



DEEP LEARNING FOR BUILDING ENERGY CONSUMPTION PREDICTION

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Abstract: In recent years, building energy consumption prediction gained a lot of research attention due to its importance in energy efficiency-related decision making. With the advancements in data analytics and machine learning, there has been numerous studies on developing data-driven building energy consumption prediction models based on support vector machines (SVM), artificial neural networks (ANN), and other statistical regression algorithms. These studies showed that each algorithm has its own advantages and disadvantages for different cases and that, therefore, the algorithms should be selected based on the specific application. However, none of the existing research efforts tested the effectiveness of deep learning – which is shown to outperform other machine learning algorithms in many other fields – in building energy consumption prediction. To address this gap, this paper (1) presents a deep learning-based model to predict cooling energy consumption of a building based on outdoor weather conditions (e.g., outdoor temperature), and (2) compares the prediction performance and computational efficiency of the deep learning-based model against other machine learning and statistical regression-based benchmark models. In order to generate a labelled dataset for training the models, a building was modelled and simulated by EnergyPlus in five locations. The models – the deep learning model as well as the other benchmark models – were trained using the simulation-generated data and the performance was evaluated in terms of accuracy and computational efficiency. The testing results showed that deep learning can be successfully applied to the field of building energy consumption prediction.

1 INTRODUCTION

Improving building energy efficiency is one of the best strategies for reducing building energy consumption without negatively affecting the comfort and well-being of building occupants. A large body of research efforts has, thus, been conducted in the area of building energy efficiency. These efforts can be classified into five categories: (1) efforts to improve the efficiency of building appliances and materials; (2) efforts toward increasing the use of renewable energy sources; (3) new policies, incentives, and regulations to reduce energy consumption; (4) efforts toward improving occupant behavior, and (5) efforts to automate building control in a way that improves building operation. All the efforts, across these categories, require accurate building energy consumption prediction for supporting energy efficiency-related decision making. Building energy simulation programs, such as EnergyPlus, eQuest, ESP-r, and TRNSYS, are being widely used for energy consumption prediction. These programs are, however, very elaborate, and therefore require a significant number of input parameters (e.g., data about the structural, geometric, and material properties of the building) that are not always available to users. Failure to provide the required input parameters, in many cases, causes poor prediction performance. In response, data-driven models that can predict building energy consumption without requiring many input parameters were developed. Data-driven models learn from historical data (e.g., cooling energy consumption, outdoor weather consumption).

A large variety of data-driven algorithms have already been utilized for energy consumption prediction. Among them, support vector machines (SVM), artificial neural networks (ANN), decision trees (DT), and

linear regression analysis are the most popular ones. However, deep learning algorithms, which have been proven to outperform other algorithms in many other tasks [e.g., image classification (Simonyan and Zisserman 2014) and speech recognition (Hinton et al. 2012)], have not been well studied in the field of building energy consumption prediction. In this study, the authors developed a deep neural network (DNN)-based model to predict hourly cooling energy consumption for office buildings. This paper focuses on comparing the performance of the DNN-based model in predicting hourly cooling energy consumption, in comparison to a set of benchmark algorithms. The results show the comparison in terms of prediction accuracy and computational efficiency.

The remainder of this paper is organized as follows. Section 2 provides a brief background on the most commonly-used supervised machine learning algorithms and their use in building energy consumption prediction. Section 3 presents the research methodology, which includes building description, energy simulations, data preprocessing, and data-driven model development and performance evaluation. Section 4 presents and discusses the results and highlights the limitations of the DNN-based model. Finally, Section 5 summarizes the conclusions and future work.

2 BACKGROUND

SVM, ANN, DT, and linear regression models are the most commonly-used supervised machine learning algorithms. Each algorithm has its own advantages and disadvantages for different cases. For example, SVM- and ANN-based models tend to provide more accurate results than DT and linear regression models, but DT and linear regression models, on the other hand, are usually simpler and easier to use (Zhao and Magoules 2012; Li et al 2014). Although a significant number of building energy consumption prediction models have been developed using these algorithms, there is no consensus in the literature on the most suitable model to use (Catalina et al. 2013).

