VERIFICATION OF ANN SOLAR RADIATION PREDICTION ALGORITHM FOR REAL-TIME ENERGY SIMULATION

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ABSTRACT

Real-time building simulations are necessary to evaluate the performance of building systems in real-time. This paper presents an Artificial Neural Network algorithm that predicts global solar radiation only using readily available weather data such as temperature and humidity. EnergyPlus weather converter program is used to calculate diffuse and direct normal radiations from the predicted global solar radiation and to generate the EPW file needed for EnergyPlus simulation. Simulations are conducted using two weather files, 1) measured 2018, and 2) predicted 2018 using ANN output. This study evaluates the accuracy of using predicted solar radiation in the building simulation process.

INTRODUCTION

Energy modeling is essential when designing sustainable buildings since it can be used to quantify initial equipment costs and operational energy costs. Real-time building energy simulation is also necessary as it can test the designed HVAC systems performance. On a larger scale, energy modeling analysis can support the development of energy codes and standards, helping utilities and governments plan large-scale energy efficiency programs.

In this paper, there are two compatible software programs used to perform the simulation. 1) EnergyPlus, which is a Building Energy Modeling (BEM) engine capable of modeling low-energy buildings and HVAC systems. 2) OpenStudio, which is a software development kit that reduces the complexity of EnergyPlus-based application development (US Department of Energy, 2018). To run a real-time building energy simulation, there is a need for a real-time weather file. One of the goals of this paper is to develop a real-time weather file using easily measured data. Using measured data from the Building Automation System (BAS) such as temperature and relative humidity is not enough to generate a real-time weather file needed for simulation. Other meteorological parameters are hard to be measured in every location. One of the most critical parameters that have a significant effect on simulation is solar radiation. There is a limitation of meteorological stations that can measure solar radiation with an accurate and calibrated pyranometer (Khatib et al. 2012, Mubiru et al. 2008). Since the solar radiation measuring process is costly, a prediction method could be taken place. In this paper, an Artificial Neural Network (ANN) algorithm is used to predict hourly global solar radiation using only easily measured data; i.e., temperature and humidity. The Coefficient of Variance of the Root Mean Square Error CV(RMSE) and Normalized Mean Bias Error (NMBE) are used to calculate the uncertainties between the measured and predicted solar radiations.

This paper aims to run a simulation using generated weather files from predicted solar radiation through the ANN model and then to make a comparison with the measured weather file. This paper uses 2018 weather data files for Raleigh-Durham (RDU) International Airport weather station. EnergyPlus weather converter program is used to generate the EPW file needed for EnergyPlus simulation. An office building in Durham, NC, is selected as a case study.

PREVIOUS STUDIES

Maqzouq et al. (2017) concluded from her review paper that ANN models are found to be effective in predicting solar radiation accurately. ANN algorithm is considered one of the most common technologies that can perform a computational simulation for complex and non-linear tasks (Gani et al., 2015). As mentioned earlier, the aim of this paper is on solar radiation prediction techniques using only readily available data like temperature and relative humidity and to use this predicted solar radiation to run real-time building performance simulation.

By looking at the previous studies that have a mutual interest area, it can be divided into two main categories. In terms of papers using the ANN model to predict solar radiation, previous studies showed that different parameters were used to predict global solar radiation. However, most of the parameters are not readily available such as wind speed, cloud cover, etc. Others focused on different prediction periods; i.e., daily or monthly. The systematic literature review paper by Qazi et al. (2015) discussed 373 documents, published from 2005 to 2014. Only 5 of them focus on hourly and daily solar radiation predictions. Zhang et al. (2017) concluded that more studies are necessary for short time intervals in solar radiation predictions. More similar

articles discussed before and could be viewed here (Gaballa and Cho, 2019).

