OPTIMIZATION OF THE THERMAL BEHAVIOR OF TROPICAL BUILDINGS

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ABSTRACT

This work is intended to optimize the thermal behavior of a building, by means of the proper selection of some of its design parameters, such as thickness, thermal properties and reflectivity of walls and roof, using a tropical building as an example. The solution methodology used in this work involved several stages. First, a data set was built using the Latin Hypercube sampling method. Then, for every sample of the data set, the maximum daily value of the mean temperature in the inner space of the building was determined, using a computationally expensive numerical simulator. These results, along with the data set, were used to train and validate a three-layer feed forward neural network, which was used as a surrogate model for two global optimization algorithms. This approach leads to a significant reduction of the time requirements of the design cycle. The results show how a proper selection of design parameters can improve the thermal behavior of the building. The improvements obtained were in the range between 3 and 11 Celsius degrees.

INTRODUCTION

The evaluation of different alternatives for the design and construction of energy-efficient buildings is an important research topic, since metropolitan areas have to reduce the costs and pollution caused by an unreasonable use of energy. Specifically, Venezuela is one of the Latin-American countries with the highest mean consumption of domestic electricity, mainly because of the construction of buildings regardless of the weather and environmental conditions, and the use of inefficient air conditioners (Nuñez, 1999).

Because of that, it is desirable to impulse the design and construction of thermally adapted buildings by the development of techniques which allow the evaluation of the thermal behavior of several design alternatives, taking into account the environmental conditions. However, most of the numerical methods currently used require about half an hour to evaluate a single building with a moderate-size bi-dimensional mesh, making impractical their implementation in optimization cycles, where it is often necessary to make many evaluations in a reasonable time.

The combination of design of experiments, surrogate modeling and global optimization algorithms has proven to be an effective methodology, applied in the solution of optimization problems that arise in different areas of science and technology, which permits a significant reduction in time-requirements of the design cycle. Therefore, it seems that it is an appropiate methodology for the optimal design of thermally adapted buildings.

PROBLEM DESCRIPTION

The main objective of this work is to determine an optimal combination of several design parameters of a building, in order to minimize the maximum value of its mean internal temperature. To do that, a model of a single tropical building with no added elements is used, and it is oriented in perfect alignment with the cardinal directions.

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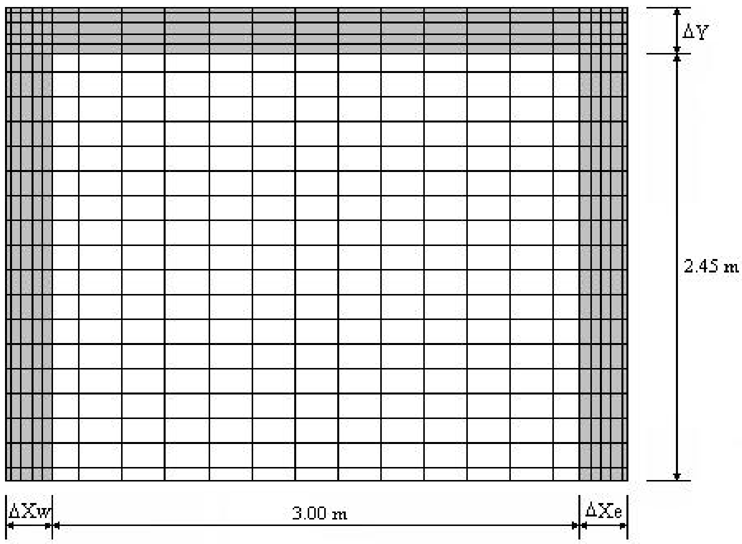

Figure 1. Bidimensional mesh used for the numerical simulation.

Table 1. Design parameters.

