DESIGN OF AN ENERGY EFFICIENT BUILDING VIA MULTIVARIATE STOCHASTIC OPTIMIZATION

By

DIWAKAR SINHA

A THESIS PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE

UNIVERSITY OF FLORIDA

2012

To the Almighty Lord Hare Krishna

ACKNOWLEDGMENTS

I want to give my appreciation to my advisor, Dr. Mrinal Kumar, for his encouragement and invaluable help in helping me start this project. I would like to express my sincere gratitude for his continuous support of my thesis and research, for his patience, motivation and the experience. I would like to thank Dr. Thomas Smith and his students for their help in the architectural aspect of my design. I would like to thank Dr. Parbir Barooah for his useful advice during the early stage of my research and for his role on my Supervisory Committee as well. I wish to thank Dr. Ravi Srinivasan for his tips in terms of building design parameters and for his advice on the overall shape of this work.

TABLE OF CONTENTS

page

ACKNOWLEDGMENTS 4

LIST OF TABLES 7

LIST OF FIGURES 8

LIST OF ABBREVIATIONS 9

ABSTRACT 10

CHAPTER

1 INTRODUCTION 11

Building Optimization Methods in Literature 13
Delimitation of this Study 18

2 PROBLEM FORMULATION 19

Decision Variables 21
Constant Parameters 26
Optimization Constraints 27
Discrete and Continuous Variables 28

3 SOLUTION METHOD 41

Simulated Annealing 41
Combinatorial Optimization: 41
Physical Annealing 42
A Simple Version of SA Algorithm: 43
Asymptotic Convergence Characteristics 44
Finite time approximations: 44
Implementation 44
Issue with Simulated Annealing 45
Information Guided SA 45
Guided Annealing Temperature: 45
Modified Algorithm 47
Enforcement of optimization constraints 48

4 OBSERVATIONS AND RESULTS 53

On Validity of Modeling Approach 53
Space Heating 53
Ventilation and Air-Conditioning 53

Windows 54
Daylighting 54
User Behavior 55
Results: 56
Building Shape: 57
Thermal Insulation: 58
Windows and Daylighting: 58
Solar Thermal and Photovoltaic Systems: 59
Heating and Cooling: 59
Lighting Control: 59
Optimum Trade-off Strategy: 59
Battery Storage: 60

5 CONCLUSION 74

APPENDIX: NOMENCLATURE 75

LIST OF REFERENCES 78

BIOGRAPHICAL SKETCH 83

LIST OF TABLES

Table page

2-1 PV array, Solar noon tilt data. 36

2-2 Window type and area 36

2-3 Description of design variables 37

2-4 Solar thermal collector type 37

2-5 PV system capacity 37

2-6 Lighting type 38

2-7 Input parameters 38

2-8 Heating, cooling and economic data 39

2-9 ASHRAE Building envelope requirements for climate zone 3A. 40

3-1 Comparison between simulated annealing and physical annealing 52

4-1 Hourly load and usage patterns 68

4-2 Describing the output values when the simulation is run for one year 69

4-3 Describing the output values when the simulation is run for two years 70

4-4 Describing the output values when the simulation is run for five years 71

4-5 Describing the output values when the simulation is run for ten years 72

4-6 Design variables and annual energy consumption data for minimum cost and low energy designs 73

LIST OF FIGURES

Figure page

2-1 Plan of the ground floor 29

2-2 Plan of all floors above the ground floor 30

2-3 Thermal model..... 31

2-4 The building daylight zones for all floors..... 32

2-5 Solar water heating..... 33

2-6 Heating system..... 33

2-7 The elevation of the building and the solar panels..... 34

2-8 Temperature chart of Asheville, NC, USA for the year 2011. 35

2-9 Daylight zone chart of Asheville, NC, USA for the year 2011. 35

3-1 Simulated Annealing..... 50

3-2 A flowchart for the Modified SA algorithm..... 51

4-1 U values of Wall Insulation and Windows 63

4-2 Percentage of total window area to floor area 63

4-3 Auxiliary lighting load..... 64

4-4 Daylight contribution of lighting load 64

4-5 Solar fraction of thermal load..... 65

4-6 Contribution of PVs to the electricity load 65

4-7 Net primary energy 66

4-8 Energy consumption (kW-hr/m2/year) with different simulation periods. 66

4-9 Cost of operating the building. Break-even point is at 9.4 years..... 67

LIST OF ABBREVIATIONS

ASHRAE	American Society of Heating, Refrigerating and Air-conditioning Engineers
HVAC	(Heating Ventilating and Air-Conditioning) refers to the equipment, distribution network, and terminals that provide either collectively or individually the heating, ventilating, or air conditioning processes for a building.
LCC	(Life Cycle Cost) refers to the concept of including acquisition, operating, and disposal costs when evaluating various alternatives.
LCEI	(Life Cycle Environmental Impact) refers to the impact on the environment during the total life of an operating device.
SA	(Simulated Annealing) this abbreviation has been properly explained in Chapter 3.

Abstract of Thesis Presented to the Graduate School
of the University of Florida in Partial Fulfillment of the
Requirements for the Degree of Master of Science

DESIGN OF AN ENERGY EFFICIENT BUILDING VIA MULTIVARIATE STOCHASTIC OPTIMIZATION

By

Diwakar Sinha

May 2012

Chair: Mrinal Kumar
Major: Mechanical Engineering

In this thesis, the model of a four storey office building has been designed with two objectives in mind: (a) minimum usage of energy and (b) minimum installation and utility cost for operating the building. A modified version of simulated annealing has been used to address the underlying multivariate coupled problem and an optimum trade-off amongst the design parameters has been found as a result. The approach is based on the fact that there is presence of multiple local minima, and the modified simulated annealing is expected to perform better than standard annealing in finding the global minimum.

CHAPTER 1
INTRODUCTION

The problem of designing a building with the objective of minimization of running energy or the cost associated with the running energy presents the designer with numerous options to choose from [1]. This is true in spite of the presence of various construction codes and building guidelines [25, 55, 56]. By the use of renewable sources the amount of electricity required to be drawn from the existing grid can be driven to zero. However this entails a significant increase in the associated cost of installation. Hence the optimal design of the building, if performed only in the sense of minimum cost or minimum energy design has conflicting requirements. In a real life scenario both need to be considered and a trade-off must be performed. In addition, optimal design models could be linear [33] in nature or have a nonlinear and possibly non convex and highly multivariate form [3, 6, 27].

In the existing literature various optimization techniques [1, 3, 6, 12, 13, 26] have been proposed to determine optimal building designs. When real life problems are considered the optimization model is invariably nonlinear, non-convex and multivariate. This creates the problem of determining a global minimum among numerous local minima. For such problems there is no universally applicable optimization algorithm to determine the global minimum [29]. This is due to the very-well known ‘no-free lunch’ theorems [42], according to which an algorithm that is effective on a particular class of problems is guaranteed to be ineffective on other classes of problems. To the best knowledge of the author there is no consensus on the existence of a well-established algorithm suited for solving optimal building design problems. Moreover, wide variety of algorithms is used and one must often settle for a local minimum. In addition, the

multivariate nature of the optimization problem demands excessive computational effort which often grows geometrically as the number of free variables increases [29]. Given these observations there is a need for an optimization method that seeks to find the globally optimal design while also reducing computational effort.

In practice, the first step towards development of such an optimization method is the determination of the feasible design variables. Unfortunately the design variables are normally pre-fixed due to architectural, aesthetic or technical requirements and hence the window for modification or of any kind of alteration is not very large. Energy conservation usually comes as a less of a priority. Moreover the design choices are normally discrete i.e. the products available in the markets do not come in all possible shapes and sizes. Such discrete nature of the parameters adds to the difficulty of solving the problem of energy efficient building design. Furthermore at the early stage of design, the designer needs to choose the different properties of design variables (e.g. dimension, U value, cost etc.) based on their availability in the markets [30] and then formulate the problem accordingly to find an optimum design. The process will likely be repeated a number of times, with different sets of design variables in each run to determine the final set of variables to be used for optimization to keep the initial cost predicted by the design to remain within feasible limits. In view of all the above restrictions the designer needs to be presented with some guidelines that would help him play with the input parameters (design variables) to obtain the final design of an energy efficient building that would be possible to build today. Therefore the presence of a set of idealized models, which are sophisticated enough to deal with the coupled

problems with respect to the energy utilization of the building, would be very useful during early stage of design.

Once a model has been created, the optimum value of all involved design variables with respect to a generic building is calculated. In this thesis the objective function is assumed known and has been derived from existing literature. The objective of the current study is to make use of a simple model of a solar low energy building and to optimize its design so that the optimum design variables minimize the energy use as well as the running utility cost. These design variables include building geometry, thermal insulation, windows, solar thermal collectors, PVs, battery capacity to name a few. The optimization scheme used over here is a modified version of simulated annealing which attempts to find the design trade-off paths between conflicting and coupled design decisions in order to find the global optimum.

In summary, there has been marked increase in the energy performance [31, 32] of new solar low energy buildings which has been constructed in recent years. The causes for this phenomenon are multifold. There is an increased awareness about the impact of the use of non renewable resources on the environment. Additionally the soaring cost of everyday living brought on by the current economic crisis has drawn the issue of energy efficiency to the forefront. Hence the motivations of this study are environmental, economic and social benefits. In future too, it is verily expected that demand for energy performance of new buildings will play a big role in shaping the buildings.

Building Optimization Methods in Literature

Numerous schemes for optimization of the performance of buildings have been proposed by researchers. The more recent among these are described in this section.

The optimization techniques used by different researchers were based on the problem they were trying to solve and there was hardly any attempt to improve upon the previously published algorithms. In Ref. [1], Peippo et al. attempted to solve the problem of finding the optimum technology mix for building projects using multiple parameters such as shape of the building, its orientation, the amount of insulation, area of windows, volume of stored water etc. In their analysis, they considered the total amount of energy required to run the building on an annual basis. A cyclic coordinate search method was used in conjunction with the method of Hooke and Jeeves (pattern search) [2] to reach a solution. Although their method was easy to visualize and implement, the convergence was slow.

Bouchlaghem [3] studied the thermal performance of a building using simulation models and obtained an optimum set of design variables by numerical techniques so as to achieve best thermal comfort conditions. Building parameters such as building envelope, fabric, aspect ratio, the orientation of the building, the glazing ratio of the windows etc. were used to study the building design and the best thermal comfort level was determined. Six different objective functions were optimized so as to get six different ways of quantifying thermal comfort. In addition the decision variables were linearly constrained. Two methods were used to perform the optimization: (a) the highly popular simplex method of Nelder and Mead [4] and (b) the so-called complex method proposed by Mitchell and Kaplan [5].Although the convergence rate is high for both these methods, neither guarantees a globally optimal result.

Genetic algorithms [7] constitute another class of frequently used optimization techniques for building optimization. Fonseca and Fleming [15] used multi-criterion

genetic algorithm to solve their optimization problem. They applied the Pareto optimal points for solving a two objective problem. Their objective function was the cost of the building and the environmental impact of the building. Wright et.al. [13] also used the multi-criterion genetic algorithm [7] to optimize the design and the operation of the Heating Ventilation and Air Conditioning(HVAC) system for a building. Caldas and Norford [6] used a method that took into account the dimensions of the windows in order to determine the least amount of energy for heating and artificial lighting. They too solved the optimization problem using genetic algorithms [7].Wang et.al. [14] also applied genetic algorithm although their study was focused towards the design of green buildings. The optimization algorithm attempted to determine the numerical values of the orientation, the aspect ratio of the rooms, and the ratio of window to wall area in order to optimize the Life Cycle Cost (LCC) and Life Cycle Environmental Impact (LCEI).Although genetic algorithms have several advantages such as their universal applicability and ease of implementation, there is no assurance that it will find the global minimum. Moreover, the large optimization response time for genetic algorithm limits it applicability in practical problems.

Jadrzejuk and Marks [8, 9, 10] describe a method in which they divide the problem into three sub-problems: (i) optimization of internal portions, (ii) the shape of the building and (iii) coordination of the solutions. The shape of the building was studied through parameters such as wall length, number of storey's, ratio of window to wall areas, etc. This was also a constrained multivariate problem which considered the construction cost, the seasonal demand for heating, pollutants emitted by heat sources to name a few. The solution method attempted to determine the optimum value using either an

analytical technique explained by Hwang CL [50],or numerical technique explained by S. Jendo and W. Marks [51]. Although these techniques are capable in finding the solution, there is no guarantee of reaching a global optimum. Additionally they take a long time to converge on a solution. Nielsen and Svendsen [11] used their method to find the optimum value of the parameters such as amount of insulation, type of glazing, window fraction of external walls etc. using a constrained optimization problem formulation for determining the optimum life cycle cost of the building. They also studied the energy consumed by the building and the position and duration of the overheating if any inside the building. These parameters define the upper limit of their constraints and the lower limits were defined by the daylight factor. Their problem formulation was quite realistic and it took into account both discrete and continuous variables.

Simulated annealing has been used by Gonzalez-Monroy and Cordoba [12] for optimizing the discrete parameters, and the method by Hooke and Jeeves [2] for optimizing the continuous variables. In a nutshell, this algorithm executes a randomized exploration of the optimization domain in order to determine the optimum solution. Although simulated annealing has numerous advantages e.g. it applies to arbitrary cost functions and is easy to implement, it is difficult to ascertain whether an optimal solution has been reached or not. Yet it is not only a very simple but also a very powerful technique for solving problems that are composed of many variables. Furthermore, it seeks to find a global optimum and statistically guarantees that the global optimum would be found [49].