Some papers focused on real-time simulations. Through the literature review, there was a lack of articles using ANN algorithms as a method to develop a real-time weather file and then use it in real-time energy performance prediction. Otherwise, they use onsite instruments or sensors to develop weather files. In some other papers, the author used different models, such as the Seo model, which requires more than six parameters to generate the solar radiation data (Gaballa and Cho, 2019).

INSTRUMENTATION AND DATA ACQUISITION

The EnergyPlus program is considered a whole building simulation software program that is traditionally used for building energy analysis (Pang X. 2011). EnergyPlus software uses an EPW file to run a simulation. In this paper, the 2018 weather data file for Raleigh-Durham weather station is used, which is provided by the National Renewable Energy Laboratory (NREL). The available file format is the comma-separated value (CSV). The provided format includes some essential parameters; i.e., dry-bulb temperature, relative humidity, solar radiation data, wind speed, wind direction. Some other parameters like solar illuminance data, extraterrestrial solar data are missing, but the work done before (Gaballa and Cho, 2019) proves that weather files with limited data could perform well within ASHRAE Guideline 14 (ASHRAE, 2014) uncertainty tolerance range. The weather converter program in EnergyPlus is used to develop the EPW file needed to use the measured 2018 CSV file to be called case_1 (C_1).

To develop the predicted weather file using easily measured data, an ANN model is used to predict hourly global solar radiation using temperature, humidity, and solar zenith angle from the measured 2018 CSV file. After the prediction process, again, temperature and humidity from the measured 2018 CSV file, besides the predicted hourly global solar radiation from the ANN model, were used to develop the new weather file using the EnergyPlus weather converter program. During the conversion process, direct and diffuse solar radiations are calculated using the Perez model (EERE, 2018) based on the predicted global solar radiation. This time the weather file is called case_2 (C_2), which identifies the predicted 2018 weather file. The two weather files developed are used to run a simulation through EnergyPlus software. Figure.1 shows the flowchart of the steps performed to reach the goal of this paper.

Table 1 shows the contents of the two weather cases developed using the EnergyPlus weather converter program.

