A Methodology for the Optimization of Building Energy, Thermal, and Visual Performance

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A Thesis

in

The Department

of

Building, Civil and Environmental Engineering

Presented in Partial Fulfillment of the Requirements

for the Master of Applied Science at

Concordia University

Montréal, Québec, Canada

September, 2008

Your file Votre référence
ISBN: 978-0-494-45703-0
Our file Notre référence
ISBN: 978-0-494-45703-0

ABSTRACT

A Methodology for the Optimization of Building Energy, Thermal, and Visual Comfort

Jérôme Conraud-Bianchi

Buildings are under the scope of environmentalists since they are the biggest energy consumers and polluters. Building performance could be greatly improved thanks to optimization. Yet, optimizing for different aspects of a building's performance is a conflicting process and building designers have to rely on their experience to make decisions.

The present work proposes a method to assess the optimal configuration for a building in terms of energy and indoor environment performances. The method relies on the good performance of Genetic Algorithms (GA) for complex optimization problems. However, GAs require extensive computations. Artificial Neural Networks (ANN) were used to alleviate the computational burden. The main concern has been to make this method as universal and easy to use as possible, resorting to widely used tools only.

The method was first successfully tested on a small-scale, four-room section of an office building and on a full-scale school. In both cases, the ANN model performed well with prediction errors in the order of 5%. Finding a better design for the school building was rather difficult since the building performed well already, but thermal comfort could be improved without increasing the energy demand or decreasing visual comfort. The limits of the method were tested by playing with the number of

inputs and outputs. The ANN performed well though its performance decreased as the number of design parameters increased. The limits of the method were established regarding the performance of the ANN and the number of cases required to train and validate the ANN.

ACKNOWLEDGEMENTS

The author wishes to acknowledge the support of Natural Resources Canada.

Special thanks to Prof. Haghighat without whom this work would not have come to fruition.

A special thought for the many people who contributed to this project in different ways: the IAQ Lab team, the ISO, CISA, the OMHM, and friends and family.

Finalement merci à ma mère et à mon frère pour croire en moi.

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CHAPTER 1

1. INTRODUCTION

1.1. On the State of Energy and Buildings

Ever growing pressure on the environment begs for solutions and considerable changes in the way buildings are designed and operated. The US National Petroleum Council, lead by Exxon Mobil's former CEO, Lee Raymond, affirmed in a July 2007 public report that the world's energy demand is expected to increase by 50% to 60% by 2030 at which time the world oil production will no longer satisfy the market demand (AFP, 2007a). At the same time, one cannot deny anymore that humans are somewhat responsible for climate change, global warming, and all its entailments.
North America accounts for more than 20% of the world primary energy consumption (Energy Information Administration, 2007). In Canada, 30% of this energy is typically consumed by buildings (including extraction and transportation of construction materials, construction, operation, demolition, and recycling). Buildings also account for as much as 20% of Canada's green house gas emissions, a figure close enough to other developed countries (NRCan, 2005).

From the above statement, it can be observed that earth does not hold the capacity to sustain humankind at such a rate, and it is necessary that we, building engineers, urgently take some action to trigger dramatic changes in building practices to cut down on buildings' energy consumption.

The National Roundtable on the Environment and the Economy published a report in July 2006 setting drastic measures to improve buildings' energy efficiency (National Round Table on the Environment and the Economy, 2006). These measures reflect a global trend amongst governments and public energy agencies pressuring the building industry into more environmentally friendly design practices. The conclusions of this report were somewhat surprising: it is possible to reduce Canada's GHG emissions by 70% by 2050 with the current available technologies. This statement relies on the assumption that 66% of the buildings standing in 2050 are already built and that 50% of commercial buildings as well as a yearly 2% to 3% of all residential buildings will undergo major retrofit by that date.

1.2. The Issue: Buildings and the Environment

This begs the question of how to mitigate buildings' harmful impact on the environment and how to achieve these goals to avoid the most undesirable scenarios predicted by scientists. In other words, how to make buildings more environmentally friendly without worsening occupants' comfort?

Fortunately, the building community has started to explore the myriads solutions available to reverse the current trend. Studies also showed that improving the work environment results in healthier employees, and therefore, in a higher productivity as well as a positive work atmosphere and mindset (Fanger, 2000), which is beneficial to the development of any company. Likewise, green projects are blossoming all around the world and an increasing number of "green buildings" are brought to day. They use recycled or more environmentally friendly materials than traditional ones; they are specifically designed to be energy efficient or even produce their own energy. For example, China illustrates this concept very well in the green city of Dongtang close to Shanghai (The Observer, 2008); big countries such as France and Sweden embedded the protection of the environment into their constitutions; in 2006, the Vatican State became the first carbon neutral country in the world (AFP, 2007b); in February 2006, Sweden announced it expected to become the first oil-free country in the world by 2020 (La Presse, 2006)—a quite edifying example for a country whose society and climate are not very different from Quebec's...

Further to mitigating our impact on the environment, cities, buildings, and infrastructures are now seen as a vector to restore and help the earth's systems: some highways in Europe are now built with special coating absorbing pollutant molecules emitted by cars; green roofs are more numerous by the day.

1.3. The Answer: Building Optimization

As Prof. Haghighat once put it, "The first step to sustainability is optimization". This is the cornerstone of this work. Solutions exist and might even seem too numerous at time, especially when it comes to different design options for a building. Furthermore, buildings are very complex energy systems and the validity and applicability of some technologies were proved to perform very poorly when not integrated in an appropriate fashion. The building community has started to conduct research to provide guidelines based on building performance optimization to help designers with the challenge of integration. A review of this research is given in Chapter 2 of this thesis. However, very seldom did researchers take into account environmental impact, energy consumption and cost as well as occupants' comfort altogether in their studies.

1.4. Objective of this Work and Thesis Outline

This study sets out to provide guidelines as how to approach whole-building optimization encompassing energy use, thermal comfort and visual comfort. Traditional optimization methods such as linear optimization or optimization techniques working on the gradient of the function to optimize are not indicated in the case of buildings due to buildings' inherent complexity. Instead, holistic methods have proven to work particularly well, with Genetic Algorithm ranking first in terms of applicability (Wetter and Wright, 2003).

The objective of this work is to set up a method to aid designers choosing between different designs for a given building. Typical qualities to optimize are: the energy required to heat or cool the premises, occupants' thermal and visual comfort, the use of natural daylighting, the environmental impact of the building, indoor air quality etc. Emphasis is placed upon the simplification of the method to the utmost in a concern to make it usable and especially to make sure it is <u>actually used</u> by designers without a strong computer programming background.

In a nutshell, the method should follow this very schematic diagram:

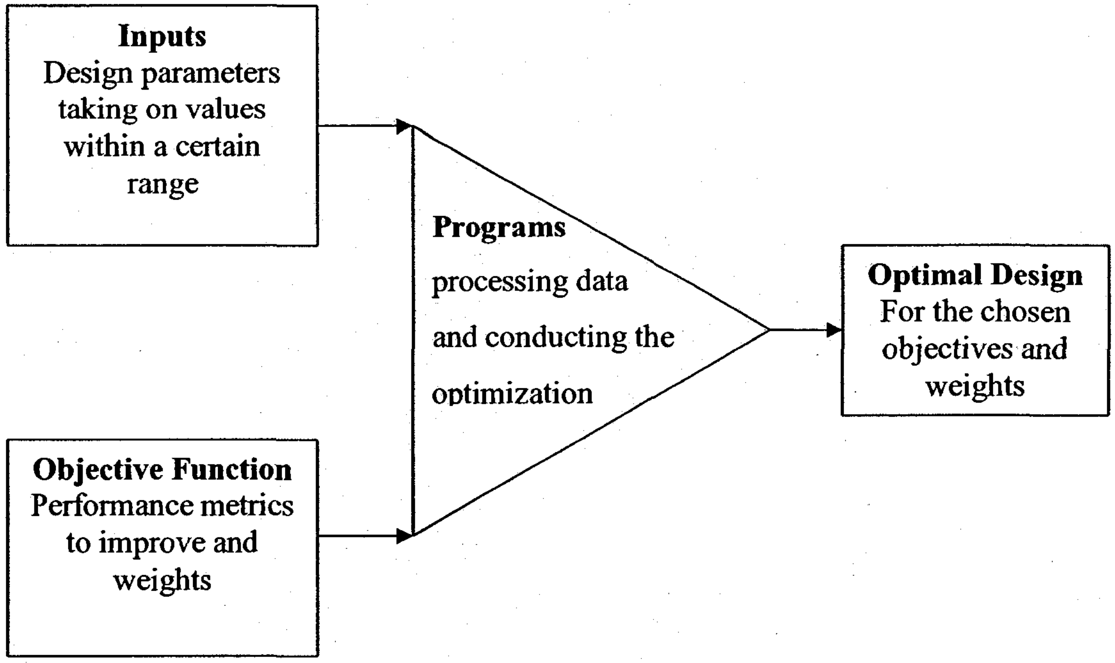


Figure 1 - Schematic Diagram of the Method

This method will be based on three main programs:

- ESP-r will be used to assess building performance;
- MATLAB will be used to carry out the optimization search through its Genetic Algorithm interface. It will also be used to set up an Artificial Neural Network to replace the energy software to avoid heavy computations, as explained further into detail;
- Perl was used to automate the batches of simulations necessary to train and test the ANN.

The second chapter of this thesis presents a review of the history of optimization with emphasis placed upon building optimization and the most commonly-used techniques, as well as a brief section on building simulation.

The structure of the proposed method encompassing the different steps to carry out an optimization study is devised in Chapter 3. The proposed scheme is tested in Chapter 4, showing the performance of the ANN compared to the building energy simulation program and documenting the results of the optimization study. Two sets of optimization studies on a large-scale building are documented in Chapter 5. Finally, Chapter 6 will close this work with conclusions and recommendations for further work.

CHAPTER 2

2. BUILDING OPTIMIZATION AND BUILDING SIMULATION

2.1. Global Definition

Optimization[1]: The art of rendering optimal—i.e. most desirable possible under a restriction impressed or implied.

Optimization[2]: An act, process, or methodology of making something (as a design, system, or decision) as fully perfect, functional, or effective as possible; specifically: the mathematical procedures (as finding the maximum of a function) involved in this.

Many definitions can be found for the term optimization. What does it really stand for? What is the key concept of optimization? What are the assumptions and implications hidden behind this apparently well-known word? More precisely, what is building optimization and how has it been applied in the building community? The purpose of this literature review is threefold:

- To address these questions,
- To summarize what has been achieved so far in the field of building optimization,
- And to determine what remains to be done.

The definitions quoted above have one thing in common: the art of optimization aims at *improving* the quality of the considered system. Some definitions even go further,

[1] Definition from http://www.wordreference.com
[2] Definition from http://www.answers.com

stating that an optimal solution should be a feasible solution. This very statement implies that there exist some constraints to optimization, and that optimization is not an absolute but rather relative concept. One optimizes a function, a design, or a system under certain conditions, over a certain space defined by these conditions. The art of optimizing lies in this very concept: working on a system with a view to make it as perfect, as functional, or as effective as possible given some limiting conditions.

2.2. History of Building Optimization

Further to the first idea of optimization as the rendering of a system most desirable as possible, optimization is a scientific field, based on rules, rationales, and methods.

The first optimization technique known is the *steepest descent* proposed by Gauss in the 18^{th} century. However, Dantzig's *linear programming* was the first technique to be referred to as optimization, in the 1940s. It was first used by the US military for logistics and training schedules. Various techniques then blossomed in the following years and were applied directly to a wide range of fields: production and transportation engineering, risk analysis, and aerospace engineering, amongst others. Today, one can count tens of optimization techniques. Gradient-descent (a.k.a. steepest descent) algorithms, the simplex method, simulated annealing, and evolutionary algorithms (with, amongst others, genetic algorithms, evolutionary strategy, particle swarm optimization…) are just a few to name. Designers have encountered many barriers on their way:

- Inherent complexity of the practice of building design due to the great number of people and disciplines involved in the project;
- Complexity of buildings as energy systems. There are a great number of parameters the influence of which cannot easily be forecast, such as weather patterns, the surrounding environment, occupancy, the aging of the building, changes of use of the premises, interactions with the surrounding buildings, just to name a few;
- Rapid growth of the use of software for building simulations. Simulation tools were developed to meet specific requirements (e.g. more accurate prediction of energy consumption; integration of new technologies within buildings; commissioning of buildings; rising demand from clients to provide building occupants with satisfactory indoor climate conducive to productivity, etc.). In the process, software developers had little thought for the interoperability of such tools, which are consequently very difficult to link together, or with any other third party tool in order to use optimization;
- Building optimization demands knowledge in optimization and sufficient computer programming skills that building designers do not necessarily have, and optimization has taken a long time to be introduced into university syllabi.

In the late 1990s – early 2000s, the Generic Optimization Program was developed at the Building Technologies Department of the Lawrence Berkeley National Laboratory. It was specifically designed to minimize objective functions computationally expensive to calculate and for which no derivatives are available, which is appropriate in the case of energy simulation and building optimization.

Wetter (2001) presented a simple case introducing the optimization tool. Wetter and Wright (2004) used GenOpt for their comparison study of different optimization algorithms (cf. section on the main optimization techniques used in building simulation). The tool consists of an interface which proposes a collection of optimization techniques. Users can write their own code and use any external program they wish to evaluate the objective function; the only requirement is that the third party program should read text input and write text output.

In the following section, an insight of the main methods used in building optimization is given in order to approach the last part of this literature review, i.e. Building Energy Management and Building Optimization, with a broader understanding.

2.3. Design Parameters and Optimization Objectives

Optimizing a system requires two main objects:

- Design parameters, which can take on different values, and whose impact on the system is to be investigated;
- And at least one objective function stating which qualities of the system are to be improved.

Scores of parameters have been studied in building optimization, depending on the purpose of the study. Examples of optimization studies are given in the next section. As far as objective functions are concerned, most of the time, they are:

- The financial cost of the project;
- The energy performance of the system;

- The environmental impact of the building;
- And occupants' comfort.

One may encounter combinations of these objective functions as well, such as thermal comfort and energy performance (Chouhdary et al. 2004), or environmental and financial cost (Wang et al. 2004). A combination of all these aspects would be the most desirable target, of course, but this would require a deep understanding of how the system to be optimized works and a non-negligible number of data, which are not always available.

2.4. Main Building Optimization Techniques

There exist two main approaches to optimization: the first option is to work on the objective function directly using mathematical tools under the guidance of gradient information in order to determine the optimal value of the function over a given search space (so called gradient-based methods). The second option is to scan the search space in a discrete fashion (i.e. try different values of the input vector of the objective function) and determine via any appropriate algorithm a near-optimal solution. The latter methods are referred to as stochastic techniques; they require a termination criterion since chances of reaching the exact target are very slim.

Gradient-based methods work well with second order differentiable functions, and in some cases, with more complex but smooth objective functions. In building optimization, however, the objective function is often estimated by using energy simulation programs which contain features that make the objective function highly non linear and non smooth. This is due to some approximations made by the tool, thus making the objective function discontinuous for some parameters. In this event, deterministic methods fail poorly whereas stochastic techniques are particularly well suited since they allow for the exploration of the whole search space, eventually focussing on regions of interest only, and finally converging toward a near-optimal solution. For this reason, stochastic techniques are more fit to the purpose of this study since very detailed simulations will be required.

2.4.1. Comparing the Performance of Different Optimization Algorithms

Wetter and Wright (2004) proposed a very interesting case study comparing the most commonly used algorithms in building optimization. Their study dealt with nine algorithms that could be classified under three categories: direct-search algorithms, stochastic population-based algorithms, and gradient-based algorithms.

Direct Search Algorithms

As far as direct-search algorithms are concerned, the performance of two Generalized Pattern Search (GPS) algorithms, and two simplex algorithms—a coordinate-search method—was studied. The main strength of direct search is that it does not require any information on the derivatives of the objective function. A GPS algorithm defines some points around the current point and aims at the point with an objective function more desirable than the current point's. If such a point exists, it will become the new current point at the next iteration. If none of the points have a better objective function, then the algorithm will try some points located closer to the current point. The algorithm stops when the value of the mesh (i.e. the ensemble of the points being investigated around the current point) reaches a certain threshold preset by the user.

Population-Based Algorithms

Two population-based algorithms were also investigated: a Particle Swarm Optimization (PSO) algorithm and the Simple Genetic Algorithm (simple GA). Both belong to the now very well-known family of evolutionary algorithms. According to Eiben and Smith (1998), evolutionary algorithms are all based on the same underlying concept: *given a population of individuals, the environmental pressure causes natural selection (survival of the fittest), which causes a rise on the fitness of the population. Given a quality function to be maximized, we can randomly create a set of candidate solutions [...] and apply the quality function as an abstract fitness measure – the higher the better.* Such methods are inspired from Darwin's theory of evolution. Candidates, or individuals, are feasible solutions; they have a genome, made of genes representing their characteristics. This genome can be interpreted as a fitness function, describing the quality of the individual. In order to represent selection pressure—the principle that drives evolution according to Darwin's theory—individuals undergo mutation and recombination to seed the next generation of individuals. With appropriate parameters defined for the algorithm, the fitness of the individuals should improve with each generation and eventually converge toward a near-optimal value.

Particle Swarm Optimization was developed by Eberhart and Kennedy (1995). It is a technique inspired by the social behaviour of flocks of birds or schools of fish.

Individuals are here called particles, and they fly through the search space. Particles are represented by their position in the space, their velocity, and their fitness value. An important aspect of the algorithm is the fact that all particles keep track of their positions and fitness values throughout the optimization process. The swarm of particles is randomly initialized and the algorithm searches for optima by updating particles at each generation. Each particle will update its position and velocity by following two best values: the best fitness value it achieved so far and the best value achieved by the whole swarm. The algorithm stops when a predefined maximum number of iteration is reached, or when minimum error criteria are reached, i.e. when the particles converge toward the near-optimal solution. The main difference between PSO and GA is that particle swarm optimization does not use crossover. As well, there is no exchange of information between the individuals of the swarm since the best particle is the only one to give out information to the rest of the swarm.

Genetic Algorithm under Scope

Before presenting the results of Wetter and Wright's study, let us focus on the most widely used optimization algorithm: the Genetic Algorithm. The GA was conceived by Holland in the 1970s though a couple of scientists had worked on some evolutionary programs before him (Baricalli simulated evolution automata that played a simple card game in 1954; from 1957 onwards, Fraser published a series of papers on the simulation of natural selection; Fraser and Burnell then published a book summarizing the different studies on computer simulation of evolution carried out through the 1960s.)[3] Even though GAs are mostly used for optimization, their application range is much wider; Nassif and Zmeureanu (2006) presented a study in which they set up and trained a grey-box model to approximate HVAC components. The grey-box models were trained using GAs.

The simple GA is the implementation of the aforementioned definition of evolutionary strategies. Most evolutionary algorithms, and more specifically the GA, are based on the following pseudo-code:

```
BEGIN
     INITIALIZE population with random candidate solutions;
     EVALUATE each candidate;
     REPEAT UNTIL (TERMINATION CONDITION is satisfied) DO
          1 SELECT parents;
          2 RECOMBINE pair of parents;
          3 MUTATE the resulting offspring;
          4 EVALUATE new candidates;
          5 SELECT individuals for the next generation
     END DO
```

Figure 2 - Basic Evolutionary Algorithm Pseudo-code

Here follows a quick overview of the simple GA:

- Representation: Representation is one of the crucial steps in setting up an evolutionary algorithm. It enables to link the real world to the world in which the algorithm works. In other words, any building in the real world could be represented by an individual which possesses a unique genome in the

1	0	1	0	0	0	0	1

Figure 3 - Genome of a random individual. Each box represents a gene; the values that each box can take are alleles of the gene.

[3] General facts from www.wikipedia.org (section on the *Genetic Algorithm*)

GA world. Mapping from the real world to the search space is a process that needs to be applicable to and the same for all the individuals of the algorithm; likewise, it needs to work both ways so that any individual generated by the program should correspond to one building case only and vice versa. In the case of the simple GA, individuals are represented by bit-strings.

- Evaluation Function: The performance of individuals has to be evaluated in order to rank individuals according to their performance and to allow for the survival of the fittest, in order to improve the quality of the population with each generation. Very often, the evaluation function is estimated via an external computer program assessing the energy performance of the building for example.
- Population: In order to preserve diversity and avoid the collapse of the population, a minimum number of individuals are necessary. The underlying concept of diversity is that individuals which might not currently perform very well might yet have some genetic material that could come in handy later in the optimization process. Maintaining a certain population size helps mixing individuals' genetic materials and it thus prevents the population from collapsing—which is, in the biological world, the equivalent to species extinction.
- Parent Selection Mechanism: This step of evolutionary algorithms has two roles: it favours fitter individuals, thus making sure the quality of the population improves over time while maintaining diversity by giving a small, but positive chance to less fit individuals to pass on their genes to the next

generation. Fitness-proportional selection is used in the simple GA; the more fit the individual, the more likely it will be chosen for the mating pool.

- Variation Operators: These operators are meant to create new individuals, and hence explore new possibilities. There are two main variation operators: mutation and recombination. Mutation is a mechanism that works on one parent and yields a slightly modified offspring. Recombination, on the other hand, works on two parents at least, and can yield more than one offspring. In the case of the simple GA, bit-flip mutation is applied and recombination is 1-point crossover, with two parents resulting in two offspring.

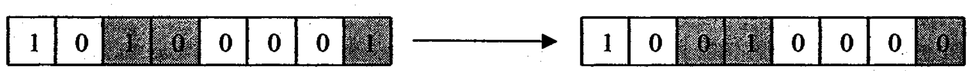


Figure 4 - Bit-flip Mutation

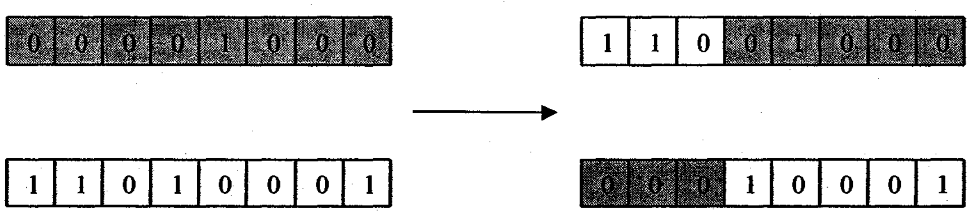


Figure 5 - One-point Crossover

- Survivor Selection Mechanism: In order to maintain a constant population size—which is not compulsory but very usual—a selection mechanism is applied to the population after it has undergone mutation and recombination. Survival individuals are chosen based on their quality and on their age. Age-based replacement or fitness-based replacement can be used. Elitism is also often used; this ensures that some of the fittest individuals be not discarded because of their age for example.

- Initialization: The initial population is generally randomly seeded. The only condition is that all individuals should satisfy the optimization problem constraints, i.e. they have to be feasible solutions.
- Termination Criterion: If the target objective is known, then the algorithm will stop once the error between the target objective and the fittest individual has reached a user-defined threshold. However, the target objective is not known in advance in most cases, and the termination condition should be one of the following (Eiben and Smith, 1998):
    - The maximum CPU time is reached;
    - The total number of fitness evaluations reaches a limit set by the user;
    - For a given period of time, the fitness of the population does not improve significantly;
    - The population diversity drops under a certain threshold.

The simple GA is only one simple implementation of GAs. There exist a lot of representations, using real or integer numbers, or even combinations of different types. Likewise, several methods for mutation, recombination, and selection mechanisms are available; however, they will not be presented here for the sake of simplifying the literature review. They are nonetheless very well documented, as in

Eiben and Smith's *Introduction to Evolutionary Computing* in particular (Eiben and Smith, 1998).