From the above survey, it is apparent that there have been a number of studies [20] in optimizing various parameters defining the design of a building. We can see that all the above mentioned papers consider the following design variables to be significant:

1. The shape of the rooms of the building or the overall shape of the building expressed in terms of aspect ratio, the number of floors or the three dimensions.
2. The orientation of the building
3. The volume/thickness of the insulation
4. The dimension/area of the windows with respect to the dimension/area of the wall
5. The type of window utilized
6. The shape of the windows
7. The amount of energy utilized in
    a. HVAC systems
    b. Hot water provisions
    c. Artificial lighting measures
8. The cost of building operation

Hence these variables must be considered for optimization of a building design.

A modified version of simulated annealing algorithm (called the information guided simulated annealing) has been used in this study for optimization of the above mentioned parameters. The optimization procedure makes use of the information gathered in the process of randomized exploration of the optimization domain to direct the search direction. The information is used as a feedback with progressively increasing gain to drive the optimization procedure [54]. This method is easy to implement and has been shown to provide significant improvement over standard simulated annealing algorithms for certain optimization problems. In particular the information guided simulated annealing succeeds in finding the global optimum in

numerous situations where standard simulated annealing fails [54]. However no theoretical results exist to back this claim for more general situations. By virtue of its randomized exploration approach the information guided version works well with high dimensional problems and typically converges in a reasonable period of time.

In this thesis the information guided simulated annealing has been used due to its above mentioned advantages and has been shown to provide improvement over the standard simulated annealing algorithm.

Delimitation of this Study

In this work, a uni-objective optimization study of a building model has been performed and consequent design decisions valid for formulations have been presented. The design parameters are constrained within reasonable limits which are decided upon by using various practical examples and available design codes. This study focuses on methods intended for the early stage of design. Consequently the detailed plan of the building has not been taken into account in the solution steps.

The principle design parameters are the aspect ratio of the rooms, the area of the windows, the U value of the thermal insulation, the amount of building envelope, etc. The parameters that decide the design and operation of HVAC systems are not considered. The performance of the building has been studied through a period of ten years with respect to energy, economy, and indoor environment. The study is mainly focused on office buildings and is not suitable for residential buildings.

The reliability and sensitivity analysis has not been considered in this study. Volatility in cost of various system elements has not been included. Development of the database management systems which may be required for managing the information for doing the calculations has not been carried out in this study.

CHAPTER 2
PROBLEM FORMULATION

A simplified model of the building has been created for this study. The layout of the building is rectangular. All the rooms in the building are identical in shape and there are 9 rooms in each floor (Figure 2-1, 2-2). The building is composed of four identical floors. The walls of each of the rooms have a window if they are exposed to direct sunlight. The staircase tower or the elevator tower is not considered in this study. The foundation of the building is assumed to be annular but it has not been included in calculations of energy performance. The orientation of the building has been defined as the counterclockwise angle from due south to the main axis of the building. Insulation has been provided to all the walls that are in direct contact with outside atmosphere. Since this is an office building, each storey is provided with bathrooms, a storage room, a mechanical/electrical room, a conference room and other offices (see Figure 2-1). The elevators and the staircases create a two-way exit from the building, which is compliant with the international building code [52].

The economic analysis is done by summing up all the costs for running the systems in the building for a given number of years. This total cost forms the objective function of this study and is expressed as:

$$C_a = \sum_i C_i + \lambda\left(E_{th}\, c_{th} + E_{el}\, c_{el} - E_{sp}\, c_{sp}\right) \tag{2-1}$$

where C_i is the cost of installing and employing a given design option i and it has been defined as follows:

$$C_i = A_f c_{A,i} + c_i x_i \tag{2-2}$$

where $A_f$is the total room floor area, $c_{A,i}$ is the cost of installing the design option per floor area, and x_i is the degree of design option employed and c_i is the associated cost with the design option. Herex_i is a fuzzy variable of sorts and allows us flexibility in designing the objective function. More detail is provided in the sequel. The coefficient λ is the energy price escalation over a period of time t and is formulated as

$$\lambda = \sum_{k=1}^{t} \left(\frac{1+s}{1+r}\right)^k \tag{2-4}$$

where s is the annual real increase in energy price and r is the real interest rate. Therefore, the cost function of Eq. 2-2 represents the financial burden accrued over the time t.

E_{th} is the annual thermal energy (energy derived from fossil fuels, which is different from the energy drawn from the grid) and E_{el} is the annual electricity taken from the grid. E_{sp} is the energy given back to the grid; or in other words it is the surplus PV electricity. The coefficients c_{th} , c_{el} and c_{sp} are the unit costs of the thermal, electrical and surplus energy respectively.

The building is connected to the utility grid. It has also been assumed that the fossil fuels are an additional source of electricity. A factor of 0.35 has been implemented whenever electricity has been expressed in terms of the raw sources of energy such as fuel etc. This factor of 0.35 may be thought of as the efficiency of the power plant. Note here that from the point of view of environmental conservation, using electricity from fossil fuels is considered less favorable than using it from solar panels or from gird. Therefore, the annual net primary energy requirement E of the building is [1]:

$$E = E_{th} + \frac{E_{el} - E_{sp}}{\mu} \tag{2-5}$$

The cost of installing various design options C_i (in equation 1) in terms of its constituent parts $c_{A,i}$ and c_i has been tabulated in table 2-1 and table 2-2. In the following passages, different decision variables (design options) have been explained in reference to their position and use in the building.

Decision Variables

The following design options have been considered in this study:

1. The shape of the rooms, and the shape of the building (in terms in of aspect ratio)
2. The area and type of windows with respect to the floor area
3. The U value and thickness of the insulation over the walls
4. The capacity the PV array required for electricity generation
5. The area solar thermal systems for room heating and hot water
6. Battery capacity

Shape of rooms. The shape of the rooms is defined by the following aspect ratios:

$$S_h = \frac{w_B}{d_B}$$

$$\text{and} \quad S_v = \frac{h_B}{d_B} \tag{2-6}$$

where, w_B is the width, d_B is the depth and h_B is the height of each room respectively. S_h and S_v are the optimization parameters. The factors that directly related to the aspect ratios are the cost of the building envelope, the cost of insulating the walls, the cost of heat loss and the passive solar light gains. The need for optimization arises because there is a trade-off between the cost of building envelope, the building insulation and

heat losses on one side, and passive solar heat gain and daylight gains on the other side. Each one of these is described below.

Building envelope: The building envelope is the physical separator between the interior and the exterior environments of a building [53]. Insulation has been provided on all the exterior walls. It has been assumed that the roof and the ground floor is also insulated with the envelope. An attempt is made to optimize the volume of insulation which is defined using the three parameters namely, the two aspect ratios and the thickness of insulation. The cost of installing the envelope may be expressed using Equation 2-2 as follows:

$$C_{en} = A_f c_{A,en} + c_{en} x_{en} \tag{2-7}$$

Where the cost of envelope per unit area of the floor

$$c_{A,en} = th \text{ x } [\left\{10 \text{ x } s_h + 14 \text{ x } s_v \right\} x4 + 2 - \frac{A_{windows}}{A_F}] \tag{2-8}$$

where th is the thickness of insulation and $\frac{A_{windows}}{A_F}$ is the total area of the windows per unit area of floor. The value of coefficient $c_{A,en}$ and c_{en} may be found from Table 2-2 to Table 2-8.The overall shape of the building is a function of the number of floors and the dimension of the envelope. In this study, the building is assumed to have four floors. The cost of building envelope is an essential because the geometry of the building is a variable parameter and optimizing it will save money and energy.

Heating and cooling: The temperature is maintained between two fixed limits which define the maximum and minimum limits using a thermostat. The cost of installing and operating the air conditioning (i.e. heating and cooling) system may be expressed using equation 2 as follows:

$$C_{ac} = A_f c_{A,ac} + c_{ac} x_{ac} \tag{2-9}$$

Where $A_f c_{A,ac}$ represents the investment cost, c_{ac} is the unit cost of heat energy supplied/absorbed from the building and x_{ac} is the amount of heat supplied/absorbed from the building. Note that the HVAC system (which is significantly more sophisticated than basic “heating and cooling”) has not been studied here in detail. The heating or cooling mechanism kicks in only when the temperature goes beyond the maximum set limit or minimum set limit point respectively. When this is not the case, the natural ventilation is assumed to be sufficient to provide for enough fresh air and comfortable temperature. The heat loss/gain is assumed to take place through conduction according to Fourier’s Law. This model has been illustrated in Figure 2-3 and may be formulated very simply as

$$Q = -KA\frac{\partial T}{\partial x} \tag{2-10}$$

where, Q is the heat lost across a boundary, K is the conduction heat transfer coefficient, A is the surface, ∂T is the temperature difference across the boundary ($= T_{amb} - T_b$ in Figure 2-3) and ∂x is the thickness of the boundary. Heat is lost through the external walls, the roof and the ground floor.

Lighting control. Lighting control is either through on/off switches (which must be manually operated), or regulators, which are much more sophisticated. Regulators can be used to determine the exact level of lighting required by the room and to adjust the output accordingly. The cost of installing lighting control, C_{lcon} may be expressed as

$$C_{lcon} = A_f c_{A,lcon} \tag{2-10}$$

where A_f is the area of floor and $c_{A,lcon}$ is the cost of installing lighting control per unit are of floor.Clearly, the cost per unit will be different for toggle switches and regulators.

Building windows and daylighting. The windows in the buildings are normally the weakest link with respect to energy conservation [28].The building under study is assumed to have same kind of window on all the sides of outer-facing walls. The daylighting model used over here is a modified version of the one which was used by J.A. Lynes, P.J. Littlefair [16]. The horizontal daylight level in the room is calculated using the following formula:

$$I_d = \frac{2.25\tau A_w}{(1-\rho^2)A_R}\varepsilon_d I_{rr} \tag{2-11}$$

Where, τ is the window light transmittance, A_w is the window area of the room, ρ is the average indoor surface reflectance, A_R is the total room interior surface area,I_{rr} is the hourly solar irradiance on a vertical surface and ε_d is the efficacy of daylight. It was assumed that $\varepsilon_d = 110\mathrm{lm/W}$ since studies have shown that 110 is a good approximation [17]. The factor 2.25 is used to convert radiation from vertical to horizontal level. The building has been divided horizontally into zones in each storey, so that availability for daylighting in each of the zones may be studied separately (Figure 2-4).If the sum total of I_d available from all the windows in a given room is less than 500lx, then, then electricity will be drawn to light up the bulbs. Hence the cost of artificial lighting is:

$$C_{al} = A_f c_{A,al} + c_{al} x_{al} \tag{2-12}$$

Where $c_{A,al}$ will constitute the cost of bulbs and lighting control cost $c_{A,lcon}$. c_{al} is the cost of electricity for operating the bulbs for x_{al} amount of time.

Solar thermal collectors. Solar thermal collectors have been used to store the warm water for domestic use. This is a practical approach because of many reasons [40]. Solar water heaters do not depend on electricity which means hot water is

available even during power cuts. They reduce chances of running out of hot water as long as there is sufficient sunlight. The heat from the sun would heat up the requisite volume of water and once that is accomplished, the heat will then be used for heating of the rooms. In case of shortage of solar energy, i.e. during cloudy or rainy days, the electricity from the grid would fulfill the needs of warm water and room heating. The variables here are the collector type and the volume of water stored. Amount of hot water required per hour has been assumed to be 0.05 liters per sq. meter of floor area. [1]. Figure 2-5 depicts a solar water heating equipment installed on the roof of a residential building. The working principle has been explained in Figure 2-6. The solar collectors warm up the water and the air for the circulation in rooms by a heat exchanger, which also acts as a storage device.

Photo-voltaic cells. In case of shortage of solar energy, i.e. during cloudy or rainy days, the electricity from the grid would fulfill the needs. Excess electricity, whatever produced, is saved in the battery or is sold to the grid. Cost of installing and money saved in running them may be expressed as

$$\mathrm{C_{sol}} = \mathrm{A_f c_{A,sol}} - \mathrm{c_{sol}\, x_{sol}} \tag{2-14}$$

where $\mathrm{A_f c_{A,sol}}$ is the installation cost, $\mathrm{x_{sol}}$ is the PV capacity in Watt peak (W_p) and $\mathrm{c_{sol}}$ is the amount of money saved or earned per Watt (W_p) in selling the electricity to the grid.

It can be expected that the PV will not be sufficient in meeting all the requirements of running the utilities of an office building [39]. This is because of two factors:

a. The cost of installing the PV to cover a large enough surface to provide sufficient electricity is quite large.

b. The space crunch is a predominant problem, especially in case of high rise buildings because while the open roof space remains constant as the building grows taller, the number of rooms and hence the need for electricity increases.

In spite of the above issues, PV systems can be very effective and practical if they are installed with proper planning. The tilt angle of the solar panels was found by determining the average of solar noon tilt data for the 12 months of the year [57] and has been depicted in table 2-1.

Battery storage. When energy requirements are not realized with the available resources, the battery is used to fulfill the demand. Currently lead acid batteries are primarily used(e.g. in manufacturing plants where power lapses cannot be tolerated) to compensate for energy requirements in a variety of applications [48]. The battery is charged using the solar power. In this study, it is considered full when the optimization schedule is initiated. The battery efficiency is assumed to be 90% and it is also assumed to have a discharge rate of 10hrs. Battery capacity has been considered as an optimization variable in this study. Cost of installing and running the battery may be expressed as

$$C_{bat} = A_f c_{A,bat} - \theta c_{bat} x_{bat} \tag{2-15}$$

where $A_f c_{A,bat}$ is the investment cost, θ is the efficiency of the battery, x_{bat} is the battery capacity per hr in KW and c_{bat} is the total number of hours of its use.