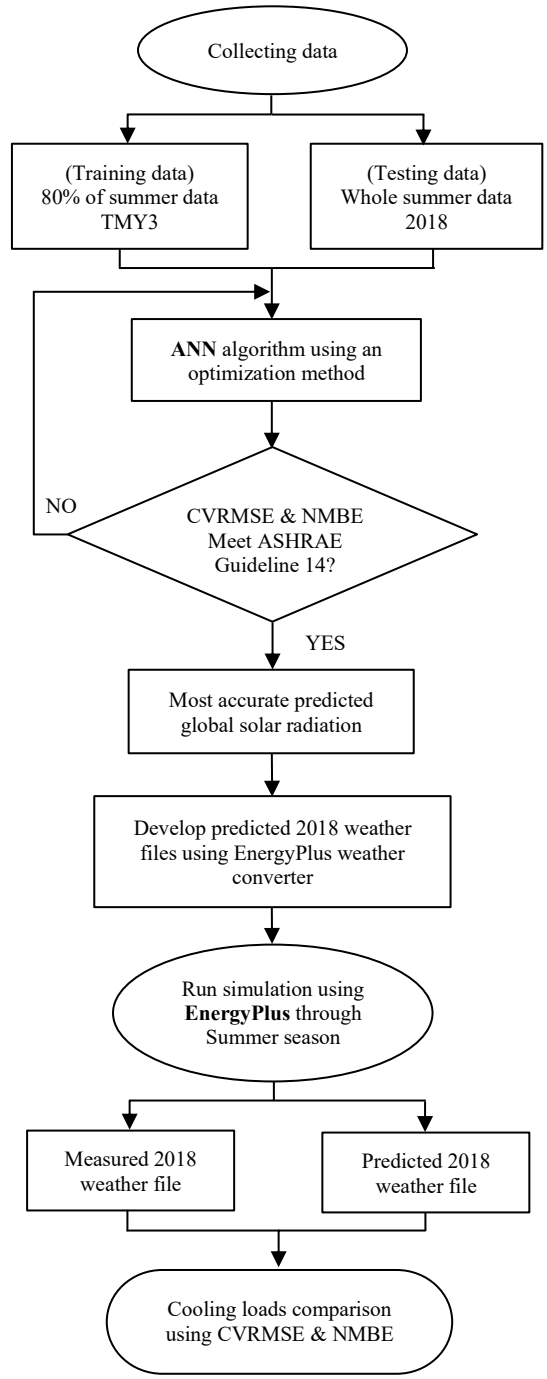

Figure 1 A flowchart of the procedure used in paper

Table 1. Contents of the two weather cases (Measured vs. Predicted)

Case	Dry-bulb temp	Relative humidity	Global horizontal solar radiation	Direct normal solar radiation	Diffuse horizontal solar radiation	Dew point temp	Wind direction	Horizontal Infrared Radiation Intensity	Wind speed	Cloud type
Case 1 [C_1] Measured 2018	√	√	√	√	√	√	√	C	√	√
Case 2 [C_2] Predicted 2018	√	√	P	C	C	C	C	C		

C: Calculated through the EnergyPlus weather converter program
P: Predicted from the ANN model

ANN ALGORITHM

Artificial Neural Network uses the processing of the brain as a basis to develop algorithms that can be used to learn and model complex patterns, besides the great ability in the prediction techniques. ANN provides no restriction on the input variables; it can learn hidden relationships in the data without imposing any fixed relationships in the data.

It was found that there is no automatic methodology that can select the appropriate input variables for ANN models (Maqzouq et al., 2017). Although ANNs are excessively used for predictive data mining methods (Hepbasli and Alsuhaibani, 2011). Also, the prediction accuracy of the ANN model is found to be dependent on the following; input parameters, training data, and ANN architecture (Kumar, 2013). So, in the following, an ANN model which has an optimization technique to deal with different variables is presented.

An ANN model is developed to predict hourly global solar radiation using Python 3.7, which is considered one of the commonly used programming languages for machine learning (Guo, 2014). The TMY3 data were divided into four seasons. As an initial step, only summer data were used in this paper. The training data is 80% of summer data picked from TMY3, while the testing data were picked from 2018 weather files (whole summer season). The process of the ANN algorithm goes through three layers; ANN needs inputs to predict the output through calculations happening in the hidden layer. This study used only the readily available meteorological data for the input layer; i.e., temperature, relative humidity, solar zenith angle, and time of every hour. The output layer is the hourly global solar radiation, as shown in figure 2. The hidden layer consists of hidden neurons. It varies depending on each case. Figure 2 shows the architecture of the ANN model and how it works, starting from the initial randomized weights assigned to each parameter in the input layer. The sigmoid function is applied to get a new number, which is the value of hidden neurons in the hidden layer. After this process, the same process is repeated but now between the hidden and output layer with different weights. The whole process is called Feed-Forward Neural Network (FFNN), starting from the input layer to reach the output layer. After that, the error rate is calculated, and then another process happens to update all weights, which is called Back-Propagation (BP). The number of the whole loop, including FFNN and BP that repeat until reaching the minimum error rate, is called the number of epochs. There is an essential parameter in the BP process called learning rate, which is used to settle the changes in the weights at the end of each epoch (Rezrazi et al., 2016).

