however, are not typically applied to building retrofit analysis, in part because there is a lack of data with useful labels. Sensing technologies such as smart meters and thermostats are becoming increasingly ubiquitous, but they are most commonly used for time series forecasting, load profile analysis or benchmarking, rather than prediction of particular building properties [20]. It is not clear what types of building characteristics can be predicted based only on time series measurement data.

With all of these considerations in mind, the contributions of this paper are threefold:

- The introduction of a deep learning approach that targets residential buildings for retrofit.
- A showcase of the types of building metadata that can be derived from multivariate time series data.
- Helping to overcome the data scarcity in the Civil Engineering domain by introducing a novel methodology for dataset generation.

To accomplish these objectives two case studies will be presented - heat pump classification and R-value prediction. Each of these cases focuses on a particular retrofitting strategy that will be

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discussed in more detail in the following section. The remainder of this paper includes a description of the deep learning methods and model architecture, preliminary findings and a discussion of next steps.

2 Methodology

2.1 Case Studies

Heat Pump Classification: Load reduction measures in building retrofits involve upgrading mechanical equipment such as appliances and HVAC systems [16]. Heat pumps are a particularly efficient HVAC technology, and government programs already exist to encourage system upgrades [1]. The ability to target homes that do not have heat pumps would be highly beneficial to these types of programs.

R-Value Prediction: Thermal resistance, R ($\frac{^{\circ}K}{W}$) is a material property that describes the effectiveness of insulation; the higher the R-value, the more effective the insulator. The area weighted average of R-values for all external surface provides a proxy for the quality of the building envelope. Envelope measures in building retrofits aim to increase the R-value by improving the constructions. An effective program should target buildings with relatively low values, but quantifying R is not trivial and the results can be difficult to experimentally validate [19].

In this paper we propose a novel approach for predicting R using whole building simulation software. In our approach, computational physical modelling is used to simulate building behaviour based on inputs such as geometry and construction definitions. Unlike typical building assessment methods which use measurement data to deduce quantities about a building, our method uses building simulations to generate synthetic time series data. We postulate that one could build a predictor for R by training a deep learning model on this synthetic data. The model could then be used predict the R-value for a real building from measured data. The work in this paper focuses on the creation of the synthetic dataset and the model training; future work will validate the use of this approach on real buildings.

2.2 Data

The dataset used for heating system classification is acquired from ecobee's Donate Your Data program[1]. This dataset consists of smart thermostat time series data measured at 5 minute increments as well as metadata describing household attributes. A detailed description of this dataset can be found at [14]. For the problem at hand indoor temperature, outdoor temperature and heating system runtimes are the input variables and presence of heat pump is the output variable. For the purpose of this study, only homes in Ontario and New York were considered. Of this subset there was a disproportionate number of homes with heat pumps. The dataset size was therefore reduced further to stratify the presence of heat pump so there was an even split in both the test set and the training set. The resulting data had 602 homes in the training set and 182 homes in the test set.

To predict R, a multivariate time series dataset with 10 minute granularity and 966 data points was created: 773 in the training set and 193 in the test set. The input variables consist of indoor temperature, outdoor temperature and heating power. Though the creation of this dataset is a significant contribution of this work, a full explanation is reserved for the Appendix.

For each case study the sequence length was limited to 2000 consecutive time steps per building[2], and mean imputation was used to handle missing values.

2.3 Model Definition, Optimization and Training

Given that the data structure for both of the above use cases is multivariate time series, the Recurrent Neural Network (RNN) is a natural choice of architecture. Gated Recurrent Units (GRUs) and Long-Short Term Memory Units (LSTMs) are extensions to the RNN that help to overcome the vanishing gradient problem and make them more suitable for learning long-term dependencies [12][6].

[1] `https://www.ecobee.com/donateyourdata/`

[2] 2000 time steps equates to one week for heat pump classification and two weeks for regression over R-value.

Both GRU and LSTM would be suitable for the work presented in this paper, however GRU was chosen because it has been shown to occasionally outperform LSTM in terms of convergence time and generalization [5]. Future work should also consider LSTM, as well as other architectures such as 2-dimensional Convolutional Neural Networks.

The same model architecture and optimization algorithm was used for both case studies. The model consisted of 3 stacked GRU layers with 80 feature units in each hidden state. As proposed by Cooijmans et al., batch normalization was included on each of the hidden-to-hidden transitions [7]. Cyclical learning rates, introduced by Leslie N. Smith, were used for training [21]; heat pump classification used a minimum rate of 1e-3, while prediction of R used a minimum rate of 1e-2. A weight decay of 1e-2 was used.[3] Finally, the training loop for the former case study used binary cross entropy loss while the latter used mean squared error loss.

