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Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption

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ABSTRACT

There are several ways to attempt to model a building and its heat gains from external sources as well as internal ones in order to evaluate a proper operation, audit retrofit actions, and forecast energy consumption. Different techniques, varying from simple regression to models that are based on physical principles, can be used for simulation. A frequent hypothesis for all these models is that the input variables should be based on realistic data when they are available, otherwise the evaluation of energy consumption might be highly under or over estimated.

In this paper, a comparison is made between a simple model based on artificial neural network (ANN) and a model that is based on physical principles (EnergyPlus) as an auditing and predicting tool in order to forecast building energy consumption. The Administration Building of the University of São Paulo is used as a case study. The building energy consumption profiles are collected as well as the campus meteorological data.

Results show that both models are suitable for energy consumption forecast. Additionally, a parametric analysis is carried out for the considered building on EnergyPlus in order to evaluate the influence of several parameters such as the building profile occupation and weather data on such forecasting.

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1. Introduction

Managing adequately the building energy demands has always been a struggle for facility managers. The proper use of the energy in a building provides lower operational costs in two aspects. The first one is achieved by evaluating the energy end-uses (lighting, electrical equipments and HVAC) and implementing actions to reduce the amount of energy for one or more of these end-uses. The second one is related to the penalties imposed by electricity companies in Brazil and other countries due to the increase in peak energy demand beyond a limit previously agreed in energy supply contract. If the facility manager could anticipate the energy demand profile and also the energy consumption of the building, he could implement actions to reduce one or both of them and, therefore, reduce the operational cost of the building.

The University of São Paulo (USP) started in 1997 a program to design and implement actions in order to reduce the energy consumption called Permanent Program of Efficient Use of Energy (PURE-USP) [1]. Among the several actions implemented by the program, an on-line measurement system for energy consumption that allows the development of building energy consumption profile database can be pointed out, which has become a very important tool for planning the retrofitting actions.

Since the beginning of the program, several retrofits have been implemented in air conditioning systems in use at the University. One of those retrofits was implemented at the University Administration Building. By analyzing its energy consumption breakdown, it was verified that the air conditioning system contributes with almost 30% of the total energy consumption in this building. Particularly in this campus, the University also has a meteorological station where the most important parameters have been registered (dry-bulb temperature, relative humidity, solar radiation, etc.) for the last 10 years, providing a reliable weather database.

2. Literature review

One of the major concerns for facility managers nowadays is how to evaluate and forecast the energy demands of a building, especially for those with air conditioning systems. The main drawback is caused by the variation in the energy consumption profile that these systems produce. These variations are due to changes in the external climate conditions, occupants' fluctuations along the day, and the internal loads installed in the building.

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There are several ways to attempt to model a building and its heat gains from external sources as well as internal ones in order to evaluate a proper operation, audit retrofit actions, and forecast energy consumption. Different techniques, varying from simple regression to models that are based on physical principles, can be used for simulation.

Yik et al. [2] developed a model to predict the energy consumption for 23 commercial buildings and 16 hotels. Their research included an evaluation of several parameters such as floor area, air conditioning system type (air or water cooled), hotel grade and year when the building was built, etc. For simulating the buildings, three programs were used for specific tasks: one for cooling load simulation, one for detailed building heat transfer and one for air conditioning system simulation. The authors used the energy and cooling load profiles provided by the detailed simulation programs to feed a simpler model based on normalized cooling load profiles related to the gross floor area of the buildings studied in their research. The results show a very good correlation (average deviations of 2% between detailed simulation programs and proposed model). It should be pointed out that this methodology is based on the evaluation of energy and cooling load profiles calculated by detailed simulation programs and calibrated energy consumption profiles.

Chirarattananon and Taveekun [3] tested a model for predicting energy consumption for buildings based on the overall thermal transfer value (OTTV). This building parameter is based on the thermal characteristics of the building (wall composition, glazing types, wall-window ratio, etc.). The OTTV values are then correlated with other parameters such as shading coefficients, lighting and equipment density in equations that are developed for different building occupations (hotels, commercial buildings, hospitals, etc.). The energy consumption of several buildings was audited as well as DOE-2 runs were performed in order to be used as reference for the proposed model. The proposed model has a fair correlation with the values evaluated in the auditing process and simulation. The model reproduces the behavior of the energy consumption profiles but it has poor prediction in several cases, especially for hotels and hospitals, and good predictions for department stores and commercial buildings.