Other Algorithms Reviewed

Further to the PSO algorithm and the simple GA, an upgraded version of the PSO and a hybrid PSO-Hooke Jeeves (a direct-search method) algorithm was investigated. A gradient-based method, namely the Discrete Armijo Gradient Algorithm, was also reviewed in the said paper. This method approximates gradients using finite differences. The method works well with smooth functions but has difficulties in case of discontinuities in the objective function on which it works.

Performances of the Algorithms

All algorithms were tested on both a simple case and a detailed case. The simple case only counted four parameters (the building azimuth, the width of the east and west windows, and the shading device transmittance.) For the complex case, thirteen independent parameters were defined (the glazing-to-wall area ratio for the four walls; the depth of the overhangs, the set point for the shading devices for the west, east, and south façades; the room air temperature set points for night cooling in summer and winter; and the cooling supply air temperature.) The objective function for both cases was the annual energy consumption set as the sum of the heating, cooling, and lighting energy consumptions. The heating and cooling loads as well as the electricity required to light the building were computed with EnergyPlus. The study concluded on the following points:

- With the detailed model, the simplex algorithm failed far from the minimum;
- Both the GA and PSO algorithms performed well, with better results for the simple GA for equivalent numbers of generations;
- The best optimization results were obtained with the hybrid PSO-Hooke Jeeves algorithm though it required a greater number of simulations than the simple GA or non-hybrid PSO, and it failed far from the minimum in one case;
- The gradient-based method failed far from the optimal solution even for the simpler problem.

The following graph, from Wetter and Wright (2003), shows the performance of the algorithms studied. For each algorithm, the distance between the optimization results and the best optimization results achieved with all the algorithms is plotted against the number of simulations required to reach the near-optimal solution.

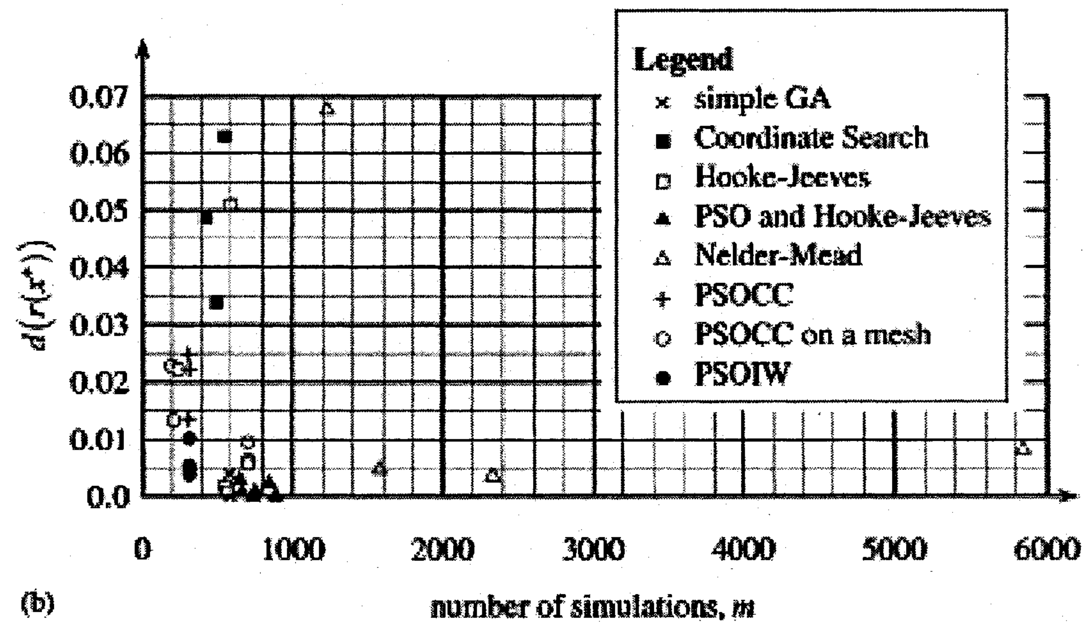


Figure 6 - Performance of Several Optimization Algorithms
From Wetter and Wright (2003) – Figure 2 b)

Some salient points of this study are:

- Setting up a hybrid algorithm using both a stochastic population-based algorithm and a direct-search algorithm is a good idea that benefits from both algorithms' assets. Indeed, in a first step, the population-based algorithm scans the whole search space and identifies the most promising region; then, the direct-search algorithm refines the search to identify the optimal result with a maximum accuracy;
- However, if one is ready to make a trade-off between accuracy and computation time, the simple GA is a good alternative since it converges more rapidly. If a high accuracy is required, the GA parameters could be changed once the promising region of the search space has been identified in order to refine the search. Likewise, and as the authors proposed, when the latter

region is identified, a second hybrid algorithm could be used to further the search;

- Gradient-based and direct-search algorithms are not appropriate for building optimization resorting to an external computer program to assess the fitness of individuals. This is mainly due to the discontinuity of the objective function with respect to some parameters. As a consequence, such algorithms fail poorly even on simple problems. However, a potential idea is to use stochastic population-based methods to identify regions of interest for the search. The function could be considered as rather smooth over small regions of the search space, thus enabling the use of direct-search functions, or even gradient-based functions in some cases, which could find the exact optimal solution over the regions they would scan.

2.4.2. Artificial Neural Networks

The last method presented here is Artificial Neural Networks (ANNs). Even though ANN techniques are not an optimization approach, they are often used in order to improve building energy management by modelling systems hard to model with traditional energy software. In that sense, it was included in this literature review. The different works leading to ANNs initiated in the late 1940s. ANNs as we know them nowadays were developed mostly in the 1980s[4]. They belong to the response surface approximation (RSA) algorithms. In a nutshell, ANNs are a simplified computer representation of the human brain. Different layers of neurons are given information input and process it to deliver an output. Several layers of neurons can

[4] General facts from www.wikipedia.org (*Neural Network* and *Artificial Neural Network* sections)

be used in series. ANNs are said to have the capacity to approximate any function if properly parameterized. ANNs are used for classification, pattern recognition, function approximation, and data processing. The underlying concept of these paradigms is that they are able to learn. Sets of data are used to train the algorithm, and then to validate it. There are scores of training functions and several software tools have been developed to help users set up ANNs; the Matlab ANN Toolbox is one of them, as we will see in the following chapters of this thesis.

More precisely, an ANN consists of a layer of input nodes, a layer of output nodes, and at least one hidden layer connecting the input and output layers. Each node, or neuron, of a given layer is linked to that of the following layer. Each hidden node works on the values it is given as inputs and delivers an output that can in turn be used as an input to the following layer.

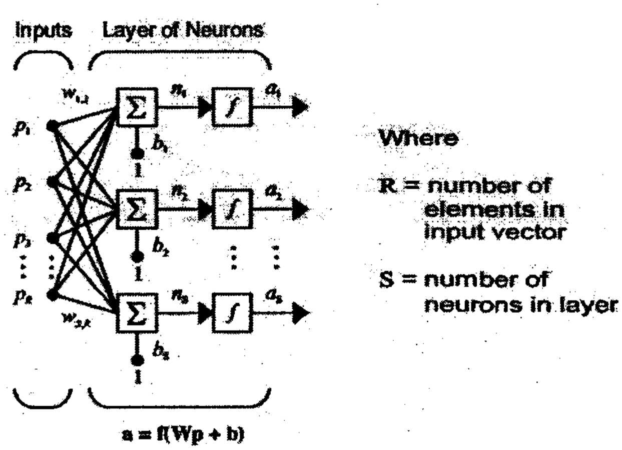


Figure 7 - Typical ANN Architecture
From the Neural Network Section, Matlab (2006)

The previous sketch represents a one-hidden layer ANN (Matlab, 2006). pi's refer to input parameters. A weight wi,j and a bias bj transform the value of pi before it is input to function f. The latter function produces an output, aj, which can in turn be fed to another layer of neurons. There are a many great deal of transfer functions f; the most commonly used are the Hard-Limit, Linear, and Log-Sigmoid transfer functions. Hidden layers can be added in series, and a two-layer network where the first layer is sigmoid and the second is linear is said to be potent enough to approximate any function with a finite number of discontinuities (Matlab, 2006).

The network is trained the following way:

- Inputs are presented to the network;
- Output values are computed and compared to the output values expected—whence the need for a database with output values corresponding to vectors of input parameters to train the network;
- Biases and weights are then updated in order to minimize the error between the expected output values and the values calculated by the network. Biases and weights can be updated after each input vector is presented to the network—i.e. incremental training—or after the whole set of inputs have been presented to the network—i.e. batch training. This step is repeated until the error value passes below a threshold defined by the user.
- Out of the training methods that can be used to optimize the weight and bias values, *backpropagation* is the one used most often. This is a gradient-descent algorithm which updates bias and weight values along the negative of the gradient of the function to be approximated.

In a nutshell, the following steps are necessary to construct an ANN to model a building:

- Create a set of training data by running building energy simulations with ESP-r in our case;
- Create the network object (define the number of neurons and layers);
- Train the network;
- Simulate the network response to new inputs to validate the network.

Several software packages have been developed for ANNs. The price of commercial packages can range from a couple of hundreds dollars for a single module—ANN-only, or ANN plus other optimization modules—to thousands of dollars. MATLAB, a tool widely recognized and used in the industry, recently developed a very user-friendly Neural Network Toolbox. User codes to set up and train ANNs are available as well, but this demands advanced programming skills, as we noticed before, and one of the objectives of this methodology is to make it accessible and easy to use to the utmost.

2.5. Building Simulation in Building Optimization

Most of the time, building optimization algorithms resort to external software to assess the performance of buildings or building systems. The author of this work chose to work with ESP-r. The Energy Simulation Program – research Version was initially developed in the 1970s. The project was initiated by Joe Clarke who developed a program to assess energy use in buildings as part of his doctoral research from 1974 to 1977. In the late 1980s, the Energy Systems Research Unit was created at Strathclyde University; one of the missions of this unit has been to keep on developing the program for British and European research projects. ESP-r now enables modelling for the assessment of acoustics, thermal comfort, and visual performance on top of energy usage. The software is equipped to model heat, air, moisture, and electrical flows. Further to its many useful modules such as the Sensitivity Analysis Module, work is under way to integrate ESP-r to Radiance, the reference tool to assess building lighting performance. Natural Resources Canada is now playing a major role in the development of ESP-r.

ESP-r is thus one of the most potent tools to model the performance of buildings and it is therefore suited for the purpose of this study. Few optimization studies used ESP-r to assess buildings' performance, mainly due to the complexity to automate the simulation process. For example, GenOpt can work with any building simulation engine providing it reads text input and it yields text output readable by GenOpt (Wetter, 2004). This is feasible, but this requires the user to program a code to transfer input information from the GenOpt text file to ESP-r model files in a first step, and to extract ESP-r results from the ESP-r RES module to a proper output text file readable by GenOpt. This will be one of the challenges of using ESP-r to assess building performance within optimization algorithms.

Information available from the ESRU website at http://www.esru.strath.ac.uk

2.6. Building Optimization

The different building optimization studies found in the literature could be classified under three categories: optimization of the design process; optimization of the three main elements of the building energy system (building structure, HVAC system, control strategies, and any combination of these); and ongoing optimization.

2.6.1. Optimization of the Design Process

Even though there is no optimization technique involved in this approach, it was judged to be relevant to this literature review because it is part of the current building practice and it aims at improving the design process; it was thus included for information purpose only. Optimization of the building process is a problem that touches more than one profession and discipline. As a matter of fact, many actors are involved in the design process, including architects, engineers (structural, mechanical, electrical), contractors, clients etc. Hence, the design process is made of many entwined links between the different actors and the different tasks to perform. A few optimization techniques relying on mathematical rationales have been developed. Choudhari et al. (2003) proposed a model which consists in dividing the design problem into subsystems hierarchically ordered and linked by mathematical functions. This approach relies on the individual optimization of each block superseded in turn by the optimization of the global process. Further to improving the building design, extensive work is carried out to make optimization technologies and tools accessible to designers whose field is not necessarily in relation with simulations or energy analysis, environmental impact assessment and so forth. Hobbs et al. (2003) documented the introduction of building energy tools within an architectural practice with a view to improve the performance of buildings designed by the practice. The paper highlights the importance to train designers—architects in this case—to use these tools adequately from the inception of the design process.

2.6.2. Optimization of the Building Energy System

A building energy system can be divided into three main systems: the structure of the building (building envelope mainly); the heating, ventilation, and air-conditioning (HVAC) system; and the control strategies (mainly control actions on the HVAC system, but also control of other elements such as solar panels, solar shading devices, etc.). The most natural approach consists in optimizing any of these elements individually and then integrating them once their optimal individual characteristics have been found. Nassif et al. (2003) worked on different algorithms to optimize the control set points of an HVAC system in their introductory work to online optimization of control strategies.

The shortcoming of optimizing one aspect of the building energy system only is that elements which were designed to perform as efficiently as possible can in fact perform very poorly as a consequence of an ill-conducted integration of the different elements constituting a building. A way to overcome this limitation is to consider the building in its entirety and to search for its optimal configuration based on some parameters and for a given objective function. The parameters under discussion should make sense with respect to the objective function studied. Most of the times, parameters are chosen based on the designer's expertise and on some general trends within the profession. However, some studies were carried out recently in an attempt to choose these parameters in a more objective manner. For example, Wang et al. (2003) presented a sensitivity analysis in finding the optimal shape of a green building. They investigated the influence of the building shape, orientation, window ratio, structural system, and insulation level. The objective functions were the life-cycle cost and life-cycle environmental impact; Pareto fronts were plotted in the performance space in order to assess the influence of each parameter on the buildings' performances. The authors noticed the influence of the window ratio: the higher the window ratio, the higher the life-cycle cost and life-cycle environmental impact. They also noted the strong linear relationship between the window ratio and the extreme life-cycle cost and life-cycle environmental impact values of the Pareto fronts. As far as the life-cycle cost is concerned, the smaller the building perimeter the better; on the other hand, best performances in terms of environmental impact were achieved for buildings with a longer edge on the south (in order to benefit from sun gains in winter, since the building was located in Montreal). Finally, the authors remarked that a higher insulation level did not necessarily result in more performing buildings.

As far as objective functions are concerned, annual energy consumption is often used as criterion (Wetter 2001 and Holst 2003) but some studies used exergy to account for the whole environmental impact of the building (Wang et al. 2003, Wang et al. 2005a, and Wang et al. 2005b). Wright and Farmani (2001) studied the simultaneous optimization of the building structure, HVAC system, and control strategies with respect to the operating energy cost of the HVAC system. Wright and Loosemore

(2001) carried out a multi-criterion optimization of a building design and control options. They used parameters reflecting the three energy sub-systems: characteristics of the envelope, dimensions of the HVAC system, and set-point control temperatures. Wang et al. (2003) proposed the optimization of a green building envelope design based on the measure of the building exergy consumption.

2.6.3. Ongoing Optimization

The last trend in building optimization deals with continuously evolving features of the system so that it may adapt to continuously evolving patterns such as weather conditions or occupancy. This is ongoing optimization. Different methods were proposed, such as ANNs, Fuzzy Neural Networks, rule-based and method-based techniques. Yang et al. (2005) investigated different ways to train ANNs for the prediction of the energy consumption of an HVAC system. Yu and van Paassen (2003) proposed the use of fuzzy neural networks to detect malfunctions of an HVAC system; according to their study, malfunctioning and ill-adapted HVAC systems can actually result in a 30% increase in the energy consumption of buildings in North America. Madhavi et al. (2001) compared a model-based and a rule-based approach within the frame of so-called self-aware buildings—i.e. buildings adapting to certain changing conditions. The study concluded the use of a hybrid method combining the assets of both approaches. The conclusion remarks mentioned another possible approach, namely compartmentalization, whose underlying concept is to first treat the problem in a rough manner and then, to refine simulations for complex zones only. Nassif et al. (2003) proposed an online optimization of supervisory control in which a

GA was coupled with a mathematical model to decide on the control strategy to follow in order to minimize the system energy consumption. Finally, Coffey et al. (2006) wrote an interesting summary of model-based control in responsive building systems.

2.7. Summary

2.7.1. The Limits of Building Optimization

One of the salient facts of this review is that optimization algorithms very often rely on an external energy program to estimate how well candidate buildings perform in whole-building optimization. Depending on the desired level of accuracy, using an external energy program can be very time consuming. There exist different ways to assess a building energy consumption ranging from assessing the energy demand of a building for some typical design days in the year (Wright and Farmani 2001) to a complete yearly assessment. Furthermore, computational time is highly dependent on the level of accuracy desired, and for example, assessing the global energy demand of a building can be achieved in a couple of minutes whereas detailed simulations used for the assessment of visual comfort can take up to one day depending on the period simulated. Another issue lies in how hard it is to modify the building model in order to simulate myriads of cases necessary to the exploration of the search space to find a near-optimal solution.

As mentioned earlier, genetic algorithms are robust at solving any type of simulation-based building optimization problems, providing the GA is parameterized correctly.

Therefore, they have been widely used and a number of studies have been carried out to investigate the influence of the algorithm parameters on the results and their limitations in solving such problems (cf. (Wetter and Wright 2003) presented in the first section of the literature review). Wright and Alajmi (2005) studied the robustness of GAs in solving unconstrained optimization problems. The influence of the algorithm parameters were tested by using GAs with different parameters (population sizes (5, 15, and 30), crossover rates (0.7 and 1.0) and mutation rates (0.01 and 0.02)). Even though no major differences were found between the results produced by the algorithms, the authors remarked that statistically, GAs with small population sizes (5 and 15) and high crossover (100%) and mutation (2%) rates performed better. Near-optimal solutions for the problem being solved were found with a competitive number of simulations (300).

2.7.2. Addressing the Shortcomings of GA

The main limitations of GAs lie in the number of simulations required for the evolution process: increasing the level of accuracy of the simulations results in an increasing computational time. Optimization objectives are most of the time the energy consumption or the running cost of the system, with a few exceptions using environmental impact. Optimizing for these aspects only can be competing with occupants' comfort—such as thermal comfort and visual comfort. It is theoretically possible to add these aspects to the objective function and thus find the best trade-off to simultaneously optimize energy use, thermal comfort, and visual comfort. When significant levels of details are required the evolution process can be very time consuming and possibly fail due to the high number of evaluations required by GAs.

To overcome this shortcoming, this works sets out to develop an ANN model of the building to mimic the building being studied. Using the optimization performance of GAs in conflation with rapid assessments obtained from ANNs, designers can get very close to the optimal solution in a fairly reasonable time. This approach has not been tested extensively, but it has some potential. Still, it is quite limited and not easily applicable by designers for the following reasons:

- First, such an approach requires a substantial amount of data for the building, which does not reflect the real conditions under which designers operate in the early phase of a project;
- Second, an ANN is built to mimic the response of a building with respect to a pre-defined set of parameters whose allowable variation ranges are pre-defined as well. This implies that in the event of any change in the building usage or in the environment of the building, the ANN model will not reflect the actual building response anymore;
- Last but not least, creating the database to train and test the ANN is a very tedious and prohibitive process which could not be applicable in real situations such as architect practices and the like.

This research project proposes to address the above issues, and first and foremost, to come up with a methodology as user-friendly and applicable as possible for designers.

CHAPTER 3

3. BUILDING OPTIMIZATION METHOD BASED ON GA AND ANN

Based on the remarks and conclusions drawn from the review of building optimization and building energy management, the author proposes to investigate methods to optimize buildings. The very idea of gathering these methods into a methodology usable by designers begs the following question: For whom should this methodology be developed? At what stage of the design process should it be applicable? What would be the best trade-off between simplicity, flexibility, and accuracy? What qualities of the building does one seek to improve, and what are the relevant study parameters?

This chapter presents the first sketch of the proposed methodology and the reasoning it stems from by analysing the different steps it is made of. The following chapter will present a simple study case to test the general concept.

3.1. Sketch of the Method

The goal is to optimize a building based on some parameters and with an objective function encompassing energy demand, thermal and visual comfort. The sequence is fairly simple and consists of the following steps:

- Choose a building to optimize;
- Define the objective function;

- Define study parameters and their allowable ranges;
- Choose a cluster of cases to thoroughly represent the whole search space;
- Simulate all the cases to create a database of outputs corresponding to input vectors;
- Set up an ANN model of the building; train it and validate it with the database created in the previous step;
- Set up a GA and use the ANN to estimate individuals' fitness.

3.2. The Methodology in Detail

3.2.1. Study Parameters

Two different kinds of studies can be carried out depending on whether one tries to assess which are the most important parameters or aspects of a system—that is a sensitivity analysis, or whether one wants to investigate the impact of some specific design parameters on the system. The methodology proposed in this work bears in mind that it should assist designers in their decision making with respect to some design parameters for which there exist some constraints. Hence, the study parameters for the optimization analysis are usually known in advance, and one seeks to determine their most promising values with respect to the desired objective function.

Allowable ranges are defined for each parameter; they are determined based on regulations in effect, such as building codes or other limiting factors applying to the building under discussion.

3.2.2. Objective Function

The objective function represents the quality of the building the designer wishes to achieve. Its complexity can thus vary greatly depending on whether it is made of one element only (e.g. minimizing the energy consumption of the building) or of a combination of various aspects of the building (e.g. minimizing the energy consumption and environmental impact of the building while optimizing occupants' thermal and visual comfort). The complexity of the objective function lies in the fact that some objectives can be competing. For example, increasing the glazing area of the building in order to reduce the lighting energy consumption can result in increased heating and cooling loads and might not necessarily be beneficial to the building occupants' visual comfort. It is consequently very important to have powerful tools to one's disposal to estimate accurately each element of the objective function.

In the light of this last statement, one of the main issues of building optimization is the complexity of the objective function and therefore, what tools to use to assess it. As discussed in the literature review, several methods can be used, ranging from simple equations to external software. The work proposed here will use ESP-r to get accurate estimates for several aspects of the building: energy, thermal comfort, and visual comfort. Since Genetic Algorithm will be used to search for the near-optimal solution to the problem, an extensive number of computations will be required. To alleviate the computational burden, a cluster of cases representing the search space will be simulated with the building simulation program and used to train an ANN to approximate the building simulation model.

3.2.3. Design of Experiments

Study parameters' allowable ranges constitute a design space on which the optimization algorithm will work. The objective function will not be determined by using an external program but rather via an ANN model of the building for the reasons previously established. ANN models are trained for a given search space, and they require finite databases to that purpose. The main challenge is thus to choose a limited number of sample cases to constitute the database and still represent the whole search space thoroughly; this step is called design of experiments.

One of the most common methods encountered to address the above issue is referred to as the Latin Hypercube Sampling (LHS) method. The underlying concept of this method is pretty simple: let us consider two design parameters. The consequent search space could be represented by a square. M intervals can be defined for each variable, with the requirement that the number of intervals (M) be equal for both variables. A so-called Latin square corresponds to a square in which there is only sample per column and per row, as shown on figure 9. Sample points can also be chosen simultaneously so that the whole search space would be sampled in an equally-probable fashion, as shown on figure 8.