Constant Parameters

A number of constant parameters have been introduced in this study because the building model has been kept as simple as possible without compromising on important details. The thickness of the un-insulated parts of the ground slab, the external and

internal walls and the roof are fixed. The internal and external walls have a thickness of 8 inches and the ground slab is 10 inches thick. The floor-ceiling assembly is made of concrete, wood and plaster and it is assumed to be 2 feet in thickness. The window panes are assumed to be 2 inches in thickness and their properties are tabulated in table 2-2. The building planned to be constructed in the city of Asheville, NC, USA (Lat/Lon: 35.57°N 82.54°W Elevation: 1981 ft) because rebates and incentives are given by the government of this state upon use of solar energy for satisfying electricity needs [58]. However these tax rebates and incentives are not a part of this research work. The building is assumed to be facing south. The HVAC systems used inside the building are preset and they can't be altered.

The physical properties of the materials used in construction of walls, roofs, windows etc are assumed unchangeable. The weather conditions, such as temperature and sunlight are taken from the archives containing the temperature and solar irradiation values recorded on an hourly basis for the past years [18]. The input data for optimization has also been enlisted in table2-1 to table 2-7. Much of the data has been obtained from a paper by Pieppo et al [1].

Optimization Constraints

All the variable parameters have been constrained to be positive values. The area of the windows cannot be larger than the area of the walls. The solar thermal collectors are constrained by the upper limit of $25\mathrm{m}^2$. ThePV cells and battery capacity have not been constrained by any upper limit because their cost and battery life respectively limit their use. The building envelope has been restricted by the requirements of the building standards laid down by ASHRAE (American Society of Heating, Refrigerating and Air-conditioning Engineers) [55]. The R values from the table 2-9 have been used for

calculation of insulation for the roofs with metal building, steel framed walls and slab-on -grade floors.

Discrete and Continuous Variables

Both these kinds of variables are used in the building design. For example, the thickness of the building material might be as such that it is easily varied between its maximum and minimum values. Window dimensions, the ventilation system etc are not as flexible as the insulation. Hence although the actual dimension of these aspects of the building may not match perfectly with the optimum solution found out by the program, i.e. it may lie between two values. At this point of time, optimum design is dependent upon the discretion of the designer as to which of the values should be chosen for the design.