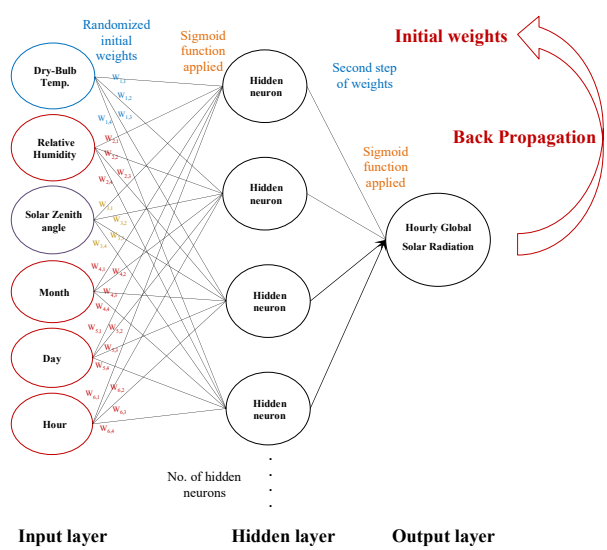

Figure 2 ANN architecture for global solar radiation prediction

In this paper, ANN hidden process has three different variables; the number of hidden neurons, the number of epochs, and the learning rate. An optimization process is

conducted to give a specific value for each one of the three variables depending on which season the simulation is done to provide the most accurate output results. The accuracy of the ANN model is verified according to ASHRAE Guideline 14 by calculating CV(RMSE) and NMBE to find the error differences between the measured and predicted global solar radiation data.

The optimization process gives a range and a distance for each variable. The ranges for the number of hidden neurons, learning rate, and the number of epochs are as follows; 10:100, 0.01:1.0, and 100:1000, respectively, while the distance was 10, 0.01, and 100. Figure 3 shows an example of some of the possible combinations between the three variables; in this figure, it shows only one graph of ten different possible graphs generated during the optimization process. On the XY-axis, there are integrations between two variables, the number of hidden neurons and learning rate, while the number of epochs in this graph is constant, which is 200. The z-axis shows the CV(RMSE). The optimum values found to be as follows; 80, 0.09, and 200 for the number of hidden neurons, learning rate, and the number of epochs, respectively. The results showed that the NMBE value found to be 4.7%, which is less than 10% according to ASHRAE Guideline, CV(RMSE) value found to be 30.9%, which is slightly higher than the ASHRAE Guideline 14 recommendations for the hourly data (ASHRAE, 2014). The same model was used by (Gaballa and Cho, 2019) but by using a different set of data for prediction.

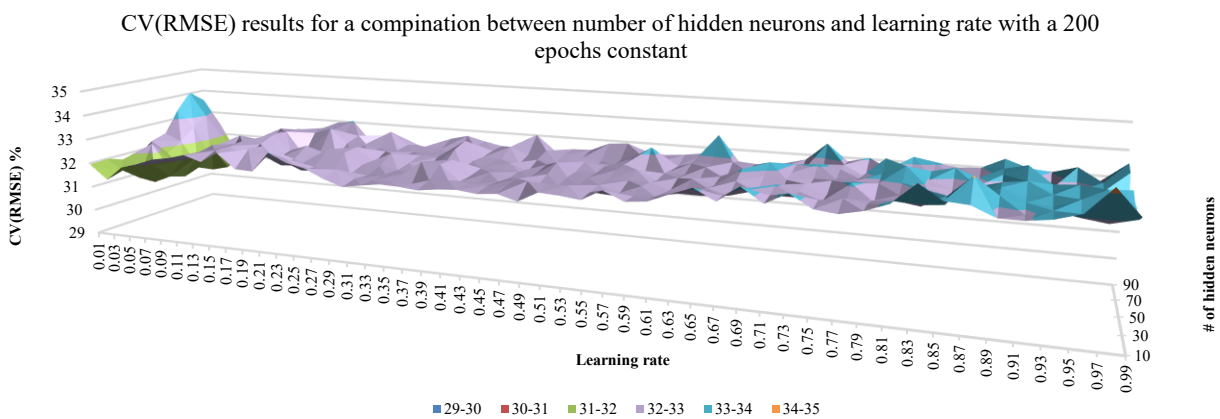

Figure 3 A portion of CV(RMSE) results from the optimization process

Figure 4 shows a comparison between the two cases and the difference between them each hour. The horizontal axis shows date and time starting from June 1st until August 31st, while the vertical axis shows the global solar radiation in Wh/m^2.