Pan et al. [4] presented a methodology for the calibration of building simulation models based on three different criteria. Among the steps of the calibration process, the authors performed several re-evaluations of the internal loads in order to decrease the uncertainty of the simulations. They pointed out that those revaluations are quite important to properly fit the models to the actual building profile. After the evaluation processes, the uncertainties for the two buildings energy consumption profiles remained around 5% and sometime even lower. The authors also emphasized that the definition of operating schedule of the internal gains was one of the most challenging tasks due to its intrinsic randomness.

Gugliermetti et al. [5] showed that the climate data aspects can play an important role on forecasting the energy consumption in office buildings. The authors identified that the use of typical month day instead of annual weather tape can induce an over or under estimation of the building energy profiles.

Botsaris and Prebezanos [6] presented a methodology for building energy auditing based on indexes such as index of thermal charge and index of energy disposition. These indexes can be used to predict the thermal behavior of the building and provide information for the building auditing and certification.

Pedrini et al. [7] described a methodology for analyzing building energy performance and applied it to 15 buildings. The authors pointed out that the calibration of the models is done by visiting the site, studying the building plans and observing the building energy demand profile. The authors emphasized that, during the process, several inputs were not available. Therefore several assumptions had to be made. By the end of the process, the uncertainties dropped from an average of 130–10%.

Zhu [8] explored the capabilities and limitations of a simulation tool called eQuest to perform energy evaluation of an office building. The author emphasized that the tool can provide important insights for the designer about the impact of different strategies for reducing energy consumption. The main drawback is that this kind of tool requires detailed information on the building constructive aspects, as well as its occupancy, lighting and equipment operation schedules.

Westphal and Lamberts [9] presented a methodology for calibrating building simulation models through the definition of parameters that most affect the main electric end-uses of a building. In the applied methodology, the authors suggested six stages for calibrating the model. A case study is presented, in which the annual electricity consumption predicted by EnergyPlus simulation was only 1% lower than the actual value.

Amjady (2001) [18] proposed a time series modeling for short term hourly forecast for peak loads based on auto regressive integrated moving average (ARIMA). The results of such model are compared to ones evaluated by an artificial neural network (ANN). The ARIMA provides better fitting (1.5–2%) to the actual hourly peak electrical loads than the ANN models (2–5%).

Kalogirou [10] analyzed the use of ANN model for simulating the behavior of energy systems. Among the different system, it can be pointed out HVAC systems energy demand prediction and forecasting building energy demand. The difference between the data and the ANN models prediction varies from 2 to 9%.

Kalogirou and Bojic [11] proposed an artificial neural network model to predict the energy consumption of a passive solar building. The ANN model is used for building thermal behavior as well for building energy consumption. The ANN model is recurrent network with dampened feedback with 5 neurons in the input layer, 46 neurons in the hidden layers and 1 output neuron. The models results fit the experimental data with a coefficient of multiple determination (R^2-value) of 0.9991, which can be considered a very good fitting.

Pao [12] presents a comparison of several linear and non-linear models including ANN models for forecast building energy consumption in Taiwan. The author concludes that, for the database used in the analyses, the ANN model is capable of catching sophisticated non-linear integrating effects through a learning process. Therefore, ANN models are more suitable for developing forecasting building energy consumption.

Ben-Nakhi and Mahmoud [13] proposed the use of ANN models for predicting building cooling load in order to optimize thermal energy storage in public buildings as well as office buildings. The cooling load profiles evaluated using the software ESP-r (a model based on physical principle) provides the database for training and validation of the ANN model. The models result fits the experimental data with an average coefficient of multiple determination (R^2-value) of 0.95.

3. Building simulation

3.1. Building description

The Administration Building of the University of São Paulo has two blocks with six floors each (Fig. 1), with gross floor area of 3000 m^2. Both blocks are oriented 43° northwest and most of the building occupancy occurs between 8:00 and 18:00. Building population is of almost 1000 employees.

Fig. 1. Front side of the University Administration building.

The building air conditioning system is composed by unitary window-type and split air conditioners spread along each floor and individually controlled by the users.

Several inspections were made in order to evaluate the different types of internal loads (lighting, computers and occupancy) and their schedules. It should be pointed out that there are no historical records of occupancy profile in this building. Therefore, some assumptions related to this profile were made in this case study.

The schedule for lighting, equipment and people was assumed to have the same pattern of the energy demand profiles. These profiles were evaluated by the previously mentioned measurement system developed by PURE (see Fig. 2). Table 1 shows the maximum and minimum values assumed for the internal loads in this study as well as for the dry-bulb temperature evaluated from the weather database. Based on inspections and previous calculations, it was also possible to evaluate an end-use breakdown (see Table 2).