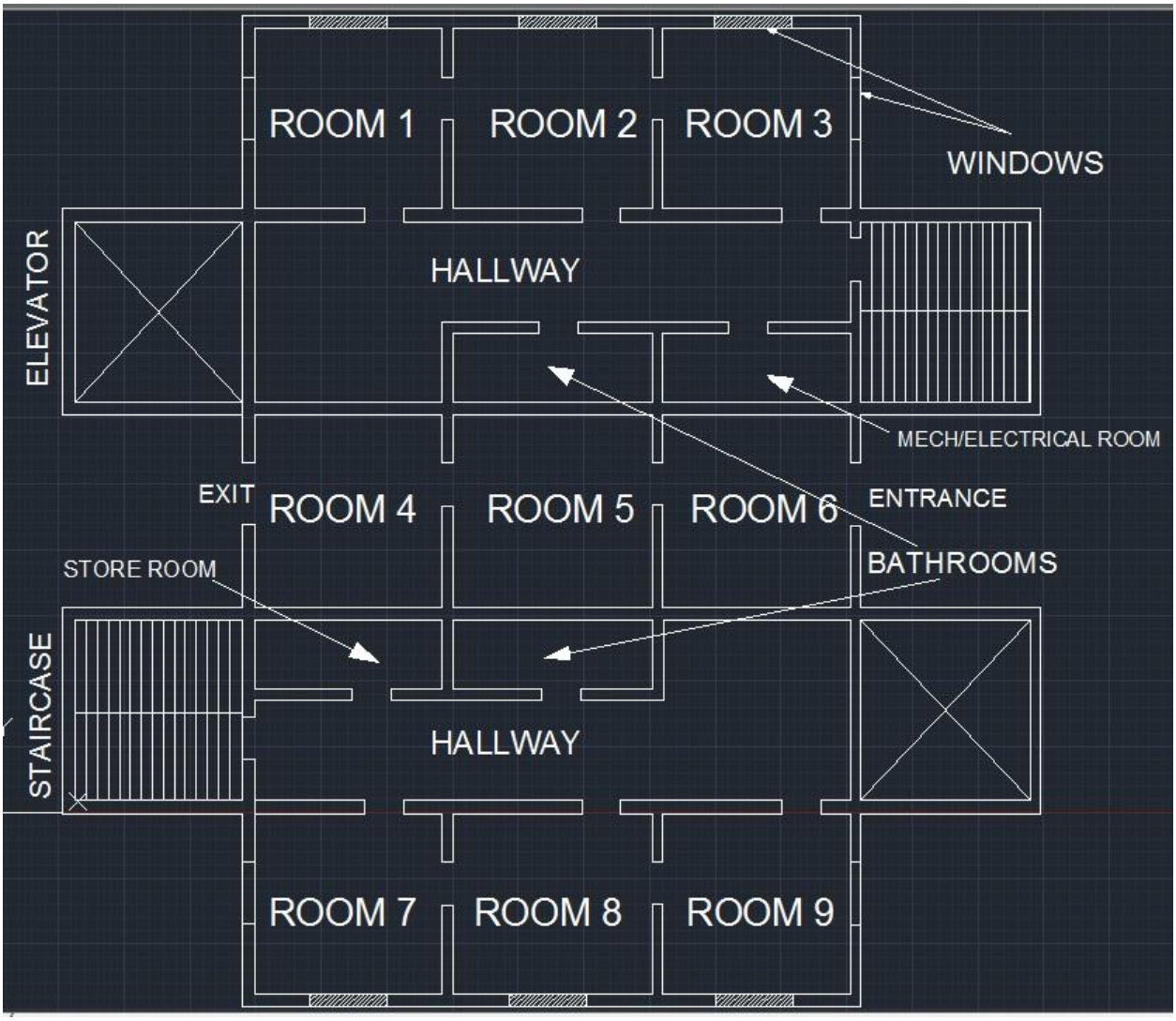

Figure 2-1. Plan of the ground floor

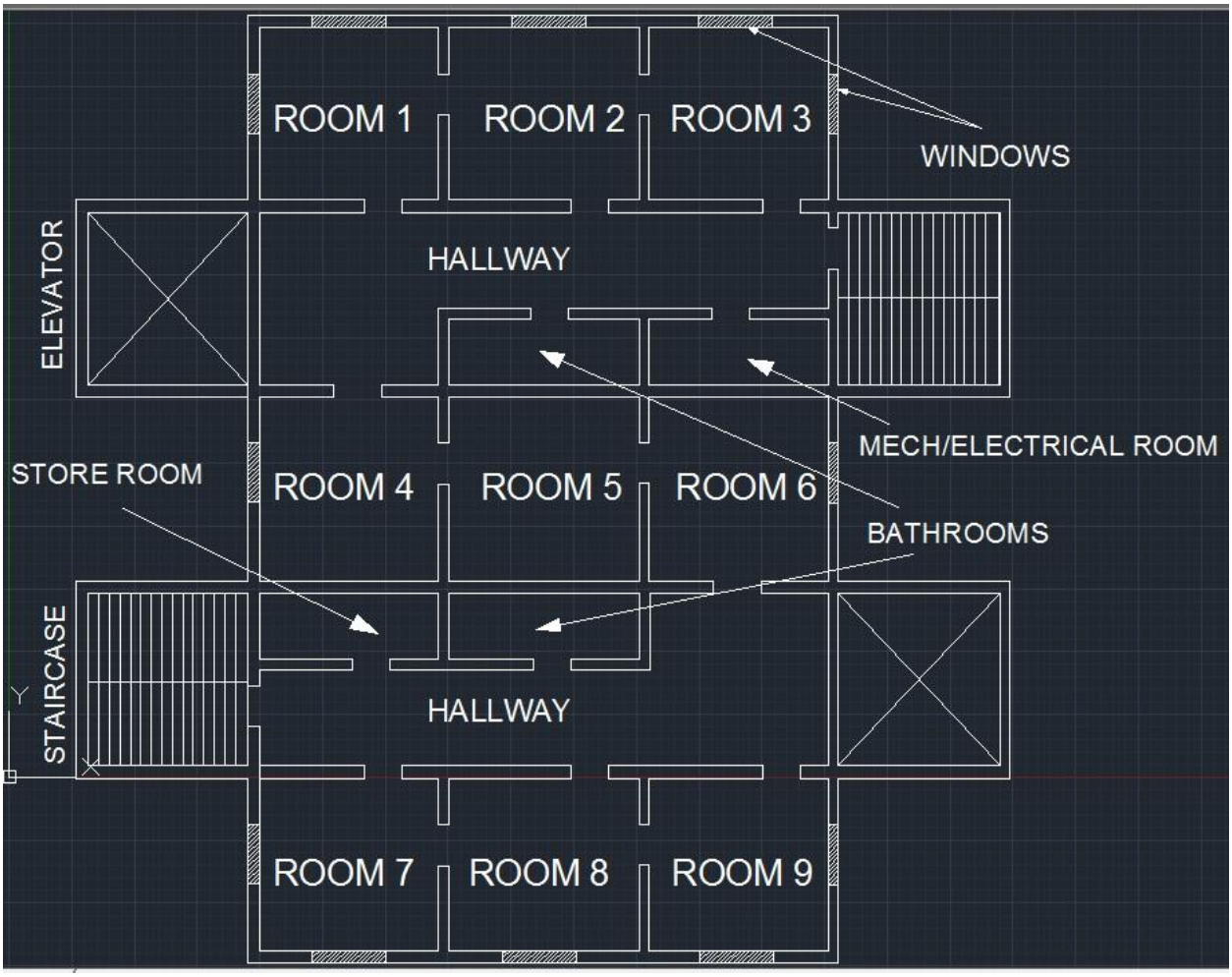

Figure 2-2. Plan of all floors above the ground floor

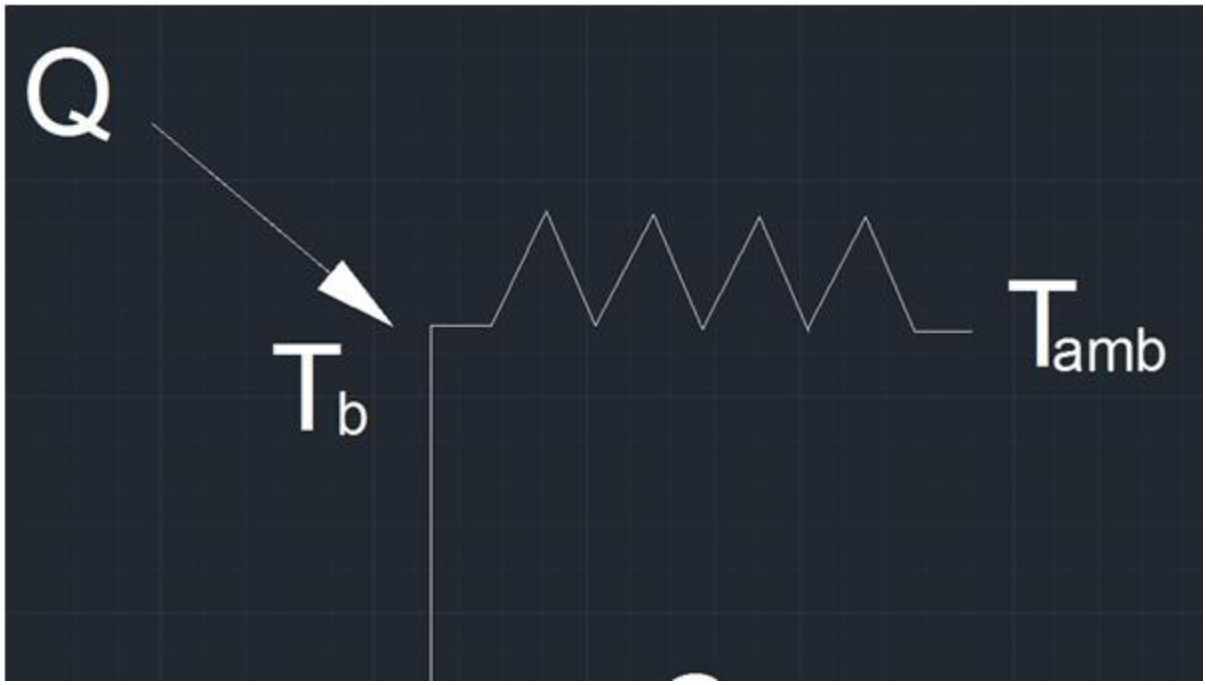

Figure 2-3. Thermal model

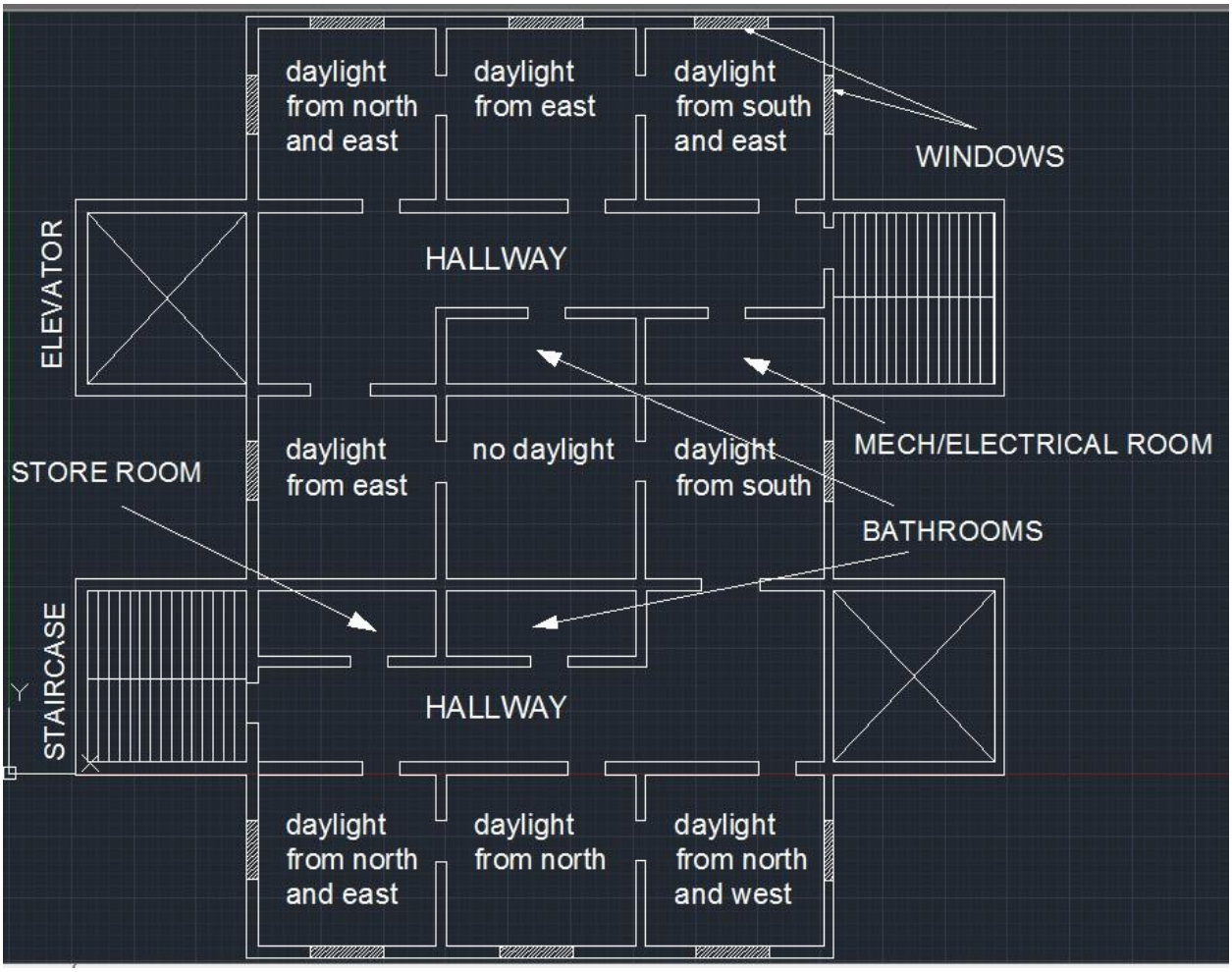

Figure 2-4. The building daylight zones for all floors

Figure 2-5. Solar water heating (Photo credit: The Australian Greenhouse Office)

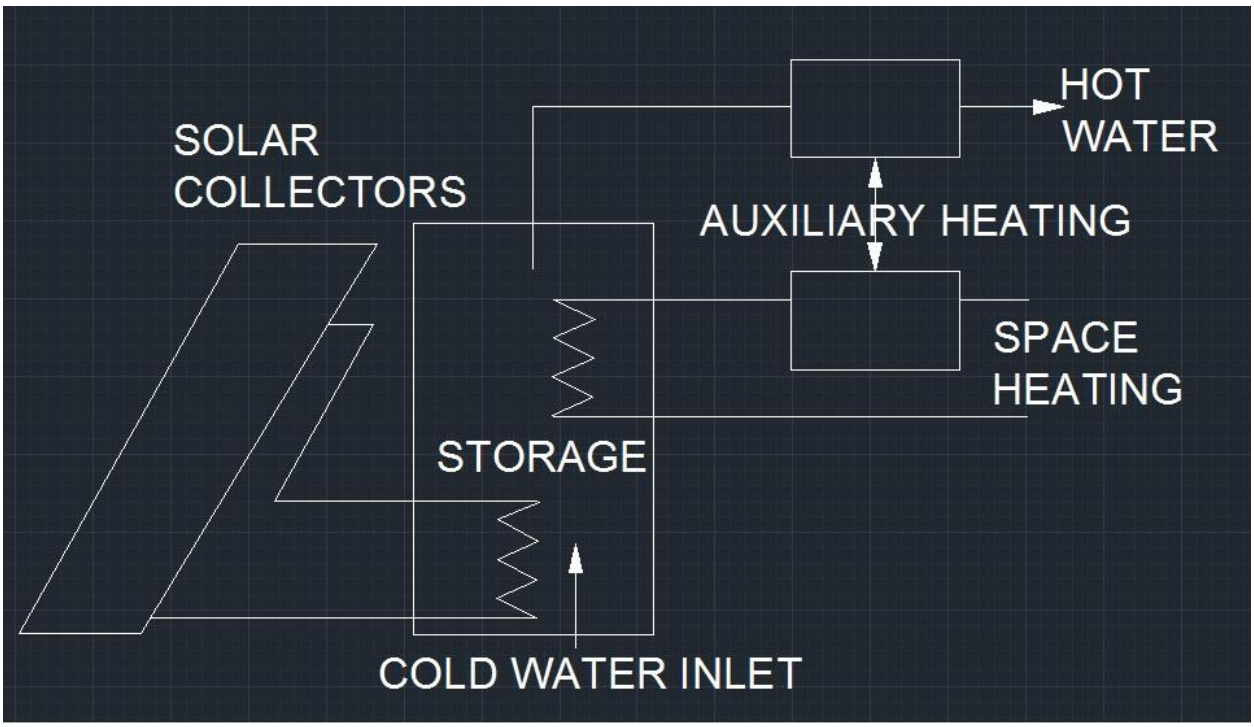

Figure 2-6. Heating system.

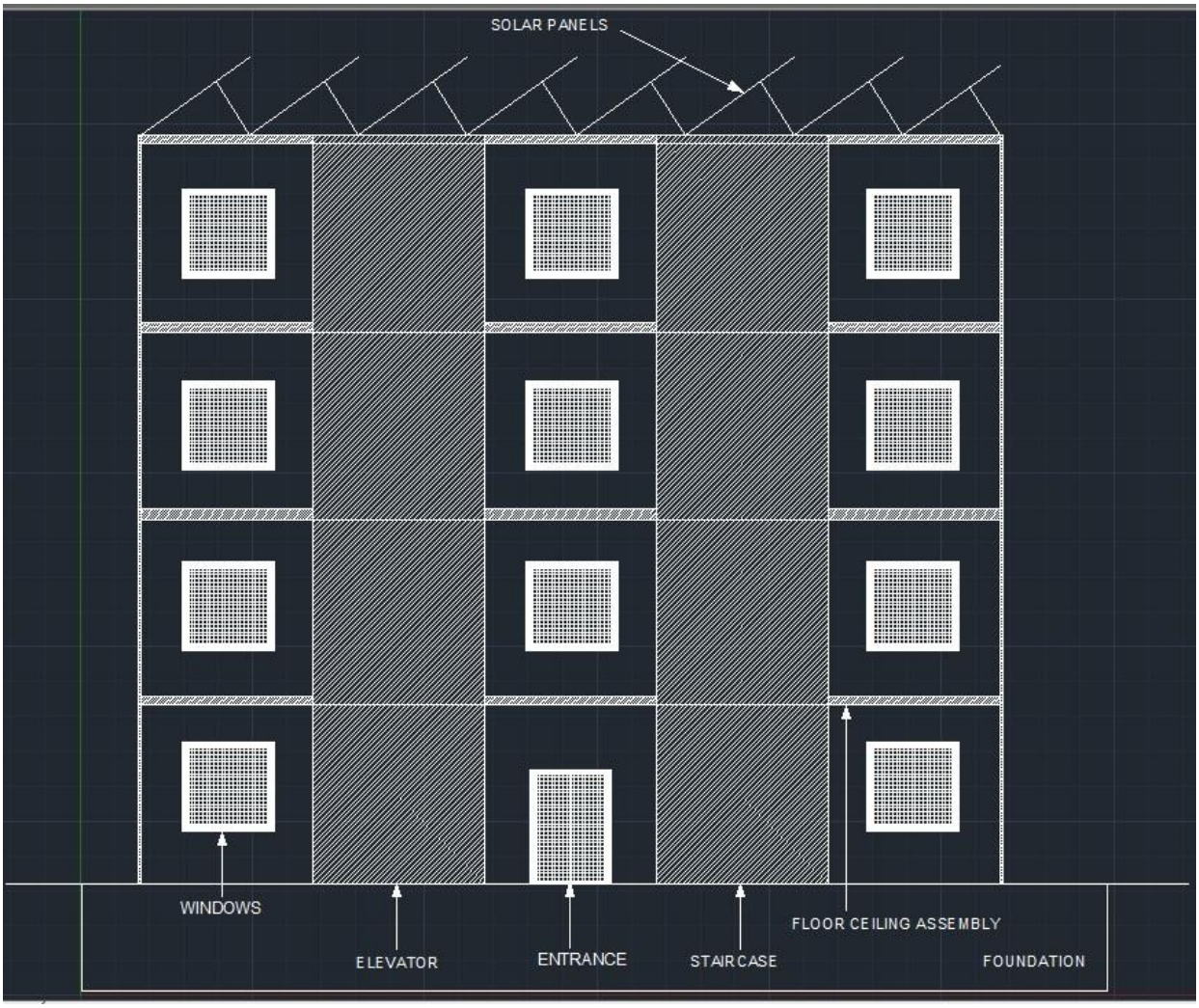

Figure 2-7. The elevation of the building and the solar panels

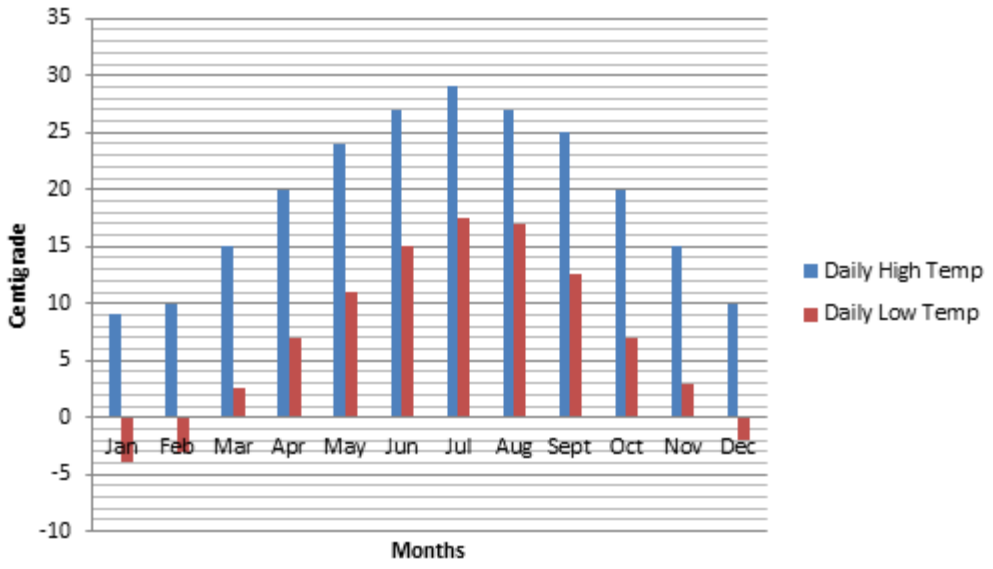

Figure 2-8. Temperature chart of Asheville, NC, USA for the year 2011. (Adapted from: http://www.climate-charts.com/, 9th Feb. 2012)

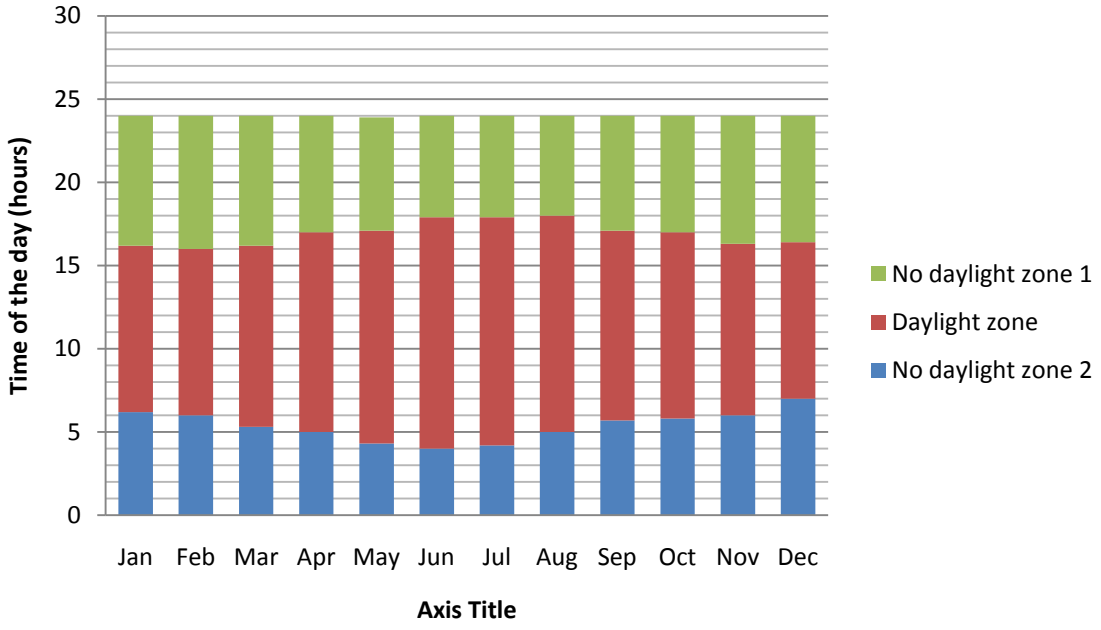

Figure 2-9. Daylight zone chart of Asheville, NC, USA for the year 2011. (Adapted from: http://www.climate-charts.com/, 9th Feb. 2012)

Table 2-1. PV array, Solar noon tilt data.