Design Parameters (for Walls and Roof)	**Lower Bound**	**Upper Bound**
Thermal Conductivity (k) [W/m.K]	0.12	3.0
Thermal Capacity (ρ.Cp) [$kJ/m^3.K$]	426.6	3624.0
Thickness [m]	0.10	0.30
Reflectivity [fraction]	0.07	0.72

The design parameters used are shown in Table 1, along with the their range of permitted values. Figure 1 shows the bi-dimensional mesh used for the numerical solution of the problem. The gray-shaded zones of the mesh correspond to the walls and roof of the building, each one with five control volumes in their thicknesses directions.

The numerical solution of this problem was obtained with a computer code capable of solving simultaneously the continuity, momentum and energy equations, applying the Finite Volume Method in a bidimensional mesh of 22x22 control volumes. The required boundary conditions for the energy equation were set using a model for outdoor temperature and global insolation (Almao, 1994), which consists of a series of time-dependent functions for outdoor temperature, relative humidity, diffuse and beam components of global insolation over horizontal planes and global insolation over vertical oriented planes. It was decided to orient the building in the East-West direction and to make the simulation using the environmental conditions of August, since these are the most adverse conditions in the city of Maracaibo (Nuñez,1999).

METHODOLOGY

Next, a brief description of each one of the stages involved in the solution of the optimization problem is presented.

Design of Experiments

Once the design parameters were selected and the optimization criterion (response variable) was defined, two data sets, of 240 and 20 samples respectively, were built using a Latin Hypercube design. This sampling method has proved to be the best suited for computational experiments when compared to random or block random sampling (McKay *et al.*, 1979), giving as a result a well balanced data set.

Feed Forward Neural Network

The second stage in the solution of this optimization problem is the training and validation of a feed forward neural network, which will be used as a surrogate model for the global optimization algorithms. To do that, the numerical model mentioned in the previous section was used to

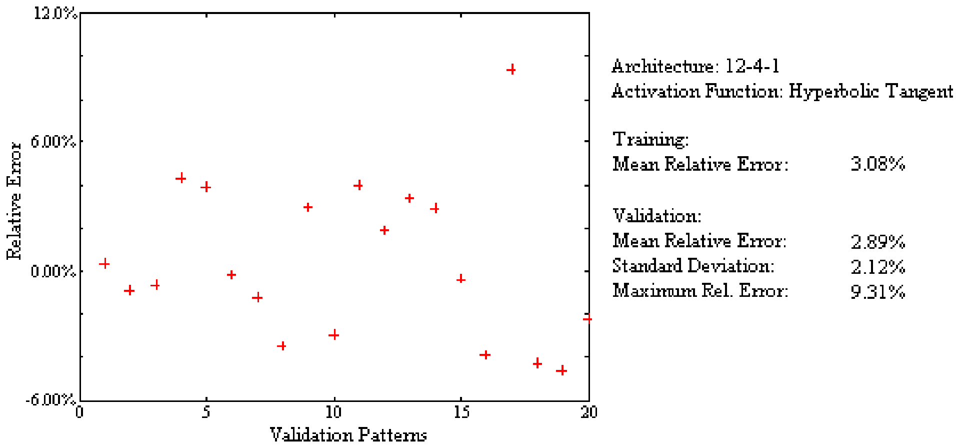

Figure 2. Validation errors of the neural network.

Table 2. Control parameters for the Simuated Annealing.

Initial Temperature	8.00
Cooling Factor	0.85
Step Length Adjustment Frequency	20 Cycles
Temperature Reduction Frequency	400 Cycles
Accepted/Rejected Ratio	1.00

Table 3. Control parameters for the Genetic Algorithm.

Population Size	50
Maximum Number of Generations	1000
Mutation Probability	0.08
Crossing Probability	0.90
Maximum Number of Chromosomes	60

determine the maximum value of the mean internal temperature of the building, for every sample of the data sets selected in the first stage. All the samples and the response of the model for each of them were linearly scaled to the closed interval [0.1;0.9], in order to avoid the saturation of the network's activation function (Fausett, 1994).