2.1 Support Vector Machines

SVM is a kernel-based machine learning algorithm (Kumar et al. 2008). Numerous energy consumption prediction studies have been conducted using SVM. For example, Wang et al. (2016) developed an SVM-based hourly heating energy consumption prediction model based on outdoor temperature, outdoor humidity, wind speed, and solar radiation. The results showed that SVM is accurate and therefore promising for heating energy consumption prediction. Jain et al (2014a) developed a number of SVM-based energy consumption prediction models with various temporal and spatial granularities. The following features were utilized: electricity consumption values for the previous two time steps, the current temperature, day type, and hour type. The results showed that temporal and spatial granularities have a significant impacts on the prediction performance; and the optimal granularity occurred at the floor level predictions in hourly temporal intervals. Chou and Bui (2014) developed a number of SVM-based heating and cooling load prediction models to facilitate early building design for energy conservation. The following features were used: relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, and glazing distribution. The results showed the applicability of the models for predicting heating and cooling loads of buildings.

2.2 Artificial Neural Networks

ANN is a non-linear computational model, inspired by the human brain. A typical ANN includes three sequential layers: the input layer, the hidden layer, and the output layer. Each layer has a number of interconnected neurons which has an activation function (Wang and Srinivasan 2015). ANN is also very popular in energy consumption prediction studies. For example, Chae et al. (2016) developed an ANN-based sub-hourly electricity consumption prediction model. The following features were utilized: type of day, interval stamp, HVAC operation schedule, outdoor dry-bulb temperature, and outdoor relative humidity. The results showed that the proposed ANN-based model is capable of predicting electricity consumption with 15-minute time intervals. Similarly, Platon et al. (2015) developed an ANN-based hourly electricity consumption prediction model. The first four principal components (PCA) of a set of potential

features were utilized as features. The results showed that ANN-based prediction with PCA-selected features is an alternative approach to predicting hourly electricity consumption. Mena et al. (2014) developed an ANN-based model to predict energy demand of a bioclimatic building. The following features were utilized: type of day, hour of day, outdoor temperature, outdoor solar radiation, and electric power demand added up with the electric power supplied by the photovoltaic plant. It was shown that the model produces quick and acceptable results.

2.3 Decision Trees

DT models use a tree to map instances into predictions. In a decision tree model, each non-leaf node represents one feature, each branch of the tree represents a different value for a feature, and each leaf node represents a class of prediction (Domingos 2012). There are few studies that utilized DT for energy consumption prediction. For example, Chou and Bui (2014) developed classification and regression tree (CART)-, and chi-squared automatic interaction detector (CHAID)-based heating and cooling load prediction models to facilitate early building design for energy conservation. For both, the heating and cooling load prediction cases, CART and CHAID performed worse than SVM. Fan et al. (2014) developed a random forest (RF)-based model for predicting next-day building energy consumption. Meteorological data (e.g., maximum dry-bulb temperature, mean dry-bulb temperature) were utilized as features. Among the eight single prediction models that were tested, RF showed the second-best performance.

2.4 Regression Analysis

Compared to other algorithms, regression analysis is a simpler solution to various problems. The goal of regression analysis is to find the best coefficients of the model by learning from the given data (Catalina et al. 2013). Regression analysis is one of the most-used statistical algorithms. For example, Jain et al. (2014b) developed a least absolute shrinkage and selection operator (Lasso) to predict energy consumption of a multi-family building with several temporal and spatial scales. The following features were utilized: energy consumption values for the previous five time steps, outdoor temperature, type of day (i.e., weekend/weekday), and hour of day. The results demonstrated that Lasso can achieve accurate predictions. Catalina et al. (2013) developed a multiple regression model for predicting heating energy demand. The model utilized only three features: building global heat loss coefficient, south equivalent surface, and the difference between the indoor heating set point and the sol-air temperature. The model performed well and was proposed as a speedy alternative for heating energy demand prediction.