3 Results

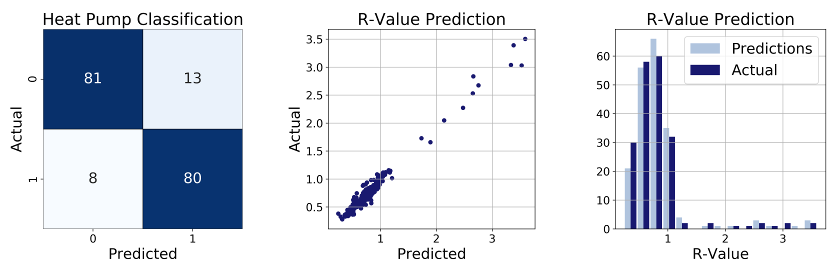

Figure 1: (a) The confusion matrix for heat pump classification. (b) Performance of R-value predictor. (c) Distribution of R-value predictions and actual values.

For heat pump classification, a validation accuracy of 0.87 was achieved on the test set, while the root mean squared error for prediction of R was 0.089 on the test set. The training for heat pump classification took 100 epochs while the training for prediction of R took 150. In both cases this is a relatively high level of performance with a relatively short training time.

A more comprehensive understanding of the results can be seen in Figure 1. The confusion matrix illustrates the precision-recall tradeoff in the heat pump classification problem, with a precision 0.86 and a recall of 0.91. The scatter plot shows the linear relationship between the predicted and actual values and the histogram represents the spread of values for R. The majority of values lie between zero and one[4]. With respect to this distribution, one can see that an RMSE of 0.089 is relatively low.

These findings should be considered preliminary; while they do indicate the usefulness of deep learning to building retrofit analysis, more work is required to improve accuracy and ensure generalizability.

4 Discussion & Conclusion

The ability to easily and accurately identify homes for retrofit is essential to inform international strategies for global energy and carbon reduction. Deep learning models in particular are affordable, scalable and reusable, and their successful application could prove invaluable in the building performance assessment industry. The findings in this paper are preliminary, but they show potential for the use of deep learning in targeted retrofit analysis. Future work should focus on continued data collection and model development in order to improve accuracy and ensure generalizability of results.

[3] The values for weight decay were chosen according to the defaults in the fastai library [13]. The learning rates were chosen using a learning rate finder, also provided by fastai. Dropout was also tried but the accuracy suffered.

[4] All of the values greater than one are from a building model with the same initial definition whose values for R are quite different than the other building definitions

Appendix

The synthetic dataset used for regression over R was generated using the Building Energy Simulation, Optimization and Surrogate Modelling (BESOS) platform[5] and EnergyPlus, as described in Figure 2. BESOS is a cloud-based research platform used for building energy simulation and optimization. Amongst other things, the platform provides functionality to produce many distinct sample buildings by parameterizing model inputs. Usually the generated samples are used for optimization (ex. using Genetic Algorithms) or for training surrogate models (ex. using Artificial Neural Networks). For the purpose of this project, the sampling functionality provided by BESOS was used to randomly vary the thickness and the density of each of the building materials, thus varying the whole building R-value and the simulated energy usage. 10 initial building designs were used to generate a total of 966 homes. Future work will continue to use the BESOS platform to generate a more robust dataset by including more building geometries, parameterizing more model inputs other than material properties and varying inputs such as weather and occupant schedules.

After many building designs were generated using BESOS, the energy use of each design was simulated with EnergyPlus, a standard software for building energy modelling [8]. This produced a multivariate time series dataset at 10 minute granularity, where the input variables consist of indoor temperature, outdoor temperature, and heating system power, for each thermal zone in the building. The time series are summed together for each thermal zone to produce a total of 3 features for each building. The output variables for prediction are the whole-building values for R, as derived from the EnergyPlus input data.

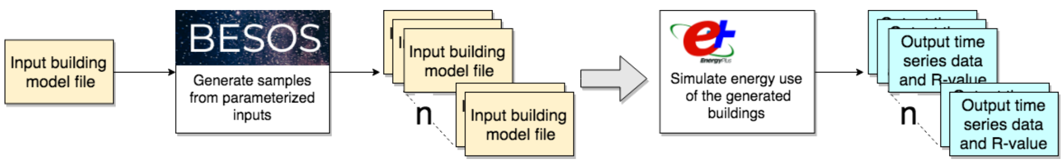

Figure 2: *Step 1*: Use the BESOS platform to generate many example buildings from a single EnergyPlus model. *Step 2*: Use EnergyPlus to run an annual simulation for each building generated in step 1.

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