During the training of the network, several runs were made with different architectures, activation functions, initial weights and training parameters, and the network with the best balance between data fitting and generalization capability was selected. The mean relative error, the standard deviation and the maximum relative error of the network with the validation samples were used as decision criteria. These parameters are shown in Figure 2, along with a graphical representation of the validation errors.

Optimization

Finally, once the network was trained and validated, it was used along with two optimization algorithms to look for an optimal combination of the design parameters. The optimization methods used were Simulated Annealing and Genetic Algorithms, since their successful applications in many areas have proved them to be not only effective but also robust, especially in the optimization of multi-modal functions in multivariable design spaces (Karaboga and Pham, 2000; Inberg, 1993; Goldberg, 1989).

The control parameters of the optimization algorithms used in the solution of this problem are shown in Tables 2 and 3. As can be seen, there was used a slow annealing schedule with a high initial temperature for the Simulated Annealing, and a high population size and high crossing probability for the Genetic Algorithm. This selection of the control parameters corresponds to an exhaustive searching, which was limited to a maximum of 50000 evaluations of the cost function (the neural network).

RESULTS AND DISCUSSION

Table 4 shows three of the solutions obtained by the optimization algorithms. The actual value of the mean internal temperature as predicted by the numerical model(T_{int}), its value predicted by the neural network(T_{net}), and the associated error are presented. It also shows, for comparison purposes, the values of the design parameters and the resulting internal temperature of a typical building (first line of the table), constructed according to the traditional practices of the zone (Nuñez, 1999).

As illustrated by the previously mentioned table, the best solutions found by the optimization algorithms share the following characteristics:

West Wall with high thickness, low thermal conductivity and high thermal capacity. This combination of parameters avoids an excessive

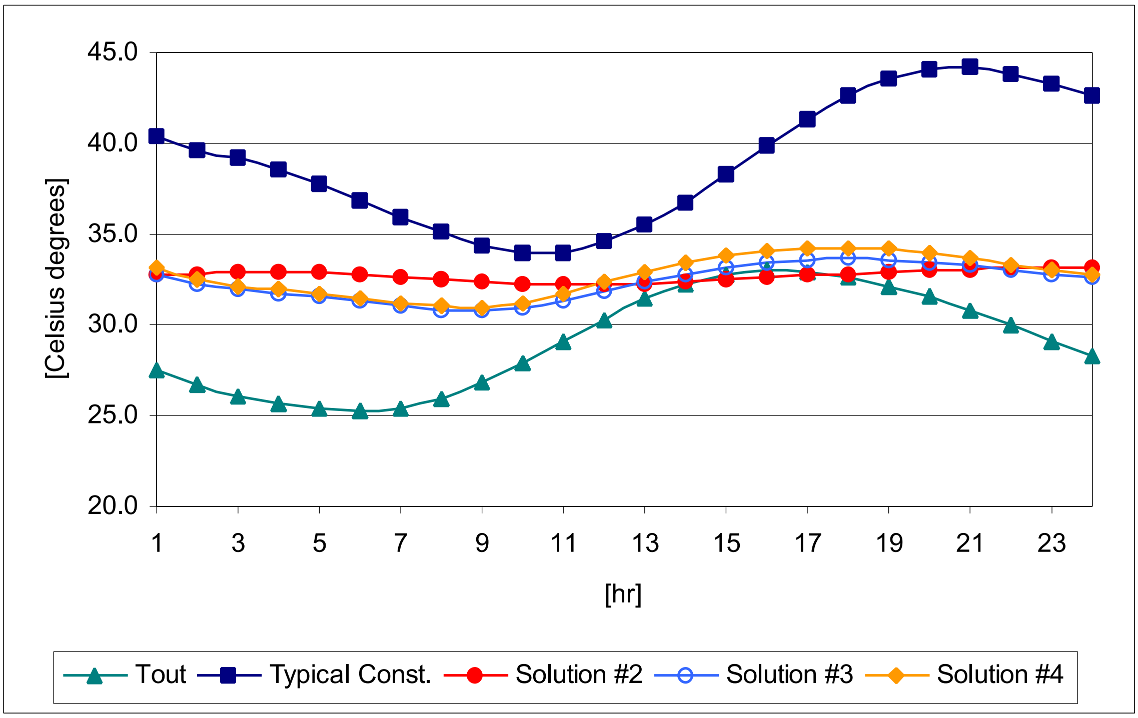

Figure 3. Transient thermal behavior of the solutions.