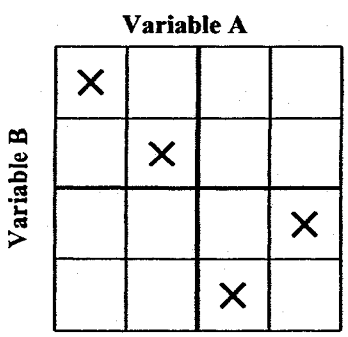


Figure 9 - Latin Hypercube Sampling

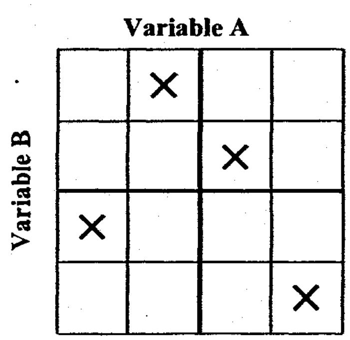


Figure 8 - Orthogonal Sampling

LHS is a technique that was first used for statistics. Several studies have concluded that for a study based on N parameters, a number M greater than twice the number of parameters is sufficient to correctly sample the search space for uncertainty and sensitivity analysis (Mackay 1988, and Yeh and Tung 1993). Fewer samples could result in a loose representation of the search space and too many more samples would result in onerous computations.

Carrying out a sensitivity analysis also enables to search for those parameters that have a greater influence on the objective function. Once the said parameters are identified, the search space for these parameters can be sampled in a finer fashion. Likewise, the search space can be sampled in a coarser way for parameters which influence less the objective function.

3.2.4. Simulations

Simulation is one of the key steps of this methodology. Indeed, any miscalculation, any mistake in the files describing the building model would result in an erroneous database, which would in turn engender an ill-adapted ANN, finally leading to a final near-optimal result that could be far from the real one. The validity of the building simulation model is also of the essence. Examples used further in this study were validated by comparing ESP-r predictions with measured data as will be shown in chapter 4. Consequently, this step needs extra care and attention. It is very important that all the simulations be run under the same conditions, but for the changing parameters—that is, the study parameters. Likewise, all parameter values should be the ones defined as per the design of experiments so that the search space is sampled effectively. These remarks might seem trivial, but when it comes to dealing with a significant number of files, mistakes can easily occur, and any rule breaking would compromise the success of the optimization search. Thus, this raises the question of the significance of manual simulations and file-handling. This issue will be addressed in the conclusion remarks of the next chapter.

3.2.5. Setting up the ANN

As we previously said, calling ESP-r to assess the fitness of each individual generated for the optimization search would imply heavy computations and would not be feasible in certain cases due to time constraints and computer resources. To overcome this limitation, an ANN model of the building will be used. Once properly trained, the ANN will give a quick and fairly accurate estimate of the function it was trained for. In the event of population-based optimization, which requires a lot of function estimations, ANNs look very promising.

3.2.6. Optimization Search with the Genetic Algorithm

A detailed description of the genetic algorithm was given in the previous chapter. In the case of building optimization, the great variety of parameters, which can be continuous, discontinuous, or Boolean—though the latter type is quite rare, makes representation, mutation, and crossover delicate operations. More details on these operations will be given in the next chapter. As we previously mentioned, the fitness of individuals will be assessed by the ANN model to approximate the building response.

Like for ANNs, several tools were developed for optimization algorithms and more specifically for genetic algorithms. However, user codes remained widely used because they are much easier to write than codes for ANNs, for example. MATLAB now has a General Algorithm and Direct Search Toolbox, which makes the software very interesting inasmuch as it has modules accommodating both GAs and ANNs. Further to MATLAB and other commercial programs, Microsoft's Excel also comprises a GA facility. Last but not least, scores of source codes in C/C++, Java, and Fortran can be found on the Internet. Once again, this begs the question of how much knowledge designers need to have in programming. GA might not be very hard to program; however, the choice of the algorithm's parameters and genetic operators (mutation, reproduction, and selection) is crucial to the success of the optimization search. Besides, such codes might not be flexible enough and consequently be hard to change for designers without advanced programming skills. Finally, the use of GA for building optimization is quite well documented and the conclusions of these various studies are quite easy to implement with commercial tools such as MATLAB, for example.

3.3. Summary

This methodology relies on methods that have been extensively used in building optimization and other fields. However, the use of ANNs in conflation with GAs has rarely been documented (Mengistu 2005, Chow et al. 2002, and Zhou 2007), even though it seems to be a very promising technique. Bearing in mind the limitations of the proposed technology, this works proposes to confront it to a small-scale case study in order to have more insights on the potential and shortcoming of each step of the method.

CHAPTER 4

4. TESTING THE METHOD

SMALL-CASE EXAMPLE

4.1. Choosing the Model to Test the Methodology

In order to test the efficacy and the applicability of the proposed methodology, a first study case was investigated. There is no real need for a complex case at this stage since the purpose was to test the methodology quickly in order to assess its strengths and weaknesses, thus getting better insights into the problem, and giving rise to a stronger methodology.

The building used for the preliminary validation stage was chosen from the database of exemplars available from within the ESP-r program. The ESP-r model is a portion of an office building located in Ottawa, Ontario.

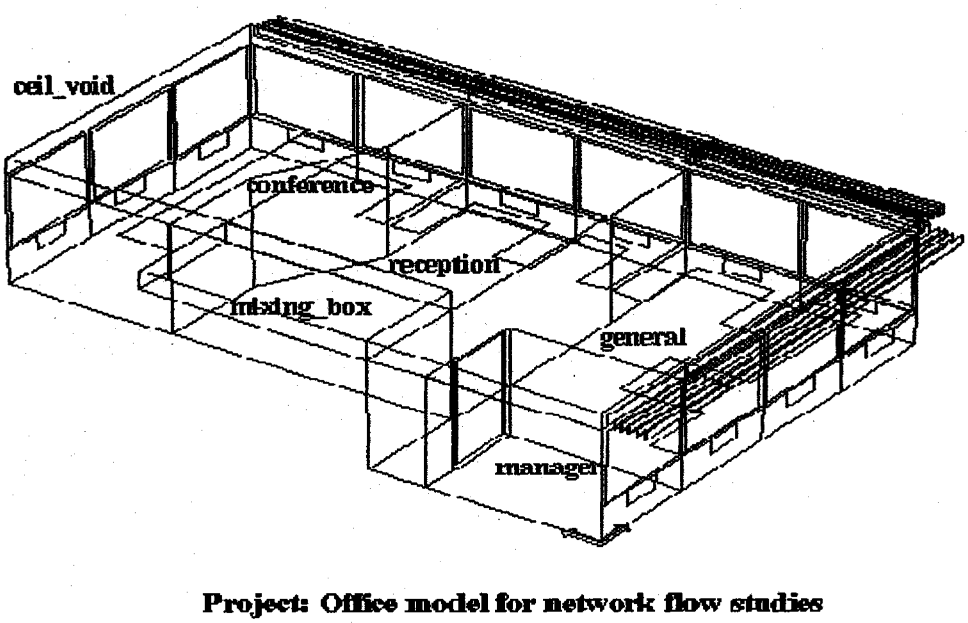


Figure 10 - ESP-r Model of the Office

As shown in this figure, the office is made up of four main zones; they represent actual rooms, namely:

- Manager, i.e. the manager's office;
- General, i.e. an open-space office;
- Reception;
- And Conference.

Further to these four zones, a zone 'ceil_void' represents the ceiling, and an extra fictitious zone 'mixing_box' is used to define a part of the HVAC operations.

The exemplar is documented with the results of basic simulations carried out from April 8th to April 15th. Those results showed that cooling was required for this office space for outside temperatures greater than 6°C.

General facts on the building are summarized in the following table. The load schedule is the one initially provided with the example and is supposed to account for the variation of loads depending on working hours and on room usage.

Geometry of the building	250 m² 3 m high
Geometry of the windows	2.8 m wide 1.9 m high
U value of the windows	2.81W/m².K
Internal loads	8 W/m² for lights 5 to 10W/m² for equipment depending on the rooms. From 0W to 500 W (latent) and 300W (sensible) depending on the time and on the room
Outside Temperature set points to activate the vents	Lower bound: 13°C Upper bound: 28°C

Table 1 - General Facts on the Original Building

The office has several windows. There are five in the Conference room; two in the Reception area; five in the General room; and one in the Manager room; which were probably installed for visual comfort concern even though they turned out to greatly influence the heating and cooling loads of the building. Vents were installed under each window. Preliminary studies recommend the use of a hybrid system based on mechanical ventilation assisted by natural ventilation through the vents located under the windows.

Thus this case clearly is very suitable to our purpose. The first idea is to study the impact of the window dimensions, the louver inclination angle, and the temperature set points to activate the vents on the building energy consumption and on its occupants' thermal comfort. This is consequently a multi-objective optimization problem, whose objectives are:

- Minimizing the annual heating load for each occupied zone;
- Minimizing the annual cooling load for each occupied zone;
- Minimizing the annual lighting energy consumption for each occupied zone;
- And maximizing the cumulative frequency for which a maximum of 20% of the occupants of the zone are dissatisfied, for each occupied zone, during occupied hours.

Each of these qualities was assessed with ESP-r for each room and for each of the five simulation seasons. These five simulation seasons are early winter (November and December), spring, summer, autumn, and late winter (January to March). Those values were then combined to assess the quality of each candidate building during the optimization search. The optimization objective is a weighted sum of all individual objectives and it takes the following form:

$$F_{obj}(X) = Min\left(\begin{array}{l} C_1\left(\dfrac{\sum_{i=1}^{n} HL_i \times NDays_i}{TotalNDays}\right) + C_2\left(\dfrac{\sum_{i=1}^{n} CL_i \times NDays_i}{TotalNDays}\right) + C_3\left(\dfrac{\sum_{i=1}^{n} LE_i \times NDays_i}{TotalNDays}\right) \\ + C_4\left(\dfrac{\sum_{i=1}^{n}(1 - TC_{Manager\,i}) \times NDays_i}{TotalNDays}\right) + C_5\left(\dfrac{\sum_{i=1}^{n}(1 - TC_{General\,i}) \times NDays_i}{TotalNDays}\right) \\ + C_6\left(\dfrac{\sum_{i=1}^{n}(1 - TC_{Reception\,i}) \times NDays_i}{TotalNDays}\right) + C_7\left(\dfrac{\sum_{i=1}^{n}(1 - TC_{Conference\,i}) \times NDays_i}{TotalNDays}\right) \end{array}\right)$$

Equation 1 - Objective Function

Where HL_i, is the heating load of the building in kWhr. CL_i is the cooling load for the building in kWhr. To truly assess the energy demand of the building, these two metrics should be weighted to account for the efficiency and energy consumption of the heating and cooling systems respectively. However, since these weighting factors would be the same for all cases for the heating load and cooling load respectively, the author disregarded them. LE_i is the lighting energy demand in kWhr of electricity. Subscript i refers to simulation period i. The year is divided into the five simulation periods previously mentioned—whence n=5. $NDays_i$ is the number of days in period i. *TotalNDays* corresponds to the total number of days in the year under consideration. X is the vector of design parameters. TC, the parameter used to assess the performance of a given room in terms of thermal comfort, is the ratio of the time for which the indoor air quality is acceptable—i.e. when PPD, the percentage of dissatisfied people, is less than 20%—out of the total time of occupancy for the room under consideration. ESP-r asks for the clothing level and metabolic rate to assess thermal comfort. The clothing level chosen was 1.0 clo in winter, 0.5 clo in summer, and 0.75 clo in fall and spring, which corresponds to typical clothing level values. As far as the metabolic rate is concerned, the value taken was 90 W/m^2, which corresponds to typical clerical activities. To have the desired optimization objective, the designer should prescribe weights C_1 to C_2 are in $kWhr^{-1}$, C_3 in kWh of electricity $^{-1}$, and C_4 to C_7 are dimensionless since our thermal comfort index is dimensionless. Weights are to the discretion of the user: if the user wishes to favour a certain aspect of the objective function, such as thermal comfort for example, then a greater weight will be given for the said aspect to drive the optimization search in the desired direction. The weights taken for the optimization were 10,000 $kWhr^{-1}$ for C_1 and 500 $kWhr^{-1}$ for C_2. These two values are in the order of magnitude of the heating load and cooling load calculated for each season for the office section. The lighting energy was disregarded in the optimization search as explained further in this section. As far as the other weights are concerned, a value of 1 was taken for each of them in order to give to thermal comfort equal importance over the optimization search.

4.2. Identifying the Study Parameters

The study parameters are the ones that most greatly influence the objective function under consideration, that is, the energy consumption and occupants' comfort, in our case. By considering the general structure of the building, the building envelope and first hand observations, three items are assumed to have a significant impact on the energy consumption of the building and are chosen to carry out the optimization.

Those parameters are the window sizes, the inclination of the external shading devices and the outside temperature set points to activate the vents and thus, use natural ventilation. These selected parameters give rise to ten design variables:

- The width and height of the windows for the south, east and north façades (resulting in six parameters);
- The inclination of the shading devices on the south and east façades (resulting in two parameters);
- And the lower and upper outside temperature set points to activate—open or close—the vents (resulting in two parameters).

4.3. Determining the Search Space

This works tries to reflect reality to the utmost; thus, for each parameter, the range of allowable values was defined in order to represent real conditions as faithfully as possible. There are many limiting factors in the design of buildings; usually, allowable ranges are determined based on designers' experience, in consultation with building codes, recommendations, design handbooks, rules of thumb, or any other appropriate limit inherent to the building's location.

4.3.1. Dimensions of the Windows

As far as the windows are concerned, the geometry of the building clearly shows that the glazing area could not be increased. On the other hand, it could be decreased providing that the total glazing area, exclusive of skylights, is not less than 10% (Ontario Building Code 1997) of the floor area of the room in which it is located. The limiting factor here is 'Reception' which has a total glazing area of 17.5 % of the floor area of the room. For aesthetic purposes, it was decided that all windows should have the same dimensions, as in the original design; this sets the lower range for the windows to be 85.0 % of their current value.

4.3.2. Inclination of the Louvers

The inclination angle of the louvers is defined from the horizontal plane corresponding to the roof. A 0° angle corresponds to the horizontal position and the inclination of the louvers can vary from 20° to 160° with a 10-degree step[5].

4.3.3. Outside Air Temperature Lower and Upper Bounds to Actuate the Vents

The lower and upper bounds for the outside temperature can vary from 12°C to 28°C (Allard and Santamouris 1998). Hence, lower temperature set points between 10°C and 15°C, and upper temperature set points from 23°C to 28°C were investigated. Extreme temperature set points seldom used for natural ventilation were considered; however, if using such temperatures does not lead to satisfactory conditions for the

[5] In the literature, values usually vary from 0° to 90°, but the scope of these studies is to optimize the luminance level of the room. Few studies consider angles whose values goes beyond 135°.

occupants of the building, they will be automatically disregarded by the optimization process which seeks to reach the best trade-off between energy consumption and occupants' thermal comfort.

In summary the following table shows the ranges for the selected variables:

Variable	Name	Nominal Value	Lower Value	Upper Value	Unit
Width of windows on the south façade	WinSW	2.8	2.380	2.8	[m]
Height of windows on the south façade	WinSH	1.9	1.615	1.9	[m]
Width of windows on the north façade	WinNW	2.8	2.380	2.8	[m]
Height of windows on the north façade]	WinNH	1.9	1.6151	1.9	[m]
Width of windows on the east façade	WinEW	2.8	2.380	2.8	[m]
Height of windows on the east façade	WinEH	1.9	1.615	1.9	[m]
Louver angle on the south façade	AngS	90	20	160	[deg]
Louver angle on the east façade	AngE	90	20	160	[deg]
Lower bound for the outside temperature set point for the control of ventilation	TOsetL	13	10	15	[°C]
Upper bound for the outside temperature set point for the control of ventilation	TOsetU	28	23	28	[°C]

Table 2 – Allowable Ranges for the Selected Parameters

4.4. Design of Experiments

One of the goals of the present work is to develop a simple approximation model, fast to compute and accurate enough over a certain design space, to make up for time-consuming building simulation programs. Building approximations involve choosing an experimental design to sample the region of interest and then construct the approximation model. The present building model consists of ten parameters, assuming each of which can take on ten different values, one would need 10^{10} runs for a complete model evaluation, which is totally inappropriate to designers' use. Thus, the design of experiments is a necessary step to minimize the number of runs required and to select a few but representative sample runs within the design space.

With 10 parameters, twice as many samples would be enough to sample the search space, according to MacKay (1988). However, due to the complexity of the objective function, 50 sets of samples were selected to represent the design space for training and 20 sets of data for testing the ANN. The sample cases were determined using the Latin Hypercube Sampling (LHS) method presented in the previous section. Sampling points are listed in Appendix A.

4.5. Running the Simulations

The simulations were performed with the ESP-r energy simulation tool. The software enables the analysis of energy and mass flows within the built environment. Thermal simulations can be run in conflation with nodal network mass flow simulations. The selected building has four rooms, each represented by a thermal zone and a mass flow node, plus one thermal zone representing the plenum ('ceil_void'), and another fictitious thermal zone representing a mixing box ('mixing_box'). The boundary conditions are set to 'exterior' for exterior walls; 'adiabatic' for the rear walls of the room; and 'similar' for the floor and the upper surface of the ceiling zone. A mass flow network represents the airflow between different interior zones and with the exterior environment.

The simulations were run for a whole year which was divided into 5 simulation periods:

- Early winter (from January 1st until April 3rd);
- Spring (from April 4th until May 8th);
- Summer (from May 9th until August 28th);
- Autumn (from August 29th until October 16th);
- And late winter (from October 17th until December 31st).

These typical seasons were determined through the automated climate module of ESP-r. Three control files—for winter; spring and autumn; and summer—define different temperature set points for weekday and weekend building occupancy times. Each simulation period was preceded by a 21-day pre-simulation. Typically, a whole-year simulation took approximately 1.25 hours (CPU time).

With ESP-r, a building model is mainly described by:

- Some geometry files which comprise information on the structure of the building. Each file contains information on one specific zone;
- Some files which describe objects casting shadow on the building—such as louvers, trees, or even surrounding buildings. Thermal and mass-flow calculations are not performed for such shading objects, but their influence on

the solar process is taken into account in calculations of the building zones. As for the previous case, each file contains information on one specific zone;

- An operation file which defines building operations, that is, mainly, HVAC strategies for different seasons with, amongst others, details on how and under what conditions to activate the vents. This file is unique and contains the information for all the zones and all the seasons of the year.

Prior to running a simulation for a building case, all these files have to be changed according to the input vectors given by the design of experiments. In the case of this preliminary study, all the files were changed manually, which proved to be a very long and tedious process, not to mention errors occurring occasionally. This will be further discussed in the conclusion remarks of this chapter.

Running the fifty simulations took three weeks[6] with a Pentium II 733 MHz computer.

4.6. Constructing the Artificial Neural Network

Once the database of simulation results was constructed, an artificial neural network ANN was set up and trained in order to approximate the building's response. After going through the database of results, some of them clearly looked erroneous, and were consequently discarded from the database in order to avoid inducing mistakes in

[6] The author ran simulations over a period of three working weeks; in other words, simulations did not take three CPU-time weeks.

the training of the ANN. 38 cases were used, 30 for training, and 8 for testing the ANN. Here follow some specifics on the ANN:

- Ten input nodes, representing the study parameters defined in Table 1;
- Seven output nodes, representing each element of the objective function defined earlier;
- 21 nodes in the hidden layer. The number of nodes was obtained by trial and error;
- The ANN was trained using a *backpropagation* method, using a user code developed by Dr. Mengitu with whom the author collaborated on this example;
- Training the ANN took approximately three hours with a Pentium IV 2.2 GHz computer.

Once the ANN was trained, a couple of cases were simulated with the ANN and compared with the simulation results given by ESP-r. These cases were obviously not included into the pool of data used to train the ANN. The average error was found to be less than 5% for all the outputs but for the lighting energy consumption, as shown on the following figures (Fig. 11-15).

