EVALUATION OF BUILDING ENERGY CONSUMPTION BASED ON FUZZY LOGIC AND NEURAL NETWORKS APPLICATIONS

Kajl, S(1)., Roberge, M-A(1)., Lamarche, L(1)., Malinowski, P(2).

(1)Ecole de technologie supeurieure, 1100, rue Notre-Dame Ouest, Montreal H3C 1K3, Canada.
(2)Technical University of Wroclaw, ul. Norwida 4/6, 50-370 Wroclaw, Poland.

Abstract. The authors have created a Neural-Fuzzy Assistant which acts as a Decision Support System and helps to perform quickly and easily the estimations of office building energy consumption. The Neural-Fuzzy Assistant presented in this paper allows the user to determine the impact of eleven building parameters on the electrical annual and monthly energy consumption, annual and monthly maximum electrical demand and cooling and heating annual consumption and demand. These eleven parameters are : length and width of buildings, number of floors, R-value of exterior wall, fenestration, U-value of windows, windows solar protection, lighting power density, occupancy density, exterior air rate per person and boiler efficiency. The neural networks training and testing data set and fuzzy rules used by the system are based on the simulation results of numerous office buildings. The simulations were carried out with the DOE-2 software program. The accuracy of the Fuzzy Assistant is quite comparable to detailed calculations. The description of the study and the discussion of the obtained results are presented in this paper.

Keywords. Office building, HVAC systems, energy consumption, electrical demand, building simulation, neural networks, fuzzy logic.

1. INTRODUCTION

During the design phases of a building, the following activities are conducted : program phase, schematic design, preliminary design and final design which includes a preparation of construction documents [6]. The first phase includes (but need not be limited to) : the client's objectives and strategies of the initial and future functional use of the building, the owner's capital and operating costs budgets and the conceptual architectural drawings. The schematic design stage involves the selection and comparison of appropriate HVAC (Heating, Ventilation and Air Conditioning) systems. Early in this phase, a mechanical engineer may be asked to provide information regarding the impact of large glazed areas, heavy lighting and other internal loads on HVAC system requirements. In this phase, the HVAC system and energy source selected must take into account the capital and operating costs which are dependent of the building utilization. These costs depend on several factors, such as : the building envelope and zoning, the HVAC systems, the heating and cooling schedules and control, the thermostat settings in unoccupied periods etc. All systems, in this stage, must be analyzed under the same assumptions. Using one system as a reference, all other candidate systems are then compared to this system. The financial constraints however, seriously limit the amount of time that can be allocated to study different systems.

Therefore, a method that can estimate building energy consumption becomes a crucial factor in the design process of a new building or a restored one. Several methods are available, depending on the complexity of the case and the level of details required. A major distinction is between steady-state methods (based on degree-days of temperature bins) and dynamic methods (based on transfer functions). Degree-day methods are the simplest. They are appropriate if the utilization of the building and the efficiency of the HVAC equipment can be considered constant. For situations where efficiency or conditions of utilization vary with outdoor temperature, the bin method is used. For greatest accuracy, the use of full-fledged dynamic models is recommended. The tests have shown that models such as DOE-2 and BLAST are acceptable for modeling phenomena with hourly time resolution [4] [7]. There are two principal disadvantages with those programs : they are very detailed and not user friendly, these making them too expensive to use on small scale projects. For these projects, there is a gap which should be filled because the degree-day and bin methods still remain valuable tools only for intuition and for simple estimate of annual loads.