Month	Sun latitude	Array tilt	Array points to
January	34	56	South
February	43	47	South
March	54	36	South
April	66	24	South
May	74	16	South
June	77	13	South
July	74	16	South
August	66	24	South
September	54	36	South
October	42	48	South
November	34	56	South
December	31	59	South

Table 2-2. Window type and area

Window type	Direct normal transmittance	U value (W/m^3K)	SGHC (Solar Heat Gain Coefficient)	Total cost (USD/m^2)
Single glazed	0.90	6.0	0.4	100
Double glazed	0.80	3.0	0.4	150
Triple glazed	0.75	1.8	0.4	200
advanced	0.65	1.0	0.4	300

Table 2-3. Description of design variables

Design Variable	Modeling Approach
Building geometry	Horizontal and vertical aspect ratios of the parallelepiped building, cost of the building envelope: 100USD/m^2
Building orientation	Building azimuth angle from south (fixed to 0 degrees)
Collector insulation	One tilt angle for both thermal collectors and PV arrays
Thermal insulation	Opaque insulation of uniform thickness on the building envelope: heat conductivity: 0.07 to 0.01 w/mK, specific heat capacity 70kJ/m^3K, cost 70USD/m^3
Thermal mass	Volume of uniformly distributed thermal mass: specific heat capacity 1600kJ/m^3K, cost 200USD/m^3
Energy storage volume	Fully mixed hot water storage, cost 500 USD/m^3
Solar Irradiation	Vertical solar irradiation on the north and south walls of the building =0.75x amount of irradiation on the east and west side walls.

Table 2-4. Solar thermal collector type

Collector type	η_0	U_c (W/m^2K)	Total cost (USD/m^2)
Simple flat plate	0.8	5.0	500
Advance flat plate	0.7	3.0	700
Evacuated tube	0.5	1.5	1100

Table 2-5. PV system capacity

Module type	Efficiency	Total system cost
Crystalline silicon	0.12	10 USD/W_p+ 100USD/m^2

Table 2-6. Lighting type

Luminaire type	Efficacy (lm/w)	Lifetime (h)	Cost (USD/W)
incandescent	10	1000	0.01
fluorescent	80	8000	0.3

Table 2-7. Input parameters (source: Pieppo et. al see ref. [1])

Parameters	Description
Building geometry	Building volume: Office building 50,000 m^3
	Virtual room dimension: width 5m, depth 5m (for lighting calculations)
	Room heat height: office building 3.5m
	Average indoor surface reflectivity: 0.5
Surroundings	Work plane height: 0.75m (for lighting calculations)
	Ground reflectance: 0.2
	Shading of the horizon: 0 degrees
	Land area restrictions: none
Battery	Cost 700 USD. Estimated life 17years.
Lighting Control	On/Off control, cost 0 USD/m_f^2
	Top up control, cost 5 USD/m_f^2
Exhaust air heat recovery	No heat recovery, 0 USD/m_f^2
	Heat recovery, cost 10 USD/m_f^2
Control of passive gains	1. Global radiation admitted at all times
	2. Only diffuse radiation admitted if room temperature exceeds comfort limit
Building cost	1000USD/m_f^2
Energy price escalation rate	Annual energy price increase s= 1%
	Real interest rate r=3%

Table 2-8. Heating, cooling and economic data (source: Pieppo et. al see ref. [1])

Parameters	Properties and cost
Heating and cooling characteristics	Heating system efficiency (from fuel to thermal energy) 0.9
	Refrigeration system COP: 3.0
	Heating system cost 0.3 USD/W_{th}
	Cooling system cost (mechanical cycle): 5USD/W_{el}
	Air infiltration rate: 0.11/h
	Hot water temperature: $55^{o}C$
	Minimum usable space heating temperature: $40^{o}C$
	Maximum water storage temperature: $90^{o}C$
	Water storage insulation U value: 0.5W/m^2K
	Fraction of water storage heat loss for space heating: 50%
	Average cold water inlet temperature: $10^{o}C$
Economic data	Real interest rate: 3%
	Price of fuel for heating c_{th}: 0.05 USD/kWh_{el}
	Price of surplus PV electricity sold to utility c_{sp}: 0.03 USD/kWh_{el}
	Primary energy to electricity conversion factor: 0.35

Table 2-9. ASHRAE Building envelope requirements for climate zone 3A.

Opaque Elements	Assembly Maximum	Insulation Min. R-Value
Roofs with Metal Building	U-0.055	R-13.0
Roofs with attic and other	U-0.027	R-38.0
Steel Framed Walls, Above Grade	U-0.064	R-13.0
Wood Framed Walls, Above Grade	U-0.089	R-13.0
Below Grade Walls	C-1.140	Not Required
Steel Joist Floors	U-0.052	R-19.0
Slab-On-Grade floors, Unheated	F-0.730	Not Required

CHAPTER 3
SOLUTION METHOD

Simulated Annealing

Simulated annealing was introduced as an interesting technique for optimizing multivariate non-convex functions in early 1980s by Kirkpatrick et al [21] and independently by Cerny [22]. It is a robust, general purpose combinatorial optimization technique (explained in the next section) which uses probabilistic methods to find an optimum solution. Its uses today are as varied, e.g. in neural networks, image processing, code design, VLSI design and many more. Simulated annealing and other similar heuristic approaches are usually applied to NP-hard problems that otherwise require exponential amount of computation time [43]. Since the problem in this study is non-convex and multivariate, it is an eligible candidate for application of this algorithm. The basic idea behind simulated annealing is to allow positive increments in the cost function during the search. This helps overcome local ``humps'' (see Figure 3-1), while avoiding getting trapped in local troughs. This acceptance of cost function increase is implemented via the so-called metropolis acceptance criteria described in the next sections.

The name simulated annealing comes from its basis in combinatorial optimization and its similarity to the physical process of annealing. In the succeeding sections combinatorial optimization and physical annealing will be explained in order to provide a better appreciation of the simulated annealing algorithm.

Combinatorial Optimization:

Combinatorial optimization problems are such problems where maximization or minimization of an objective function is executed by determination of the optimum or

‘best’ solution out of a given/possible set of choices/alternatives. These kinds of problems are fully defined by the search space and the cost function.

The search space S is the set containing the possible choices that can be accepted by the algorithm as a valid solution. The objective function is defined as f: S→ $\mathbb{R}$ such that it maps every possible solution in the search space to the real line. This is a measure of how good the solution is with respect to the other possible solutions. For an objective function f, such that there is a point in search space x_{opt} which makes $f(x_{opt})<f(x)$; for all $x \in S$, then the problem is described as

$$x_{opt} = \underset{x \in S}{\operatorname{argmin}} f(x) \tag{3-1}$$

x_{opt} and $f(x_{opt})$ are known as the global optimum and the optimal cost respectively.

Physical Annealing

In annealing, a solid body is cooled from a very high temperature to ambient temperature at a very slow rate. The aim of this process is to achieve a state of minimum internal energy. The cooling rate is slow because lowering the temperature slowly maintains a thermal equilibrium at each stage of the cooling. The thermal equilibrium can be described by the following Boltzmann distribution

$$P_T\{X = x\} = \frac{e^{-E_x/k_B T}}{\sum_{\text{all states } i} e^{-E_i/k_B T}} \tag{3-2}$$

where X is a random variable which describes the current state, E_x is the energy of state x and k_B is the Boltzmann’s constant, and T is temperature.

In order to emulate this process in simulated annealing Monte Carlo techniques proposed by Metropolis et al [23] in 1953 are used to simulate the phenomenon of evolution of the state of solid body in a heated bath undergoing a process of slow

cooling. The algorithm basically makes use of the current state x and generates a new state y by application of a small perturbation. Then the transition from x to y is done with following probability:

$$P_{accept}(x,y) = \begin{cases} 1, & \text{if } E_x - E_y \leq 0 \\ e^{-(E_x - E_y)/k_B T} & \text{if } E_x - E_y > 0 \end{cases} \quad (3\text{-}3)$$

If the value of y is accepted, then it becomes the current state and the whole step is repeated. This act of accepting the new value over the current value based on the probability is known as Metropolis criterion.

The optimization function f(x) above represents the "current cost" in the combinatorial optimization procedure and is equivalent to the current energy level of the solid in the physical process. An analogy between simulated annealing and the physical process of annealing has been shown in table 3-1.

A Simple Version of SA Algorithm:

Following algorithm is used:

1. **Initialization:** Initial temperature is put at $T = T_{max}$ and a starting value is chosen for the search, $\widehat{x_0} = x_{curr}$. The value of L (x_{curr}) is calculated.
2. **Random Jump Proposal:** A new value x_{new} is found from proposal density N~(x_{curr}, P) where N is a N dimensional Gaussian distribution with mean x_{curr} and covariance matrix P. The value of $L(x_{new})$ is calculated.
3. **Acceptance:** Two cases are possible depending on the value of $\delta \triangleq L(x_{new}) - L(x_{curr})$.
   1. Cost reduction: If $\delta < 0, x_{new}$ is accepted and x_{curr} is updated withx_{new}. Also, L(x_{curr}) is updated with L(x_{new}).
   2. Cost increase: If $\delta \geq 0$ then the new value, x_{new} is accepted if $u \leq \exp(-\frac{\delta}{kT})$ where u is a random number from a uniform distribution between 0 and 1. This is known as the Metropolis acceptance step. Next, x_{curr} is updated withx_{new}. Also, L(x_{curr}) is updated with L(x_{new}). Else, x_{new} is rejected.
4. **End Chain for Current:** More values are sampled till the stopping criteria is reached, i.e. computational resources are exhausted or ending temperature is reached or there have been too many rejections at step 3(2), etc.

5. **Cooling:** The temperature T is reduced according to a predefined cooling schedule e.g. Steps from 2 are repeated after updating $T_{new} = \gamma T_{curr}$ ..
6. **End:** If $T_{new} \leq$a predefined threshold temperature or other stopping criteria have been satisfied, then the program is ended. Optimum value or solution is the most current value of x.

Asymptotic Convergence Characteristics

Finite time approximations:

SA is an exploratory algorithm and the extent of exploration is governed by the temperature T. The cooling schedule is a very important parameter in this regard mainly because it defines the progressive change of the standard annealing temperature i.e. the rate of cooling. Much research has been done on use of different types of cooling schedules [24] and a range of such cooling schedules [45, 46, 47] has been created. In case of discrete domain of optimizations, simulated annealing converges in probability if the cooling schedule is proportional to 1/log k (k = iteration number) [47]. Results for more general conditions especially for continuous optimization domains are not available.

The same jump in cost function is accepted with lower probability when temperature is lower. Thus exploration decreases over time with fall in numerical value of temperature. When high temperature is given, jump is accepted with higher probability; hence there is more exploration of S.

Implementation

This algorithm is quite easy to implement in any standard computer software. The program code needs the following four things to be specified:

1. The search space
2. The objective function
3. The perturbation mechanism
4. The cooling schedule

Issue with Simulated Annealing

It has already been stated that simulated annealing (SA) accepts an increase in the cost function via the metropolis criterion. This is actually helpful in reducing the probability of getting trapped in local minimum points and in searching the entire domain to determine the global minima (Figure 3-1). But the same can become a shortcoming because the algorithm may jump out of the trough containing the global min.

The design problem of this study consists of 18 different variables. The implementation of simulated annealing algorithm gave different results at each run. Sometimes it was quite evident that the solution given by the SA algorithm was definitely not an optimum one. This could either mean that there are multiple minimum points where the SA algorithm gets trapped or that its cooling schedule was not slow enough to converge to the optimum value.

Information Guided SA

To address the above problem, a modified form of SA has been used which is termed as information guided SA [49], which involved the addition of an information feedback term d^* (explained in the next section). The new algorithm tries to guide the search process on the basis of exploration performed during its run. In other words it adds an exploitation feature to the purely exploratory nature of the basic simulated annealing algorithm. The modified form of standard annealing temperature in information guided simulated annealing is termed as guided annealing temperature (T_g).