2.5 Deep Neural Networks

DNN is a feed-forward ANN that has more than one layer of hidden units between its inputs and its outputs. Due to the recent advances in both machine learning algorithms and computer hardware, more efficient methods were built to train DNN (Hinton et al. 2012). For example, DNN was successfully applied in the applications of image classification (Simonyan and Zisserman 2014) and speech recognition (Hinton et al. 2012). Nevertheless, DNN has not been well studied in the field of building energy consumption prediction. The objective of this paper is to examine the feasibility and applicability of DNN in the area of building energy consumption prediction.

3 RESEARCH METHODOLOGY

In order to develop the proposed simulation-based energy consumption prediction model, a dataset which includes hourly cooling energy consumption levels and corresponding weather variables was generated using a whole building energy simulation program. The machine learning-based prediction model was trained on this generated dataset. A four-step methodology was used: (1) modelling an office building, (2) conducting energy simulations, (3) data processing, and (4) developing data-driven based models by learning from the generated data.

3.1 Building Description

A 3-story, 15-thermal zone office building was selected to examine the feasibility and applicability of DNN in cooling energy consumption prediction. As shown in Figure 1, the building was modelled in SketchUp. The size of the building is 61 m * 31.5 m * 10.98 m. The floor to floor height is 3.66 m. The perimeter zone depth is 6.1 m. The exterior windows in the building are at the height of 0.76 m above floor level and the window-to-wall ratio is 40%. The building has packaged rooftop units used for all zones but all core zones are served by one heat pump system and the remaining zones are all served by another heat pump system. The construction properties of the building are summarized in Table 1.

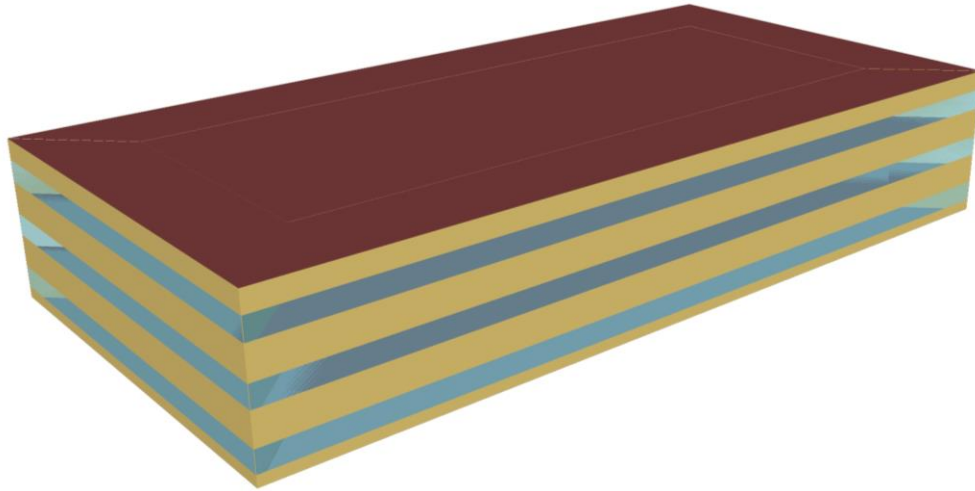


Figure 1: Elevation of the office building

Table 1: The construction properties of the building

Building property	Value
Exterior wall	12.7 mm gypsum + 110 mm wall insulation + 203 mm high weight concrete + 25 mm stucco
Interior wall	G01a 19 mm gypsum board + F04 wall air space resistance + G01a 199 gypsum board
Roof	Metal decking + 210 mm roof insulation + roof membrane
Window	Clear 3 mm

3.2 Operational Characteristics and Energy Simulations

The energy performance of the building was simulated under the following operational characteristics and locations. The building serves as an office with an open-office layout. The building is occupied from 8 a.m. to 6 p.m. weekdays. The operational characteristics of the building are shown in Table 2. To ensure that the proposed models were tested in several climates, the building was simulated in five different locations from May to October, using the typical meteorological year (TMY) conditions. Table 3 shows the locations and their climate properties. EnergyPlus 8.6.0 was utilized to conduct the energy simulations.