Table 3 shows minimum, maximum and average values for the main weather parameters between 1 January and 31 March 2005, obtained from the campus meteorological station managed by the Institute of Astronomy, Geophysics and Atmospheric Science of the University (IAG-USP). This period was chosen because it represents the highest outdoor temperature period in the year. Due to the high temperature and solar radiation profiles in this period, the air conditioning system will be working more often, allowing a more accurate evaluation of its influence on the building energy demand.

Table 1
Internal loads maximum and minimum values

Internal load	Minimum value	Maximum value
Occupancy	110 persons	1008 persons
Lighting	10 kW	82.8 kW
Electrical equipment	8 kW	57.6 kW

Table 2
End-use breakdown distribution

End-use	Contribution (%)
HVAC	45
Lighting	30
Electrical equipments	21
Others	4

Table 3
Main weather parameters

Parameter	Maximum	Average	Minimum
Dry-bulb temperature (°C)	33.2	27.0	18.4
Wet-bulb temperature (°C)	24.6	22.0	18.0
Global solar radiation (W/m^2)	1328.9	971.6	244.8
Wind speed (m/s)	4.1	2.4	1.5
Wind direction (°)	330	150	10

Another important assumption is the use of an average COP for the unitary air conditioners, since the equipment was acquired in different periods and it is impossible to impose a COP unless a full performance evaluation of each equipment is implemented.

3.2. Models description

3.2.1. EnergyPlus

For building simulation, first a complex model using EnergyPlus [14] was implemented, which is a robust building simulation software that allows the user to implement the geometry and materials of the building as well as its internal loads and HVAC systems characteristics. It allows the user to set two kinds of simulation: a design day and annual simulation. For the later, a weather parameter profile should be provided in which the main

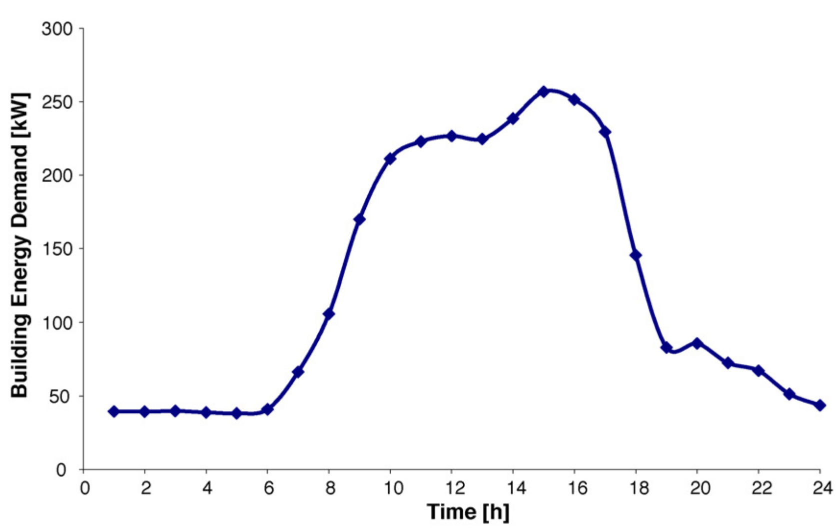

Fig. 2. Typical measured building energy demand profile.

parameters (dry/wet-bulb temperature, direct/diffuse solar radiation, wind speed/direction, etc.) are given in an hourly basis and the software can provide an annual profile of several outputs (cooling/heating loads, zone temperature, building energy consumption, etc.). For the design day simulation, the user should supply a group of parameters such as maximum and minimum dry-bulb temperature, wet-bulb temperature when the maximum dry-bulb temperature occurs, wind speed and direction, etc. for a single day. The software will provide for such day the same outputs mentioned for the annual simulation.

For this study, the description of the building and its internal loads is kept as simple as possible in order to avoid an over-detailed modeling, which can be very time-consuming. It should be emphasized that the purpose of this research is to forecast, within a reasonable uncertainty, the energy profile of a building using a simulation tool with a set of parameters that briefly describes the building and the climate data. Therefore, the design day simulation option available in EnergyPlus was used.

3.2.2. Artificial neural networks

Artificial neural network is a generic denomination for several simple mathematical models that try to simulate the way a biological neural network (for instance the human brain) works. The main characteristic of such models, which is important for this study, is the capability of learning the "rule" that controls a physical phenomenon under consideration from previously known situations and extrapolate results for new situations. This learning process is called *network training*. The development of artificial neural networks is based on the observation of the biological neural network behavior (cf. [15]).