In order to reach this goal, we have developed a Fuzzy Decision Support System called Fuzzy Assistant described in [1] which is based on the simulations performed on the DOE-2 software. It then enables the user to perform quick and accurate building energy estimations of total annual and monthly energy consumption and maximum electrical demand. This Fuzzy Assistant concerns the office buildings and it permits to estimate the energy consumption depending on five following parameters : number of floors, fenestration, lighting power density, exterior air rate and ventilation rate. However, we know that there are other very important parameters which can have an influence on the building energy consumption as building shape, R-value of exterior wall, etc... To include more parameters in our Assistant, the fuzzy logic does not seem appropriate because, in this case, the number of rules increase considerably. Consequently, in this paper we propose a recently developed Neural-Fuzzy Assistant, which is also based on the simulations performed on DOE-2 software, but the energy estimation depends on eleven parameters and it gives more outputs as for example, annual and monthly electrical energy consumption , maximum electrical demand and the required heating or cooling loads and consumption. Since the neural networks (called here NN) training data set and fuzzy rules are based on DOE-2 building simulations, the energy estimations take into account the interaction between building envelope, HVAC and other building systems. The idea that underlies the base of the Neural-Fuzzy Assistant is the usually applied assumption that the energy performance of a building depend on several architectural and maintenance factors such as : fenestration, building shape, receptacle and lighting power densities, occupancy density, ventilation and exterior air rate and etc... Based on provided information about the value of the most important factors, the Neural-Fuzzy Assistant estimates the different annual and monthly energy consumption and the maximum electrical demand. The proposed approach agrees well with certain works presented recently in this domain [3], [8], [10]. The description of the research and the discussion of the obtained results are presented in the following sections.

2. OBJECTIVES AND METHODOLOGY

The principal objective of our research is to create a simple and quick estimation method for predicting building energy consumption. This method should be applicable during the schematic and preliminary design stages of building. Its accuracy should be comparable with currently used detailed software of building simulation and it should give a large set of results, such as : total and electrical monthly and annual energy consumption, maximum electrical demand, heating/cooling energy consumption and its maximum demand, etc... Since the building energy efficiency depends on the several parameters, the proposed method should permit to evaluate the impact of the principal parameters on energy consumption. As the most important we can mention the following parameters :

- the shape and orientation of the building (length, width, number of floors) ;
- the R-value of the exterior walls ;
- the fenestration ;
- the occupancy density (m^2/person) ;
- the lighting and equipment power;
- the exterior air rate ;
- the ventilation rate ;
- the mass of the building (kg/m^2) ;
- the type of HVAC system (heating, cooling and air conditioning) ;
- the zoning of the building
- the occupancy schedule of building

To consider all these parameters it is necessary to develop a model of the building and to perform the detailed simulation on DOE-2 or other appropriate software. Our objective is to choose the most important parameters and to estimate the energy consumption as a function of them. In order to achieve this objective for a given type of building (i.e. : schools, office buildings, hospitals, etc...) the following methodology is used :

- classification of the building energy parameters and choice of the most important for a given type of building
- simulations of the modeled buildings by DOE-2 software to create the training and testing data set for neural networks and the knowledge base for fuzzy logic applications ;
- NN’s training and establishment of fuzzy rules ;
- validation of the Neural-Fuzzy Assistant against the results obtained by DOE-2 simulations.

Table 1. Example of a classification for the parameters used in the Neural-Fuzzy Assistant

Parameters « variable »	**Parameters « systems »**	**Parameters « default »**
Building shape	VAV (Variable Air Volume)	Building zoning
Fenestration	Dual Duct	Occupancy schedule
Exterior walls R-value	Multizone	Mass of building
Lighting power	Rooftop Units	HVAC control systems
Occupancy density	Heat Pump System	Type of chiller
Exterior air rate per person, etc...	etc...	Heat recovery, etc...

Table 1 shows the classification of the energy parameters used during the simulations performed with the DOE-2 software. This is only an example of classification, because it can depend on the type of building. The class « variable » parameters is the most important for building energy consumption. The class « system » includes the candidate HVAC systems which could be selected for the given type of building. The Neural-Fuzzy Assistant should permit to evaluate the impact of the parameters of those two classes on the energy consumption. The class « default » includes the parameters which must be selected for the building simulations, but they are invariable in Neural-Fuzzy Assistant and consequently they must be representative of the given type of building and of each HVAC system candidate.

3. EXAMPLE OF THE NEURAL-FUZZY ASSISTANT FOR OFFICE BUILDINGS.

In this section, we present an application of our method to office buildings which total area is between 9294 and 46468 m^2. We use the classification of the building energy parameters presented in the previous section. We have chosen eleven parameters classified as « variable » and, for this example, only one parameter classified as « system ». The « variable » parameters and their limits are presented in the table 2.

Table 2. The variable parameters and their limits.