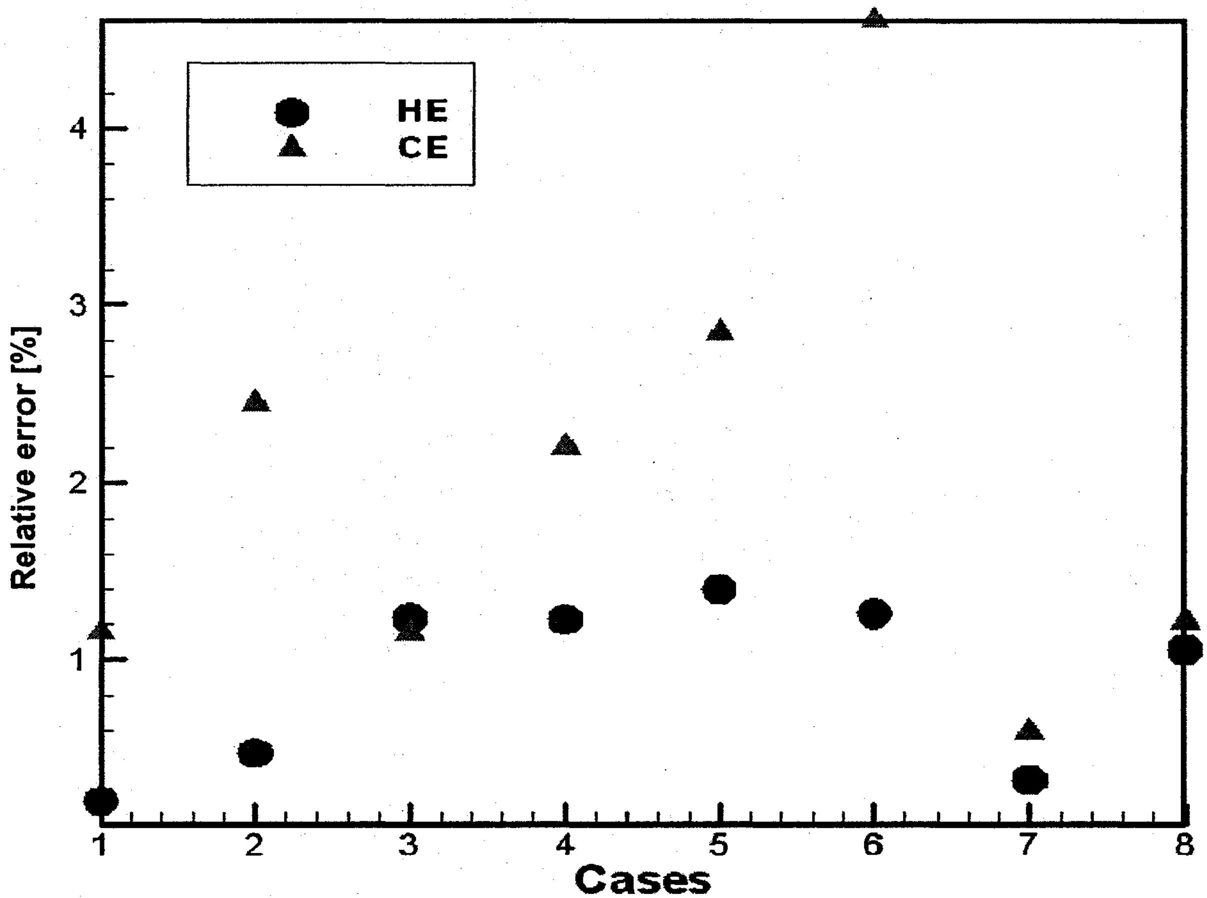


Figure 11 - Relative Error for the Heating (HE) and Cooling (CE) Loads
ANN vs BS

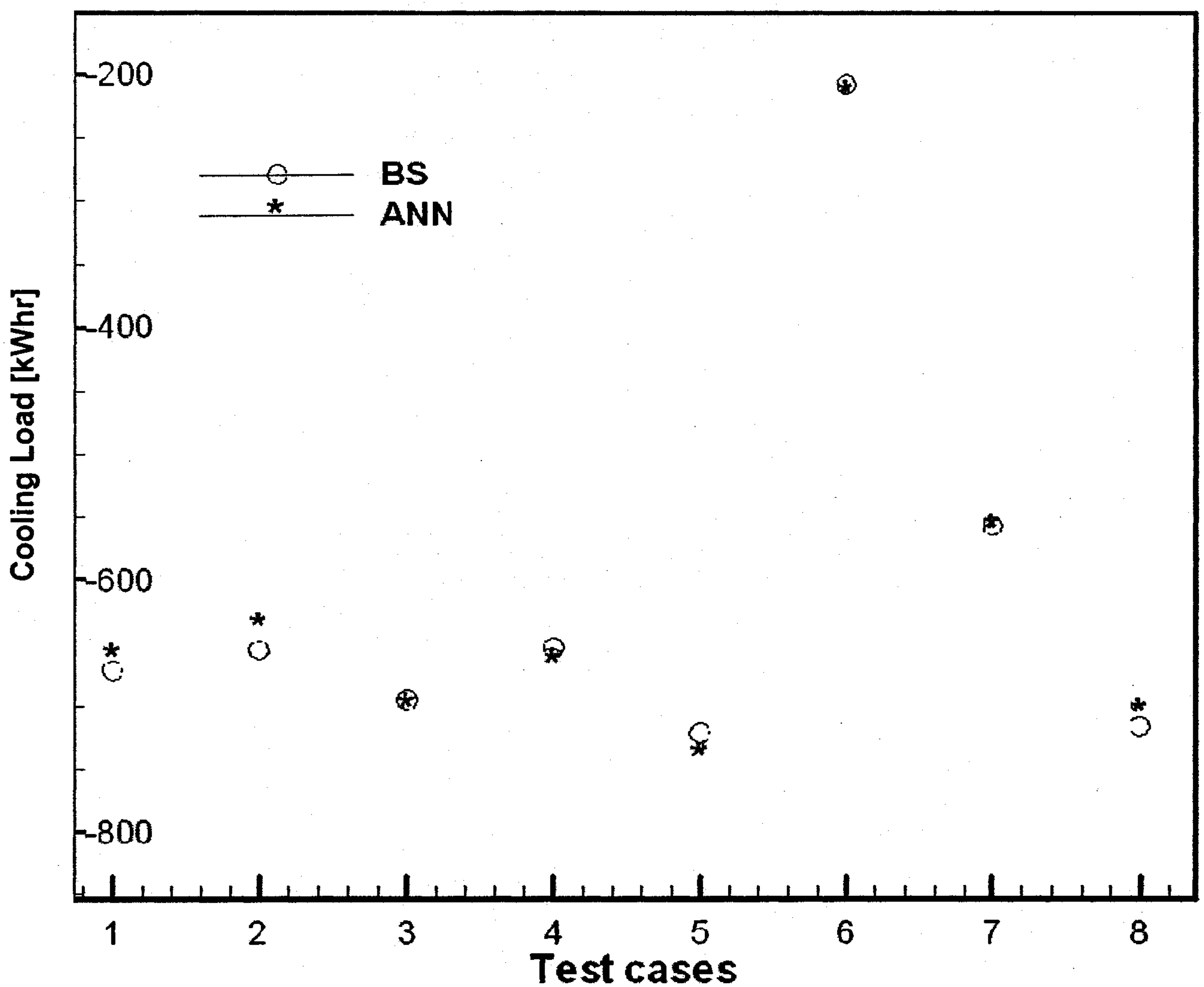


Figure 12 - Validation of the ANN - ANN vs BS
Average Annual Cooling Load [kWhr]

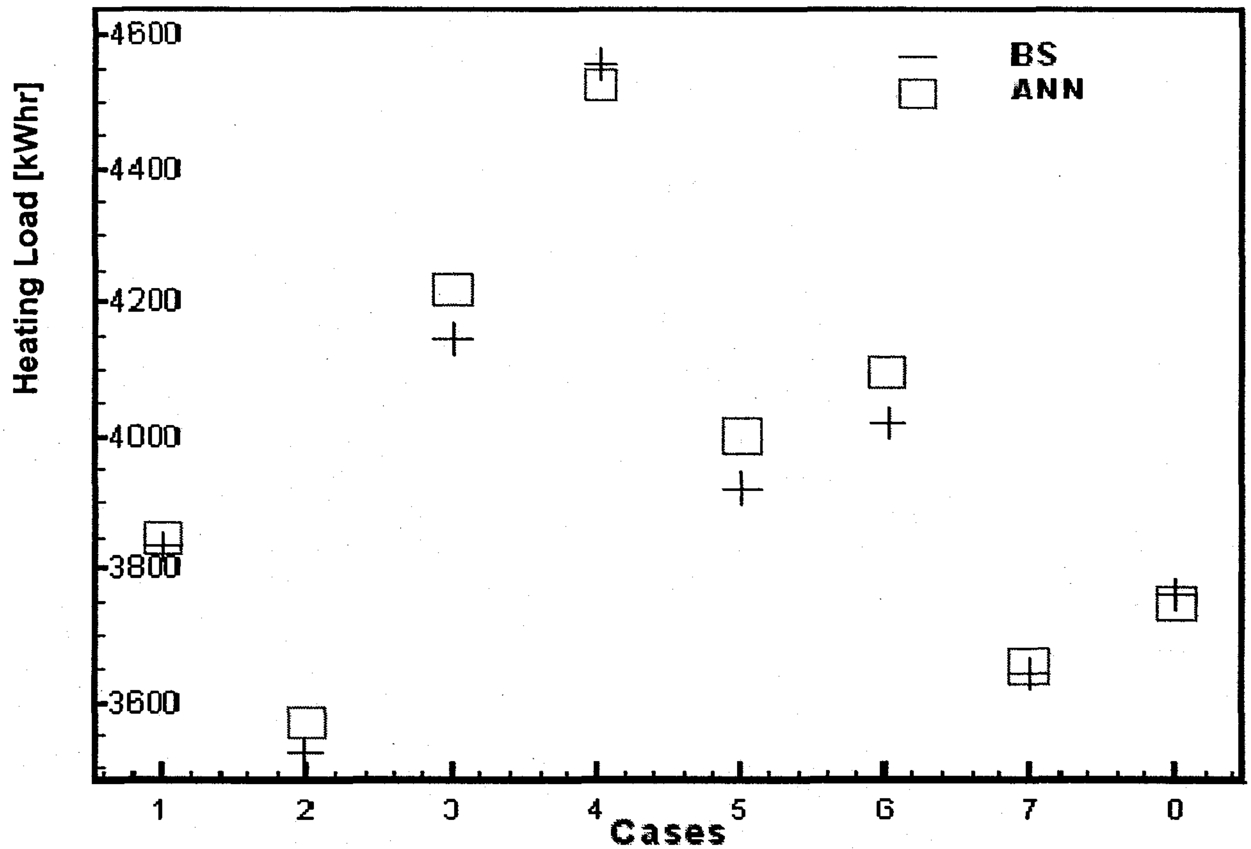


Figure 13 - Validation of the ANN - ANN vs BS Results
Average Annual Heating Load [kWhr]

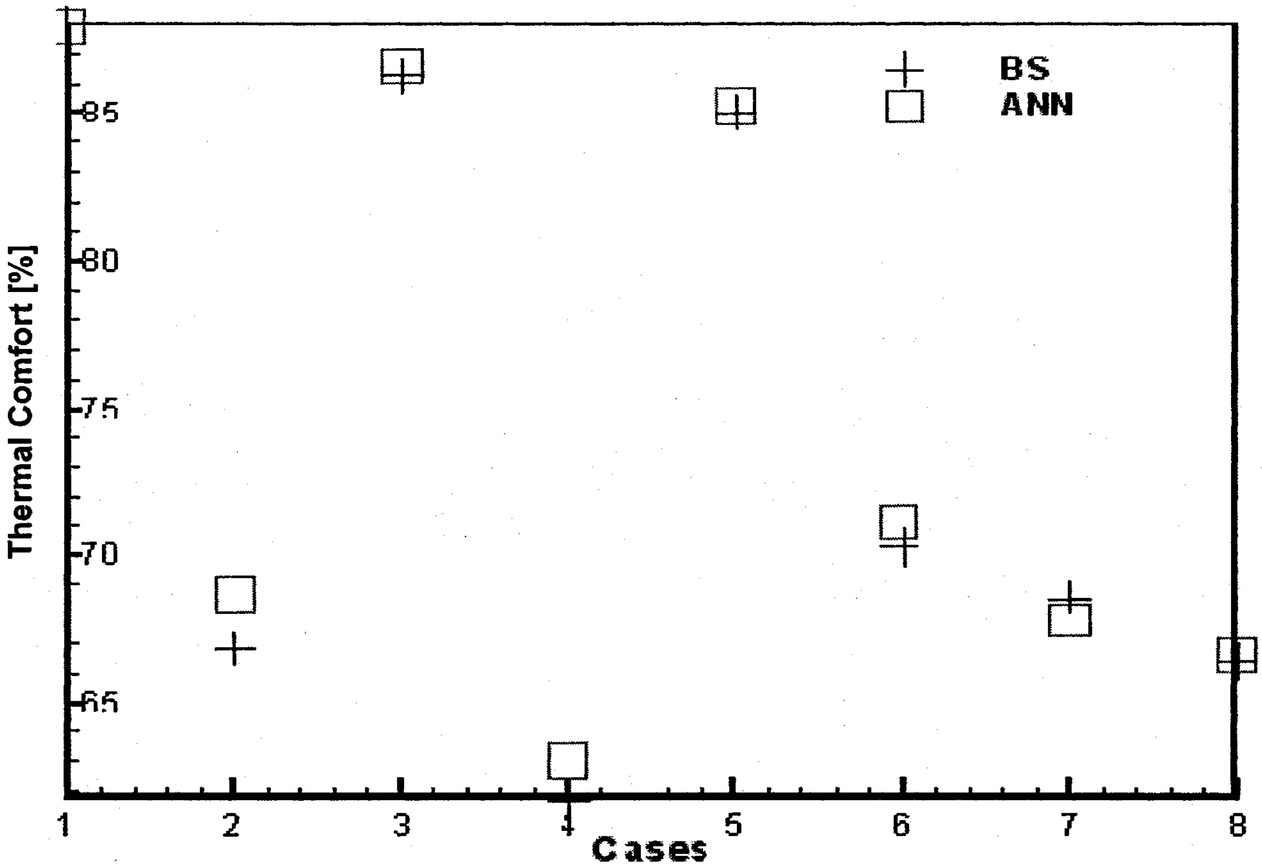


Figure 14 - Validation of the ANN - ANN vs BS Results
Average Annual Thermal Comfort Index for the Reception

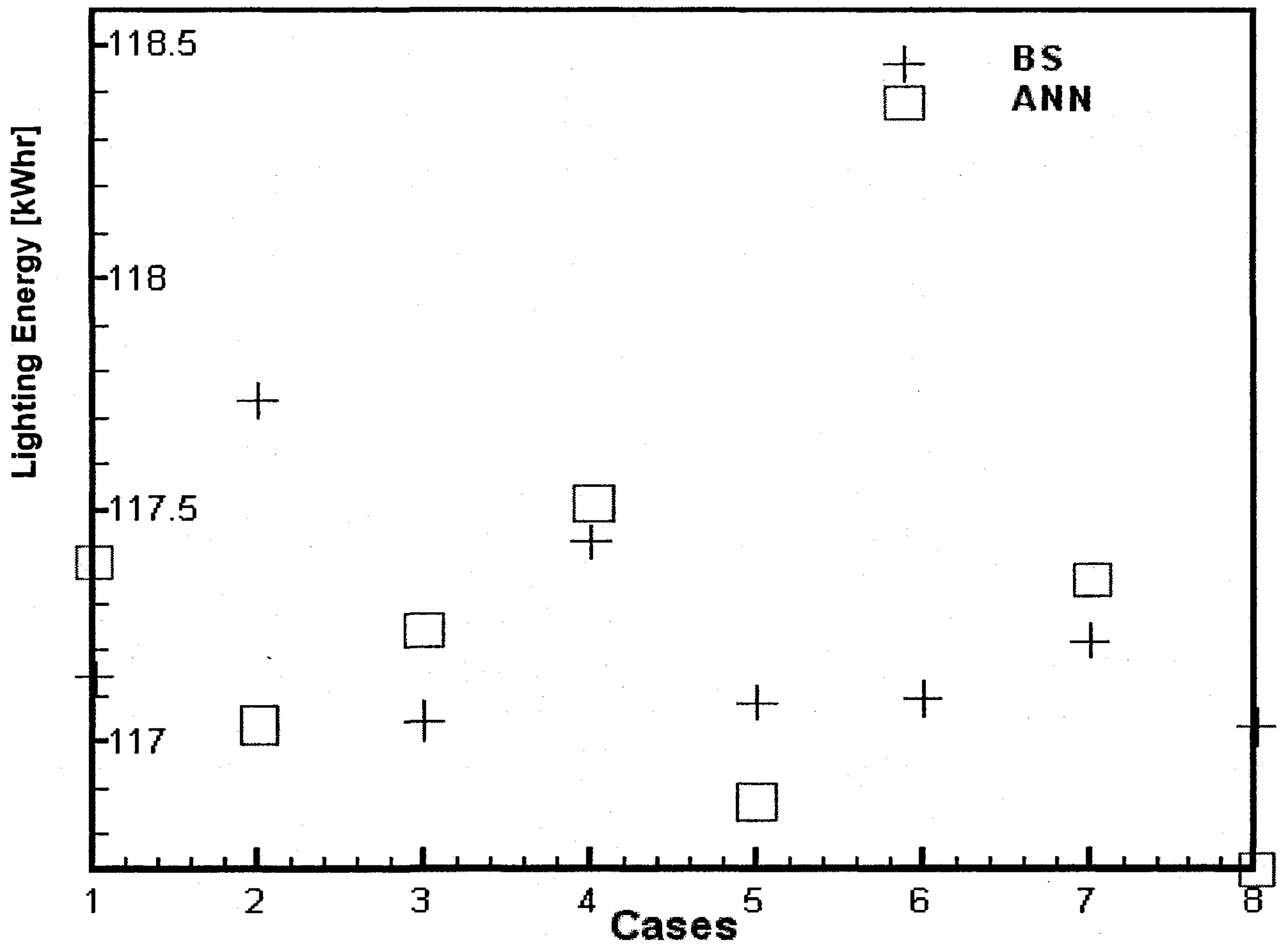


Figure 15 - Validation of the ANN - ANN vs BS Results
Average Lighting Energy Consumption [kWhr]

Figures 11 to 14 show that the ANN approximation is in good concordance with the actual results, that is, the ones given by ESP-r, for the cooling and heating loads as well as for occupants' thermal comfort. However, Figure 15 shows there are important discrepancies between the ANN and ESP-r for the lighting energy consumption. As a matter of fact, the author decided to define some control strategies to reduce the use of artificial lights in the rooms when the illuminance level inside the room reaches a certain level defined by general regulations in effect in Canada. After looking into this problem more seriously, and after consulting the ESP-r community online, the author realized that the calculations given by ESP-r were not correct. ESP-r developers are confident that solar processes are correctly taken into account in the energy balance of the different zones, and consequently that the corresponding heating and cooling loads are computed correctly. However, the heat gains and thus the lighting energy associated with control actions on the lights available from the result files are not correct for some reason. All the results associated with the lighting energy consumption for each room are thus erroneous, and this accounts for the mismatch between the ANN model estimates and the ESP-r calculation results. The author got confirmation, however, that the impact of the lighting on the heating and cooling loads were correctly accounted for. Consequently, the lighting energy will be disregarded for this part of the study.

4.7. Using the ANN for the Optimization Search

With the ANN model ready for use, the last step was the optimization search per se. The ANN model was indeed meant to be used in conflation with a genetic algorithm (GA) to replace energy tools which would not have made possible the use of population-based stochastic optimization algorithms due to expensive computations, as we already pointed out.

The GA was developed under C++ by Mengistu (2005). The latter gentleman worked in cooperation with the author of this work and provided him with assistance regarding all the technical problems—only for this introductory example—related to optimization, including the ANN artificial neural network, and the GA. As explained earlier, the genetic algorithm generates potential solutions and evaluates their performance—also referred to as 'fitness'—in order to let the fittest individuals survive and get close to the near-optimal solution. The evaluation function is used to determine how well buildings perform, and in the case of this study, it is the trained ANN model of the building. Using the ANN within the GA proved to be quite easy.

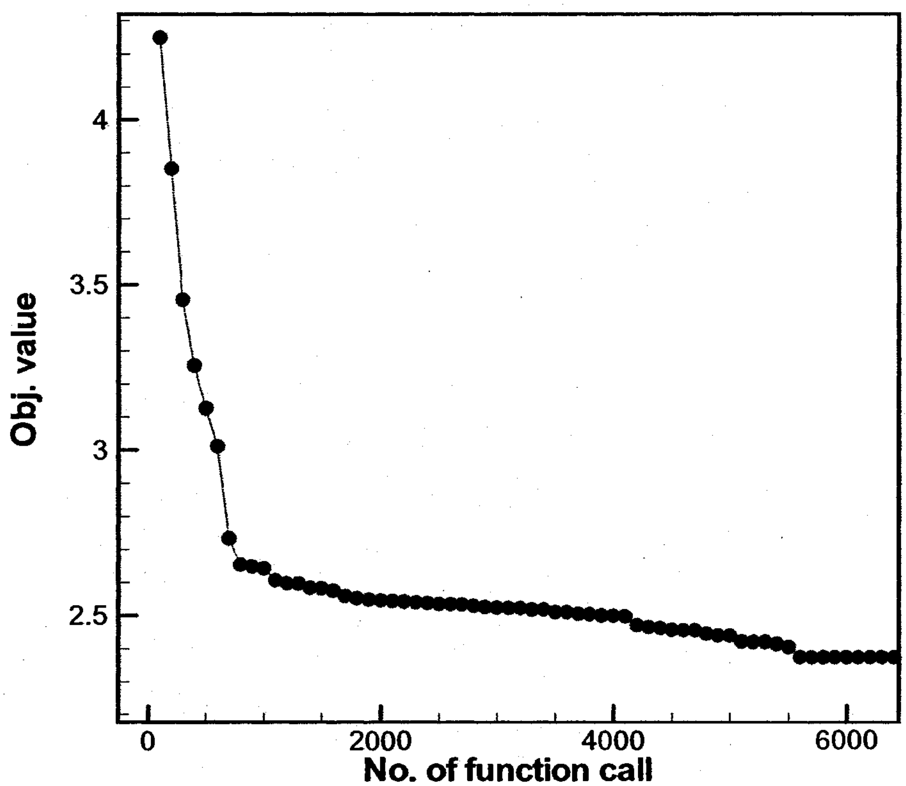


Figure 16 - Optimization Search - Number of Function Calls

The optimization search took less than ten minutes. Figure 16 shows the evolution of the objective value, as defined in Equation 1, along the search. It is common practice to use the number of function calls, that is, the number of candidate buildings evaluated by the objective function, as a time scale. This figure also shows the total number of function calls necessary for the search to converge. The authors calculated that without using the ANN model, the optimization search would have taken more than a year to converge.

Table 3 shows the values of the design parameters for the near-optimal solution compared to that of the existing building.

Parameter	**Unit**	**Original Value**	**Optimal Value**	**Change [%]**
Window south (WxH)	[m]x[m]	2.8 x 1.9	2.4 x 1.7	- 23%[7]
Window north (WxH)	[m]x[m]	2.8 x 1.9	2.4 x 1.7	- 23%
Window east (WxH)	[m]x[m]	2.8 x 1.9	2.4 x 1.7	- 23%
Louver angle south	[deg]	90	139	+ 54%
Louver angle east	[deg]	90	135	+ 50%
Lower and upper bounds for outside temperature set point	[°C, °C]	[13,28]	[13, 26]	[0%, -7%]

Table 3 - Design Parameter Values

The optimization advocates a decrease in the glazing area and an increase in the louvers' angle. This is sensible since decreasing the glazing area would enable to decrease both the heating load in winter and the cooling load in summer. Likewise, the optimal louver angle proves to be the best way to reduce the cooling load

[7] Global change in the glazing area.

associated with direct sun beams. However, since the lighting energy consumption was not taken into account for the optimization search, one cannot draw any conclusion as to what the best trade-off would be between decreasing the cooling load and an extensive use of artificial light in the workspace. Figure 17 shows the comparison between the optimized and the original buildings' heating demand. The heating and cooling loads were thus reduced by 12% and 4.8%, respectively for the whole building. The value of the thermal comfort index was, on the other hand, increased by 1% to 4% on average, depending on the room.

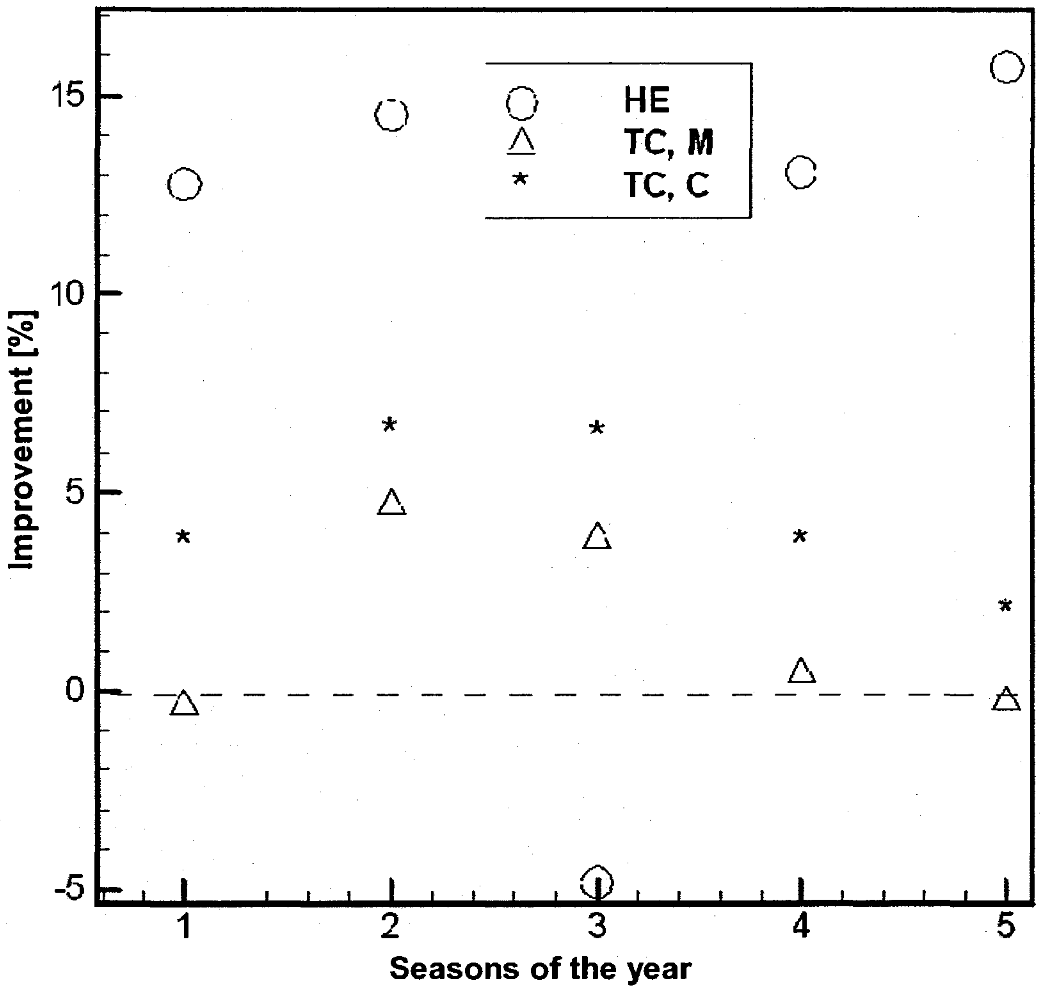


Figure 17 - Energy Savings for the Building and
Thermal Comfort Improvement for the 'Manager' and 'Conference' Zones

It was finally decided that windows should all have the same dimensions regardless their orientation. This is a purely arbitrary choice in order to respect the original structure of the building for which all the windows were the same size. Since the ANN has been trained for different window dimensions, had the authors decided to allow for different windows for the three façades, all they would have needed to do is run another optimization search, and determine the new near-optimal building.