Since it is not well known how a biological neurons is arranged, several possible arrangements for artificial network were suggested, generating distinct network models. The most known, simple and used network arrangement is the *feed-forward model*. In this model, the neurons are placed in several layers. The first one is the *input layer*, which receives inputs from outside. The last layer, called *output layer*, supplies the result evaluated by the network. Between these two layers, a network can have none, one or more intermediate layers called *hidden layers*. The input layer is usually considered a distributor for incoming signal, the hidden layers are signal classifiers, and the output layer is the organizer of obtained responses.

Fig. 3 shows a feed-forward neural network with eleven neurons arranged in four layers (two of them are hidden ones), which is the model used in this paper. It must be pointed out that in the feed-forward model, the neurons of a given layer are only connected with the previous layer and the next one. There are other possible more sophisticated network arrangements, as well as the *SelfOrganizing Maps*, models in which the network itself changes its arrangement during the training phase.

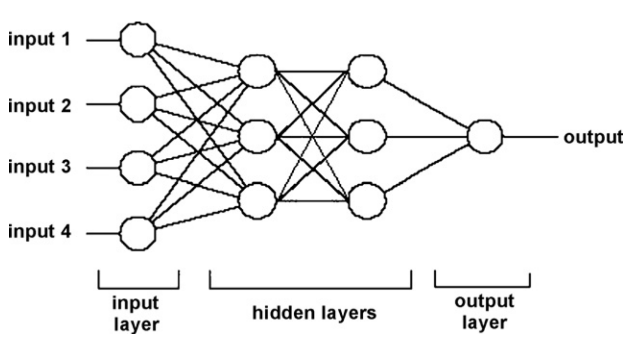

Fig. 3. Feed-forward artificial neural network with four inputs, one output and eleven neurons placed in four layers with two hidden layers.

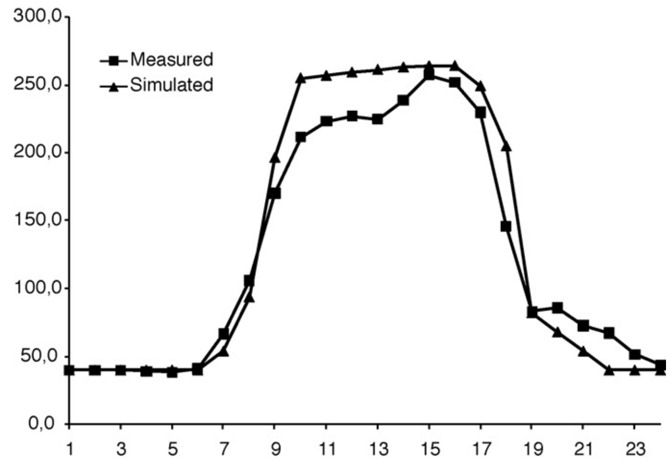

Fig. 4. Comparison between measured and EnergyPlus simulated energy demand profile.

4. Simulation and results

4.1. EnergyPlus results

Using the data obtained by the energy demand measurement system, the energy consumption for each business day between 1 January and 31 March 2005, was evaluated providing a 54-day database.

The building characteristics (geometry, wall and window materials, lighting, equipment and occupancy schedules) were implemented in EnergyPlus. Each day was simulated using the design day simulation option and the daily total energy consumption was compared with the actual available data. Fig. 4 shows a comparison between the measured and EnergyPlus simulated energy demand profile. One can verify that, for 80% of the period, the simulated results fairly agree with the measured energy demand profile. The gap is larger in the first hour of occupancy and this can be explained by analyzing Fig. 5.

Fig. 5 shows the outdoor dry-bulb temperatures (obtained from the weather data) and the indoor dry-bulb temperatures calculated by EnergyPlus for two situations: with all windows close and open, and both considering that air conditioning equipment is powered off. One can notice that in the period between 07:00 and 11:00 the indoor dry-bulb temperature profile varies from 22 to 26 °C for both conditions (open and close windows).

Considering the principle of adaptive thermal comfort addressed by Nicol et al. [16], which states that "*If a change occurs such as to produce discomfort, people react in ways, which tend to restore their comfort*", between 7:00 and 11:00, the occupants can achieve its own thermal comfort by opening windows instead of turning on the air conditioning equipment, reducing the energy demand and imposing the difference between the energy demand profiles shown in Fig. 5.