Variable parameters	Units	Limits		
length of building	[m]	30.48	to	91.43
width of building	[m]	15.24	to	91.43
number of floors		3	to	10
R-value of exterior wall	[m^{2o}C/W]	2.64	to	5.283
fenestration	[%]	10	to	80
windows solar protection	[%]	0	to	60
U-value of window	[W/ m^{2o}C]	1.14	to	8.52
lighting power density	[W/m^2]	10.76	to	43.04
exterior air rate	[l/s/person]	2.36	to	11.8
occupancy density	[m^2/person]	9.29	to	23.23
boiler efficiency at full load	[%]	70	to	90

The system HVAC chosen is Variable Air Volume system (VAV) with the perimeter heating. Even if an entire Neural-Fuzzy Assistant for the office buildings requires more « systems » parameters and maybe more « variable » parameters, the example presented here is, in our opinion, adequate to evaluate the usefulness of proposed approach. During the simulations performed on DOE-2 software several parameters classified « default » were used. Some of these parameters are mentioned here.

The building shape is rectangular, with variable aspect ratio depending on the length and width and their limits. The zoning of the building consist of the four perimeter and one interior zones per floor (except the first floor including lobby) which is the same as proposed by ASHRAE Standard 90.1 for the energy calculations of prototype building [9]. Moreover, the schedules of the office occupancy and the lighting and receptacle energy profiles are also assumed according to the same Standard. There are two systems VAV used in this building, one for the four perimeter zones and second for the interior zone. For the simulations by the DOE-2 software the following assumptions are used :

• meteorological conditions	TMY weather file for Montreal
• total area of building	9294 to 46 468 m^2
• R-value for the roof	same as R-value of exterior wall
• floor-to-floor high	3.6 m
• the infiltration in the perimeter zones when the HVAC systems are OFF	0.15 air changes/hour
• the ambient temperature	$22.2^{\pm 1}$ °C (winter), $23.8^{\pm 1}$ °C (summer)
• relative humidity	20 to 60%

The HVAC plants include a gas boiler and a centrifugal chiller respectively with an efficiency of 80% and the COP (coefficient of performance) of 3.57 at full load. The other parameters, as for example : absorptivity of opaque elements, curves standard as function of chiller and boiler PLR (part load ratio), power required by the fan and pump motors which depend on the air or water rate, are specific for the VAV system and assumed by default like that proposed by DOE-2 software.

The model of the office building was created by concerning the limits of the « variable » parameters. The training data set for NN's application was built using the results of 700 energy simulations. During these simulations all parameters classified as « variable » were varied, except the boiler efficiency which was fixed to 80%. For each record of ten inputs values (« variable » parameters) the training data set contains the following outputs :

- annual and monthly electrical energy consumption ;
- annual and monthly maximum electrical demand ;
- annual gas consumption and demand by heating system ;
- annual energy consumption and demand by cooling system.

The neural networks used in this study have one input, one output and one hidden layer containing principally 22 neurons. The tan sigmoid function was the activation function for the hidden units while the output layer was linear. The neural networks were training using the training data set containing 700 data records. The Levenberg-Marquard method was used during the NN's training.

As it was mentioned above, the parameters classified as « default » are invariable, but some of them could also have an impact on the energy consumption. Consequently, we propose to add the second step in our Neural-Fuzzy Assistant, which consist of a correction of the results obtained from the first step (NN's model). The one of several possible corrections are presented in this paper. It concerns the boiler efficiency since the results obtained in the first step take into account the efficiency equal to 80%. In this case, the correction concern only the annual consumption of gas (m^3) and gas demand (m^3/h) which change when the efficiency varies from 70 to 90%. The correction was introduced using fuzzy logic because it allows us to avoid the retraining the neural networks. The knowledge base which is necessary to this application was built using the results obtained from 18 specifically chosen energy simulations. Three fuzzy subsets for each parameter, (boiler efficiency gas consumption and gas demand) are determined taking into account their limits. This knowledge base was expressed by 9 fuzzy rules of the MISO type (Multiple Input Simple Output) for each output. Example of a rule for annual gas consumption is presented below :

IF	the boiler efficiency is	high
AND	the gas consumption is	medium
THEN	the correction of gas consumption is	medium_2