Guided Annealing Temperature:

In this algorithm, the Metropolis acceptance step is calculated using guided annealing temperature T_g instead of using the standard annealing temperature, T. We

shall define the guided annealing temperature as $T_g = \alpha T + (1-\alpha)d^*$ where T is the standard annealing temperature which is identical to the annealing temperature used in SA algorithms;$d^*$is the information feedback term that is used to track the progress of the algorithm. d^*has been defined as follows:

$$d^* = ||x_e - \widehat{x^*_{curr}}|| \tag{3-4}$$

where, $\widehat{x^*_{curr}}$ is the current estimate of the global minimum, x_e is the ending position of the algorithm for the pervious value of T_g. Thus it can be inferred that x_e is the end point of the Markov chain made for the latest value of T_g. Hence d^* is the estimate of how far away is the end point of the algorithm from the currently discovered of global minimum. In order to control this parameter, the variable α has been used. It is called the information effectiveness parameter. $\alpha \in [0,1]$, which is a function of standard annealing Temperature, T. Information effective parameter may be defined as follows:

$$\alpha(T) = [1 - \exp\{-c(\frac{T}{T_{max}})^2\}] \tag{3-5}$$

It might be remarked that $T_g = \alpha T + kd^*$ where k is the feedback gain term. This gain term is controllable with use of the variable c. Let us see how this works:

At the time when the algorithm begins, the value of α is too close to 1 to have any appreciable effect in $T_g$and hence$T_g \approx T$.As standard annealing temperature T is progressively reduced according to the cooling schedule, the numerical value of α starts to decrease. Although it decreases very slowly yet soon after, its value becomes small enough such that the k term in $T_g = \alpha T + kd^*$ can no more be neglected. But before reaching this stage, the program has explored much of the domain and it might be hoped that it has crossed through the global minima. When the value of $\frac{T}{T_{max}}$ reaches a

predefined value, ε then the information feedback starts dominating the exploration procedure and it starts influencing the algorithm.

Modified Algorithm

Due to the introduction of the information effectiveness parameter, the algorithm has been divided into two phases.

During the first phase is the same as the SA discussed before. The program mainly tries to explore the entire domain of search and tries to find out the optimum value of the objective function. But at the same time, due to metropolis acceptance step, it also runs a probability of rejecting the optimum value and move on to different values inside the domain. $\widehat{x^*_{curr}}$ keeps track of the present estimate of global optimum that the algorithm has been able to find out.

The second phase ensues once the above mentioned random exploration is completed, At this time, T has sufficiently cooled down and the feedback from the information function d^* decides what to do.

The first phase continues as long as $T \geq \varepsilon T_{max}$, the feedback gain starts to become greater and greater in value and plays an important part in trying to direct the program towards the present estimate of global optimum. It is essential to understand that this step should continue only after T has sufficiently cooled down because otherwise, the program will have higher chance of converging to a local optimum point. Following steps are used in the algorithm (see Figure 3-2):

1. **Initialization**: Initial temperature was put at $T = T_{max}$ and a starting value was chosen for the search, $\widehat{x_0} = x_{curr}$. x^*_{curr} and x_e were initialized with $\widehat{x_0}$. The value of L (x_{curr}) and $d^* = ||x_e - \widehat{x^*_{curr}}||$ were calculated.

2. **Determination of information effectiveness**: the value of α was calculated and the guided annealing temperature was calculated.

3. **Random Jump proposal:** the value of α was compared and based on that, one of the following two steps were executed:
Information not effective: if $\alpha \geq \alpha^*$ then draw a new sample x_{new} from proposal density q(x)=N(x_{curr}, P)
Objective function was calculated i.e. the value of L(x_{new}).
Information effective: if $\alpha < \alpha^*$ then draw a sample from the proposal density q(x)= N(x_{curr}, $\frac{d^*}{\eta}$). This step means that new value of x is calculated from a normal density whose standard deviation is dependent on how far the end point of the algorithm is from its estimate of global minimum.
Objective function was calculated i.e. the value of L(x_{new}).

4. **Acceptance:** There are two cases here depending on the value of $\delta \triangleq L(x_{new}) - L(x_{curr})$.

   1. Cost reduction: If $\delta < 0, x_{new}$ is accepted and x_{curr} is updated with x_{new}. Also, L(x_{curr}) is updated with L(x_{new}). A check is done to see if the global minimum was found

      a. New Global minimum found: If L(x_{new}) < L(x^*_{curr}), x^*_{curr} is updated with x_{new}. L(x^*_{curr}) is updated with L(x_{new}) and information function is updated to $d^* = ||x_e - \widehat{x_{new}}||$

      b. Global minimum not found: no new steps taken

   2. Cost increase: If $\delta \geq 0$ then the new value, x_{new} is accepted if $u \leq \exp(-\frac{\delta}{kT})$ where u is a random number from a uniform distribution between 0 and 1. This is known as the Metropolis acceptance step. Next, x_{curr} is updated with x_{new}. Also, L(x_{curr}) is updated with L(x_{new}). Else, x_{new} is rejected.

5. **End Chain for Current**: the process from step 3 is continued until the ending criteria is satisfied i.e. computational resource for the current value of T_g is exhausted etc.

6. **Cooling**: The temperature T is reduced according to a predefined cooling schedule e.g. update $T_{new} = \gamma T_{curr}$ and repeat steps from 2-5.

7. **End:** The algorithm is stopped if the guided annealing temperature has reached a value below a predefined threshold value. The global minimum found by the algorithm is the optimal solution for the given objective function.

Enforcement of optimization constraints

The perturbation mechanism is designed in such a fashion that it would not generate states that fall outside the boundaries specified by the constraints. This is done by putting a check each time a new value has been proposed. If the value does

not lie within the defined constraints, then it is discarded and the process is repeated till constraints are satisfied.

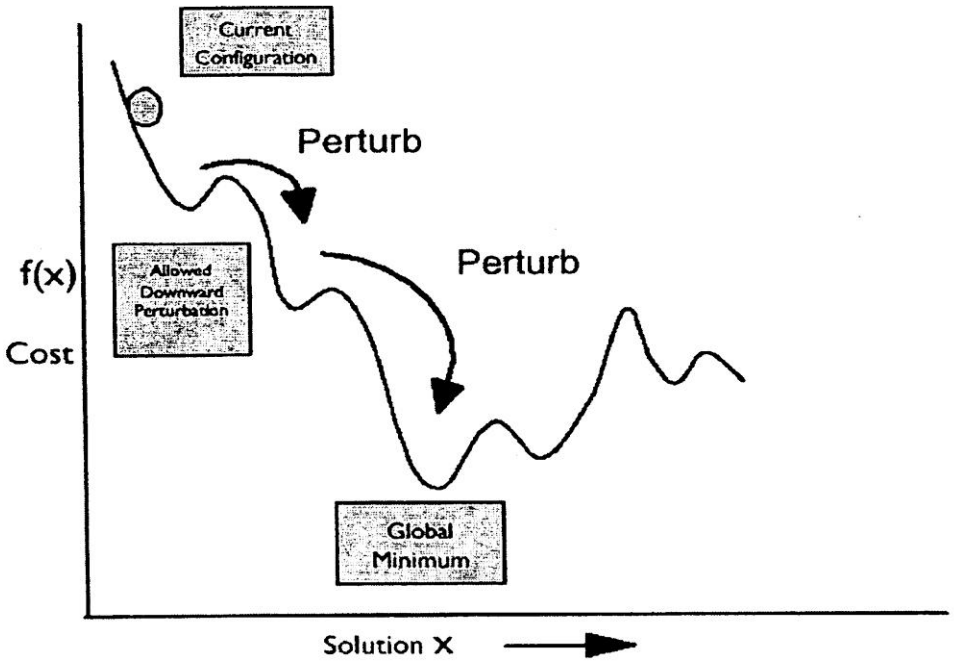

Figure 3-1. Simulated Annealing (source: http://ashakhov.wordpress.com/2011/01/27/-simulated-annealing/, 9th Feb. 2012)

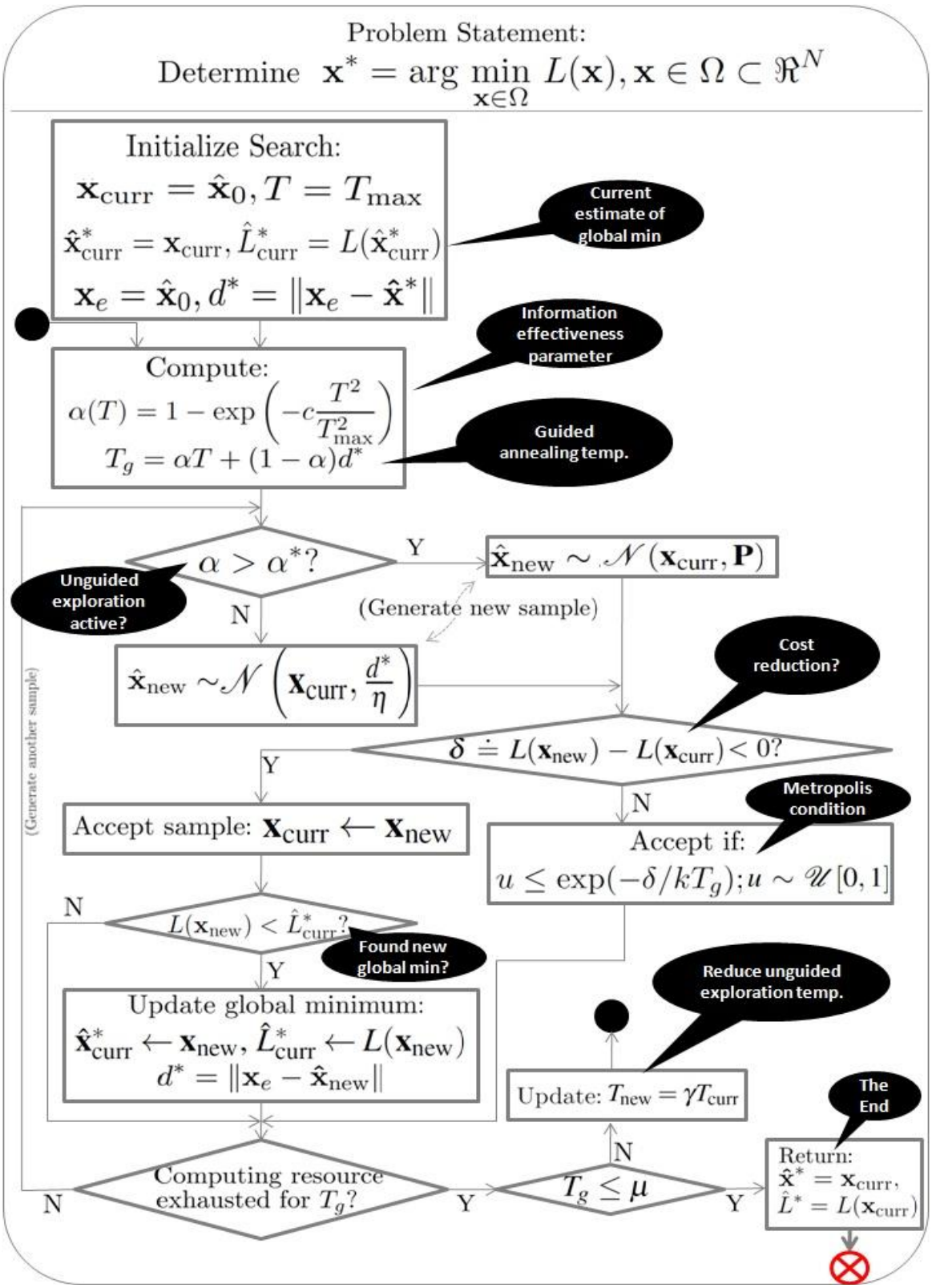

Figure 3-2. A flowchart for the Modified SA algorithm

Table 3-1. Comparison between simulated annealing and physical annealing

Optimization using SA	Physical Annealing process
Solution x	Current (hidden) states of the solid
Objective function f(x)	Current Energy level of solid, E_x
Optimal solution	Ground (~ minimum energy) state
Control parameter	Temperature

CHAPTER 4
OBSERVATIONS AND RESULTS

On Validity of Modeling Approach

The modeling features have been made appropriately detailed and numerous so as to reflect the design requirements of an actual building but at the same time, the focus is on the simplicity of the design so that this problem will be solved without excessive computing power or time. The results obtained were cross checked with the available information about the existing and running buildings in order to assure that the results made sense. Following key points were considered in order to verify the validity of the results obtained:

Space Heating

The results obtained for space heating were compared with more detailed simulations [34] and were found to be in good agreement, to within 10%, with the predicted annual space heating load for office building that has been modeled in this study. However, there is a need to go deeper into more detailed numerical simulations to make this study more accurate, e.g. the thermal comfort in different zones etc.

Ventilation and Air-Conditioning

Natural ventilation has been utilized for this study. This choice amply simplifies the model. The model of the building in the problem statement is assumed to be situated in Asheville, North Carolina, USA. In a state such as North Carolina, one doesn't need to provide measures to cool the buildings because the ambient air temperature is quite low and opening the building windows etc, would be sufficient to cool the room interiors for most months of the year. Passive cooling might also be a good way to go about cooling the buildings, but this is not yet a viable technology to use with respect to cost

considerations. This kind of treatment of the problem might underestimate the need of auxiliary cooling load, but this consideration has been left for future studies.

Windows

It was assumed that the light transmission properties and the heat transmission properties of the windows were equal. This is not a perfectly practical approach since it is known that there are numerous kinds of windows available in the market [28] and hence the present properties of the available windows will not be properly utilized unless a detailed study is conducted e.g. making use of wavelength dependent models etc. which would consider the above two properties separately. But in case of windows, the aesthetic value and the visual comfort are as important as the usefulness of windows in terms of lighting and heating. Hence the assumption made over here is not too far a stretch from reality.