Fig. 6 shows a comparison of simulated and actual energy consumption data. It can be noticed that 80% of the database is included in a ±13% region. One should consider that the uncertainty of the evaluation of the internal gains (especially occupants) in such building is high, as mentioned in Section 3.1. Taking also into account the uncertainties related to the input parameters previously mentioned and pointing out that the focus of this study is to compare a detailed model against a simpler model for a quick energy demand evaluation, the achieved result is quite fair. It should be addressed that this result is similar to those reported in other works

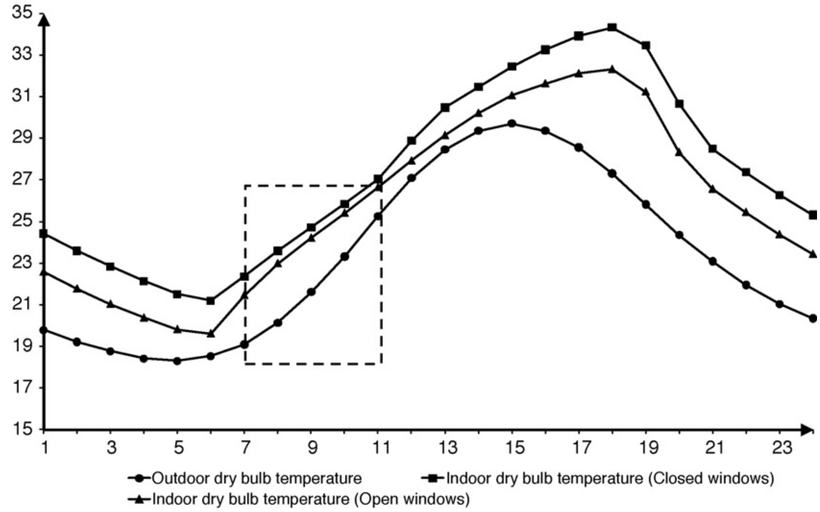

Fig. 5. Indoor and outdoor dry-bulb temperature for two conditions: open and close windows.

presented in the literature review. Nevertheless, by performing a regression analysis in the data points of Fig. 6, it was found a very low slope line (almost horizontal).

The explanation of such behavior is based on the user possibility of individually changing equipment set point as well as opening building windows in order to achieve its desired thermal comfort condition, as mentioned before. It should be also pointed out that, according the Energy Plus simulation results, the total installed capacity of air conditioning unitary equipments is lower than necessary to maintain good thermal comfort conditions in the building.

In hotter days, in order to promote a better thermal comfort condition, it was noticed that the occupants are used to bring additional fans or mobile air conditioners to the building. Probably, this action is the main cause for the increase in the energy consumption, and it is quite difficult to be evaluated by EnergyPlus. This happens because those equipments are used in very arbitrary way.

In colder days, there is an overestimation of energy consumption that can be explained by windows being opened by the occupants also in order to achieve thermal comfort. It was adopted for the simulation that the windows are closed all the time. Since the building envelope allows having a large heat gain (mainly solar radiation), EnergyPlus evaluated a higher energy consumption due

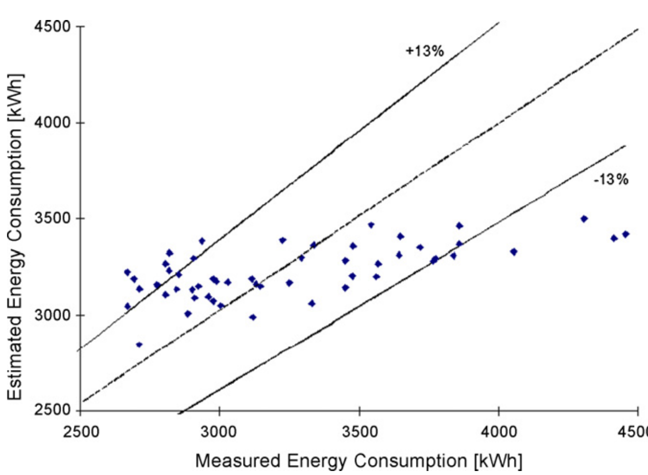

Fig. 6. Comparison between EnergyPlus-simulated and measured daily energy consumption.

to the intense use of air conditioning systems caused by this closed window condition. In the actual building, the occupants can choose between using the air conditioning or opening the windows. This behavior is also quite difficult to take into account in EnergyPlus simulations and is more critical when the maximum outdoor dry-bulb temperature is around 23–24 °C.

In order to enhance the result confidence, the influence of some input parameters and software settings on energy consumption prediction were also investigated. The first parameter analyzed was the solar radiation level. As a default setting for EnergyPlus, it is assumed that the building experiences a clear sky condition where solar radiation profile achieves its highest values. This is not a common situation, and therefore the user can correct the solar radiation level by changing a program variable called *SkyClearness*. Nevertheless, the level of such variable is not readily available in advance for the facility manager.