Table 4. Optimization results.

#	East Wall				Roof				West Wall				T_{int}	T_{net}	$e_{\%}$
	ρCp	K	Δx	φ	ρCp	K	Δx	φ	ρCp	k	Δx	φ			
1	1947555	044	0.15	0.33	1984032	1.75	0.20	0.33	1947555	0.44	0.15	0.33	44.16	44.21	012
2	3520204	0.77	0.12	0.72	3219849	0.45	0.26	0.63	3113375	0.71	0.25	0.67	33.18	32.48	2.11
3	737906	0.53	0.14	0.60	3021930	0.45	0.30	0.72	2845473	0.20	0.20	0.68	34.27	32.45	5.32
4	426600	0.12	0.10	0.72	2514302	0.12	0.29	0.72	3624000	0.12	0.30	0.72	33.61	30.84	8.26

increment of the wall temperature and helps reducing the heat flux transferred to the inner space of the building through this wall, which receives an important amount of solar radiation.

East Wall with medium/low thickness and low thermal conductivity. The thermal capacity of this wall seems to have no influence in the thermal behavior of the building, since the amount of solar radiation over this wall is negligible.

Roof with high thickness, high thermal capacity and low thermal conductivity. The roof receives an important amount of solar radiation too. Because of that, it is necessary to select thermal and optical properties that allow us to reduce the heat flux transferred to the inner space of the building.

High reflectivity in all exterior surfaces. This optical property helps the building to reflect an important amount of solar radiation, reducing the total heat absorption of the building, and thus reducing the inner temperature of it.

Figure 3 shows a graphical representation of the transient thermal behavior of the solutions presented in Table 4. It is also included a plot of the outdoor temperature (Almao, 1994) for comparison purposes.

It can be observed that it is possible to reduce the internal temperature of the edification by means of a proper selection of construction materials. Specifically, a temperature reduction was obtained in the range between 2.8ºC (10:00am) to 10.9ºC (8:30pm), when compared with the traditional construction practices of the zone. Finally, it can also be observed that the solutions found by the methodology are less sensitive to environmental conditions than the typical construction, as can be concluded comparing the amplitudes of the wave-shaped temperature plots of the solutions. Specifically, the temperature plot of the typical construction has amplitude in the order of 10ºC, meanwhile the amplitude of the less favorable of the solutions was only one quarter of that.

CONCLUDING REMARKS

The combination of Design of Experiments, Feed Forward Neural Networks and Global Optimization Algorithms is an effective methodology for the solution of optimization problems, since it reduces the duration of the design cycle, reducing the number of evaluations and the time required for each of them. Specifically, it reduced the time required for the evaluation of the thermal behavior of a building from 20 minutes, time required by the computer code (numerical model), to only 1 second, which is the time required for the evaluation (feed forward) of a trained neural network. In addition, this large reduction in time requirements (near 1200 times) was made without sacrificing accuracy in the results, since the maximum validation error was only 9.31%.

As suggested by the results obtained in this work, the applied methodology can be useful during the design stage of thermally adapted buildings, since it permits the evaluation of many design alternatives in a reasonable time, leading to an optimal selection of design parameters.

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NOMENCLATURE

Cp	Specific heat
k	Thermal conductivity
T_{int}	Actual value of the indoor temperature as predicted by the numerical simulator
T_{net}	Indoor temperature as predicted by the surrogate model (neural network)
T_{out}	Outdoor temperature
$\Delta x, \Delta y$	Wall and roof thickness
φ	Reflectivity
ρ	Density