Daylighting

It has been found that 20-30% of the electricity needs is used up by the artificial lighting in office buildings equipped with air conditioners [42]. Hence use of daylighting opens up a wide window for energy saving opportunity. The model under study has been found to be in good agreement with the previous numerical calculations [1] for similar kind of rooms situated in similar areas, to within 10% accuracy. Hence this model works well for the present design under consideration. One might want to use automated lighting control. But that is a rather complicated issue, since user behavior is random and therefore it is still one of the open areas of research, as to how to make a simple enough model to capture the user behavior in terms of use of lighting for low energy buildings.

Off-site Electricity Generation

Photo Voltaic panels are the sources of electricity generation. It might be possible that the owner of building has a renewable alternative that is lower than the cost of PV. But the pre assumption of availability of PV system is very applicable since it is one of the best ways to harness solar power [31, 41].

User Behavior

User behavior is very non deterministic and it needs to be modeled so that the results may reflect an actual situation. In practice it has been observed that heating requirements of the same establishment might be 1.5 times of expected load [36] due to the user behavior. So this uncertainty would definitely affect the optimum value of the building parameters. One way to model this would be to study the distribution of the variables and then sample the values from a p.d.f. during the running of the program. That process would require enough data in the first place to form a p.d.f before samples may be drawn. Another way would be to use previously recorded data. It appears that for this study both methods are equally practical since the use of either of the methods do not give different results.

The main objective of this study is to optimize and find out a set of parameters that will give an economic/minimum value of the objective function, i.e. optimum design. The objective here is not to model the building very intricately. Some studies even insinuate that user behavior does not appreciatively affect the building design [35]. Hence if making use of deterministic parameters gives agreeable results, then it might be understood that such a process is viable, since not only does it gives good solution, but it brings down the computation cost also. In this study, the user behavior has been assumed to be deterministic and the data have been taken from a publication by

Pieppoet.al. [1]. Number of people in the office at a given hour is however assumed to follow a normal distribution as shown in the table 4-1.

In the design of the building, normally the consideration of energy conservation is not a major concern. There are other criteria which take priority, such as architecture, functional requirements, end use efficiency [19] and user preference. It is also worth mentioning that designer tends to neglect some parameters such as interest rate, and rise in price of energy and the value of electricity itself may not be properly portrayed while it affects the optimum design to a good extent. Also, construction of a building is very area specific. The same building may be built at much lower cost somewhere else and that might as well be a better idea to be implemented such a case.

Results:

The program code for modified SA was written in Matlab 7.0 and was run on a 1.74MHz core2duo laptop and it takes 3-9 hours (depending on whether the calculation is done for 1 yr. or 10 yrs.) to run one simulation. At first, the code is run to obtain the optimal system configuration in the sense of annual total of the building i.e. to determine the cost of installing and operating the building for one year. In order to achieve confidence, the optimization procedure is repeated 5 times, following which a mean is computed. The consumed energy which corresponds to this minimum cost was recorded and was termed as 100% relative primary energy. Clearly this consumed energy was received from non renewable sources since minimum cost was a priority. Next the target was to see how the design configurations were influenced by use of 75%, 50% and 0% of this energy. Due to such a constraint, the algorithm will have to explore the renewable energy options to complete the energy demand. Hence the whole optimization process was repeated with the above stated constraint. Thus, four

separate cases for cost minimization were considered (i.e. 100%, 75%, 50% and 0% of relative primary energy).The entire above stated process was repeated ten times; with progressively increasing simulation run time(starting from 1 year to 10 years) in order to record the change in the parameters over a 10 year period. Although slashing the energy received from non renewable sources saved money in running utility cost, there was be a noticeable increase the installation cost. However the calculation of optimum design by this method has one important advantage. It revealed amount by which the energy consumption through non renewable sources should be reduced so that the increased cost of the whole project may still remain within affordable limits. Additionally, if the simulation is run for a longer time then breakeven point could be estimated. Following are the results obtained that reflect how the configurations must change with inclusion of renewable energy sources.

Building Shape:

In order to save energy, ideally the optimum shape is when the rooms are the most compact i.e. when their shape is a cube. This leads to minimum heat loss without affecting the amount of sunlight entering the room through the windows. From the table 4-2 it is evident that the simulation too determined the aspect ratios to be 1:1 for optimum design for the minimum cost case with 100% relative primary energy target. As the relative primary energy target is reduced from 100%, the need for utilizing the heat coming through the walls from the east and west directions increases. As a result the rooms tend to have greater area of walls on the east and west and lesser area of walls on the other two sides. This is evident as the aspect ratios change from 1:1 in case of relative auxiliary primary energy target at 100% to 1.2:1 in case of 0% relative auxiliary primary energy target (table 4-3, 4-4, 4-5).As the size of rooms is increased, the amount

of daylight required is of greater importance than that of the heat loss or the cost of the envelope. Hence the shape of the room becomes such that the ratio of floor area to that of walls starts to approach 1.

Thermal Insulation:

The U value for the objective of minimum cost at 100% relative primary energy is 0.19 W/m^2K (Figure 4-1) for the insulation thickness of 50cm of fiber glass. For the minimum cost with 0% primary energy target, the U values of the wall are 0.06 W/m^2K, which might be noticed to be a little lesser than the U values used for today's buildings (0.07W/m^2K). If insulation is increased, the chances of saving energy also increase and so insulation plays a major role in saving energy. But after a certain level, adding more insulation stops having any appreciative effect on the heat loss.

Windows and Daylighting:

Presence of large windows causes heat loss which results in rise of utility bills. That is why the minimum cost design (at 100% relative primary energy target) shows the percentage of window area to floor area to be a little more than 5% (Figure 4-2). However, larger windows allow daylighting. When PV systems are available for electricity the optimal window area increases to 15%.

The daylight contribution to room illumination in office buildings can be anywhere in the range of 20% to 90% of the lighting load [1]. It is actually good that the illumination requirements are high at times when the daylight is strong.

In the Figure 4-3, the plot for 100% relative primary energy target depicts how the lighting load progressively decreases for minimum energy design over a 10 year period. However the minimum cost design, i.e. 0% relative primary energy target can be seen to have remained unaffected with time.

Without daylight contribution the annual lighting load requirement is 146 MJ_{el}/m_F^2.The daylight contribution in this study increases as the simulation is run for longer and longer periods of time for all the four cases. It eventually saturates at 77% of the lighting load (Figure 4-4). There are rooms in the interior of the building which are not open to the external sunlight. In such rooms the only available option is the use of stored energy or electricity from grid for artificial lighting.

Solar Thermal and Photovoltaic Systems:

Contribution of PVs to thermal load of the building i.e. the solar fraction of thermal load increases constantly with time (Figure 4-5) but it saturates at 51% at the end of 10 year equivalent of simulation run time for all four cases. PVs contribute to the electricity load and eventually they end up producing more than the electricity needs (Figure 4-6). This excess energy is either stored in the batteries or sold to the grid.

Heating and Cooling:

The exhaust heat recovery systems have been applied in this model and as a result, the heating load was considerably reduced. Natural ventilation has been assumed although practical experience from the office buildings does not match with this assumption. This area will be in focus for future studies.

Lighting Control:

It is very clear from the table that an automated lighting control is the best way to go. It not only saves energy but also helps in maintaining a uniform illumination level inside all the rooms separately.

Optimum Trade-off Strategy:

Since the installation of PV is the costliest investment in the whole project, therefore the best way will be to utilize all the other sources of energy which are

available at hands of the designer that are lower in cost than the PVs. Once such resources are exhausted, then investment should be made into PVs. In this manner, it has been observed that 20% energy savings could be realized at only 6.7% increase in the total building cost. Hence one doesn't really need to go for minimum cost design, rather a middle path, where there is energy saving and at the same time there is a presence of affordable cost can be realized.

Battery Storage:

Optimum battery capacity has been found to be 35kW hr. This capacity is influenced by the discharge time of 10hrs for the battery. Hence with the present technologies and cost, it is a good idea to sell some of the excess energy instead of storing all of it because the battery loses its capacity over a short period of time.

The net primary energy of the building at 100% relative primary energy target progressively reduces to zero over a period of about 10 years (Figure 4-7). Even when both the renewable and non renewable sources of energy are available, it can be seen that use of renewable resources is economically rewarding after about a decade. Space heating consumes maximum energy (Figure 4-8) per year. However, if the electrical appliances in the office are also considered, then they are greatest energy consumers. Figure 4-9 shows that after a period of 9.4 years, the building owner will not have to pay for the monthly utility bills if the building is designed with 0% relative primary energy target. Additionally the investment in installation of renewable devices of energy will be returned in form of the savings made from the lowered utility bills. A similar study was performed by Pieppo et. al. [1]. Although they didn't use battery storage as an optimization variable, the number of the rooms on each floor and the input data for all the calculations used by them is identical to the study done in this thesis. Although their

work was based on a building in a different city, the weather conditions (in terms of maximum/minimum temperature per month and average number of hours of available daylight) too are very similar to the city that has been chosen for this work. Additionally this study also considers the electricity requirements of the hallways, bathrooms, a mechanical/electrical room and a storage room on each floor. Pieppo et. al. had employed the method of Hooke and Jeeves to solve their optimization problem. As a result of the optimization, they suggested that total annual cost of 82 USD/m^2 of floor area would be generated. From Figure 4-9, it is clear that information guided simulated annealing has provided better results. The suggested total annual cost for 100% relative primary energy target is 78 USD/m^2. Hence there is an improvement of 4.8% over the previously available results. It has already been mentioned that the standard SA did not converge at all whereas information guided SA gave better results. Hence the above improvement is due to the information guided feedback part of the SA algorithm. In depth analysis of all the results obtained has been tabulated in table 4-2, 4-3, 4-4 and 4-5.

The floor area of each room was assumed to be $25m^2$. Thereafter the numerical values of the results shown in table 4-2 to table 4-5 were calculated again. Table 4-6 enlists the important parameters and the difference in their numerical value for the minimum cost design (at 100% primary energy target) and minimum non-renewable energy design (i.e. 0% primary energy target).

Climate plays an important role in the whole plan [37]. In this study, the location of the building is quite sunny but at the same time, the average temperature is about 14.5 degrees. Hence the room heating takes up a major part of the energy resources. At the

same time, artificial lighting too consumes a significant part of the total electricity (Figure 4-8). However, this kind of a house represents most of the places in USA; hence a design under these climatic conditions is useful.

The program was run for a period of 10 years and it was observed that the cost of installing the building starting from construction to paying for the utility cost without the use of renewable sources or energy efficient methods was equal to the cost of running the building for 9.4 years with the use of renewable resources and energy efficient methods (table 4-7). Hence if the office building is constructed along with installation of the PVs and other energy efficient devices, then the cost will be high initially. However after a period of about 10 years, the invested money will reap its benefits. The breakeven point for this design has been calculated to be 9.4 years.