Table 2: The operational characteristics of the building

Operational characteristic	Value
Cooling setpoint (occupied)	24.0°C
Cooling setback (not occupied)	26.7°C
Occupancy	0.056 people/m ²
Lights	10.656 W/m ²
Equipment	7.642 W/m ²

Table 3: Climate properties of the locations

Location	Climate type	Cooling degree days (CDD) (18.3°C Baseline)
San Francisco, CA	Warm - marine	79
Golden, CO	Cool - dry	312
Tampa, FL	Hot - humid	1954
Chicago, IL	Cool - humid	468
Sterling, VA	Mixed - humid	622

3.3 Data Preprocessing

Prior to machine learning, the outdoor weather-related parameters were preprocessed for compatibility with the machine learning algorithms. Non-occupied hours (e.g., weekend hours) were removed from the dataset because the operational characteristics of the building differ in these hours. The potential feature pool to predict hourly cooling energy consumption included 22 weather-related variables. A stepwise regression was performed for feature selection. As a result, 14 features remained and were used for machine learning: dry-bulb temperature, dew point temperature, relative humidity, atmospheric pressure, extraterrestrial direct normal radiation, direct normal radiation, diffuse horizontal radiation, direct normal illuminance, zenith luminance, wind direction, wind speed, opaque sky cover, ceiling height, and precipitable water. Each feature was centered and scaled by its mean and standard deviation, respectively. The cooling energy consumption data generated by EnergyPlus and the 14 features were integrated into one dataset. The dataset, as a result, consisted of 6,435 sample data points.

3.4 Data-Driven Model Development and Performance Evaluation

A multi-layered feedforward DNN model with three hidden layers that uses a Bayesian regularized neural network model with Levenberg–Marquart (LM) backpropagation algorithm was developed. The MATLAB's neural network training tool was used to build the network. The hyperbolic tangent sigmoid transfer function and the linear transfer function were used in the hidden layers and output layer, respectively. Models with different number of neurons in their hidden layers were tested to determine an optimal performance. As a result, each layer consisted of 12 neurons. Figure 2 shows the structure of the proposed DNN.

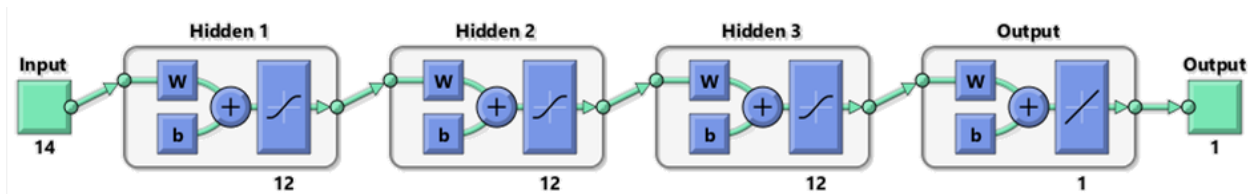


Figure 2: The diagram of the proposed DNN

In addition, SVM, RF, and linear regression models were developed to serve as benchmark models. These models were trained using the MATLAB's statistical and machine learning toolbox. The authors tuned the algorithm parameters to achieve an optimal performance. The following parameters, as a result, were chosen: (1) SVM – kernel: Gaussian, kernel scale: 6.5687, box constraint: 538.99, and Epsilon: 0.38428; (2) RF – number of trees: 50; and (3) linear regression model – model type: linear, and weight function: Bisquare.

