Prediction of City-Scale Building Energy and Emissions: Toward Sustainable Cities

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Building energy use estimation relies on building characteristics, its energy systems, occupants, and weather. Energy estimation of new buildings is considerably an easy task when compared to modeling existing buildings as they require calibration with actual data. Particularly, when energy estimation of existing building stock is warranted at a city-scale, the problem is exacerbated owing to lack of construction drawings and other engineering specifications. However, as collection of buildings and other infrastructure constitute cities, such predictions are a necessary component of developing and maintaining sustainable cities. This paper uses Artificial Neural Network techniques to predict electricity consumption for residential buildings situated in the City of Gainesville, Florida. With the use of 32,813 samples of data vectors that comprise of building floor area, built year, number of stories, and range of monthly energy consumption, this paper extends the prediction to environmental impact assessment of electricity usage at the urban-scale. Among others, one of the applications of the proposed model discussed in this paper is the study of urban scale Life Cycle Assessment, and other decisions related to creating sustainable cities.

Keywords: Energy Use Estimation, Life Cycle Assessment, Urban Scale, Artificial Neural Networks.

I. INTRODUCTION

Cities and urban areas use 50% of all energy that amounts to 35% of total greenhouse gas emissions [1]. Reducing building energy use has been considered as one of the critical strategies for sustainable urban development and environment [2]. The estimation of building energy use and the ensuing emissions is crucial for improving city living. Energy estimation of individual buildings is a widely discussed topic. However, there are only a few studies that have analyzed energy consumption by building clusters at city-scale. In the case of city-scale evaluation of building energy use, the impact of building type, characteristics, age (built year), number of stories, and energy system types should be understood. Most of the current work focuses on the distinction between residential and commercial buildings and pay less attention to the differences of building types. In order to analyze building performance at city-scale, it is recommended to include weather data (e.g., temperature, humidity, solar radiation, and etc.), energy system type and demand (e.g., heating, cooling, lighting and etc.), construction material type, building components (e.g., window, material of envelope, overhangs, etc.). This paper is organized as follows: firstly, the paper reviews the recent research associated with predicting energy consumption using Artificial Neural Networks (ANN) and regression analyses. And, secondly, this paper develops a model to predict building energy use and compared to actual usage and predicted usage. This ANN model uses energy dataset of buildings situated in the City of Gainesville, Florida.

II. LITERATURE REIVEW

Although ANN has been widely used in research related to building energy estimation, most of the previous work applied typical data such as weather data, i.e., temperature, humidity, solar radiation, etc. Some several regression model were configured for energy consumption related to the residential building sector, and the following input and variables investigated: dry-bulb temperature, global horizontal radiation [3]. The performance of cost estimation models were examined by ANN, multiple regression analysis, and case-based reasoning with built year, area, duration, and number of units [4]. Estimated the electricity consumption modeling was made by using ANN method and this model support vector regression with seasonal index and time/ month index [5]. ANN, and grey model, regression model, and polynomial model for prediction the future energy demand in the urban residential buildings [6]. Energy performance models developed recently were reviewed and, which used physical principles, regression model, ANN, support vector machines, and grey model [7]. Building electrical energy forecasting methods were reviewed that used ANN, support vector machine, and hybrid method [8].

A total nine parameters (daily average dry-bulb temperature, daily average wet-bulb temperature, daily global solar radiation, daily average clearness index, solar aperture, daylight aperture, overhang projection, side fins projection, and day-type) were used as the input variables for the ANN model [9], also twenty parameters were used as input variables related to building characteristic, heating and cooling systems, window characteristics [2]. Thirteen variables related to building characteristics, emission, and heating & cooling systems were used to analyze energy performance [10], ten variables associated with temperature, energy demand, and weather were used to analyze total energy demand of a case building [11]. The results from the above researches were analyzed for R^2, and it was found that regression models showed R^2 between 0.85 and 0.95 whereas ANN models reported R^2 between 0.50 and 0.70. In other words, the prediction models using regression showed improved accuracy over ANN. One reason, based our review of the above-mentioned researches, is due to the

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appropriate selection of input variables. Therefore the selection of input variables has an impact on the predicting energy consumption and usage. Also, ANN model being more accurate is needed from going through few, but accurate selecting variables.

