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Energy Efficiency: Prediction of the Heat and Cooling Requirements of Buildings

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Abstract : The aim is to develop an artificial neural network to see the best training parameters that efficiently predict the energy efficiency. We will be using input parameters including relative compactness, surface area, wall area, roof area, over all height, orientation and glazing area and out parameters such as heating and cooling load to develop an artificial neural network (ANN) to predict the energy consumption in buildings of north Cyprus during the early stage of architectural design. ANN was obtained by analyzing the output variables and number of hidden layer neurons. Results showed ANN with multiple outputs provide better prediction performance.

Keywords: **Energy efficiency, Solar Energy, Power generation, Smart grids, Energy measurement, Artificial Neural Networks**

I. INTRODUCTION

The climate change is the main concern in any designing and construction of new buildings. This is resulting in increase in researches to find new ways in order to predict the energy efficiency of the buildings for sustainability. There are many studies showing different affects related to the effect of external environmental changes in building energy consumption. The nest way the building can handle climate change is to become sustainable and energy efficient.

According to [1] “The energy efficiency of a building is the extent to which the energy consumption per square meter of floor area of the building measures up to established energy consumption benchmarks for that particular type of building under defined climatic conditions.”

The term energy efficiency in buildings can be defined as, providing comfort conditions by not sacrificing the indoors quality with minimum energy consumption. The necessity of replacing the lost or excessive gains in order to protect the indoor comfort conditions makes it necessary to use energy in buildings. The energy load of a building is the amounts of heating or cooling energy that must be taken on by heating and cooling systems. The energy efficiency in buildings will be achieved by ruling the heat transitions through the envelope components like walls, windows, roof, etc.

[2] States that the main goal of the Renewable City Strategy in Vancover, Canada is that the city will become a city that uses only renewable sources of energy while valuing the principles of sustainability. The main two target sectors for strategy are the main energy consumers in housing and transportation sectors besides other sources of greenhouse gas emissions that the City will continue to address in partnership with residents and businesses. According to the report residential, commercial, industrial, and institutional buildings are the largest single source of emissions in Vancouver, constituting 56% of the city’s total in 2014. The City of Vancouver is tackling building energy use according to where it can have the largest carbon reduction impact—primarily in space heating and hot water. Also we can only have a zero-emission building if it is energy efficient and relying minimum on the energy resources which are not clean in order to minimize greenhouse gas emissions

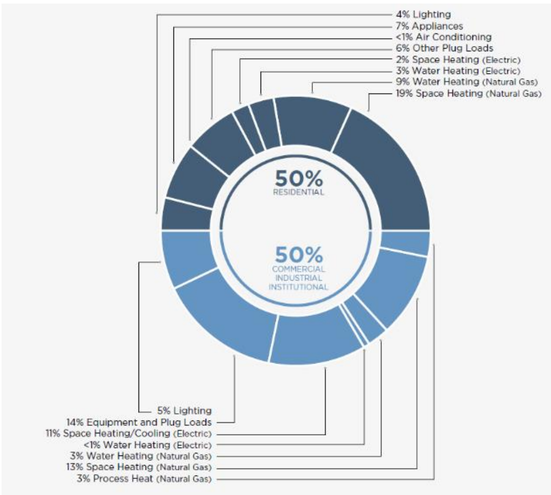
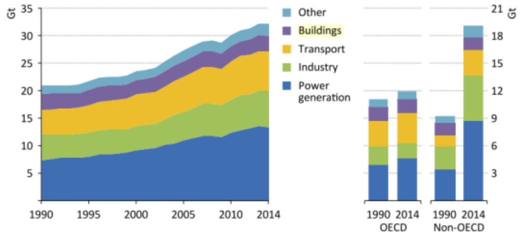


Figure 1 building energy used in Vancouver, 2014 ((The City of Vancouver (COV), 2015)

[3] present a review on the technological developments in each of the essential ingredients that may support the future integration of successful net zero and positive energy buildings NZEB/PEB, i.e. accurate simulation models, sensors and actuators and last but not least the building optimization and control.