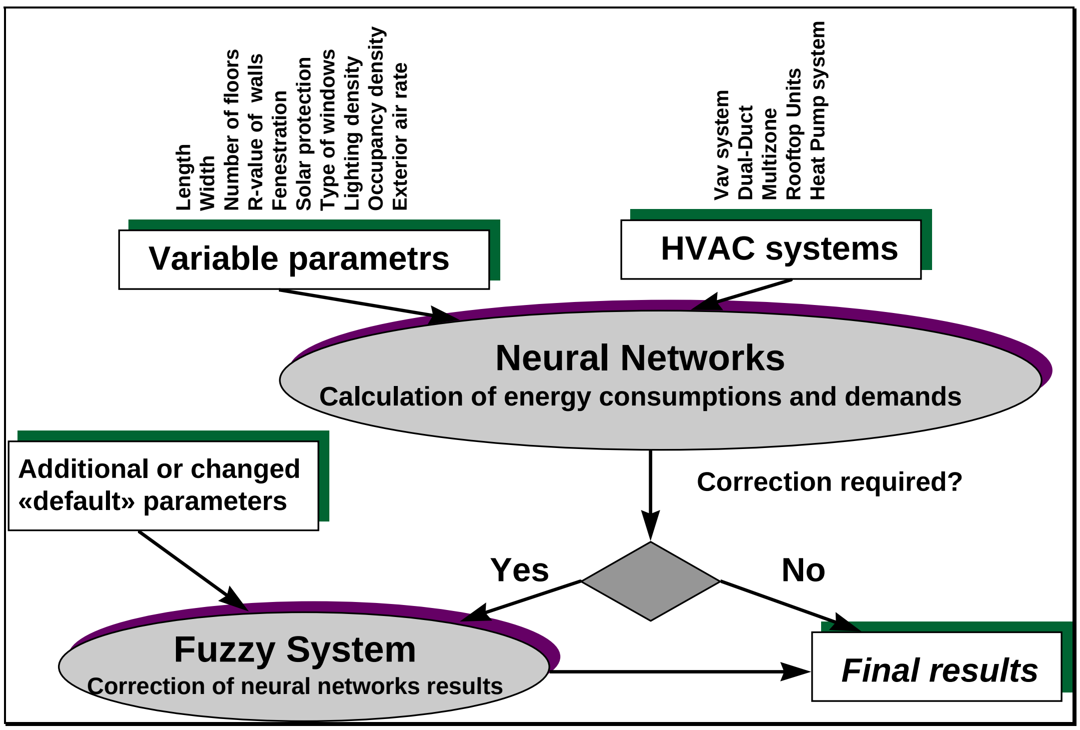

Figure 1. Schematic diagram of Neural-Fuzzy Assistant

The figure 1 shows the schematic diagram of Neural-Fuzzy Assistant. The other possible corrections which could be added soon are the correction concerning the chiller COP and the correction concerning the meteorological conditions.

4. VALIDATION OF THE NEURAL-FUZZY ASSISTANT

The Fuzzy Assistant was verified against the results of 52 building energy simulations performed on DOE-2 software. The « variable » parameters for these simulations were randomly generated by a computer. The comparison of Neural-Fuzzy Assistant predictions to the simulation results for annual electrical consumption is shown in figure 2. The figure 3 shows the comparison of annual profile of maximum monthly electrical demand for one simulation chosen among the 52 simulations using in Neural-Fuzzy Assistant validation.