For performance evaluation, a 10-fold cross validation was used to minimize bias in selecting the data for training and testing (Chou and Bui 2014). The following performance metrics were utilized: coefficient of variation (CV) and coefficient of determination (R^2). CV is a performance metric, provided by ASHRAE, for evaluating building energy consumption prediction models. CV determines how much the overall prediction error varies with respect to the target's mean (Edwards et al 2012). CV was calculated using Eq. (1). R^2 is

a measure to assess how much of the variance in y is explained by a model. R^2 was calculated using Eq. (2).

$$[1] CV(\%) = \frac{\sqrt{\frac{\sum_{i=1}^n (y_{predict,i} - y_{data,i})^2}{n-1}}}{\bar{y}_{data}} \times 100$$

$$[2] R^2(\%) = \frac{\sum_{i=1}^n (y_{predict,i} - \bar{y}_{data})^2}{\sum_{i=1}^n (y_{data,i} - \bar{y}_{data})^2} \times 100$$

where $y_{predict,i}$ is the predicted energy consumption at hour i , $y_{data,i}$ is the actual (simulated) energy consumption at hour i , n is the number of hours in the dataset, and \bar{y}_{data} is the average energy consumption. The smaller the CV and the larger the R^2 are, the more similar dispersions are between the predicted and the actual consumptions.

4 RESULTS AND DISCUSSION

Figure 3 shows the hourly cooling prediction results of 643 days by the four models – for all five locations combined. The prediction performance of the DNN, SVM, and RF models are comparable, whereas the linear regression model has a notably lower performance. Table 4 presents the results for all four models. The results illustrate which model is the best at cooling energy consumption prediction in terms of accuracy (CV and R^2) and computational efficiency. All models except the linear regression model achieved a satisfactory performance. The SVM-based model showed slightly better CV and R^2 than the DNN-based model. However, the DNN-based model converged approximately in the tenth time of the SVM model, which makes the DNN-based model a potentially good candidate to select for energy consumption prediction – especially as the size of the data becomes larger. The RF-based model, on the other hand, performed worse than the SVM and DNN-based models in terms of CV and R^2 , but converged faster. The linear regression model showed the worst CV and R^2 performance, but its training time was only one second. These findings indicate that, in this cooling energy consumption prediction case, DNN and RF are the best models considering both accuracy and computational efficiency.

Figure 4 shows the hourly cooling prediction results of the DNN-based model by location. The predictions of the DNN-based model showed a good fitness with the cooling energy consumption calculated by EnergyPlus, on all five locations. This indicates the potential stability of the predictions across locations.

Table 4: Results for all models (all five locations combined).

Model	Training time	Testing dataset ¹		Training dataset ¹	
		CV	R ²	CV	R ²
Deep Neural Networks	13.926 s	8.88%	96.11%	8.02%	96.84%
Support Vector Machines	146.464 s	8.59%	96.36%	7.95%	96.90%
Random Forest	8.605 s	9.35%	95.69%	5.84%	98.33%
Linear Regression	1.034 s	19.99%	79.11%	18.74%	82.08%

¹Best results are shown in bold font.