In order to check the influence of that parameter, two sets of simulation runs were undertaken in the first one this variable was kept equal to 1 (program default), and in the second one the *SkyClearness* was changed until the solar radiation profile became similar to the actual one. The adjusted *SkyClearness* values ranged from 0.18 to 0.80 for the considered period. By comparing the two sets, the building energy consumption evaluated with *SkyClearness* equal to 1 was 1.3% higher than that for adjusted *SkyClearness*. This low difference can be explained by analyzing Fig. 8, where the building energy demand and indoor dry-bulb temperature profile are shown for simulations with two different *SkyClearness* values. One can notice that even with 20% variation in the value of *SkyClearness* the energy demand practically did not change but the dry-bulb temperature shows a drop in most of the day period. As mentioned before, the actual building air conditioning capacity is below the required to maintain a steady indoor temperature. Therefore, the variation in solar radiation profile provided by the *SkyClearness* change has a small effect in the energy demand because the air conditioning has to work in its full capacity in both situations. But, by analyzing the indoor dry bulb, there is an average decrease of 0.8 °C in its values when the SkyClearness is changed from 1.0 to 0.8, which is quite acceptable for the purposes of managing the facilities and might indicate that the solar radiation is a second-order input parameter for these purposes (Fig. 7).

In this paper the influence of the other weather parameters is also evaluated using a series of simulation where each parameter is modified based on its uncertainty evaluated from the meteorological

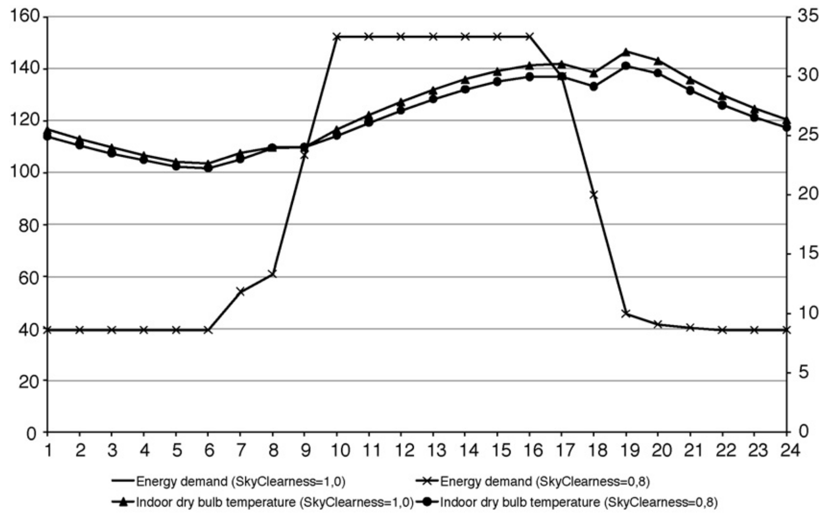

Fig. 7. Comparison between EnergyPlus-simulated and measured daily energy demand and indoor dry-bulb temperature.

database. Table 4 presents those uncertainties and the uncertainty promoted by each parameter.

Based on uncertainty for each variable presented in Table 4, the total uncertainty due to the weather parameters is ±2.2%, which is much lower than the difference between the simulated and the actual energy consumption data.

The latter statement is reinforced by the results achieved when variations in the schedules for lighting, equipment and occupants are imposed. For the simulation sensitivity analysis purposes, a variation range of ±20% was imposed for those schedules. This variation was set in the hourly value of each schedule while keeping the others unchanged. The weather parameters were also kept unchanged. The results of such analysis are presented in Table 5.

By analyzing Table 5, one can observe that the different results for the same variation for each schedule can be explained due to the different contribution of each internal load in the total building energy consumption profile. Besides that, the uncertainty caused by these variations is 5–10 times higher than the one produced by the weather parameters uncertainty, and it is of same order of the difference between actual and simulated energy consumption.

Another parameter that significantly influences energy consumption prediction is the COP value. Such parameter typically ranges from 2.0 to 3.0 for window-type air conditioners. For the present study an average value of 2.5 was assumed, and variations within the typical range may lead to prediction errors of 12–16%, similar to those for building schedules.

Table 4
Sensitivity analysis results for building energy consumption for a variation on the weather parameters

Weather parameter	Uncertainty	Building energy consumption variation (%)
Dry-bulb temperature	±1.0 °C	±1.2
Daily range	±1.4 °C[a]	±1.2
Relative humidity	±5%	±0.8
Global solar radiation	±20 W/m^2	±1.2

[a] Observation: the daily range uncertainty is calculated based on the ±1.0 °C uncertainty of the maximum and minimum dry-bulb temperature.