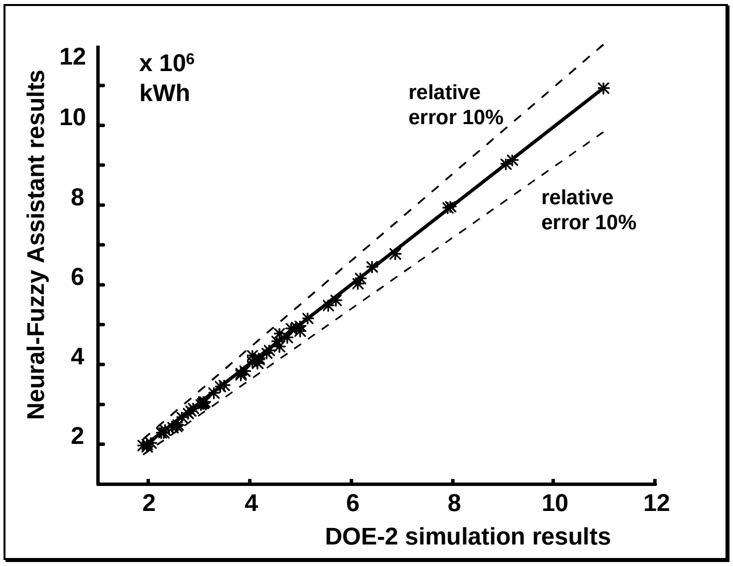

Figure 2. Comparison of Neural-Fuzzy Assistant prediction to the simulation results for electrical annual consumption

The coefficient of variation *CV* is the root mean square *RMS* error (between the results obtained by Neural-Fuzzy Assistant and by simulations performed on DOE-2 software) divided by the mean value of the 52 simulations results. The table 3 shows the CV and the RMS error which is presented in MWh for the electrical and cooling consumption, in kW for electrical and cooling demand and in m^3 or m^3/h for gas consumption and demand. The comparisons show that the Neural-Fuzzy Assistant predictions, for building area between 9294 and 46 468 m^2, are quite comparable with those obtained with DOE-2 simulations.

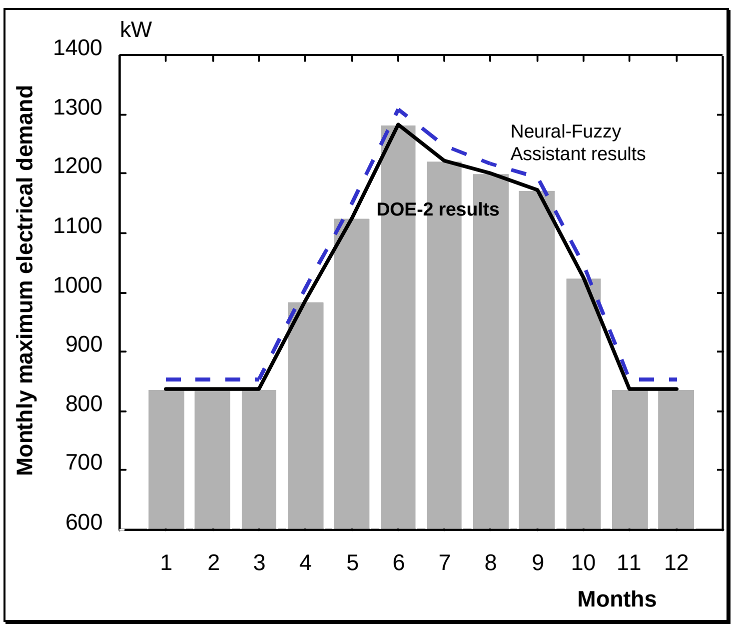

Figure 3. Comparison of Neural-Fuzzy Assistant and simulation profile of monthly electrical demand

As it was mentioned above, the objective of this research was to propose an estimation method for predicting building energy consumption that has to be simple, quick, accurate and that has to give a large set of results. The accuracy was proved above. The real time of computing is one to several seconds depending on the computer, it means that the proposed method is simpler then the steady-state methods (based on degree-days or temperature bins) which also are recognized as a very simple. We have developed the software *SAEE* (Système d'Aide aux Estimations Énergétiques) version « demo » based on our method. The *SAEE* concerns office buildings with area between 9294 and 46 468 m^2. Unfortunately, actually the data are in the imperial system units and only the French version of *SAEE* is available. For these reasons, instead of presenting the out print screen of the *SAEE*, we present an example of the converted data input and the obtained results in the tables 4, 5, 6. To interpret the *SAEE* results correctly, it should be noted here that :

- the cooling consumption and demand are the electrical consumption and demand of the chiller and not the refrigerating load and consumption ;
- the heating demand (in m^3/h) is the dynamic simulation result, taking into account all exterior and interior heat gains, and not the design heating load used during HVAC system design and calculated with the design procedures.