III. METHODOLOGY

A. Artificial Neural Networks

ANN is widely used method for forecasting of building energy consumption, which has an advantage for analyzing and predicting energy consumption. In order to use ANN, two factors need to be considered namely, structure of ANN, training datasets and testing datasets. Structure refers to input, hidden, and output layers; these layers can be controlled by the researcher. In the case of datasets, they should be chosen randomly to prevent overtraining.

B. Performance Assessment

In order to test the accuracy of prediction model, this research employed three evaluation metrics namely the root mean square error (RMSE), the mean absolute percentage error (MAPE), and the mean absolute error (MAE). The expression of these metrics are expressed as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{k}(\hat{y}_t - y_t)^2}{k}}$$

$$MAPE = \frac{100}{k}\sum_{t=1}^{k}\frac{|\hat{y}_t - y_t|}{y_t}$$

$$MAE = \frac{\sum_{t=1}^{k}|\hat{y}_t - y_t|}{k}$$

where $\hat{y}_t$and y_t are the predicted value and actual value for electricity usage respectively, and k is the number of predicted value. RMSE of zero meant that the predicted value match with perfect accuracy with the actual value. MAPE and MAE are measures of accuracy for series values in statistics, especially in trend forecasting.

IV. DATASETS USED FOR CITY-LEVEL BUILDING ENERGY USE PREDICTION

The datasets used for this research comprises of monthly building electricity consumption obtained from Gainesville Green [12]. The data included number of bedrooms and baths, conditioned space, roof material, number of stories, built year, and parcel data. A total of 32,267 samples were selected from which was 33,379 samples after eliminating outliers. This dataset included energy use from January 2009 to September 2013, i.e, for 57 months. The proposed ANN prediction model was executed in SPSS Clementine 10.1 [13]. The input variables used in this ANN were built year, floor area, number of bedroom, stories, and electricity consumption. In the ANN model, 30% of total samples were used as training set, and the model predicted the electricity usage which was then used to estimate CO_2 emissions. The ANN model used 3 hidden layers with a 0.9 alpha value. The predicted model was divided into 5 clusters based on built year: “before 1971,” “1971 to 1980,” “1981 to 1990,” “1991 to 2000,” and “after 2001.” While ‘before 1971’ refers to all buildings constructed before 1971, i.e., including 1970, ‘after 2000’ includes buildings constructed from 2001.

TABLE I
NUMBER OF SAMPLES CLUSTERED

Cluster	Number of Samples
before 1971	7,664
1971-1980	8,111
1981-1990	7,311
1991-2000	5,762
After 2000	3,419
Total	**32,267**

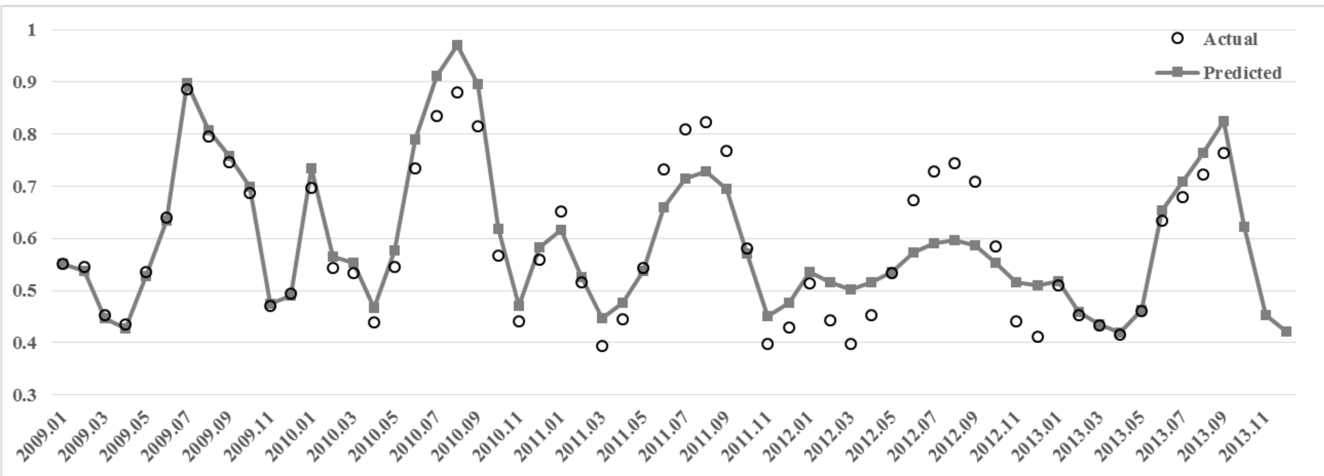

FIGURE I. PREDICTED AVERAGE EUI FOR WHOLE SAMPLES (KWH/SQFT)

V. RESULTS AND DISCUSSION

The results of proposed ANN prediction model was shown above figure I compared to actual data. The graph showed predicted and actual monthly average energy use intensity (kWh/square foot) of 5 clustering model. From Jan. 2009 to Dec 2009, these value showed very close to actual value. On the other hand, from 2010, the model showed little differences from actual value, however, this average model showed a yearly repeatability for summer and winter season.