The sustainable building designs of the building with the integration of smart grids and electric vehicles is impacting on the future designing of the buildings as well. This growing awareness along with the introduction of renewable energies is not just approach towards the net zero- but instead positive energy buildings. Besides use of renewable energy it is important to do research in the field of energy efficient buildings in order to reduce energy consumption and minimize the wastages. [4] states that the fifth and final dimension is future research, innovation and competitiveness includes efficient energy systems and energy-neutral buildings; and sustainable transport systems. The IEA proposes a bridging strategy that could deliver a peak in global energy-related emissions by 2020. Increasing energy efficiency in the industry, buildings and transport sectors is one of the five scenarios the bridge scenario is depending on. Also for building sector , in OECD countries the higher levels of emissions are because the countries are located in more temperature climate and require low levels of space heating[5]



Notes: "Other" includes agriculture, non-energy use (except petrochemical feedstock), oil and gas extraction and energy transformation. International bunkers are included in the transport sector at the global level but excluded from the regional data.

Figure 2 Global energy-related CO2 emissions by sector and region Gt (IEA, 2015)

As discussed earlier the buildings are a considered as a key factor of energy concerns and consumers. Therefore an accurate estimation of energy efficiency of residential buildings based on the computation of Heating Load (HL) and the Cooling Load (CL) is an important task. The use and development of new computational tools and methods for prediction of energy performance specifically in sustainable buildings will help to outline the future strategies for efficient design of building [6].

According to [7] as there is a steady increase in building energy consumptions over the past few decades globally so it is very important and need of time to provide controls to building operations and initial building design in order to increase the energy efficiency. The most important aspect of Building design is of heating and cooling loads in reducing the total energy consumption in buildings. The architects and building designers in order to develop sustainable and energy efficient design need to analyze the parameter that has significant impact on the heating load (HL) and cooling load (CL).

Now a days unsolved and complex problems can be tackled by the use of artificial neural networks (ANNs). Instead of programming in different ways the solutions are found by training the historical data which is defining the behavior of the whole system. So ANN can be used as a design tool in many areas of building services engineering [8].)

[9] used neural networks to develop an efficient prediction method for energy performance of residential buildings. The Neural Network model with back propagation is used to predict the building cooling load and energy consumption. The model has a simple structure and can be used by professional engineers as a basis for optimal operation of air conditioning automatic control systems for large public buildings.

The mostly used learning algorithms are the back-propagation and its variants. The epoch is the training of all patterns of a training set. The training set must be a representative collection of input–output examples. Back-propagation training is a gradient descent algorithm. It tries to improve the performance of the neural network by reducing the total error by changing the weights along its gradient. The error is expressed by the root-mean-square value (RMS)[10]. In our research, neural network model will be developed to do the prediction of the heat and cooling requirements of the buildings. In our research, neural network model will be developed to do the prediction of the heat and cooling requirements of the buildings. The total of seven inputs variables will be investigated to predict the two responses of the system.

II. DATA COLLECTION

Simulation tools are generally used to analyze and predict energy usage of buildings by utilizing these tools, engineers are able to exactly predict the energy use of buildings before construction has started. These simulation tools are able to compare two buildings that are identical in all forms with the exception of a single parameter; this direct comparison can yields good insight into how a given parameter affects the overall energy usage of a building. In this study the data is collected using the "Ecotect Analysis design software".

Energy Analysis will be conducted using 4 different orientations simulated in Ecotect Analysis which is a comprehensive concept-to-detail sustainable building design tool that can improve performance of existing buildings and new building designs. According to [11] Ecotect Software is basically used in order to find and calculate building's energy consumption by simulating its context within the environment. It is mostly used by the architects and building engineers to improve their designs. Research Studies on many existing buildings have been performed to evaluate its building's performance. As the software is related to the environment so it can be used to deal with solar heat, nature for day-lighting, natural airflow for ventilation, and building's energy consumption for man-made systems such as Air Conditioning and Lighting.