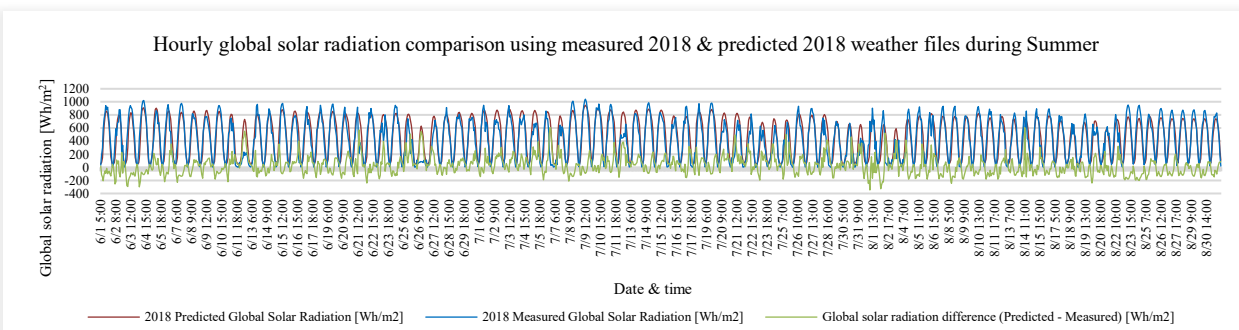

Figure 4 Hourly global solar radiation comparison between the two cases

SIMULATION

Using EnergyPlus software V8.9.0, two different scenarios were conducted using two different weather files; measured 2018, and predicted 2018 weather file. A case study was chosen to be an office building in the Research Triangle Park (RTP) region. This location is about 5 miles away from Raleigh-Durham (RDU) International Airport, which is climate zone 4A. The building mainly has open and closed offices besides some meeting rooms, lounges, and utilities divided into three floors. The total area of the building is 43,265 $ft^{2,}$ including the conditioned space of 42,332 ft^2. There are 29 thermal zones divided as follows; lake level, 1st floor, and 2nd floor with 11, 9, and 9 thermal zones, respectively. The south elevation is assigned to be adiabatic as it is attached to another building. An 80-ft tall building is located 30 ft away from the east elevation, so a shading surface group was drawn with the same dimensions and distance in the model, as shown in Figure 5. The window to wall ratio is 42%, with a total glazing area of 18,245 ft^2.

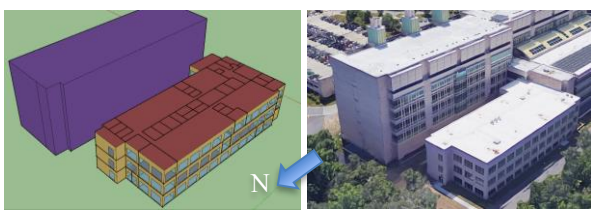

Figure 5 Case study building, Durham, NC

The simulation was performed during the summertime, starting from June 1st until August 31st. This period reflects the testing data used in the ANN model, indicating the predicted global solar radiation. Everything in the two files was the same except the weather files used to run the simulation.

DISCUSSION AND RESULTS ANALYSIS

Cooling loads are selected as an indicator to make a comparison between the two cases as the simulation was conducted in the summer season. Figure 6 shows the total cooling loads comparison. The total cooling loads found to be as follows; C_1 is 676,573 kBtu, while for C_2 is 769,762 kBtu. The results show a 93,189 kBtu difference between the two cases, which means 12%. Figure 7 shows a detailed graph for the cooling loads' comparison for the two cases. The horizontal axis shows the date and time every hour starting from June 1st and ends August 31st, while the vertical axis shows the cooling loads in kBtu/hr.