Table 5
Sensitivity analysis results for building energy consumption for a ±20% variation on the internal loads values

Internal load	Building energy consumption variation (%)
Occupancy	±6.2
Lighting	±12.4
Electrical equipment	±10.6

4.2. ANN results

As mentioned before, a *feed-forward* approach for neural network development was chosen for this work. The implemented simulation program, based on proposed algorithms by Freeman and Skapura [17], is intended to be the most flexible possible, and in this sense it uses input files in which the input/output variables and the network parameters (number of layers, number of neurons in each layer, learning phase or simulation, etc.) are informed.

4.2.1. Consumption forecast based on external temperatures

The first attempt for ANN was the implementation of a simpler neural network, using only the external dry-bulb temperature as input parameter. Available consumption and weather data were divided into two groups. The data from the period between August 2003 and December 2004 was used for the network training process, and the period between 1 January and 31 March 2005 (which is the same period used for the EnergyPlus simulation) was used for model validation. As network input, daily maximum and minimum external dry-bulb temperatures T_{min} and T_{max} (°C) were used, and the output was the corresponding daily total consumption C (kWh).

Three different networks were implemented: one for all days (both working days and weekends), and two others for working days only and weekends only. Table 6 shows the networks parameters, and Table 7 the comparison of energy consumption predicted by the networks and actual data.

The all days network, in spite of receiving the day type (working day or weekend) as an extra input, presented a bigger error between predicted and actual data than the distinct networks for working days and weekends. Similar results were obtained increasing the number of hidden layers and the number of neurons in each hidden layer.

Fig. 8 shows the results for the working days network. It can be noticed that 85% of data is within a ±13.5% error range for working days, similarly to the obtained result for EnergyPlus simulations. It can also be noticed, like the previous EnergyPlus results, the very low slope line (almost horizontal).

Table 6
Parameters for temperature-consumption networks

Parameters	All days	Working days	Weekends and holidays
Inputs	3 (T_{min}, T_{max}, day-type)	2 (T_{min}, T_{max})	2 (T_{min}, T_{max})
Output	1 (C)	1 (C)	1 (C)
Training database	335	200	135
Validation database	79	53	26
Layers	3	3	3
Neurons (input layer)	3	2	2
Neurons (second layer)	18	18	18
Neurons (output layer)	1	1	1
Activation function	Linear	Linear	Linear

Observation: T_{min} and T_{max} (°C): daily minimum and maximum external dry-bulb temperature, respectively. For the day-type input: 1 for working days and 0 for weekends and holidays.

Table 7
Results of temperature-consumption networks validation

Results	All days (%)	Working days (%)	Weekends and holidays (%)
Average error (training phase)	13.9	4.5	9.8
Average error (validation phase)	21.0	10.8	10.5

Table 8
Parameters for weather-consumption networks

Parameters	All days	Working days	Weekends and holidays
Inputs	5 (T, U_{rel}, R_{glo}, R_{dif}, day-type)	4 (T, U_{rel}, R_{glo}, R_{dif})	4 (T, U_{rel}, R_{glo}, R_{dif})
Output	1 (C)	1 (C)	1 (C)
Training database	227	142	85
Validation database	59	39	20
Layers	3	3	3
Neurons (input layer)	5	4	4
Neurons (second layer)	21	21	21
Neurons (output layer)	1	1	1
Activation function	Linear	Linear	Linear

Observation: T_{max} (°C)—daily maximum external dry-bulb temperature; U_{rel} (%)—relative humidity; R_{glo} (W/m^2)—global solar radiation; R_{dif} (W/m^2)—diffuse solar radiation.

Table 9
Results of weather-consumption networks validation

Results	All days (%)	Working days (%)	Weekends and holidays (%)
Average variation (training phase)	10.5	4.9	9.4
Average variation (validation phase)	16.5	9.5	9.7

4.2.2. Consumption forecast based on temperature, humidity and solar radiation

The next step was to increase the network complexity by using the external dry-bulb temperature T (°C), relative humidity U_{rel} (%), global solar radiation R_{glo} (W/m^2), and diffuse solar radiation R_{dif} (W/m^2) as network input parameters. Daily average values were used for weather data instead of maximum/minimum values. Similarly to the previous section, data from August 2003 to December 2004 were used for network training, and the period of January to March 2005 for validation, and three different networks were implemented.

Tables 8 and 9 present the networks parameters and the comparison of predicted and actual consumption. Like the previous case, the separation in two different networks for working days and weekends improves the consumption forecast, although the introduction of additional weather parameters only slightly improved the results, and it may be concluded that such additional parameters have a smaller impact on energy consumption than dry-bulb temperature for the building complex considered, as expected from the parametric analysis performed for EnergyPlus.