4.8. Conclusion on the Preliminary Study

This preliminary work proved that the methodology yields sensible results. The ANN faithfully models the building's energy consumption and occupants' thermal comfort. The GA identified the best trade-off for the defined research parameters, and the building could potentially be improved.

However, the methodology also clearly showed its limits:

- Preparing all the simulation files for the database by hand is <u>not a viable solution</u>. As a matter of fact, further to being a very time-consuming process, it is also a very likely source of errors since users could easily make mistakes while changing the parameters' values in the ESP-r files.
- ESP-r also proved to be a limiting factor to this methodology as far as the lighting energy consumption is concerned. However, this is partly due to the fact that the tool is under continuous development, and new versions will probably be available in a near future to address the current shortcomings. For the time being, it was decided to use Radiance simulations in parallel to ESP-r in order to estimate occupants' visual comfort for later studies, as documented in the following section.
- Last but not least, it is our hope that this methodology will be flexible and simple enough to be actually used by designers. This last remark begs for a dramatic simplification, or at least automation, of all the file-handling process.

Based on the conclusions drawn from this preliminary study, the author devised an improved methodology meant to address the limitations of the first sketch.

CHAPTER 5

5. CONFRONTING THE PROPOSED METHOD TO A LARGE-SCALE EXAMPLE

Chapter 4 showed evidence of the validity and applicability of the methodology for a section of a building. The present chapter documents the optimization study of a full-scale building and different sets of design parameters and objective functions will be studied. The two main issues encountered during the validation stage of the methodology are also handled as follows:

- The author of this work wrote a program in the Perl programming language in order to automate the whole simulation process. This language is quite straightforward and free software exists to program in Perl under most operating systems. The role of the program is manifold. 1) It updates the ESP-r model for each case defined by the design of experiments; 2) it runs the simulation by invoking of ESP-r; 3) it extracts the simulation results from the ESP-r files and writes them into an output text file later used to train the ANN; and finally 4) it deletes all the temporary files.
- An attempt was made to use Radiance to assess visual comfort more comprehensively. Unfortunately, this proved to be a tedious process and after consulting ESP-r developers at Strathclyde's University Energy Systems Research Unit (ESRU) and at National Research Council Canada (NRCC), the author got the confirmation that work was under way to calculate daylighting

metrics within ESP-r. Unfortunately again, the Beta version of the software was not yet available at the time this thesis was written.

The first section of this chapter presents the building used for the optimization study as well as a summary of a preliminary sensitivity analysis conducted by another researcher. The objective function is discussed in the following section with emphasis put on the different metrics used to evaluate the building. Finally, two optimization study cases are documented in the remaining two sections.

5.1. Presenting the Building Model

The building selected is a school located in Grong, Norway, whose main feature is a hybrid ventilation system. An ESP-r model of the building was developed by Wachenfeldt (2003). This building was designed with a concern to reduce the heating and ventilation energy consumption and to provide pupils with optimal indoor air quality conditions. Energy-saving measures include extensive use of natural ventilation and natural daylight, and an underground duct through which the air passes before being injected into the classrooms. The culvert enables the preheating or pre-cooling of the air, depending on the season. The main classrooms are connected to an extract chamber. The extract chamber has a large glazing area as shown on Figure 18. Its purpose is twofold: first, it acts as a buffer space containing

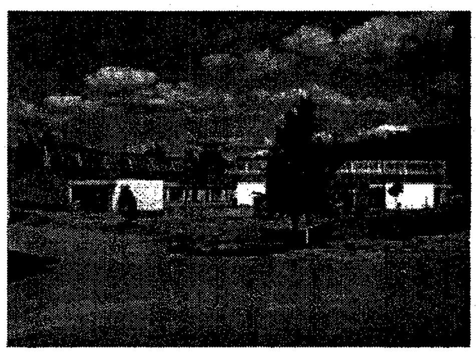


Figure 18 - Global View of the Mediaa School

a large mass of warm air, thus enhancing natural ventilation; it also allows for an extensive use of natural daylight in two of the classrooms. This extract chamber is in turn connected to an exhaust tower whose purpose is to create draft, hence participating to the natural ventilation of the building.

In the final section of his thesis, Wachenfeldt documented a sensitivity analysis he conducted after having set up an ESP-r model of the premises (Wachenfeldt 2003). After discussing with Dr. Wachenfeldt and one of his colleagues from the Norwegian Technology University in Trondheim, it seems that the building design has two main shortcomings:

- From a general perspective, the geometry is too complicated. On top of increasing the price of construction, the geometry favours heat loss as well as pressure drop, thus reducing the potential for natural ventilation.
- Further to thermal bridges, both gentlemen agreed on the fact that floor insulation was not sufficient in most of the classrooms and that energy performance was quite poor.

These two aspects notwithstanding, the school works relatively well since it provides pupils with a very satisfactory work environment. According to Dr. Wachendfeldt, the pre-cooling potential of the duct is unfortunately very little used, since the school is left unoccupied throughout summer. In light of this, and bearing in mind the introductory comments to this thesis on building rehabilitation, studying the potential of the building for summer usage and thus investigating the optimal design of the school, should it be used in summer, is an interesting challenge.

For the purpose of this work, major changes were made to the original ESP-r model of the building. In order to operate under more constraining conditions, the exhaust and intake fans were removed, thus leaving natural ventilation as the only driving force in the building.

Figure 19 shows a cross section view of the school with the underground intake duct to preheat or precool the air connected in turn to the underground distribution duct, located under the corridor. Air is then distributed to the classrooms, collected by the extract chamber and finally exhausted outside by the exhaust tower.

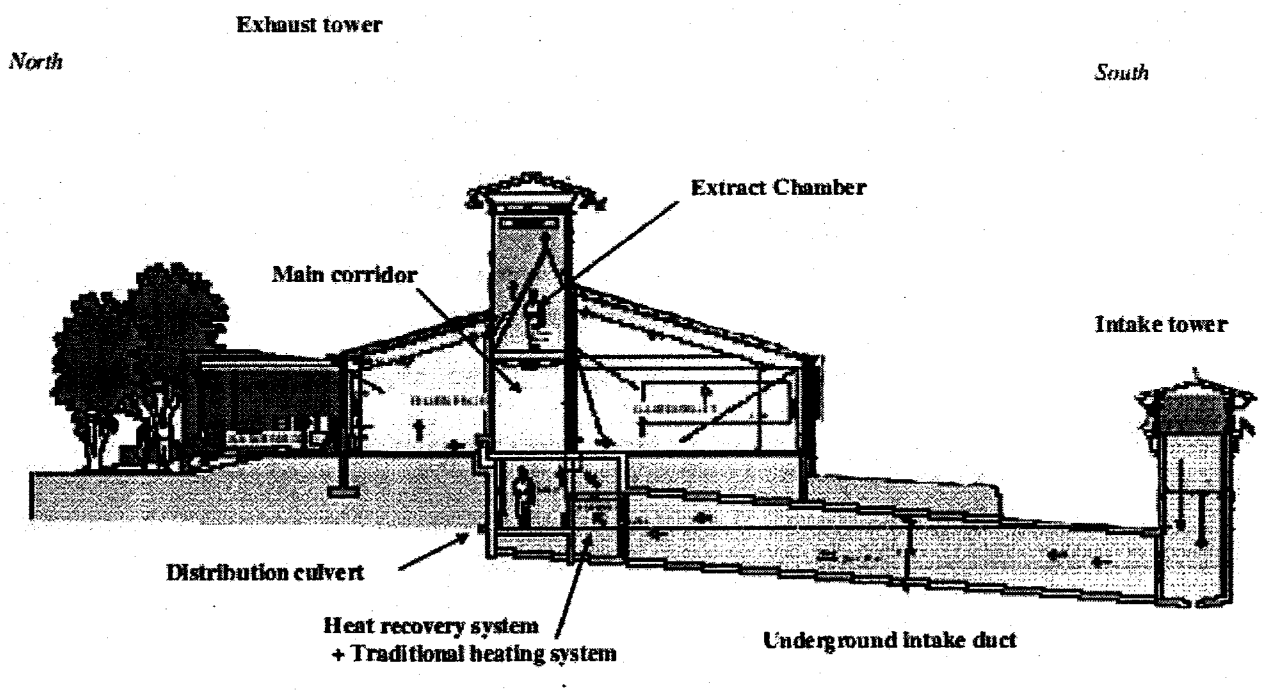


Figure 19 - Cross-sectional View of the Ventilation System

Finally, Figure 19 shows a bird view of the ESP-r model of the school with the three main classrooms.

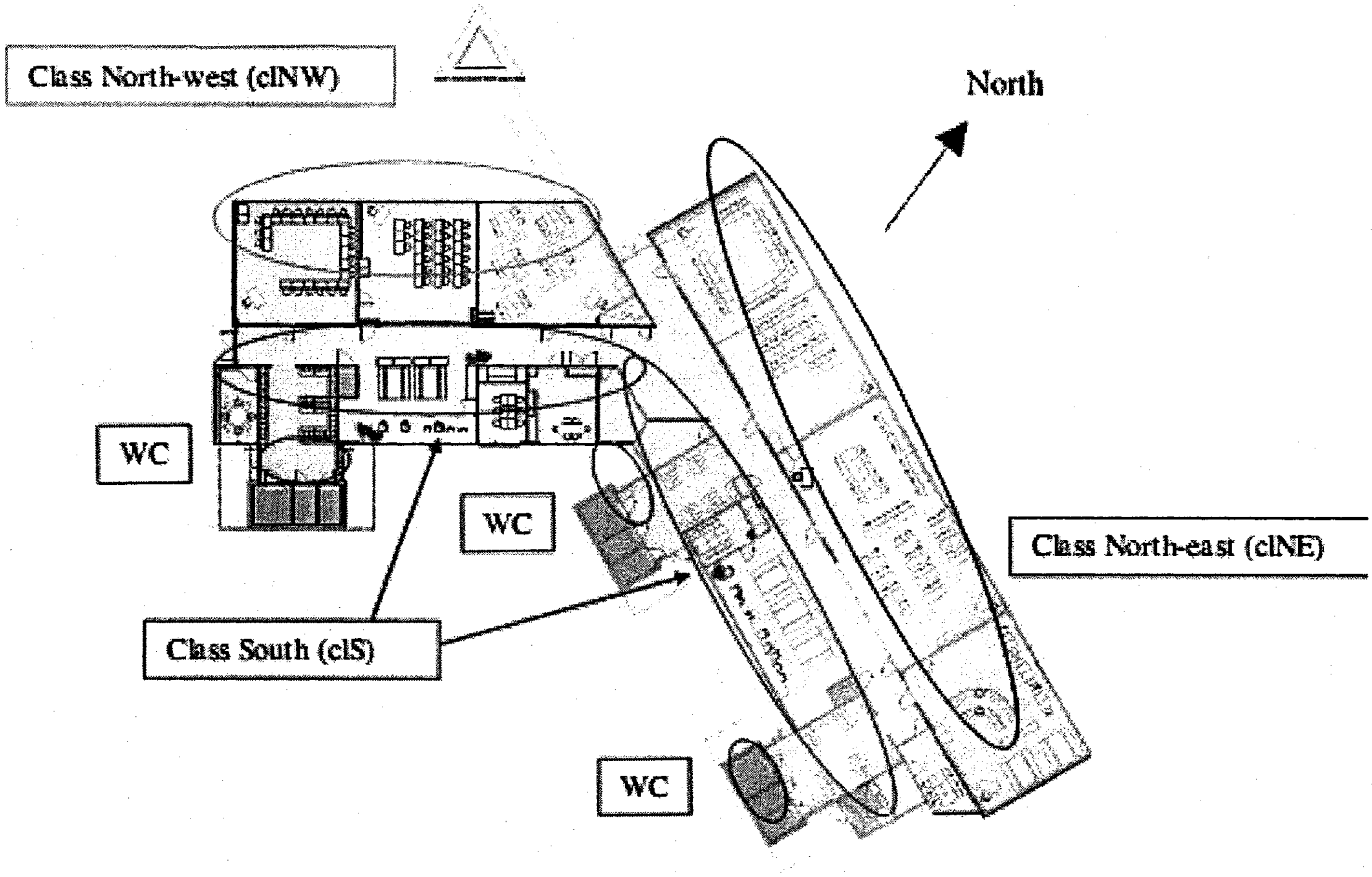


Figure 20 - Bird View of the Model

5.2. Identifying the Metric Function

It would be convenient to have a performance metric to rate buildings and which would encompass environmental impact, energy performance, occupants' comfort (in terms of thermal comfort, indoor air quality, visual comfort, acoustic comfort etc.) as well as financial considerations altogether. However, such a performance metric does not exist and is very unlikely to see the day. It has already taken much time for the international building community to reach consensus as to what metrics to use to evaluate thermal comfort, for example, and some aspects such as daylighting are still under discussion (Reinhart et al. 2006). As already mentioned, the ESP-r energy tool was used for the simulation part of this work; consequently, the metrics chosen to assess the performance of the building are those easy to compute with the software. Let us have a brief review of the indices used to assess building performance in this study:

5.2.1. Energy Performance

Energy performance is already taken into account in the environmental performance metric, but since the energy bill happens to be one of the most important driving forces pushing clients to buy more energy-wise homes, it is of the essence. The heating demand, cooling demand, and lighting energy are the most commonly used metrics. However, more detailed metrics are also used at time, such as the energy efficiency of a heat recovery system for example. Scores of energy tools have been developed since the first oil crisis. TRNSYS, Energy Plus, and ESP-r are some of the most widely used tools.

5.2.2. Thermal Comfort

Unlike visual comfort, thermal comfort has been thoroughly studied for a couple of decades and there exist guidelines as to what metrics to use, how to measure them, and provisions on acceptable values. ASHRAE standards 1993 (55-2204) list a couple of metrics usable for the purpose of assessing thermal comfort in a room. PMV, the predicted mean vote, as well as PPD, the predicted percentage of dissatisfied people are two very popular metrics. PMV is the predicted mean vote of a large population exposed to a given environment. The PMV value is derived from the physics of heat transfer and empirical correlations; it ranges between -3, for which the environment is considered to be "too cold" and +3, where the environment is "too warm". Obviously, any environment should ideally score around zero. PPD is derived in turn from the PMV value. When the PMV value deviates away from the neutral value (i.e. zero) then the value of PPD starts increasing. Software tools such as ESP-r can now accurately predict these values too.

5.2.3. Indoor Air Quality

Indoor Air Quality is a domain that deals with the presence of contaminants in the indoor air such as microbes, chemicals, allergens etc. Several indices are used to assess the quality of indoor air, such as the mean age of air or the concentration of gases, just to name a few (ASHRAE 2001). They usually require a substantial amount of detail and thus, computational effort.

5.2.4. Visual Comfort

Some provisions exist as far as the minimum lighting level is concerned, but as of today, there is no general consensus as to what metrics to use to evaluate the quality of daylighting. As a matter of fact, daylighting, or the use of natural light instead of artificial light, is gaining in popularity due to the significant cost associated with artificial lighting. Most countries have regulations with respect to the level of light on work planes. For example, Human Resources and Social Development Canada recommends 300 lx to 500 lx on the work space for typical clerical work (HRSD

1989). Provisions are also given regarding how to take measurements. In spite of this, it is quite hard to assess the performance of a building in terms of visual comfort, especially when it comes to natural daylight. Reinhart conducts extensive research to determine what metrics to use to assess daylight performance in sustainable buildings (Reinhart et al. 2006). Daylight factor is by far the most used metric to estimate the performance of a building in terms of visual comfort. It is defined as the "interior horizontal daylight illuminance expressed as a percentage of the horizontal daylight illuminance available to an unobstructed site". Due to its definition, it is a static metrics based on the geometry of the building and therefore does not account for changes in outside daylight illuminance. According to a researcher at the NTNU University, the next update of the Norwegian building code will advocate for a daylight factor of at least 2% at a point located one meter from the side wall, halfway through the room from the window. Several other metrics were proposed to assess dynamic daylight performance. Daylight autonomy for example can be defined as the percentage of occupied time per year when target illuminance can be maintained by daylight alone. This proves to be quite a useful and intuitive metrics since it can be expressed as the percentage of lighting electricity saved by a lighting system ESP-r developers are working on improving the interface to perform Radiance calculations from within ESP-r. Reinhart's team is also working on linking their tool for calculation of dynamic daylight performance to Radiance and ESP-r.

5.3. Performance Metrics under the Scope of this Study

5.3.1. Energy Usage

For the first example, the heating energy consumption in the classrooms, bathrooms, corridor, and heating battery was used to assess the energy performance of the building. In the second example, a cooling capacity was added to each of the rooms to investigate the need for air conditioning in summer and the optimal cooling capacity to install. Determining the GHG emissions due to the operation of the building would be straightforward. Software to calculate GHG emissions does exist, such as the Athena program in Canada for instance, but the lack of data for Norway would impede the calculations and it was thus decided not to take GHG emissions into account.

5.3.2. Thermal Comfort

As in the previous chapter, thermal comfort is here represented by the cumulative frequency of time for which the PPD is the classroom is below 20%. Clothing levels of 1.0 clo in winter, 0.75 clo in autumn and spring, and 0.5 in summer were used, as previously. The metabolic rates used were 100 W/m² to account for children's activity.

5.3.3. Visual Comfort

Finally, visual comfort is represented by the average of daylight factors estimated at a series of points located halfway through the room from the windows, and one meter away from the side walls, to compare it to the provisions given by the Norwegian Building Code.

5.3.4. Objective Function

The optimization seeks to minimize the heating energy consumption while maximizing the thermal and visual comfort factors.

5.4. First Case – Testing the Method on a Large-scale Example

5.4.1. Design of Experiments and Choice of Parameters

In this first example, only a limited number of parameters are studied to test the applicability of the method with a complex case. Thus, the influence of the size of the extract chamber windows and the height of the exhaust tower on the energy, thermal, and visual performance of the building is investigated in this first example. Changing the glazing area of the extract chamber has an impact on both the building energy consumption and the occupants' thermal and visual comfort. These aspects are conflicting since increasing the glazing area results in more daylight in the rooms, but a worse thermal comfort, as some preliminary studies showed. The height of the roof tower was allowed to change in order to help natural ventilation.

Three design parameters were perturbed to study their impact on the energy consumption, and thermal and visual comfort. This defines three inputs that correspond to the fifteen outputs for the first case. The upper-bound values were arbitrarily chosen following the Norwegian building code which recommends a minimum daylight factor of 2% halfway through the room from the window, and one meter from the side walls. There is no restriction as to the size of the exhaust tower; however, the architect who designed the school would need to give his consent prior to any modification in the building envelope.

Design parameter	Lower bound	Upper bound
Extract chamber window facing south – height [m]	0.4 *(25% of original value)*	1.7 *(original value)*
Extract chamber window facing southwest – height [m]	0.4 *(25% of original value)*	1.7 *(original value)*
Exhaust tower – height [m]	2 *(original value)*	6 *(arbitrarily chosen)*

Table 4 - Parameters Maximum and Minimum Values

As for the previous case, LHS was used to sample the search space as efficiently as possible. As already mentioned, though several studies have concluded that for a study based on N parameters, a number M greater than twice the number of parameters is sufficient to correctly sample the search space for uncertainty analysis, by experience, more samples are required when dealing with energy simulations. Due to the number and different natures of outputs, 250 cases were simulated, that is approximately five times the product between the number of inputs and the number of outputs. LHS allows for an optimal coverage of the search space. The cases are reported in Appendix B.

5.4.2. Simulations

As mentioned in the introduction to the current chapter, and based on the conclusions drawn from the preliminary case study, it is necessary that the simulations be automated, if only to avoid human errors. A lot of attention was thus placed on the writing of a program to prepare the ESP-r model, run the simulation, extract and save the simulation results, and erase all temporary files. One of the main concerns of this work is to devise a method *usable* by building designers. It thus needs being fairly simple to understand and to implement, regardless of the computational background of the user. The Perl programming language is a simple language whose syntax is similar to that of the most commonly used programming languages such as C, C++, Java and the like. Furthermore, it is free of charge and rather well documented. Hence, it appeared to be well suited to the purpose of this work. Any designer acquainted with the basics of programming should be able to didactically write a program with Perl to automate energy simulations.

The performances of the different building cases previously defined were computed with ESP-r. Each case—which involves changing and updating the model files, running the simulations, and saving the results—required approximately 5 minutes CPU time for a total of 1,250 minutes—i.e. 20 hours.

5.4.3. Training the ANN

The ANN was trained with the MATLAB Neural Network Toolbox using 200 cases. The 50 remaining cases were used to validate it. MATLAB's Neural Network Toolbox is easy to use and fairly well documented. A *feedforward* network with one hidden layer was trained with the *Baysian regularization backpropagation* training function available within MATLAB. There are 25 neurons in the hidden layer.

The two following figures illustrate how well the ANN performed in general. Figure 21 shows the relative error between the ANN model and ESP-r for the energy consumption. Figure 22 shows the relative error between the ANN model and ESP-r for visual comfort (referred to as VC) and the thermal comfort (referred to as TC).