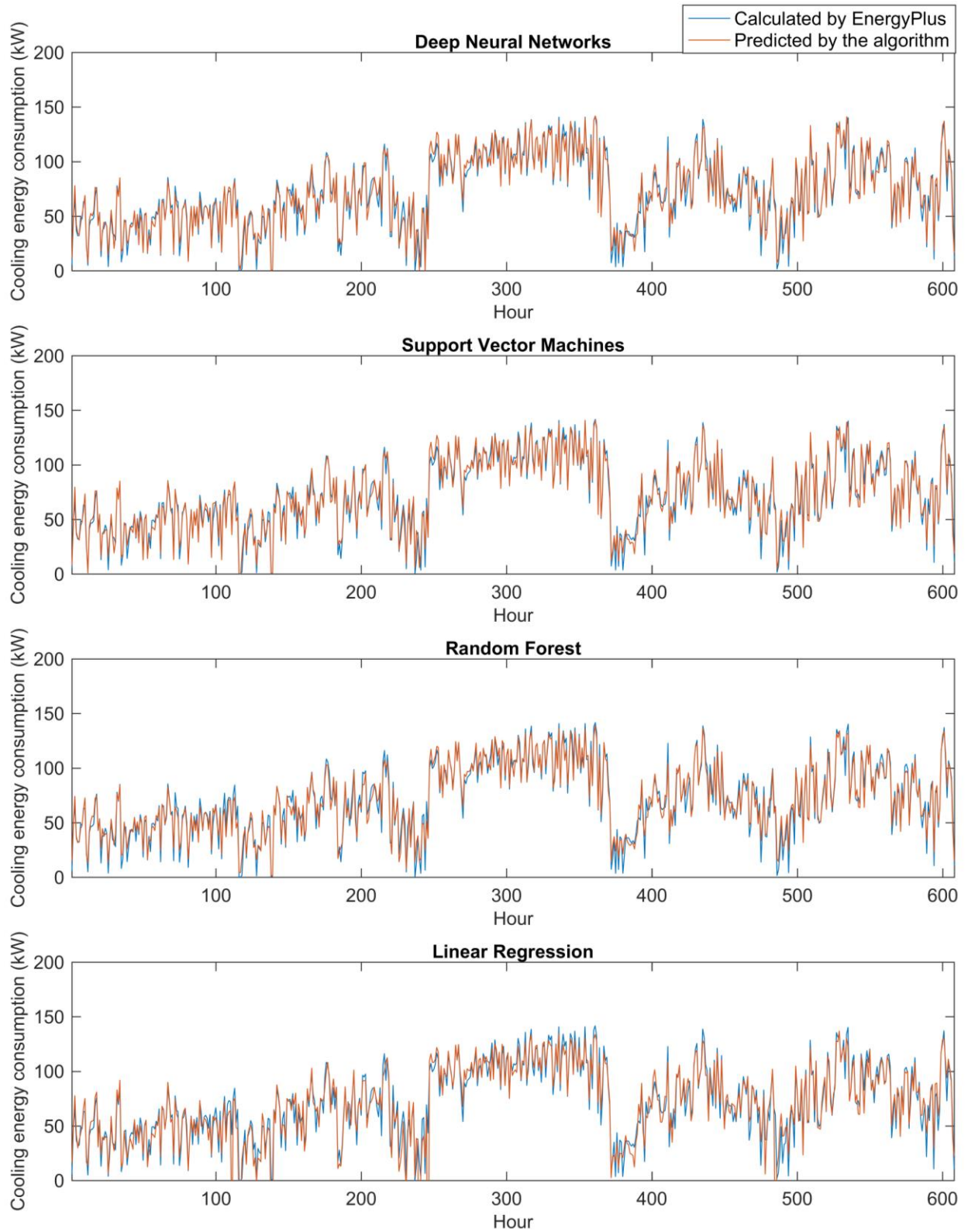


Figure 3: Cooling energy consumption prediction by the models (all five locations combined)