Table 3. The validation results

	Electrical energy		**Cooling system** *(electrical energy)*	
	Consumption	Demand	Consumption	Demand
CV [%]	1.0	2.0	4.0	5.0
RMS	63.06	27.5	20.16	20.53
	Gas *(NN's step)*		**Gas correction** *(fuzzy logic step)*	
	Consumption	Demand	Δ Consumption	Δ Demand
CV [%]	6.0	5.0	4.0	3.8
RMS	8873.0	4.5	607.4	0.35

The described method seems very useful during the schematic and preliminary design stages. Even if, in these stages, the architectural and internal loads are preliminary and will change as the building design proceeds, these informations are definitive enough to compare system or building performance because all candidate systems are sized to meet the same loads. The proposed method retains all the advantages of the simple steady-state methods (degree-day and bin). In addition, it allows to :

- analyze the impact of the most important parameters (class « variable ») on the building energy efficiency taking into account the cross effects resulting from their variations ;
- take into account the interaction between the HVAC systems and the envelope of the building ;
- obtain a large set of results with a precision comparable to DOE-2 software.

Still one question remains : Is this method applicable to the existing office buildings ? In the introduction we present the following opinion : « The tests have shown that models such as DOE-2 and BLAST are acceptable for modeling phenomena with hourly time resolution » [4]. Although the results obtained by our method agree well with the DOE-2 simulation results, the model of existing buildings must consider the specific feature of the HVAC systems, the building envelope and its functional use. Consequently, it should be noted here that the classification of the energy parameters, and especially the determination of the « default » parameters, is very important. These parameters are invariable in Neural-Fuzzy Assistant. They should be as much representative as possible of the given type of buildings. The more realistic these parameters are, the better the models of the buildings and consequently the better the simulation results which are the base for the establishment of training data set and the fuzzy rules. We can then argue that our method is also applicable to the existing office buildings, but the accuracy of the results obtained depends on the difference between the sets of « default » parameters in a real building and those used in the simulations by DOE-2 software to establish the knowledge base for Neural-Fuzzy Assistant. The corrections using the fuzzy logic, added in second step in our method, seem very promising because the fuzzy rules could be established taking into account the results of analyses concerning the existing building, especially when it is a question of the fuzzy inputs data or observations like as : building age, building envelop damaging, windows quality, etc...

Table 4. The data input.

Input parameters	**Units**	**Data**
Length of building	[m]	60.96
Width of building	[m]	45.72
Number of floors		10
R-value of exterior wall	[$m^{2o}C/W$]	3.52
Fenestration	[%]	50
Windows solar protection	[%]	20
U-value of window	[$W/m^{2o}C$]	2.95
Lighting power density	[W/m^2]	18.29
Exterior air rate	[l/s/person]	7.08
Occupancy density	[m^2/person]	10.22
Boiler efficiency at full load	[%]	80

Table 5. The annual results

	Electrical energy	**Cooling system** *(electrical energy)*	**Gas**
Consumption	5019.493 MWh	609.135 MWh	213663.7 m^3/h
Demand	1594.79 kW	586.97 kW	154.83 m^3/h

Table 6. The monthly results for the electrical energy

	Consumption [MWh]	Demand [kW]
January	373.193	960.84
February	353.066	960.84
March	378.379	960.84
April	386.101	1186.75
May	446.383	1416.37
June	470.276	1594.79
July	519.615	1516.67
August	498.496	1484.28
September	450.130	1457.55
October	411.342	1239.01
November	363.683	960.84
December	368.830	960.84

5. CONCLUSIONS

The application of Neural-Fuzzy Assistant for office buildings proves that the proposed method is very useful for the prediction of building energy consumption during the schematic and preliminary design stages. Furthermore, it should be noted that the SAEE can be used without the DOE-2 software which represent an advantage for the building managers. The comparison shows that the Neural-Fuzzy Assistant predictions are quite comparable with those obtained from DOE-2 simulations. The idea to make the corrections using the fuzzy logic, added in the second step of our method, could be very useful for the existing building. However the « default » parameters must be chosen carefully because they must be representative of the given type of buildings. It has to be underlined that the proposed method retains all the advantages of the simple steady-state methods (degree-day and bin) and additionally it gives certain advantages of the detailed dynamic methods as for example, the interaction between the envelop and the HVAC systems of the building. It seems that the proposed method can fulfill the gap between the simplified and detailed estimation methods of the building energy consumption.

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