The below Figure II was shown the predicted average Energy Use Intensity (EUI) for divided 5 clusters based on built years. Generally the monthly average EUI of 4th (1991 to 2000) and 5th (after 2001) cluster showed lower values than other clusters. This prediction models' results was shown in Table II below. The proposed ANN model showed the 2nd (1971-1980) cluster showed better result than other clusters. The MAPE and MAE of the whole model configuring average values showed mid-accuracy between all models.

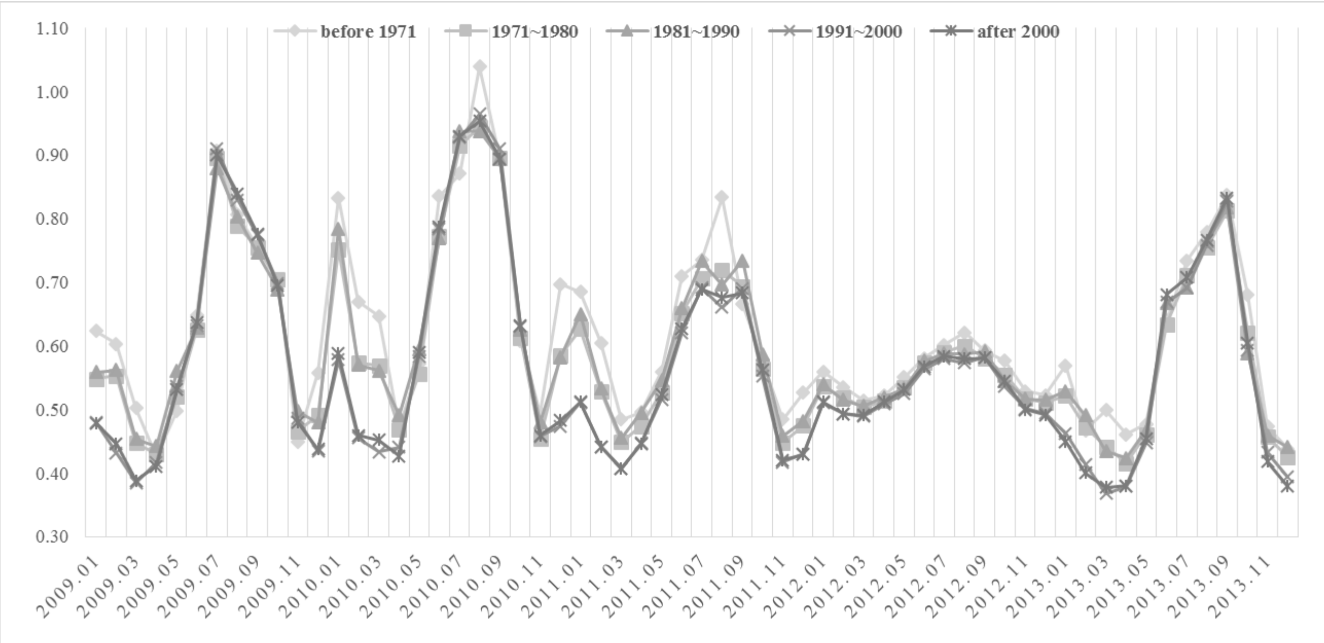

FIGURE II. COMPARING PREDICTED ANN AVERAGE EUI MODEL FOR 5 CLUSTERS BASED ON BUILT YEAR (KWH/SQFT)