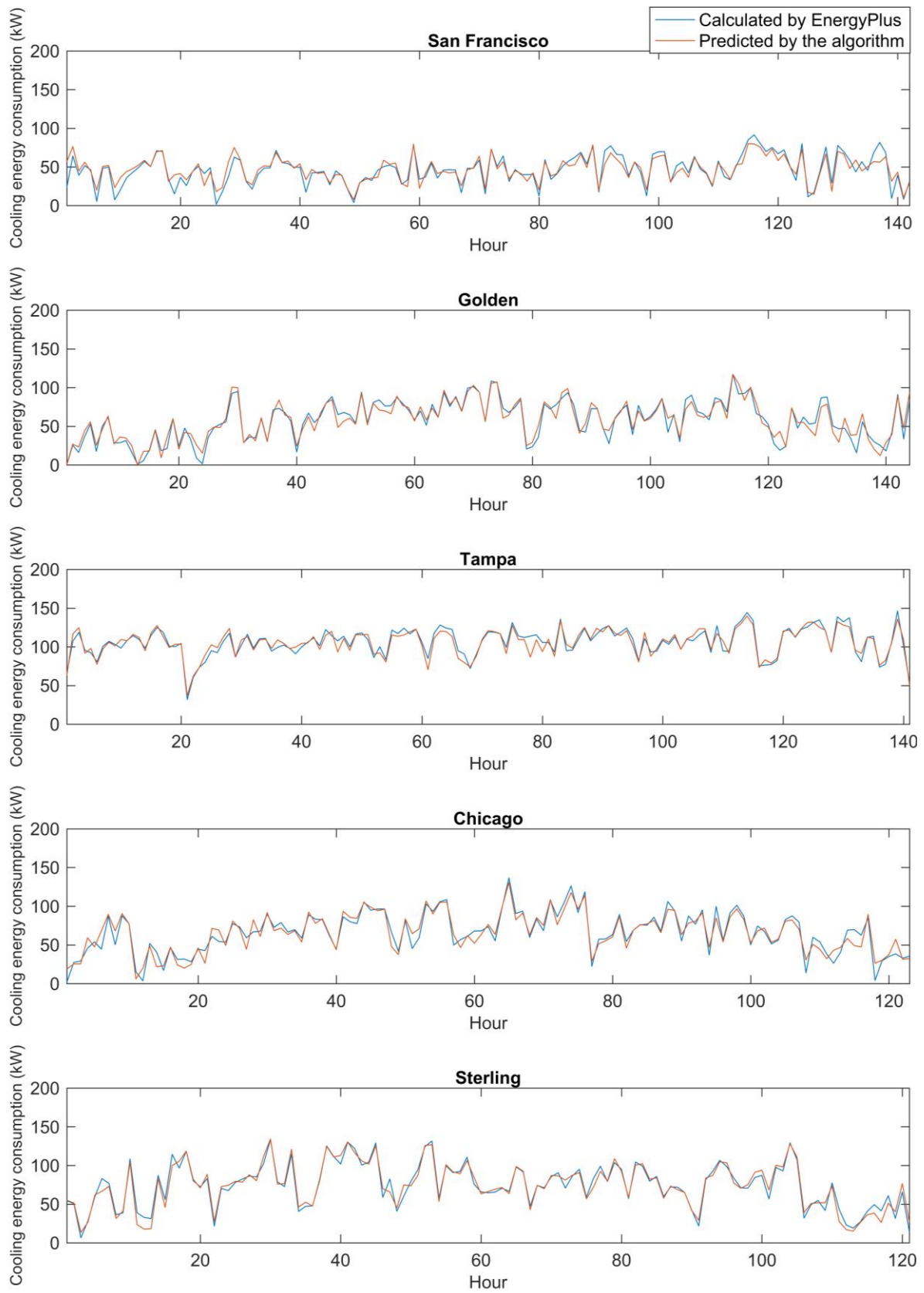


Figure 4: Cooling prediction results of the DNN-based model by location

5 CONCLUSION AND FUTURE WORK

Four data-driven based algorithms, including DNN, SVM, RF, and linear regression were implemented and tested – in terms of accuracy and computational efficiency – in predicting building hourly cooling energy consumption. The models were trained and tested, using 10-fold cross validation, on a dataset that was generated through simulating a building in different locations. The SVM-based model achieved the best performance with 8.59% CV and 96.36 R². Closely, the DNN-based model achieved 8.88% CV and 96.11% R². The RF and linear regression models achieved 9.35% CV and 95.69% R², and 19.99% CV and 79.11% R², respectively. In terms of computational efficiency, the linear regression model was the fastest with 1-sec training time, followed by the RF and DNN-based models. The SVM-based model was the most computationally expensive among the four models. In addition, the predictions by the DNN-based model showed a good fitness with the cooling energy consumption calculated by EnergyPlus, on all five locations. This work demonstrates the applicability of DNN in building energy consumption prediction due to its reasonable accuracy and computational efficiency.

In their future work, the authors will test the proposed DNN-based model, as well as the benchmark models, in a real building testbed and will further improve the proposed model, if/as needed. Currently, the authors are conducting a set of empirical energy studies in residential and office buildings to capture sufficient real data, including energy use behavior data. The models will be tested using the real data, and will be retrained if/as necessary. The authors will also test the proposed model with different temporal granularities.

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