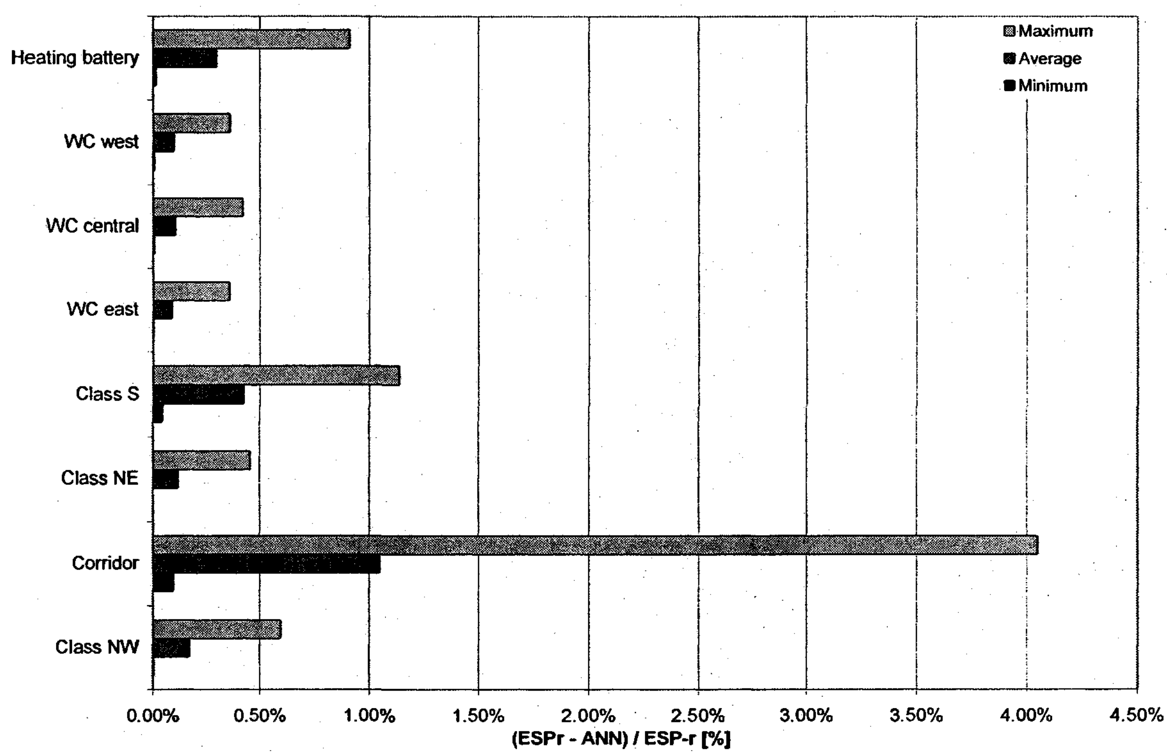


Figure 21 - Absolute Relative Error - Heating Energy Consumption

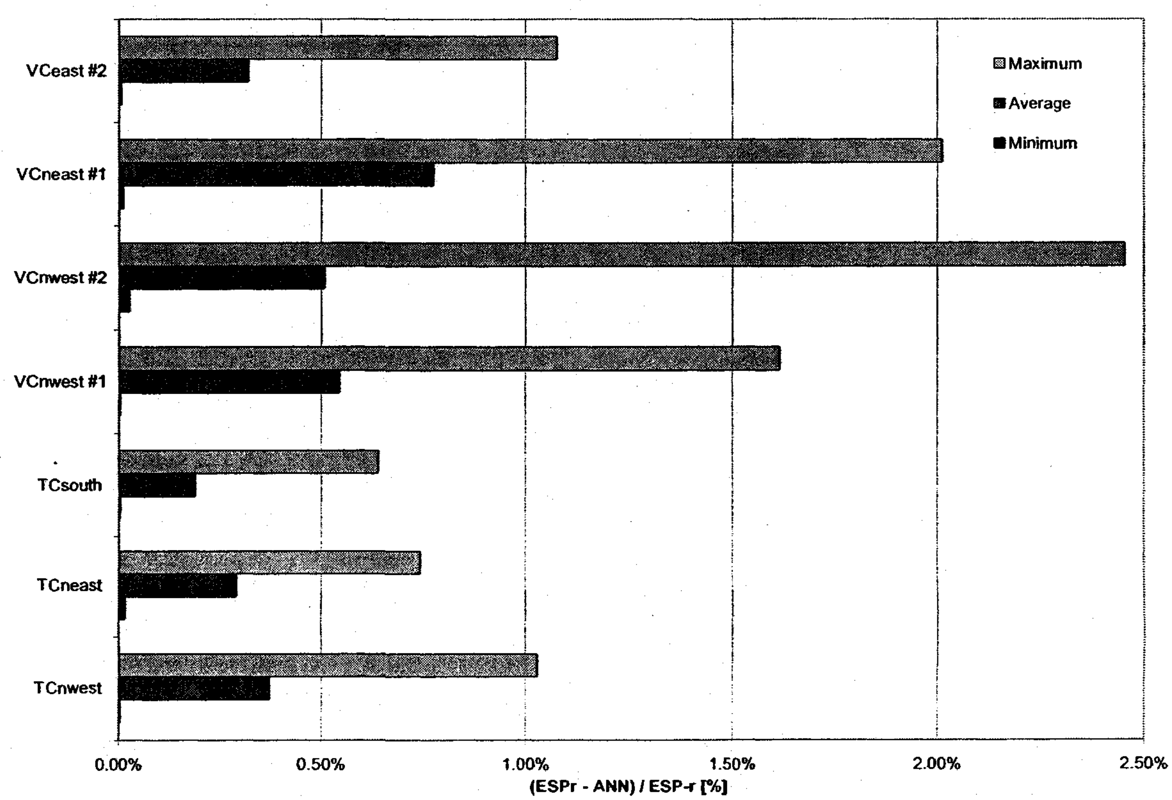


Figure 22 - Absolute Relative Error - Thermal Comfort (TC) and Visual Comfort (VC)

As far as the heating energy consumption is concerned, the average difference between the ANN predictions and ESP-r simulations remained below 0.5% in all cases but one. Likewise, the maximum relative error between the ANN model and ESP-r is slightly above 1%. For the Corridor thermal zone, however, the average relative error is slightly greater than 1%, and the maximum error is above 4%. This might be due to the fact that the corridor is connected to the three main rooms of the building and to the outside as well, and thus it is more complex to model. More training cases might have yielded a better approximation for this output, but a maximum error of 4% is still very good. Another ANN with 30 neurons instead of 25 in the hidden layer of the ANN was trained; the maximum error was decreased to 3% but the computation time to train the ANN increased significantly.

The ANN model and ESP-r are, as well, in very good agreement as far as visual comfort (referred to on this figure as VC) and thermal comfort (referred to on the figure as TC) are concerned. Consequently, there is more discordance between the ANN model and ESP-r as far as visual comfort is concerned, since visual comfort is harder to model, but the maximum error is still below 2.50%. The ANN was thus validated and used as the evaluation function of the Genetic Algorithm.

5.4.4. Optimization Search

In order to evaluate which aspect of the objective function had the most potential for optimization, three optimization studies were carried out. In the first case, the objective function was the global heating demand of the building only. For the second case, only the thermal comfort factors were taken into account. Finally, only visual comfort was studied in the last case. Optimizing each aspect of the building separately yields different optimal designs. Indeed, optimizing for the energy consumption only results in maximizing the extract chamber glazing area and increasing the height of the exhaust tower. Maximizing for occupants' visual comfort yields similar changes. On the other hand, maximizing for the thermal comfort in the rooms results in decreasing both the size of the glazing area and the height of the tower. The parameters' original and optimal values as well as the building performance improved values are listed in Table 5. Optimization results given by the GA were counter checked with the Generalized Pattern Search (GPS) algorithm also available with Matlab and for all cases the GPS corroborated the GA's results.

Performance Factor	**Original input** [m m m]	**Optimized input vector** [m m m]	**Improvement** [%]
Heating Energy Consumption	[1.7 1.7 2.0]	[1.7 1.7 4.9]	0.58%
Thermal Comfort	[1.7 1.7 2.0]	[0.4 0.4 2.0]	50.44%
Visual Comfort	[1.7 1.7 2.0]	[1.7 1.7 2.9]	0.14%

Table 5 - Results of the Three Single-Objective Optimizations

These preliminary results show that thermal comfort has the greatest improvement potential. It also evidences the obvious: simultaneously optimizing different aspects of a building is conflicting.

Reducing the extract chamber glazing area improves, according to the preliminary single-objective optimization results, the thermal comfort in the classrooms a great deal, but this also results in a poorer visual comfort and an increase in the energy consumption for this period of the year. The first requirement of a building is to protect its occupants from the outdoor and to provide them with optimal indoor conditions, conductive to their daily activities. In light of this, it was decided to give in a first step equal weights to energy consumption, thermal comfort, and visual comfort in the objective function to optimize. In general, no single optimal solution can simultaneously yield an optimal value for all the single-objective functions. Our purpose here is to use a single objective function combining all the aspects to improve—energy demand, thermal comfort, and visual comfort. Scaling each component of the aggregated objective function between zero and one is a way to ensure that all aspects will equally drive the optimization search. This can be achieved by using the Lp norm, as in Malard et al (2004):

$$\min Lp(x) = \min_{x\in\Omega}\left[\sum_{i=1}^{m}\omega_i^p\left|\frac{f_i(x)-\min f_i(x)}{\max f_i(x)-\min f_i(x)}\right|^p\right]^{1/p}$$

Equation 2 - Objective Function: Minimizing the Lp Norm

Where:

- x is an input vector belonging to the search space Ω, delimited by the lower and upper bounds as defined in the Design of Experiments;
- f_1 to f_3 are, for each of the classrooms, the ratio of time out of the whole occupancy time for which PPD is less than 20%. This value is multiplied by -1 to actually maximize thermal comfort;

- f_4 to f_{11} are the heating energy consumption of class NW, corridor, class NE, class S, the three bathrooms, and the heating battery respectively, in kWhr of electricity;
- f_{12} to f_{15} are the average daylight factors, in %, for the side walls of the classrooms facing northwest and northeast;
- ω_i are the weights associated to these functions. They are dimensionless since all the aggregates of the objective function are dimensionless;
- $1 \leq p \leq \infty$. The greater p, the more importance is given to the deviation in the metric function.

Table 6 summarizes the results of the first optimization, for which equal weights were given to the three main performance indices of the building. As for the previous results, the near-optimal solutions were validated using a GPS algorithm as shown in Table 7. The GPS and GA both lead to the same conclusion.

Performance Factor	**Improvement [%]**	**Original input [m m m]**	**Optimized input vector [m m m]**
Metric Function $L_2(x)$	+45.53%	[1.7 1.7 2.0]	[0.4200 1.1468 4.5278]
Heating Energy Consumption	-8.26%		
Thermal Comfort	+30.31%		
Visual Comfort	-33.05%		

Table 6 - Optimization Results with Equal Weights

Performance Factor	Improvement [%]	Original input [m m m]	Optimized input vector [m m m]
Metric Function $L_2(x)$	+45.53%	[1.7 1.7 2.0]	[0.4200 1.1568 4.5278]
Heating Energy Consumption	-8.26%		
Thermal Comfort	+30.31%		
Visual Comfort	-33.05%		

Table 7 - Verification of the Optimization Results with GPS

These results are not very surprising. Indeed, the individual optimizations showed that in the case of this building, and for the conditions defined, only thermal comfort had a strong potential for improvement. As a consequence, it is not surprising that the best solution should be one that favours thermal comfort over visual comfort, and to a lesser extent, over the energy performance of the building. It was then decided to change the weights ω_i for each function according to their improvement potential. Visual comfort will thus be favoured over energy performance which will in turn be favoured over thermal comfort. The results of this second optimization are listed in the following table.

Performance Factor	Improvement [%]	Original input [m m m]	Optimized input vector [m m m]
Metric Function $L_2(x)$	+23.77%	[1.7 1.7 2.0]	[0.6558 1.7400 2.000]
Heating Energy Consumption	-3.05%		
Thermal Comfort	+12.90%		
Visual Comfort	-23.22%		

Table 8 - Optimization Results with Different Weights

For this optimization, weight values of 1, 1/3, and 3 were defined for the energy performance, thermal comfort, and visual comfort respectively. Thermal comfort and visual comfort are clearly the most conflicting aspects in this optimization problem. Just by changing the geometry of the envelope of the building, one could not improve one of these two aspects without seriously worsening the other one. After running a few simulations with ESP-r, it appeared that the rooms were indeed too hot for most of the time, from June onward. This accounts for why the optimization tends to recommend a smaller glazing area on the south façade; the maximization of the southwest glazing area might stem from the need to make up for the reduction in the global glazing area of the extract chamber to guarantee satisfactory ventilation flow rates. However, the optimization does not seek to increase the height of the tower, thus reducing the draft, and limiting the airflow rates in the rooms, which causes occupants' discomfort. This is contradictive with the positive action a bigger tower would have, allowing more fresh air to flow into the rooms, and improving thermal comfort. After analysing the climate data, it appeared that the ambient air was unusually warm for Norway—i.e. over 25°C—for most of the summer. Since the air is only cooled through the underground duct, and since the ambient temperature is so high, low flow rates are favoured for they allow the air to cool more before being injected into the rooms. Changing the geometry of these three parameters only will not improve thermal comfort sufficiently and other options should be investigated, such as those proposed in the second example.

Using other weight values, such as 10, 1, and 1/10, yielded a global improvement of 0.03% and 0.10% in the energy and visual performance of the building, and to a drop of 0.33% in the thermal performance for an input vector of [1.6932 1.7400 3.2479]. However, the main conclusion to draw here is that such variations are to take with precaution, mainly because they are of the same order than the ANN's relative errors. Care should thus be given to avoid choosing too disparate weights. Besides, there is no interest in an optimization that advocates so little changes. When designers face problems, decisions have to be made. Reducing the size of the south window and, to a lesser extent, that of the southwest, is a solution to improve thermal comfort. However, other measures should be taken in order to make up for the loss in visual comfort.

The choice of the weighting factors can be based either on a trial and error approach or left to the user's discretion. Some optimizers put forward the argument that building energy performance should be as important as occupant comfort, and therefore would tend to allocate similar weights to both scalars.

5.5. Second Case – Testing the Limits of the Method

5.5.1. Design of Experiments and Choice of Parameters

This case study set out to investigate more parameters such as night setback temperatures, adding cooling capacity to the system, adding shading devices on windows, changing the sizes of other windows, adding an insulation layer to the floors in the classrooms. Adding these parameters will give more insights on the influence of each of those on the global performance of the building. It will as well permit to test the limits of the method by having a more complex objective functions and more design parameters. Table 9 lists the parameters studied as well as their lower and upper bounds.

Zone	**Variables**	**Upper Bound**	**Lower Bound**	**Conditions**
Extract Chamber	Window Southwest Height	1.7 m	50% (0.85 m)	Continuous
	Window South Height	1.7 m	50% (0.85 m)	
Exhaust Tower	Height	6 m	2 m	
Class Northeast	Window – Length	5 m	50% (2.5 m)	
	Window – Height	1.7 m	50% (0.85 m)	
Class Northwest	Window – Length	17 m	50% (8.5 m)	
	Window – Height	1.7 m	50% (0.85 m)	
Class South	Window SE – Length	12.2 m	50% (6.1 m)	
	Window SE – Height	1.7 m	50% (0.85 m)	
	Window SW – Length	18.78 m	50% (9.39 m)	
	Window SW– Height	1.7 m	50% (0.85 m)	
Class Northeast	Insulation Thickness	15 cm	5 cm	{5,10,15}
Class Northwest	Insulation Thickness	15 cm	5 cm	
Class South	Insulation Thickness	15 cm	5 cm	
Class Northeast	Cooling Capacity	3,000 kW	0,0 kW	Continuous
	Temperature Setpoint	30°C	25°C	
Class Northwest	Cooling Capacity	3,000 kW	0,0 kW	
	Temperature Setpoint	30°C	25°C	
Class South	Cooling Capacity	5,000 kW	0,0 kW	
	Temperature Setpoint	30°C	25°C	
Corridor	Cooling Capacity	1,000 kW	0,0 kW	
	Temperature Setpoint	30°C	25°C	
Distribution Duct	Cooling Capacity	8,000 kW	0,0 kW	
	Temperature Setpoint	30°C	25°C	

Table 9 - Study Parameters and Their Lower and Upper Bounds

As previously mentioned, the size of the main windows for each classroom was investigated on top of the dimensions of the extract chamber and tower. Likewise, the floor insulation for the main classrooms was allowed to take on three values, namely 5cm, 10 cm, or 15 cm. Small cooling capacities were allowed in the classrooms, corridor, and distribution duct in an attempt to make up for the times when the duct could not meet the cooling requirements.

Using the same sampling method as for the previous cases, 1,500 simulation cases were defined; a quite significant number of simulations. This number is justified by the number of input parameters, namely 24, and the number of outputs, 8. The outputs for this case are, as previously, the cumulative frequency of time for which a maximum of 15% of the people in the room are dissatisfied for each of the three classrooms; the average daylight factors for each of the three classrooms, estimated at the same measuring points; and the heating and cooling demand for the system.

5.5.2. Simulations

The same Perl program was used to automate the simulations and the 1,500 simulations took about 5 full days to run. The reason is twofold: firstly, of course, the great many number of simulations implied more computations. Secondly, Radiance calculations were assessed for three classrooms instead of two, which significantly increased the global computation time. (Note that in the first case, the extract chamber had but a limited impact on the level of daylight in the classroom facing south; hence, it was not taken into account in the optimization.)

5.5.3. Training the ANN

The MATLAB toolbox was used for the ANN training and its validation. Training the ANN proved more tedious this time. A network with 15 neurons in the hidden layer was trained overnight. As shown in Table 8, the ANN performed rather well as far as the heating demand, thermal comfort, and daylight factors are concerned with an average relative error below 2%. However, the ANN performed less well at predicting the cooling demand and the south daylight factor for a few cases.

	Heating demand	Cooling demand	TC NWest	TC NEast	TC South	VC NWest	VC NEast	VC South
Max	0.60%	**81.98%**	5.06%	1.33%	1.24%	3.61%	8.02%	**21.10%**
Min	0.00%	0.01%	0.00%	0.00%	0.01%	0.00%	0.00%	0.01%
Average	0.13%	**6.45%**	0.44%	0.22%	0.29%	0.72%	1.91%	**2.50%**
Deviation	0.11%	9.40%	0.45%	0.19%	0.22%	0.60%	1.54%	3.18%

Table 10 - Relative Error between BS and ANN

For the south daylight factor, the relative error was well below 10% for 90% of the cases, as shown on Figure 23. On the other hand, figure 24 shows that for 90% of the cases, the relative error on cooling demand was below 15% only.

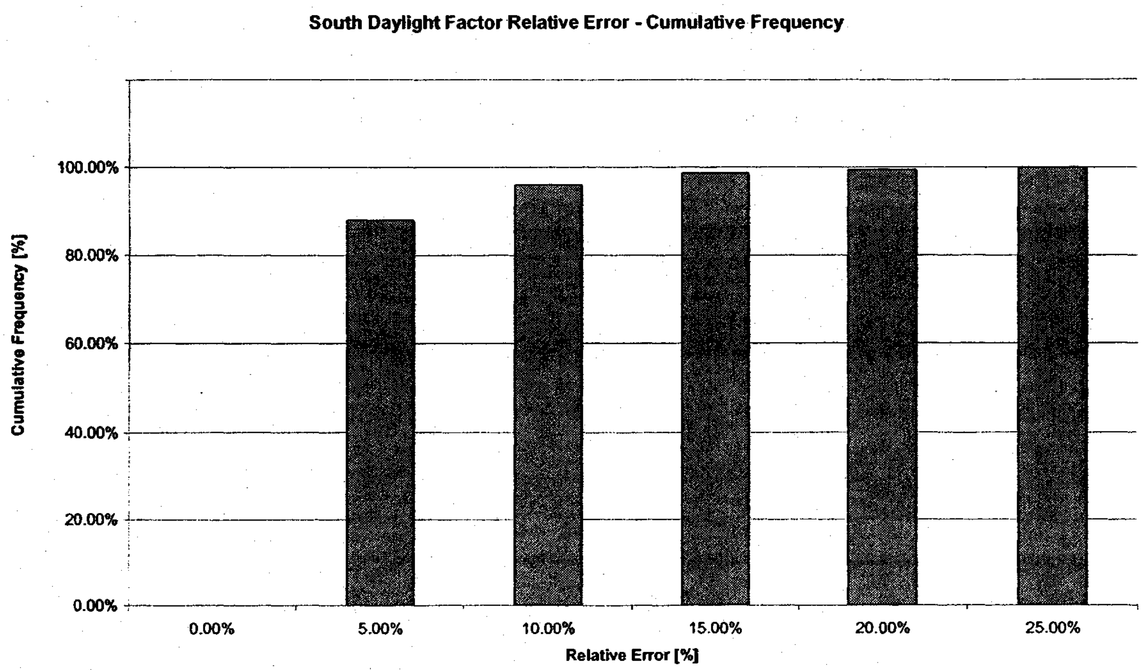


Figure 21 - Cumulative Frequency of the Relative Error between BS and ANN for the South Visual Comfort Metric

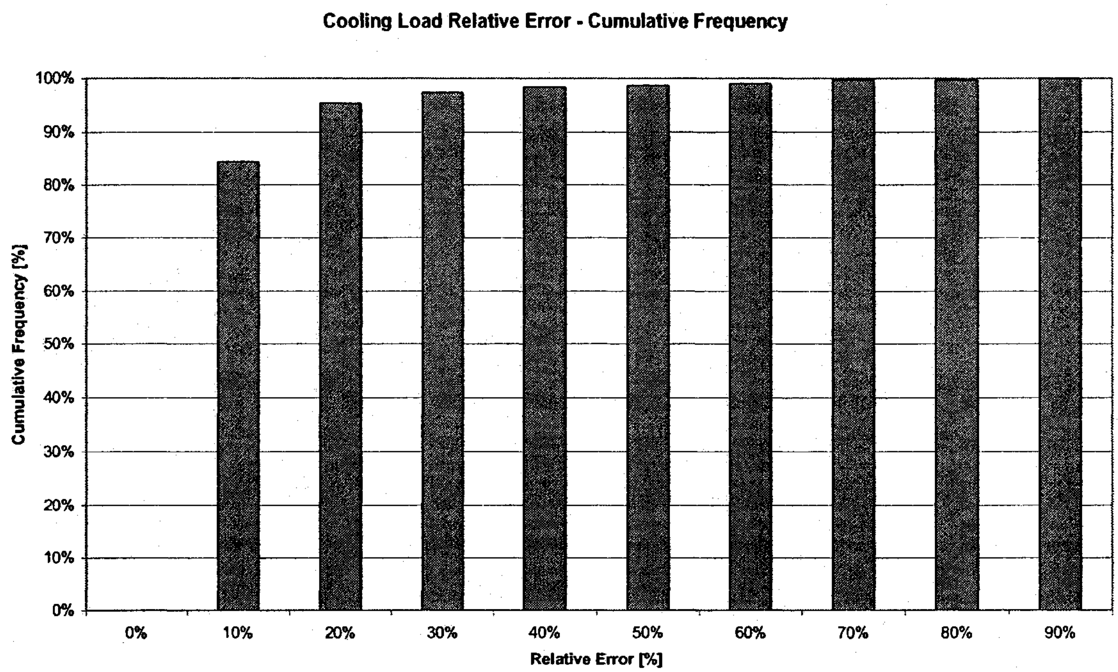


Figure 22 - Cumulative Frequency of the Relative Error between BS and ANN for the Cooling Demand

Despite this mediocre performance for both these aspects, the quality of the ANN could not be improved by adding more neurons in the hidden layer: the number of neurons in the hidden layer could not be increased least heavy computations would make the method totally unpractical. Adding a second hidden layer would result in as heavy computations. The solution would be to increase the number of simulations to train the ANN, and thus to run again a whole new set of simulations. This option was not chosen because in a real situation, more time-consuming simulations would mean the project would be given up. Besides, this second example set out to test the limits of this methodology, and this is clearly one of them. This issue will be further addressed in the concluding remarks of this thesis. In the meanwhile, the author decided to use the ANN in spite of its mild performance regarding the south daylight factor and the cooling demand.

5.5.4. Optimization Search

As for the previous cases, GA was used to determine the optimal design for the building given the chosen study parameters. The global performance metric used for the optimization is the same as in the previous case, namely:

$$\min Lp(x) = \min_{x \in \Omega} \left[\sum_{i=1}^{m} \omega_i^p \left| \frac{f_i(x) - \min f_i(x)}{\max f_i(x) - \min f_i(x)} \right|^p \right]^{1/p}$$

Where:

- x is an input vector belonging to the search space Ω, delimited by the lower and upper bounds as defined in the Design of Experiments;
- f_1 to f_3 are the thermal comfort factors for the classrooms facing northwest, northeast, and south respectively;
- f_4 and f_5 are the total heating energy demand and total cooling energy demand;
- f_6 to f_7 are the average daylight factors for the classrooms facing northwest, northeast, and south respectively;

By applying similar weights, i.e. 1.0, the optimization yielded the results presented in Table 11 while the original and the near-optimal vector are listed in Table 12.