Similar to the methodology used in the EnergyPlus results, a sensitivity analysis was made to the ANN model and the results are

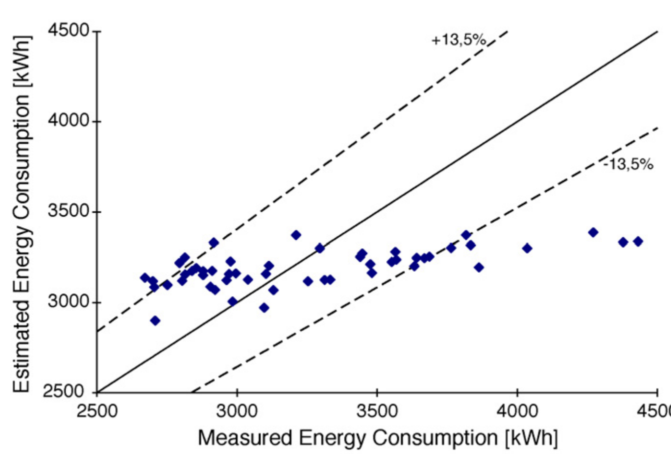

Fig. 8. Comparison between temperature-consumption ANN and measured daily energy consumption for working days.

Table 10
Sensitivity analysis results for building energy consumption for a variation on the weather parameters

Weather parameter	Uncertainty	Building energy consumption variation (%)
Dry-bulb temperature	±1.0 °C	±2.3
Relative humidity	±5%	±1.6
Global solar radiation	±20 W/m^2	±0.3

shown in Table 10. As it can be seen, the effect of weather parameter's uncertainties on the building energy consumption is slightly higher than those observed in the EnergyPlus results. These higher values, as well as the 13% uncertainty achieved by the ANN model, might indicate that the feed forward is not the most suitable model for such application.

5. Conclusions

This paper compared both a simpler ANN model and a detailed building HVAC design and simulation software as forecasting tool for the energy demand for the Administration Building of University of São Paulo.

The results show that EnergyPlus consumption forecasts presented an error range of ±13% for 80% of the tested database. The major source of uncertainties in the detailed model predictions are related to proper evaluation of lighting, equipment and occupancy schedules when one compares to the uncertainties produced by weather parameters. An adequate evaluation of the COP also plays a very significant role in the prediction of the energy consumption of a building.

Regarding the ANN models, the results for the simpler (temperature-only input) and the more complex (temperature/relative humidity/solar radiation inputs) neural networks showed a fair agreement between energy consumption forecasts and actual values, with an average error of about 10% when different networks for working days and weekends are implemented. Considering the small difference in the results for both input groups, it may be considered that the effects of humidity and radiation on energy consumption are less significant than those of external temperature for the building used as case study.

Parametric analysis performed for EnergyPlus model leads to a similar conclusion. Such analysis showed that internal heat gains and equipment performance are more significant for the present case.

It should also be pointed out that the occupant's behavior in a building where the air conditioning equipment are mainly unitary systems (window-type air conditioners and split systems) can significantly affects the energy consumption profile, making its forecasting more difficult or inaccurate for both models. This conclusion is based on the analysis of Figs. 5 and 6 where the EnergyPlus and the ANN model under predicts the energy consumption in the hotter days and over predicts in the colder days. These differences are quite dependent on the user behavior in order to achieve thermal comfort. Even though, the ANN model provides a slight better prediction for the energy consumption than the Energy Plus but these results can be improved by using a more suitable ANN model.

Moreover, for the detailed model, it would also provide insights for the facility manager on opportunities for reducing the building energy consumption. Since it is a model that is based on physical principles, evaluations of new strategies for reducing energy consumption will be more easily evaluated. In this sense, it should be stressed that the schedules of the internal loads must be periodically revaluated to assure an updated description of the building usage and, therefore, a more accurate evaluation of the energy demand. It should be added that the use of adaptative thermal comfort parameters might also improved the energy demand prediction for model that is based on physical principles.

The ANN model is only capable of predicting the energy consumption based on previous measurements. Therefore, evaluation of new strategies for energy consumption reduction can only be evaluated after they are implemented.

Nevertheless, after a proper calibration, both the detailed model and the ANN model would become useful tools for forecasting the building energy demands. This is a preliminary study and several others should be developed in order to improve the methodologies to evaluate the energy consumption in air conditioned buildings in order to better predict the energy consumption profile.

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