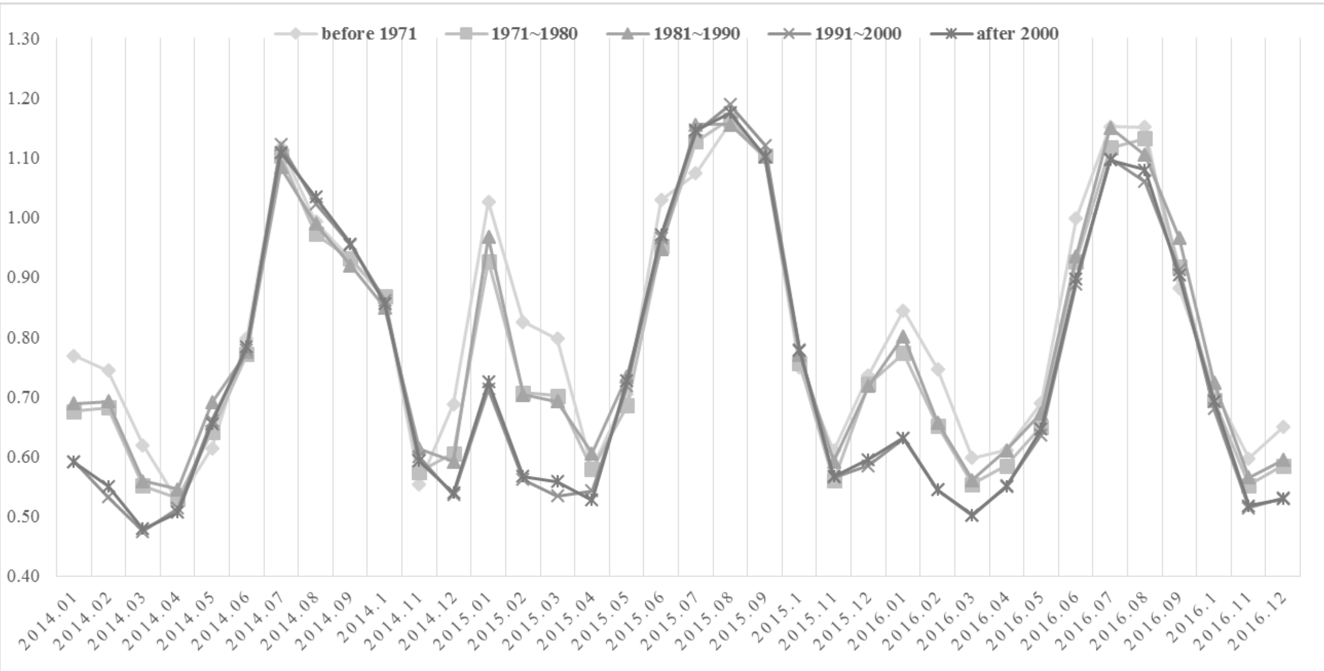

FIGURE III PREDICTION MODEL OF CO2 EMISSION FOR 5 CLUSTERS BASED ON ANN MODEL (LBS/SQFT)

Above Figure III shows the estimation of CO_2 emission from ANN results. The quantity of CO_2 emission was derived from the eGRID year 2010 data [14]. This data is the national average CO_2 output rate for electricity generated in 2010 was 1,234.4 lbs CO_2 per megawatt-hour.

TABLE II
PERFORMANCE ASSESSMENT OF ANN PREDICTION MODEL

Cluster	MAPE (%)	RMSE (kWh/sqft)	MAE (kWh/sqft)
Before 1971	6.968	0.0652	0.0462
1971-1980	6.555	0.0598	0.0414
1981-1990	7.010	0.0556	0.0415
1991-2000	16.995	0.0895	0.0806
After 2000	15.595	0.0861	0.0763
Whole	**7.029**	**0.0565**	**0.0417**

VI. CONCLUSION

Building energy consumption forecasting was often needed in the evaluation of building performance, optimization of building operation, fault detection and diagnosis and demand side management for smart grid [15]. This research proposed models for prediction energy use and environmental impact, especially electricity usage and CO_2 emissions using ANN methodologies. The ANN model stabilizing nonlinear variables between input and output variables was able to predict electricity use and, thereby, CO_2 emission in both training set and testing set. The proposed model is useful to estimate building energy and emissions in city-scale that can also be adopted as a system to manage future building clusters in cities.

This research used only ANN methodology for prediction, however, in order to improve accuracy, it may need a verification mechanism using other methods to compare and verify, e.g., autoregressive–moving-average model with exogenous inputs model, autoregressive integrated moving average model, etc. This research calculated only operational electricity use. In order to develop city-scale LCA model, whole life cycle of building construction, operation, and demolition and other impacts (i.e. global warming, acidification, eutrophication, and etc.) should be considered.

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