We will be using input parameters including relative compactness, surface area, wall area, roof area, over all height, orientation and glazing area and out parameters such as heating and cooling load to develop an artificial neural network (ANN) to predict the energy consumption in buildings of north Cyprus during the early stage of architectural design.

The Dataset will contain seven inputs (denoted by X1…X8) and two responses (denoted by y1 and y2). Following are the inputs and outputs being used in our study. There are total of 499 values in our data set that will be used in design of neural network model.

Inputs used are:
X1: Relative Compactness
X2: Surface Area
X3: Wall Area
X4: Roof Area
X5: Overall Height
X6: Orientation
X7: Glazing Area

Whereas the Outputs are:
Y1: Heating Load
Y2: Cooling Load

III. ARTIFICIAL NEURAL NETWORKS

When we are using different parameters it is difficult to obtain the results of building energy consumption prediction simultaneously as most of the softwares used can only calculate one target variable. Also the process of calculations is very time consuming and difficult for the development of the prediction model. In our study we have seven input variables and two (2) target output variable so the best prediction model can be made using Artificial Neural Networks.According to [12] the Artificial neural works on the same principles as of the human brain. Just like human brains it can do the learning and the prediction. In order to perform a desired function the modification of the weights and the variables of the activation and transfer functions can achieve the learning of the network in minimum time. The structure of the ANN is similar to the nervous system and the learning is based on the biological learning. The neurons are interconnected together and these interconnections carry the weights of the network. The main benefit of the ANN is that complex, difficult and time consuming problems which have multiple inputs and outputs can be solved very easily in minimum time period. In our study we will be using multilayered feed forward back propagation network.

According to [13] a back-propagation neural network is a layered network consisting of an input layer, an output layer, and at least one layer of nonlinear processing elements which can be called as a hidden layer. For control engineers, it is suitable to consider back-propagation neural networks as a tool to solve function approximation problems rather than pattern recognition problems. Also the same interconnections are used to send back the errors of the output of back propagation which are used for the feed forward mechanism by the derivation of the feed forward transfer function. A basic two-way memory incorporation is made the learning function in this network.

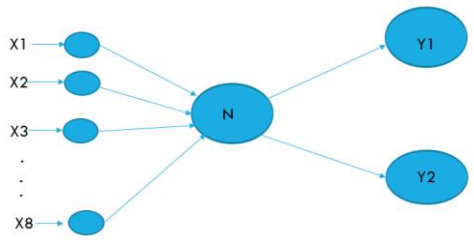


Figure 3 Neural Network

IV. THE COMPARING RESULTS OF ANNS WITH DIFFERENT OUTPUT VARIABLES

In this study the output variables of ANN are the Heating Load (HL) and the Cooling Load (CL). The reason we are using ANN is that this model can predict either single variable or multiple variables at the same time. In order to get the best prediction effects we will be comparing prediction effect of Heating and Cooling Loads using ANN separately and then jointly. Specifically we will train the network with 70% of all data, 15% will be used for validation and 15% for Testing. In our simulations we will increase the number of hidden layers in order to get the best results with minimum root mean squared (RMS) errors. In this study we used Levenberg-Marquardt algorithm for data sampling to train the data samples.

4.1 THE ANN WITH SINGLE OUTPUT VARIABLE

As a first case we will check the performance of ANN by using only one output variable i.e. Heating Load (HL), the simulation result is shown in figure below.

The regression R values of training, in Figure 4. The training process was terminated at the 33th epoch. The regression R values of training, validation and test data were 0.99547, 0.9953, and 0.99759. The regression value for all data is found to be 0.99578. The MSE was 0.000689. In addition, the error distribution of most forecasts was between -0.0309 and 0.0383 in Figure 4. Satisfying the normal distribution characteristic.

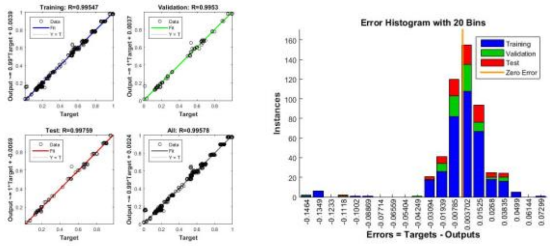


Figure 4 Training results of the ANN with Heating Load as output variable. (a) The regression R values of training; (b) The distribution of training error.