Performance	Improvement
Factor	[%]
Metric Function $L_2(x)$	25.73%
Energy Consumption	-1.78%
Thermal Comfort	7.64%
Visual Comfort	-1.46%

Table 11 - Result of the Optimization Search - Rate of improvement

Zone	Variables	Original vector	Near-optimal solution	Global change
Extract Chamber	Window Southwest Height	1.70	1.69	=
	Window South Height	1.70	1.70	=
Exhaust Tower	Height	2.00	6.00	+
Class Northeast	Window – Length	5.00	2.50	-
	Window – Height	1.70	1.69	=
Class Northwest	Window – Length	17.00	17.00	=
	Window – Height	1.70	1.70	=
Class South	Window SE – Length	12.20	12.19	=
	Window SE – Height	1.70	1.70	=
	Window SW – Length	18.78	14.06	-
	Window SW – Height	1.70	1.69	=
Class Northeast	Insulation Thickness	0.05	0.15	+
Class Northwest	Insulation Thickness	0.05	0.15	+
Class South	Insulation Thickness	0.05	0.15	+
Class Northeast	Cooling Capacity	0.00	1,238.85	+
	Temperature Setpoint	25.00	25.00	=
Class Northwest	Cooling Capacity	0.00	2,999.86	+
	Temperature Setpoint	25.00	25.00	=
Class South	Cooling Capacity	0.00	0.00	=
	Temperature Setpoint	25.00	25.00	=
Corridor	Cooling Capacity	0.00	0.06	=
	Temperature Setpoint	25.00	25.07	=
Distribution Duct	Cooling Capacity	0.00	2,999.99	+
	Temperature Setpoint	25.00	29.98	+

Table 12 - Result of the Optimization Search - Original Vector vs Near-optimal Solution

5.5.5. Discussion

The most salient fact of this optimization is the increase in the exhaust tower height from 2.0 m to the maximum value allowed, 6.0 m. The bigger the tower, the more draft there is and it thus helps natural ventilation, bringing more fresh air to the classrooms. This can explain in part the improvement in the thermal comfort metric. Adding small capacity air-conditioning units of 3,000 W would also make up for the hot days when natural ventilation alone cannot provide occupants with fully satisfactory thermal comfort conditions. This results in greater energy consumption, but adding extra insulation layers of 15 cm in the floor of the classrooms counterbalances the negative impact of air-conditioning by decreasing the heating demand for the cool summer days when heating is required. It is interesting to note that the glazing area of the extract chamber remains the same, most likely to help natural ventilation and visual comfort. However, the glazing area in the north east classroom is decreased by 50%. This is the classroom that gets least sun and this window surely is a path to heat loss by radiation heat transfer with the sky. A smaller glazing area, however, results in a worse visual comfort and one could replace it for a more energy-wise window instead of decreasing the area of the window. Last but not the least, the south west glazing area in the south classroom is decreased by 25%; this makes sense inasmuch as this is the façade of the building that gets most sun and there is overheating in the south classroom during the bright summer days. Thermal comfort is thus improved albeit for a loss in visual comfort.

From a more general perspective, the building performed already very well, which accounts for the overall mild improvement in the building performance.

5.6. Conclusion

This set of examples proved that ANNs can faithfully represent the performance of complex buildings in terms of energy demand, thermal comfort, and visual comfort. In the first case, the influence of three parameters only was studied, and the ANN gave accurate predictions with less than 5% maximum errors when compared to the ESP-r predictions. In the second example, however, more cases were required to train the ANN and the ANN also required a greater number of neurons in the hidden layer. The cooling demand and the visual comfort metrics were the two hardest aspects to predict. On average, error between the ANN and ESP-r's predictions remained below 5% but for one case—6.5% for the cooling demand. The global performance could be increased by adding more samples to the training pool and another hidden layer to the ANN. On the other hand, this would substantially increase the computational time. This is clearly one limit of this method: the more design parameters and objectives in the objective function, the heavier the computations.

The GA found near-optimal results in a matter of a couple of minutes. These results were corroborated by a GPS algorithm available within Matlab. The Matlab Optimization Toolbox thus offers the possibility to verify the results of an optimization search with seemingly performing algorithms.

One of the most salient facts is that the 2*N (two times the number of design parameters) law does not seem to hold when it comes to building simulations involving thermal simulations, fluid mechanics, and visual simulations. It would be interesting to study for example the relationship between the number of input over the number of output ratio and the minimum number of cases to sample the search space efficiently in the case of building simulations.

In terms of results, this set of examples showed the complexity of optimizing for conflicting aspects of a building such as thermal comfort and energy demand, or thermal comfort and visual comfort. The first example gave the best trade-off between improvement in thermal comfort and loss in visual comfort by playing on three parameters only. This first example also showed that the three parameters were not the most important ones since playing on them only did not yield any satisfying results. The second example was more comprehensive and different solutions were proposed at the same time to test their viability. The optimization results are interesting since adding a cooling capacities in the class rooms did not have a too negative impact on the overall energy demand over the summer and it improved occupants' thermal comfort. The optimization also showed the importance of improving floor insulation, which is in accordance with remarks made by NTNU researchers who worked on the building. Likewise, it validated the general agreement that the exhaust tower ought to be increased to help natural ventilation, and thus, the energy performance of the building.

CONCLUSION

6. REMARKS, TEACHINGS, AND RECOMMENDATIONS FOR FURTHER WORK

6.1. Remarks on Building Optimization

The literature review preparatory to this study showed there has been confusion between 'improvement' and the field of optimization for a long time within the building community. Yet, much has been done over the past decades and various optimization techniques were successfully applied to buildings. GAs have been extensively studied and have proven to perform well at solving building optimization problems. GAs' only flaw is that they require a significant number of simulations to find a near-optimal solution. As a result, building optimization studies with GAs have used fairly simple objective functions only. To this day, very few studies dealt with comprehensive objective functions encompassing aspects as diverse as energy demand, thermal comfort, and visual comfort for example, mainly because of the computational challenge this would pose. However, optimizing for a single objective function only may result in poorly integrated buildings. As a matter of fact, different aspects of a building are often competing such as energy usage and thermal comfort. From this stemmed the idea of using an ANN to replace the building simulation program, and thus, alleviate the computational burden. Resorting to an ANN enables to optimize for more complex objective functions using evolutionary algorithms such as GAs.

6.2. Conclusions on the Present Work

The method proposed was tested with a set of examples to different extents. It was first successfully tested on a small-case example: a four-room portion of an office building in Ottawa. The ANN performed well with prediction errors below 5% compared to ESP-r. The GA found a near optimal solution yielding a 1% to 4% increase in thermal comfort, 12% reduction in the heating load, and 4% in the cooling load. For the second set of examples, a full building was used: a school located in Norway. More design parameters were added to test the limits of the method. As well, visual comfort was added to the objective function on top of energy and thermal comfort. More cases were required to train the ANN but with sufficient training it performed well with average prediction errors below 5% except for one aspect: the cooling demand for which the average prediction error was 6.5%. The Mediaa School case proved much harder to optimize; it was indeed designed to be a high-performance building using natural ventilation and providing optimum indoor air quality. It was extensively studied by NTNU researchers within the frame of the International Energy Agency's research programs. Therefore, it was hard to improve, whence the mitigated optimization results.

The study showed that ANNs can faithfully represent very complex functions to assess the performance of a building in terms of energy, thermal comfort, and visual comfort. Besides, it was shown that using an ANN embedded within a GA was feasible and the process is fairly straightforward with Matlab. It would thus be easy to use for any designer with minimum knowledge in programming, which was one of the main concerns of this work: to propose a methodology easy to implement with accessible tools.

On the other hand, the method also showed its limits, namely the number of inputs (design parameters) versus the number of outputs (aggregates of the objective function). Likewise, the two times the number of inputs rule of thumb does not hold for complex cases: the more complex the objective function, the more samples are required for the ANN training. The empirical relation between the number of inputs and the number of simulation cases for the sampling method should perhaps take into account the number of outputs.

6.3. Recommendations for the Future – Building Optimization

It seems essential to study the optimal number of sample cases to train the ANN as a function of the complexity of the outputs, i.e. the functions to approximate. The relation does seem to hold when only energy equations (thermal and mass flow) are taken into account, as in our first example. There were ten inputs for six outputs. 35 cases were used to train the ANN and 15 to test it.

The introduction of lighting equations requires a much greater number of samples to train and validate the ANN, as shown in the second example. With three inputs and 15 outputs, 200 cases were required to train the ANN and 50 to validate it. The last example comprised 24 inputs and eight outputs. 1,200 cases were used to train the ANN and 300 to validate it. The average prediction error for this last trained ANN was below 5% for seven of the eight outputs but for one case with a 6.5% average error. Such great numbers require a significant amount of computational time, even with an automated process. It is therefore essential to have a precise idea of the number of cases necessary to the ANN training and validation in order to avoid losing time and having to start simulations again with another training pool.

In the case of building simulations, the minimum number of cases to train and validate an ANN seems to depend not only on the number of inputs, but also on the number of outputs and possibly on the complexity of the output to calculate.

Other sampling methods might be more appropriate in the case of lighting simulations.

6.4. Potential of ESP-r

From an ESP-r perspective, it would be interesting to use the sensitivity analysis module to estimate parameters of interest. This module could also be developed so that it could generate the ANN training pool in an automated fashion.

There is a need to investigate the lighting simulation capacity within ESP-r once the tool is made available, and to test the ability of ANNs to approximate these simulations.

ESP-r works with GenOpt, one of the most promising building optimization tools. When using population-based optimization algorithms, GenOpt calls the building simulation program for fitness evaluation. The use of these potent algorithms with ESP-r is thus reduced for the moment due to the extreme computation time required, whence the need to approximate the building simulation program and to exploit its strengths with an ANN. In that sense, this aspect could possibly be included to

GenOpt to be able to build a response surface approximation model of a complex building evaluation function in a first step, and then use it for the optimization search.

REFERENCES

Agence France-Presse New York (July 18, 2007), *L'ex-PDG d'Exxon prône une réduction de la demande en énergie*, La Presse, Montreal, Quebec

Agence France-Presse Paris (July 16, 2007), *Le Vatican bientôt le premier État « neutre » pour les émissions de CO2*, Le Monde, Paris, France

Allard, F. and Santamouris, M. (1998), *Natural Ventilation in Buildings - A Design Handbook*, Earthscan, London, United Kingdom

ASHRAE (2001), *ANSI/ASHRAE Standard 62-2001: Ventilation for Acceptable Indoor Air Quality*, Atlanta, Georgia, USA

ASHRAE (2004), *ANSI/ASHRAE Standard 55-2004: Thermal Environmental Conditions for Human Occupancy*, Atlanta, Georgia, USA

Choudhary, R., Malkawi, A., and Papalambros, P.Y. (2003), *A Hierarchical Design Optimization Framework for Building Performance Analysis*, Proceedings of the 8th International IBPSA Conference, Eindhoven, the Netherlands

Chow, T.T., Zhang, G.O., Lin, Z., and Song, C.L. (2002), *Global Optimization of Absorption Chiller System by Genetic Algorithm and Neural Network*, Energy and Buildings 34 (2005)

Coffey, B., Morofsky, E., and Haghighat, F. (2006), *Model-based Control of Responsive Building Systems: A Summary of Its Potential Challenges*, Canadian Conference on Building Performance Simulation eSim 2006, Toronto, Ontario

Eiben, A.E. and Smith, J. E. (2003), *Introduction to Evolutionary Computing*, Springer Natural Computing Series, Berlin, Germany

Energy Information Administration (2007), *Annual Energy Review 2007 (International Energy): Table 11.3 [online] available at http://www.eia.doe.gov/emeu/aer/inter.html*

Fanger, P. O. (2000), *Provide Good Air Quality on Air Distribution in Rooms*, Reading, United-Kingdom

Hobbs, D., Mortziber, C., Spires, B., Strachan, P. and Webster, J. (2003), *Experience of Using Building Simulation within the Design Process of an Architectural Practice*, Proceedings of the 8th International IBPSA Conference, Eindhoven, the Netherlands

Human Resources and Social Development Canada (1989), *Revised Part II of the Canada Occupational Safety and Health Regulation, "Lighting"*, published in the Canada Gazette, Part II October 26, 1989, Ottawa, Ontario

Kennedy, J. and Eberhart, R. (1995), *Particle Swarm Optimization*, Proceeding of the IEEE International Conference on Neural Networks, Perth, Australia

La Presse (Septembre 10, 2006), *La verte Suède tourney le dos à l'or noir*, La Presse, Montreal, Quebec

Madhavi, A., Brahme, R., and Gutpa, S. (2001), *Self-aware Buildings: A Simulation-based Approach*, Proceedings of the 7th International IBPSA Conference, Rio de Janeiro, Brazil

Malart, J.M., Heredia-Langner, A., Baxter, D.J., Jarman, K.H., and Cannon, W.R. (2004), *Constrained De Novo Peptide Identification via Multi-objective Optimization*, 18th International Parallel and Distributed Processing Symposium, Santa-Fe, New Mexico, USA

Matlab (2006), *Documentation*, Version 71, MathWorks Inc.

Mengistu, T. (2005), *Aerodynamic Design and Optimization of Turbomachinery Blading*, Ph.D. Thesis, Concordia University, Montreal, Quebec

Ministry of Municipal Affaires and Housing (1997, updated in August 2004), *Ontario Building Code and Supplementary Guidelines*, Government of Ontario, Toronto, Ottawa

Nassif, N. and Zmeureanu, R. (2006), *Dynamic Data-driven Grey-box Models of HVAC System Components, Canadian Conference on Building Energy Simulation eSim 2006, Toronto, Ontario*

Nassif, N. Kajl, S. and Sabourin, R. (2003), *Two-objective On-line Optimization of Supervisory Control Strategy*, Proceedings of the 8th International IBPSA Conference, Eindhoven, the Netherlands

National Round Table on the Environment and the Economy (2006), *Advice on a Long-term Strategy on Energy and Climate Change, Government of Canada, Ottawa, Ontario*

Natural Resources Canada (2005), *Energy Use Data Handbook Tables (Canada): Table 2 & 3 [online] available at http://oee.nrcan.gc.ca/corporate/statistics/neud/dpa/handbook_totalsectors_ca.cfm?attr=0*

The Observer (January 8, 2006), *Shanghai plans eco-metropolis on its mudflats*, The Observer, London, United Kingdom

Reinhart, C.F., Mardaljevic, J., and Rogers, Z. (2006), *Dynamic Daylight Performance Metrics for Sustainable Building Design*, National Research Council Canada, Ottawa, Ontario

Wachenfeldt, B.J. (2003), *Natural Ventilation in Buildings. Detailed Prediction of Energy Performance*, Ph.D. Thesis, Norwegian University of Science and Technology, Trondheim, Norway

Wand, W., Zmeureanu, R., and Rivard, H. (2005b), *Two-phase Application of Multi-objective Algorithms in Green Building Design*, Proceedings of the 9th International IBPSA Conference, Montreal, Quebec

Wang, W., Zmeureanu, R., and Rivard, H. (2003), *Optimizing Building Design with Respect to Life-cycle Environmental Impacts*, Proceedings of the 8th International IBPSA Conference, Eindhoven, the Netherlands

Wang, W., Zmeureanu, R., and Rivard, H. (2005a), *Applying Multi-objective Genetic Algorithms in Green Building Design Optimization*, Building and Environment 40 (2005)

Wetter, M. (2001), *GenOpt(r) - A Genetic Optimization Program*, Proceedings of the 7th International IBPSA Conference, Rio de Janeiro, Brazil

Wetter, M. (2004), *GenOpt(r) Generic Optimization Program User Manual Version 2.0.0*, Lawrence Berkeley National Laboratory, Berkley, California

Wetter, M. And Wright, J. (2003), *Comparison of a Generalized Pattern Search and a Genetic Algorithm Optimization Method*, Proceedings of the 8th International IBPSA Conference, Eidhoven, the Netherlands

Wetter, M. and Wright, J. (2004), *A Comparison of Deterministic and Probabilistic Optimization Algorithms for Non-smooth Simulation-based Optimization*, Building and the Enrivonment 39 (2004)

Wright, J. and Alajmi, A. (2005), *The Robustness of GAs in Solving Unconstrained Building Optimization Problems*, Proceedings of the 9th International IBPSA Conference, Montreal, Quebec

Wright, J. and Farmani, R. (2001), *The Simultaneous Optimization of Building Fabric Construction, HVAC System Size, and the Plant Control Strategy*, Proceedings of the Seventh International IBPSA Conference, Rio de Janeiro, Brazil

Wright, J. and Loosemore, H. (2001), *The Multi-criterion Optimization of Building Thermal Design and Control*, Proceedings of the 7th International IBPSA Conference, Rio de Janeiro, Brazil

Yang, J., Rivard, H., and Zmeureanu, R. (2005), *Building Energy Prediction with Adaptive Artificial Neural Networks*, Proceedings of the 9th International IBPSA Conference, Montreal, Quebec

Yeh, K.C. And Tung, Y.K. (1993), *Uncertainty and Sensitivity Analyses of Pit-migration Model*, Journal of Hydraulic Engineering WWRC-93-05

Yu, B. And van Paassen, D.H.C. (2003), *Fuzzy Neural Networks Model for Building Energy Diagnosis*, Proceedings of the 8th International IBPSA Conference, Eindhoven, the Netherlands

Zhou, L. (2007), *Optimization of Ventilation System Design and Operation in Office Environment*, Ph.D. Thesis, Concordia University, Montreal, Quebec

Annex A

Design of Experiment

Small-Case Example – Office Building in Ottawa

Case Number	Window South Width [m]	Window South Height [m]	Window North Width [m]	Window North Height [m]	Window East Width [m]	Window East Height [m]	Louver Angle South [deg.]	Louver Angle East [deg.]	Lower Outside Temp Setpoint [°C]	Upper Outsid Temp Setpoin [°C]
1	2.4682	1.79455	2.695	1.73185	2.5606	1.68055	30	40	10	2
2	2.4346	1.71475	2.5018	1.75465	2.611	1.61785	120	50	11	2
3	2.5858	1.83445	2.4598	1.64065	2.527	1.85725	40	40	12	2
4	2.6362	1.82875	2.7118	1.78885	2.7874	1.82305	30	120	11	2
5	2.5774	1.70905	2.6866	1.70335	2.4346	1.80595	80	70	15	2
6	2.5018	1.84015	2.5522	1.85725	2.6194	1.72045	120	140	14	2
7	2.653	1.76035	2.401	1.82875	2.3842	1.73755	50	120	11	2
8	2.3926	1.70335	2.527	1.65205	2.4094	1.73185	90	100	14	2
9	2.6446	1.74895	2.7874	1.86865	2.779	1.89715	110	20	13	2
10	2.779	1.82305	2.5774	1.63495	2.737	1.77745	140	160	13	2
11	2.6698	1.84585	2.5102	1.81165	2.7454	1.64065	100	120	12	2
12	2.5942	1.81735	2.3926	1.65775	2.4178	1.78315	90	160	13	2
13	2.7874	1.65205	2.485	1.79455	2.5774	1.86865	120	100	10	2
14	2.5438	1.72045	2.6782	1.80025	2.5018	1.72615	50	150	11	2
15	2.4766	1.77175	2.4346	1.69195	2.695	1.71475	100	60	14	2
16	2.5522	1.69195	2.6698	1.74895	2.7202	1.62355	40	150	15	2
17	2.6866	1.74325	2.4766	1.85155	2.6866	1.81165	20	90	15	2
18	2.7538	1.63495	2.7202	1.62925	2.5438	1.66345	140	120	12	2
19	2.6614	1.85725	2.5186	1.77175	2.7118	1.66915	80	30	13	2
20	2.6194	1.78315	2.4094	1.88005	2.4682	1.84015	150	50	13	2
21	2.4514	1.73185	2.7286	1.67485	2.7622	1.81735	70	70	13	2
22	2.569	1.73755	2.7706	1.68625	2.6278	1.89145	60	150	11	2
23	2.7118	1.66915	2.4682	1.66915	2.653	1.67485	70	110	12	2
24	2.611	1.65775	2.6026	1.84585	2.4766	1.63495	70	40	14	2
25	2.5354	1.64635	2.7958	1.78315	2.6782	1.76605	130	130	12	2
26	2.4178	1.64065	2.6446	1.83445	2.5102	1.78885	130	30	12	2
27	2.3842	1.80025	2.7538	1.88575	2.7958	1.74895	70	80	13	2
28	2.6026	1.88005	2.779	1.80595	2.569	1.79455	140	130	14	2
29	2.4262	1.62925	2.4178	1.89145	2.5942	1.86295	30	90	12	2
30	2.527	1.81165	2.7622	1.68055	2.5186	1.74325	160	50	15	2
31	2.7958	1.86865	2.6278	1.62355	2.7706	1.69195	40	90	13	2
32	2.7622	1.62355	2.4514	1.70905	2.6446	1.76035	110	40	14	2

33	2.7202	1.77745	2.5858	1.61785	2.7286	1.84585	120	30	11	2
34	2.695	1.69765	2.6614	1.66345	2.4934	1.80025	90	70	10	2
35	2.4094	1.89715	2.4262	1.71475	2.7538	1.75465	20	130	12	2
36	2.5102	1.76605	2.5606	1.72045	2.3926	1.82875	140	110	10	2
37	2.5606	1.67485	2.3842	1.86295	2.4262	1.69765	110	140	14	2
38	2.401	1.86295	2.653	1.76035	2.4598	1.88005	50	110	13	2
39	2.4934	1.66345	2.569	1.73755	2.6614	1.87435	150	110	14	2
40	2.485	1.80595	2.5438	1.84015	2.4514	1.68625	60	70	13	2
41	2.7286	1.88575	2.7034	1.74325	2.485	1.64635	80	140	14	2
42	2.5186	1.68625	2.443	1.64635	2.5858	1.77175	60	60	11	2
43	2.6278	1.85155	2.737	1.89715	2.5522	1.65205	150	90	11	2
44	2.6782	1.72615	2.6194	1.77745	2.6362	1.65775	160	60	14	2
45	2.7454	1.87435	2.6362	1.81735	2.443	1.83445	50	80	11	2
46	2.7034	1.68055	2.5942	1.82305	2.7034	1.70905	40	50	10	2
47	2.7706	1.61785	2.611	1.76605	2.5354	1.85155	90	140	15	2
48	2.4598	1.89145	2.5354	1.87435	2.6698	1.88575	100	80	11	2
49	2.443	1.78885	2.7454	1.69765	2.6026	1.70335	130	100	12	2
50	2.737	1.75465	2.4934	1.72615	2.401	1.62925	110	20	12	2