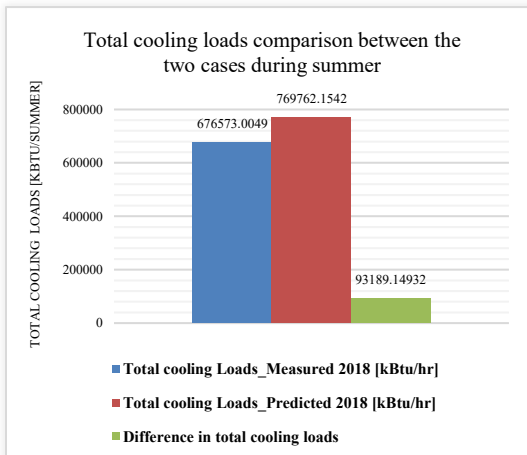

Figure 6 Total cooling loads comparison between the two cases during summer

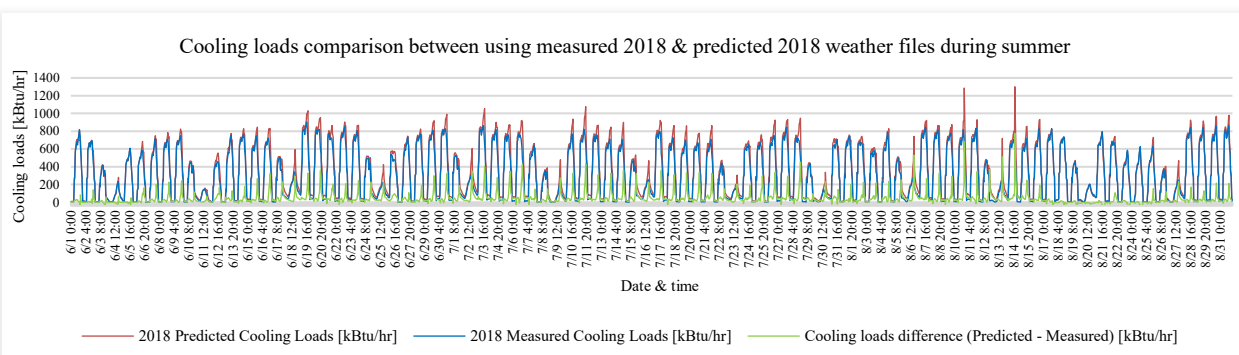

Figure 7 Cooling loads comparison between the two cases during summer

To see the error differences between the two cases, the CV(RMSE) and NMBE are calculated and found that CV(RMSE) is 21.9%, and NMBE is 12%.

CONCLUSION

This paper demonstrated a tool for real-time building energy simulation. It provides a comparison between measured and predicted building performance. The measured performance is developed using 2018 weather data files, while the predicted performance is developed using predicted 2018 weather files. ANN model is used to develop the predicted hourly global solar radiation needed in the predicted weather files to run the simulation. From measured 2018 weather file, temperature, relative humidity, and solar zenith angle are the only three parameters used through the prediction process to generate the predicted global solar radiation using the ANN model. This means the ANN model uses only the readily accessible measured data.

The simulation is done using EnergyPlus software in a specific period starting from June 1st until August 31st, which indicates the whole summer season. It shows some differences between the two cases related to the prediction error by using the ANN model and also associated with the missing parameters. While the predicted global solar radiation shows a CV(RMSE) of 30.9%, the cooling loads show only 21.9% difference between the measured and predicted. This lowered value indicates the portion of solar radiation affecting the whole building's thermal performance.

The 2018 weather files were used to generate the cooling loads of an office building in Durham, NC. For future work, the actual cooling loads would be taken from Building Automation Systems (BAS). The predicted cooling loads would be developed using predicted weather files; this time, temperature and relative humidity from BAS will be used in the ANN model to develop the predicted solar radiation in real-time. Then a comparison should be made between the actual case and predicted simulated case. By doing so, it can prove or disprove that this method will give a reasonable error difference, which will enable building operators to have a look at building performance real-time and check if any problem happens or the building systems are working ideal.

Also, the developed ANN algorithm will be tested in other locations for different climate zones other than mild, such as cold and hot climate.

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