After using only Heating Load (Y1) as a Target, we now proceed with using Cooling Load (Y2) as an only target for 7 inputs. The training process was terminated at the 33th epoch. The regression R values of training, validation and test data were 0.98387, 0.980789 and 0.98148. The regression value for all data is found to be 0.98287. The MSE is 0.0020152. In addition, the error distribution of most forecasts was between -0.04865 and 0.05562 in Figure 5. Satisfying the normal distribution characteristic.

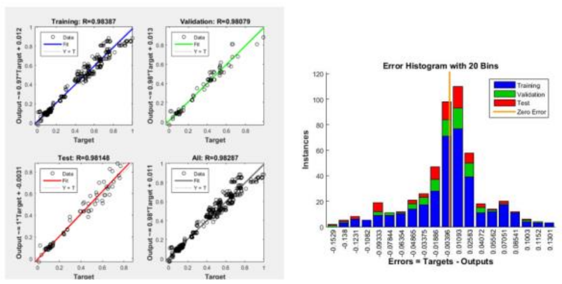


Figure 5 Training results of the ANN with cooling load as output variable. (a) The regression R values of training; (b) The distribution of training error.

V. THE ANN WITH MULTIPLE VARIABLE OUTPUTS

The figure below shows the training results of the ANN with heating and cooling load as output variables. The training process was terminated at the 26th epoch. The regression R values of training, validation and test data were 00.99126, 0.98923 and 0.98498. The regression value for all data is found to be 0.99011. The MSE is 0.0015. In addition, the error distribution of most forecasts was between -0.03096 and 0.0327 in Figure 5. Satisfying the normal distribution characteristic. In addition, the distribution of errors was more concentrated than the previous results. To summarize, the ANN with multiple output variables should be applied to predict results.

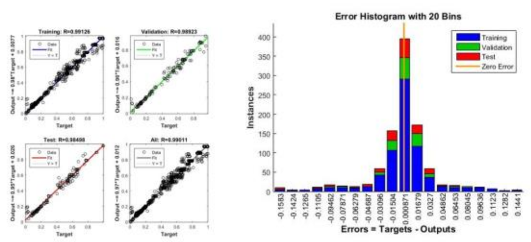


Figure 6 Training results of the ANN with both heating and cooling

loads as output variable. (a) The regression R values of training; (b) The distribution of training error.

VI. THE COMPARING RESULTS OF ANNS WITH DIFFERENT

In this section the effects of the change in number of neurons in hidden layer on ANN are analyzed. In our training we are selecting 5, 15 and 20 as three different scenarios for hidden layers. The training process were terminated 64th, 43th and 28th epoch. Table 1 shows the results of the performances of ANNs with number of neurons in hidden layer.

Table 1. The performances of the ANNs with different number of neurons in hidden layer

The Number of Hidden Layers	R Value of Training	R Value of Validation	R Value of Test	R Value of All Data	MSE
05	0.98653	0.98839	0.98757	0.98698	0.0018511
10	0.98964	0.98868	0.99142	0.98978	0.001767
15	0.99128	0.98796	0.98456	0.98989	0.001738

From the above table it is clear that the worst performance of the network is when number of hidden layers is 5 and improves when we increase the hidden layers to 10 and keeps on improving till 15 but with minimum changes. The best MSE we get is 0.001738.

VII. CONCLUSION

In this study an ANN model was established to predict the heat and cooling requirements of buildings. The proper sampling methods, output variables and the number of hidden neurons in the hidden layer were all determined by a series of analysis. The main conclusion from this study is that the prediction of heating and cooling loads with multiple output ANN is much better than the single output model. Also for the ANN developed show that the number of hidden layers should be greater than 5 and the best results are obtained between 10 and 15 hidden layers. The best MSE is 0.001738. It is also observed that the time consumed in prediction is very less.

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