Annex B

Design of Experiments

Inputs for the First Large-Scale Example – Mediaa School

Case Number	Extract Chamber South Window Height [m]	Extract Chamber Southwest Window Height [m]	Exhaust Tower Height [m]
1	0.694903	0.714651	4.256061
2	0.499039	1.046237	4.443211
3	1.44154	0.601498	4.695622
4	1.45405	1.65967	5.750887
5	0.543088	1.089361	4.11244
6	1.234819	0.68644	3.740518
7	0.739251	1.326071	4.781923
8	1.503149	1.362879	5.208132
9	1.138462	1.33735	2.251663
10	0.840565	1.054636	4.498902
11	0.746959	1.451033	5.423155
12	0.438895	1.614707	4.949741
13	1.632976	0.694345	3.556667
14	1.286096	1.37483	5.49781
15	1.091188	1.106923	4.563552
16	1.618735	1.132104	4.527649
17	0.593998	0.874281	2.677329
18	1.136257	0.624598	5.450187
19	0.512483	1.686402	5.40591
20	0.673377	0.553342	5.637789
21	0.624679	1.155232	5.766668
22	0.92417	0.697486	4.391136
23	0.520701	1.562806	3.223432
24	1.05317	1.101813	4.541628
25	1.552719	1.308123	4.767736
26	0.886622	1.312711	5.009182
27	0.44533	1.224187	3.780033
28	1.44856	0.755047	2.365938
29	1.601729	1.210257	3.304078
30	1.120914	1.543302	4.834973
31	0.828764	1.725607	2.877043
32	0.769273	1.488189	3.914138
33	1.53961	0.474407	2.484699
34	1.459726	1.195079	4.426533
35	0.465796	0.585588	3.961591
36	1.634539	1.680809	5.028189
37	0.754622	0.743796	2.012778
38	1.596294	0.559472	3.155609
39	0.525112	0.680377	5.6775
40	1.433154	1.076944	5.256777
41	0.681313	0.49606	3.39018
42	0.837982	1.114815	5.970975
43	0.606378	0.648972	3.533172
44	0.632435	1.202189	2.454673
45	1.272578	1.699172	3.052086
46	1.20324	0.993803	4.36062
47	1.211911	1.056643	3.003751
48	0.980232	0.731366	3.637085
49	0.557075	1.30359	2.073264
50	0.927924	1.391064	2.54668
51	1.543322	1.168361	4.611025
52	1.474595	0.445791	2.189655
53	0.715416	0.926902	3.321251
54	1.646715	0.746582	4.547525
55	0.959372	0.655756	2.470198
56	1.248309	1.228013	5.560064
57	0.492737	1.625006	2.951429
58	0.573877	1.325058	5.325722
59	1.672068	0.630998	4.318938
60	0.517447	1.55573	5.994725
61	1.300186	0.52009	3.491555
62	0.659844	0.526003	3.189241
63	0.883797	1.636688	4.109352
64	0.863034	0.5443	2.622537
65	0.818367	1.143147	3.138275
66	1.331449	1.319835	5.462195
67	1.043171	0.981398	5.379231
68	1.49779	0.43415	3.948534
69	1.207919	0.621183	2.631383
70	1.125895	1.242953	3.094645
71	0.629736	0.966046	5.928559
72	1.625408	1.159846	2.924072
73	0.873913	1.608234	2.502813
74	1.403452	1.677829	4.494768

75	1.536974	1.275595	2.780402	123	0.667815	0.900994	2.58512
76	1.056779	1.500554	3.107442	124	1.177077	1.445529	4.788407
77	0.795488	1.601256	4.064892	125	1.590528	0.711571	2.371303
78	0.458463	1.348479	4.7211	126	1.426765	1.6699	2.115766
79	0.731284	0.94238	5.722404	127	1.253068	0.565594	3.084101
80	0.786149	0.598093	5.425764	128	0.992981	1.574926	2.539976
81	0.456634	1.712061	2.931013	129	0.69728	0.811139	3.977089
82	1.445194	0.911223	3.477522	130	0.536633	1.266782	2.277211
83	1.187576	1.434963	5.118048	131	0.773267	1.254759	4.99713
84	1.563595	1.083493	3.828767	132	0.564174	1.54222	5.356998
85	0.707296	0.991065	2.884195	133	1.515616	1.111355	4.683009
86	1.040984	1.070641	3.855534	134	0.853671	0.890477	4.645687
87	1.239912	1.044813	4.198461	135	0.916923	1.039368	2.789625
88	0.635543	0.639278	5.591984	136	1.034089	1.030476	4.744415
89	1.268386	0.898326	3.433657	137	1.342325	0.937461	5.48473
90	0.595619	1.009818	3.760116	138	1.188355	0.763681	2.963195
91	1.471964	1.412095	5.899461	139	1.487253	0.920159	3.986965
92	0.99819	1.68906	4.591113	140	1.387855	1.61619	3.469393
93	0.804474	0.836234	5.549568	141	1.000743	0.930957	3.509619
94	0.42425	0.489905	5.800516	142	0.548348	1.281284	5.846532
95	1.507497	0.958249	3.540141	143	1.525081	0.501555	2.990447
96	0.81314	1.418566	2.565613	144	1.130036	1.239182	4.248606
97	1.324027	0.787939	5.044371	145	1.295695	1.595216	4.30273
98	0.798701	0.921694	4.343741	146	0.654853	1.248905	3.014585
99	1.385759	1.58272	2.131713	147	1.076857	1.549175	2.652122
100	1.015164	1.462706	4.448693	148	0.436125	1.259518	3.212959
101	1.074463	0.873156	5.915449	149	1.554278	0.440354	2.048059
102	1.365627	0.799313	5.961418	150	1.650546	1.468542	3.339495
103	0.482461	1.06453	5.284478	151	1.062964	0.534634	4.899639
104	0.902941	1.199887	2.669092	152	1.029368	1.394966	4.161849
105	0.50441	0.523808	5.512624	153	1.167303	0.672325	2.434779
106	1.143235	1.342881	5.188811	154	0.976843	1.144337	5.274586
107	1.496491	1.420702	4.991125	155	0.486671	1.644307	5.621518
108	1.663753	1.430282	5.601394	156	1.325391	1.218753	4.82959
109	1.107025	0.884355	5.14397	157	0.852329	1.485398	5.784326
110	1.020976	0.592038	2.228966	158	0.617564	1.007831	2.704661
111	1.170791	0.801361	4.974726	159	0.640548	0.8619	2.175925
112	1.688731	1.479122	5.304879	160	1.346011	1.406613	5.233057
113	0.577974	0.831771	5.818196	161	0.661395	0.579165	2.100816
114	1.28035	0.455917	3.621278	162	1.262473	1.126726	3.696279
115	0.450762	0.774511	2.046636	163	0.943828	1.212516	4.219779
116	1.665115	0.971978	3.58842	164	1.48406	1.491853	2.346336
117	1.158231	1.183598	3.895228	165	1.255086	0.606116	3.031547
118	1.655632	1.705418	2.602407	166	1.465997	1.28471	2.803267
119	1.376288	0.95354	5.839785	167	1.418843	1.715322	3.25705
120	1.114555	0.79264	4.912364	168	0.678084	1.368167	4.016989
121	1.572963	1.444131	3.130743	169	1.083805	0.725248	4.130728
122	1.151799	0.664032	2.391673	170	1.276299	0.750432	3.234273

171	0.583059	1.456692	3.649336
172	1.009259	0.458594	4.93405
173	1.363956	1.569483	5.688597
174	0.93108	1.024307	2.818997
175	1.51858	0.571841	5.086206
176	0.98691	0.689499	3.714698
177	1.574229	1.634988	3.803461
178	1.60483	0.46625	3.392918
179	1.218686	1.381815	4.176042
180	0.473284	1.095934	4.374342
181	0.792605	1.335405	2.215763
182	0.42993	1.398567	4.32635
183	1.372475	0.868212	4.409671
184	1.643809	0.766187	5.868654
185	0.778913	0.849816	2.850892
186	1.3122	1.588417	4.035002
187	0.914247	0.974349	4.473798
188	1.480895	0.854943	2.901047
189	1.612859	1.511834	2.256915
190	0.904699	0.449758	5.364694
191	0.891622	1.298538	2.328134
192	1.623847	0.511105	5.569335
193	0.718674	1.516447	3.360735
194	0.871962	1.666851	3.691783
195	0.898851	0.509891	4.662051
196	1.070836	1.591372	3.448281
197	0.951597	1.023614	4.158422
198	1.227519	0.844903	4.238085
199	1.393285	1.529197	4.806708
200	0.688532	1.015029	5.735467
201	0.530018	0.778106	2.754447
202	1.585199	1.502273	3.175303
203	1.561524	0.641974	2.724652
204	0.55275	1.427083	2.406666
205	0.767187	1.291268	3.271601
206	0.648689	0.821654	3.872648
207	1.104489	1.65237	5.711867
208	1.309431	0.480524	4.598074
209	0.963582	1.723975	4.060064
210	1.317558	1.626895	3.745106
211	0.758324	1.650999	4.848721
212	0.495889	0.826027	3.280346
213	1.410805	1.526977	4.713042
214	1.047124	0.839589	3.581029
215	1.424039	0.71854	4.001635
216	1.582833	0.985726	5.103242
217	1.41489	1.27287	5.133344
218	0.974807	0.666662	4.63822
219	1.683165	0.488938	3.823573
220	1.01828	0.998524	3.351833
221	0.825406	0.655583	2.419799
222	1.217032	0.617955	4.871768
223	0.600628	0.949546	2.844302
224	1.180138	1.17407	2.742627
225	1.229174	1.117724	2.028088
226	1.676561	0.546937	2.088176
227	0.844969	0.816149	3.062049
228	0.75071	1.176151	4.284124
229	0.701599	1.233444	2.198911
230	1.352205	0.613982	2.307832
231	1.098316	1.534206	5.227522
232	0.7347	1.187585	5.069542
233	0.724946	1.38742	3.93346
234	1.400958	1.470541	3.862902
235	0.587509	0.572794	2.523277
236	1.52951	0.703152	5.879787
237	1.338488	0.883938	5.657085
238	0.812074	0.905028	5.941933
239	1.291567	0.735389	3.615155
240	1.358556	1.357739	3.671801
241	0.948642	0.469451	5.178796
242	0.471064	1.138074	2.303874
243	1.19453	0.537613	5.163961
244	1.153381	1.149869	4.095673
245	0.567756	1.567911	4.895322
246	0.96739	1.073805	5.521917
247	0.614653	1.520094	2.699852
248	0.863914	0.782602	5.335228
249	1.093118	1.696131	2.150542
250	0.937042	1.354999	3.414585

Annex C

Design of Experiments

Outputs for the First Large-scale Example – Mediaa School

Case number	TCnwest [%]	TCneast [%]	Tcsouth [%]	Hnwest [kWhr]	Hcor [kWhr]	Hneast [kWhr]	Hsouth [kWhr]
1	24.09	28.12	29.74	150.05	4.15	242.41	110.79
2	23.27	27.3	28.79	142.71	3.86	233.65	107.51
3	22.26	25.91	28.01	132.59	3.35	224.8	104.6
4	17.62	20.9	23.92	111.67	2.37	195.56	94.22
5	22.87	26.8	28.46	139.41	3.63	231.46	107.79
6	22.39	26.49	28.12	135.7	3.59	227.06	106.04
7	21.31	24.56	26.9	126.94	3.06	218.2	102.77
8	18.67	22.12	24.8	116.28	2.55	200.76	96.22
9	20.02	23.2	25.88	121.27	2.81	208.93	98.27
...	...	...	...	...	...	...	...

Case number	Hwc_east [kWhr]	Hwc_c [kWhr]	Hwc_west [kWhr]	Hdist [kWhr]
1	110.46	106.99	117.01	2169.42
2	108.97	105.41	115.21	2145.07
3	107.26	103.55	113.07	2123.26
4	100.15	96.59	105.07	2052.76
5	108.43	104.77	114.48	2134.61
6	107.81	104.16	113.76	2123.04
7	105.6	101.8	111.02	2113.46
8	101.86	98.15	106.75	2079.69
9	103.9	100.11	108.99	2077.07
...	...	...	...	...

Case number	DFnw_01 [%]	DFnw_02 [%]	DFne_01 [%]	DFne_02 [%]
1	1.5520416	1.27144	0.4085028	1.9581672
2	1.3152719	1.1044296	0.4872119	2.06534
3	2.4211827	1.7426478	0.3831163	1.9245827
4	2.4223054	1.7344268	0.5997282	2.1986784
5	1.3889991	1.1470623	0.5024035	2.0736576
6	2.2178812	1.6375527	0.410565	1.9478381
7	1.6105816	1.3012833	0.5496077	2.1177446
8	2.4793056	1.787405	0.5506164	2.1368186
9	2.1087194	1.5689652	0.5498311	2.124089
...	...	...	...	...

Annex D

Design of Experiments

Inputs for the Second Large-scale Example – Mediaa School

Extract Chamber		Exhaust Tower	Class Northeast		Class Northwest	
Window Southwest Height	Window South Height	Height	Window – Length	Window – Height	Window – Length	Window – Height
[m]	[m]	[m]	[m]	[m]	[m]	[m]
1.70	1.15	4.00	4.18	1.50	8.59	1.21
0.92	1.46	2.98	4.99	1.49	10.06	0.99
1.05	1.54	2.67	3.06	1.37	10.62	1.01
1.07	1.58	5.53	3.70	1.24	15.99	1.18
1.24	1.59	4.19	3.37	1.58	11.70	1.28
1.29	1.01	4.74	3.06	1.04	13.32	1.11
1.00	1.05	4.88	4.44	1.29	15.85	1.03
1.13	1.34	5.42	4.74	1.25	14.15	1.18
1.57	0.94	5.43	3.48	0.93	13.48	1.54
1.40	1.52	4.52	3.46	1.52	16.13	1.61
1.19	1.08	5.50	2.76	0.94	15.43	1.43
...	...	...	...	...	...	...

Class South				Class Northeast	Class Northwest	Class South
Window SE – Length	Window SE – Height	Window SW – Length	Window SW– Height	Insulation Thickness	Insulation Thickness	Insulation Thickness
[m]	[m]	[m]	[m]	[cm]	[cm]	[cm]
10.03	0.94	13.39	1.19	15.00	5.00	15.00
6.89	1.22	12.26	1.35	10.00	15.00	10.00
7.24	1.23	15.05	1.53	15.00	5.00	10.00
7.55	1.22	13.59	0.89	5.00	5.00	10.00
8.38	1.52	12.22	1.08	15.00	15.00	5.00
11.95	1.37	11.50	1.11	10.00	5.00	5.00
8.04	1.57	14.80	1.01	10.00	15.00	5.00
11.15	1.48	14.94	1.49	10.00	5.00	15.00
9.38	1.33	12.90	1.55	10.00	5.00	15.00
9.51	1.36	14.17	1.53	15.00	5.00	15.00
7.63	1.68	12.59	0.92	10.00	5.00	15.00
...	...	...	...	...	...	...

Class Northeast		Class Northwest		Class South	
Cooling Capacity [kW]	Temp. Setpoint [°C]	Cooling Capacity [kW]	Temp. Setpoint [°C]	Cooling Capacity [kW]	Temp. Setpoint [°C]
2,859.83	27.86	722.59	28.60	2,140.85	29.93
2,554.89	26.67	346.93	28.32	2,286.99	25.74
185.68	29.18	759.38	28.26	836.93	26.67
2,289.09	25.17	1,315.26	26.07	3,696.31	27.92
2,269.00	26.12	944.42	27.03	4,683.07	26.07
427.73	26.98	686.79	27.98	2,148.74	28.37
1,604.67	29.23	728.77	25.12	1,238.33	28.62
2,589.28	29.26	2,104.78	28.35	1,330.53	27.63
2,640.54	27.15	1,912.52	25.27	1,908.37	29.87
1,504.24	26.30	1,752.62	29.80	307.90	26.66
401.87	29.18	1,460.15	28.50	2,906.82	26.24
...	...	...	...	...	...

Corridor		Distribution Duct	
Cooling Capacity [kW]	Temp. Setpoint [°C]	Cooling Capacity [kW]	Temp. Setpoint [°C]
820.30	28.46	748.19	29.95
368.73	25.39	4,728.74	27.04
804.51	28.88	584.35	28.97
719.22	29.79	4,721.54	25.57
95.36	29.46	2,895.31	25.89
529.60	29.36	3,388.48	26.38
711.67	28.27	3,435.32	27.69
235.31	27.44	1,676.98	26.48
4.93	28.61	4,958.94	28.99
944.62	26.31	3,713.40	25.63
846.65	26.88	2,232.07	25.32
...	...	...	...

Annex E

Design of Experiments

Outputs for the Second Large-scale Example – Mediaa School

TCnwest [%]	TCneast [%]	TCsouth [%]	Htot [kWh]	Ctot [kWh]	DFnw [%]	Dfne [%]	DFs [%]
59.35	61.04	59.32	7,516	-364	1.75	0.26	0.57
60.54	65.45	65.79	7,875	-1,448	1.20	0.29	0.36
60.81	62.80	60.94	7,679	-385	1.34	0.29	0.62
63.92	68.46	64.63	8,080	-1,502	1.56	0.30	0.42
58.77	64.46	66.46	7,778	-1,775	1.56	0.30	0.52
60.33	63.65	61.96	7,852	-351	1.64	0.24	0.89
60.33	63.96	62.67	7,776	-649	1.43	0.25	0.46
59.04	62.64	57.66	7,589	-488	1.56	0.28	0.95
63.96	63.55	59.18	7,623	-1,273	1.96	0.23	0.62
56.54	61.72	57.89	7,462	-800	1.99	0.29	0.68
59.59	64.23	62.84	7,811	-1,020	1.73	0.24	0.44

Annex F

Verification of the GA Optimization Results with a GPS Algorithm

Second Large-Scale Example

Performance Factor	Improvement [%]
Energy Consumption	-1.83%
Thermal Comfort	7.74%
Visual Comfort	-1.61%

Zone	Variables	Original vector	Near-optimal solution	Global change
Extract Chamber	Window Southwest Height	1.70	1.70	=
	Window South Height	1.70	1.70	=
Exhaust Tower	Height	2.00	6.00	+
Class Northeast	Window – Length	5.00	2.50	-
	Window – Height	1.70	1.70	=
Class Northwest	Window – Length	17.00	17.00	=
	Window – Height	1.70	1.70	=
Class South	Window SE – Length	12.20	12.20	=
	Window SE – Height	1.70	1.70	=
	Window SW – Length	18.78	13.90	-
	Window SW– Height	1.70	1.70	=
Class Northeast	Insulation Thickness	0.05	0.10	+
Class Northwest	Insulation Thickness	0.05	0.10	+
Class South	Insulation Thickness	0.05	0.10	+
Class Northeast	Cooling Capacity	0.00	1,396	+
	Temperature Setpoint	25.00	25.00	=
Class Northwest	Cooling Capacity	0.00	3,000	+
	Temperature Setpoint	25.00	25.00	=
Class South	Cooling Capacity	0.00	0.00	=
	Temperature Setpoint	25.00	25.00	=
Corridor	Cooling Capacity	0.00	0.00	=
	Temperature Setpoint	25.00	25.30	=
Distribution Duct	Cooling Capacity	0.00	3,000	+
	Temperature Setpoint	25.00	30.00	+

Annex G

Original Performance vs Optimization Search Solution

First Large-scale Example

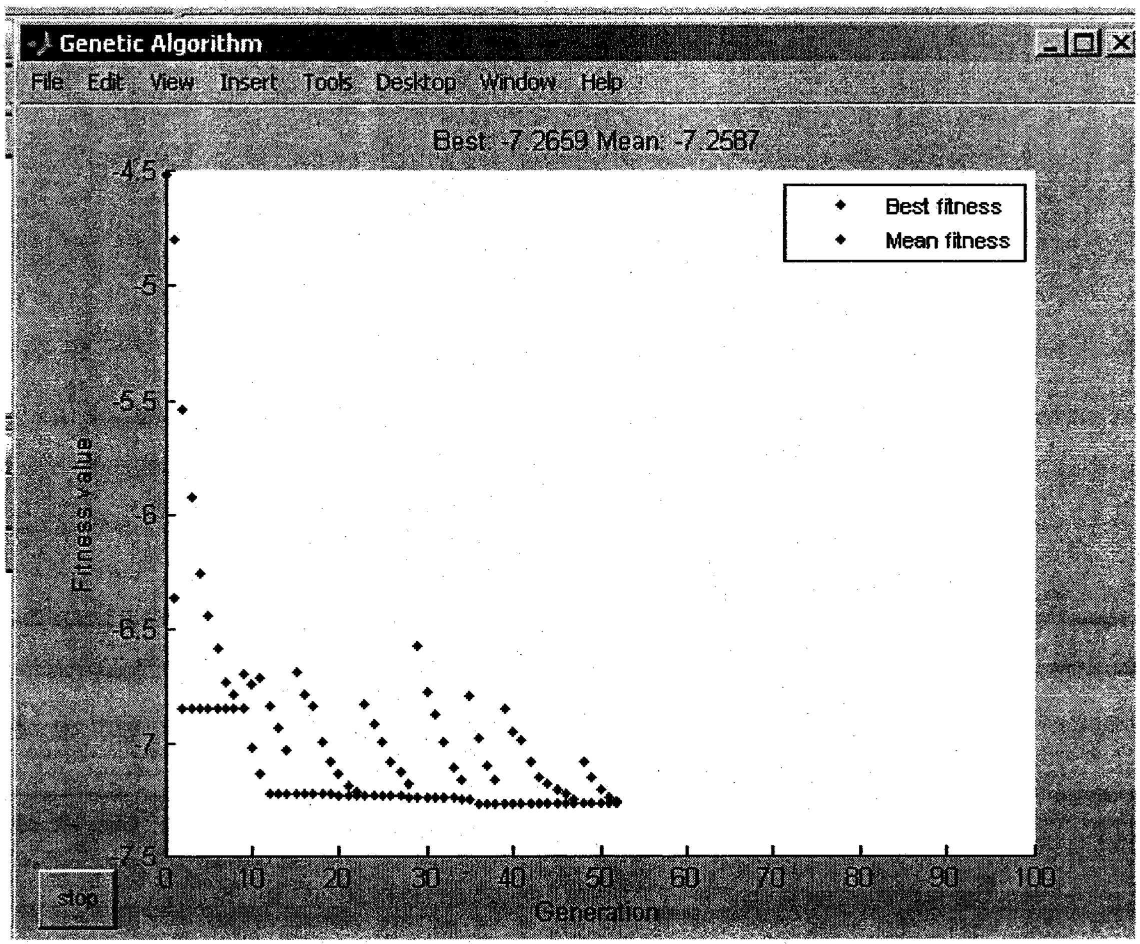
	Original Performance	Result of the Optimization Search
Thermal Comfort Index[8] NE	17%	23%
Thermal Comfort Index[1] S	20%	27%
Thermal Comfort Index NW	24%	29%
Heating Demand [kWh]	2,729	2,951
Daylight Factor NW #1	2.6%	1.2%
Daylight Factor NW #2	1.8%	1.0%
Daylight Factor NE #1	0.6%	0.5%
Daylight Factor NE #2	2.2%	2.1%

[8] Thermal Comfort Index is here the cumulative frequency of time with a PPD less than 20%

Annex H

Convergence of the GA

First Large-scale Example



Annex I

Original Performance vs Optimization Search Solution

Second Large-scale Example

	Original Performance	Result of the Optimization Search
Thermal Comfort Index[9] NE	60.60%	69.30%
Thermal Comfort Index S	65.40%	68.30%
Thermal Comfort Index NW	60.90%	63.60%
Heating Demand [kWh]	7,874	8,014
Cooling Demand [kWh]	-700	-2,043
Daylight Factor Index[10] NE	2.2%	2.2%
Daylight Factor Index S	0.3%	0.3%
Daylight Factor Index NW	1.1%	1.1%

[9] Thermal Comfort Index is here the cumulative frequency of time with a PPD less than 20%
[10] Daylight Factor Index is here defined as the average of daylight factors taken at two different locations in the room.