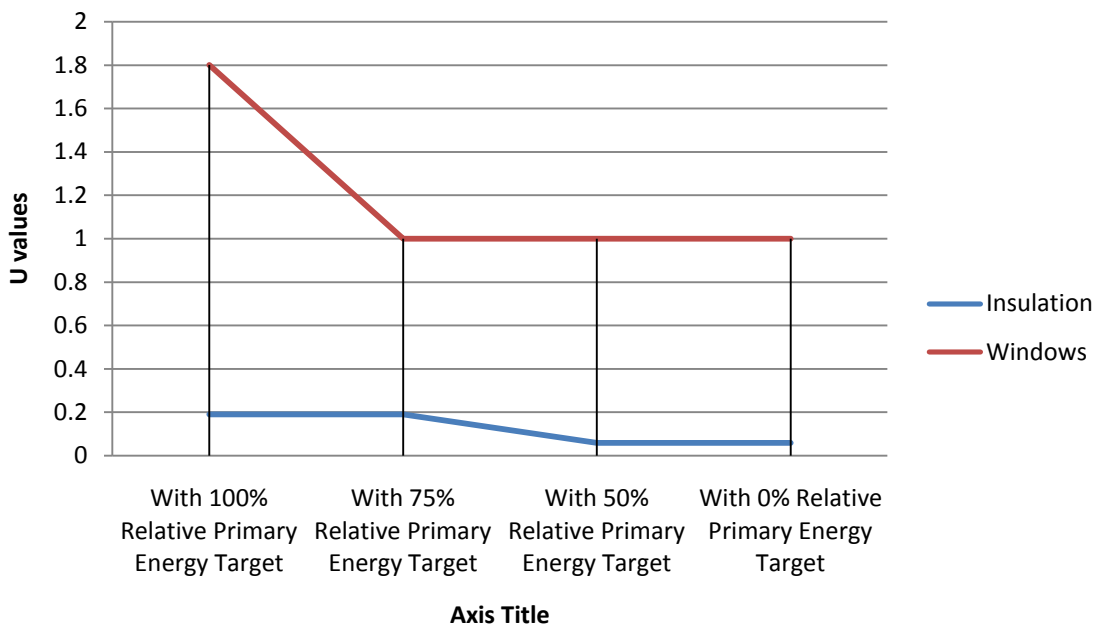

Figure 4-1. U values of Wall Insulation and Windows

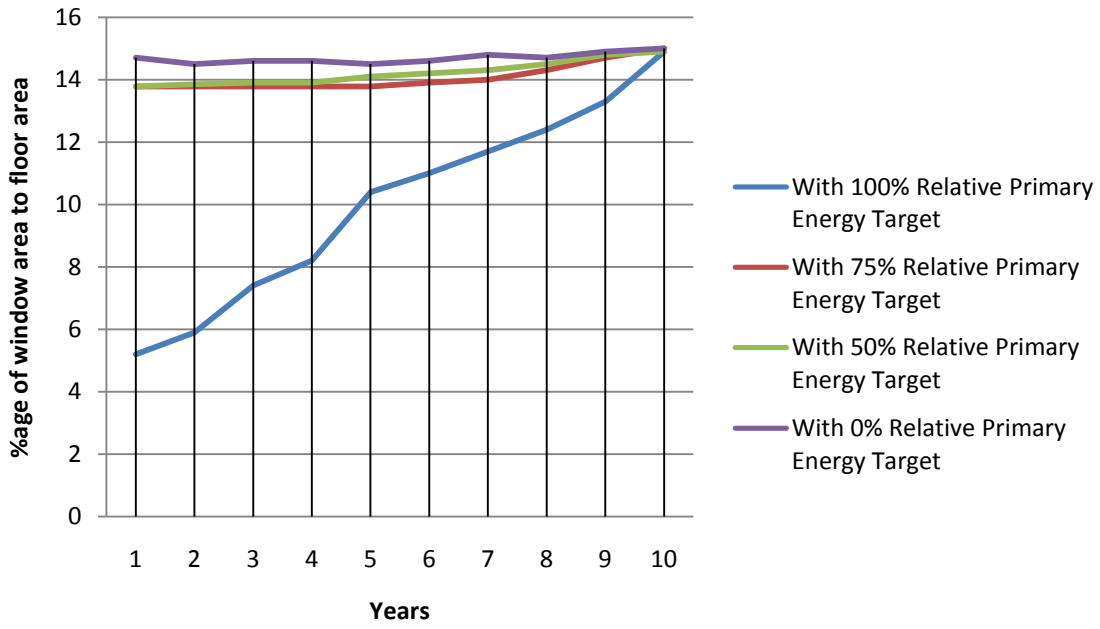

Figure 4-2. Percentage of total window area to floor area

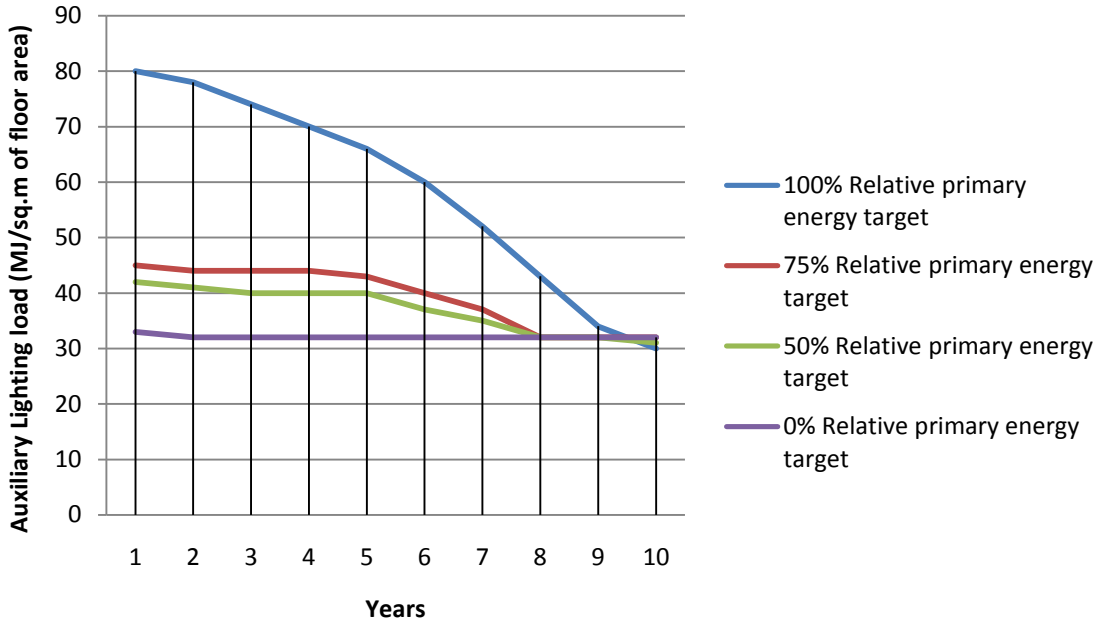

Figure 4-3. Auxiliary lighting load

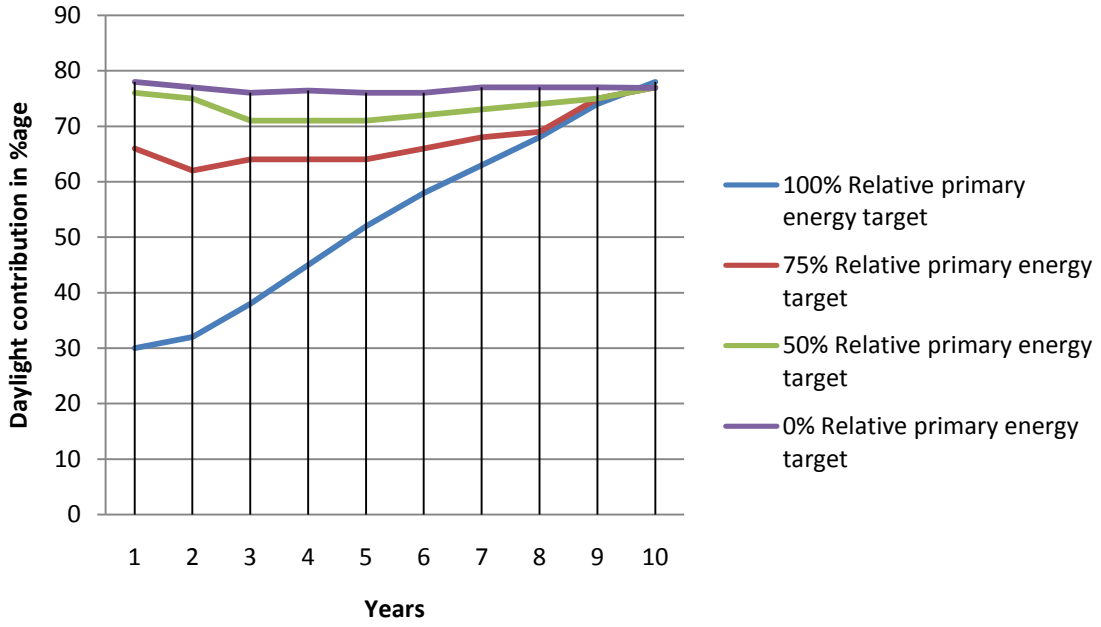

Figure 4-4. Daylight contribution of lighting load

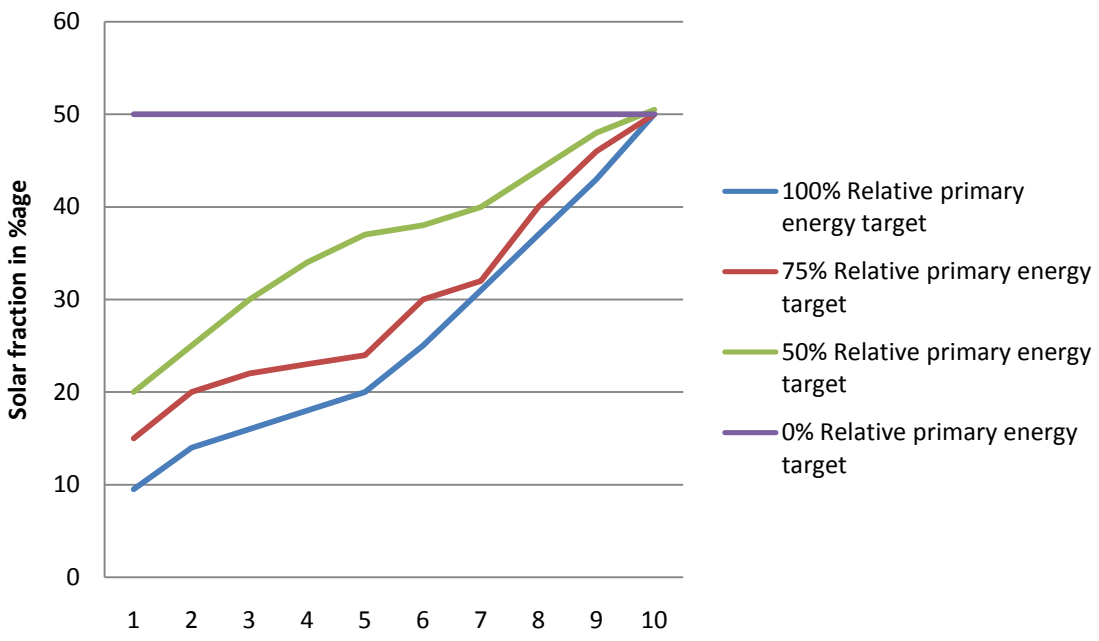

Figure 4-5. Solar fraction of thermal load

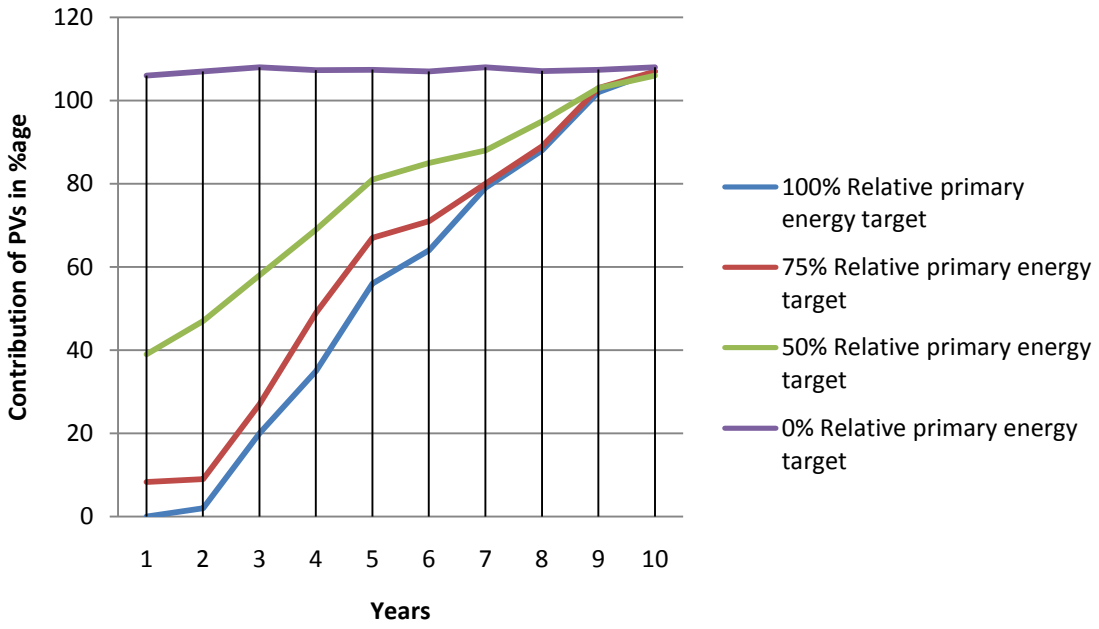

Figure 4-6. Contribution of PVs to the electricity load

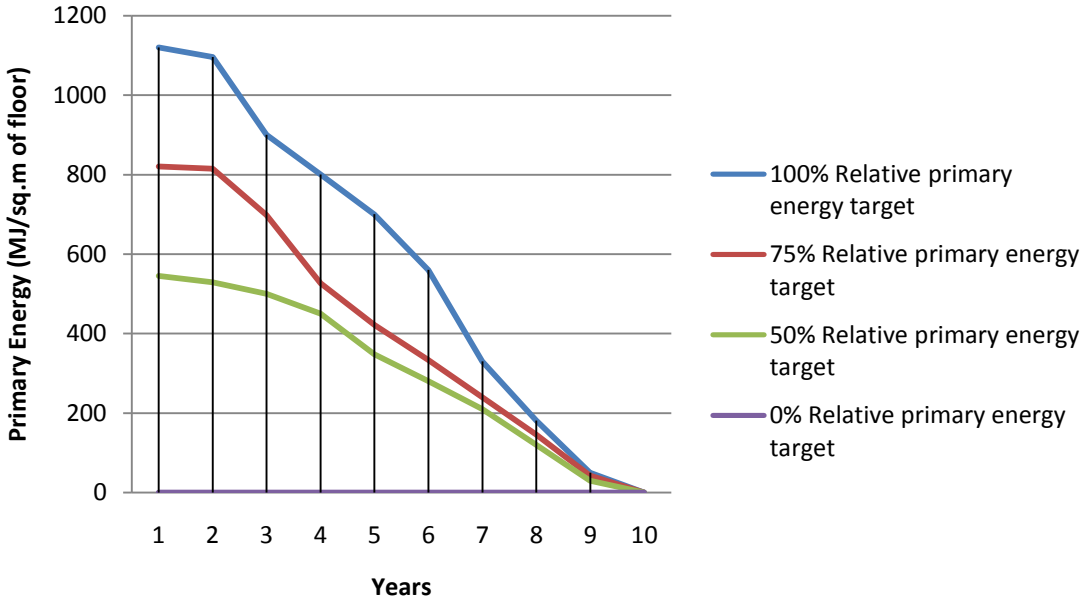

Figure 4-7. Net primary energy

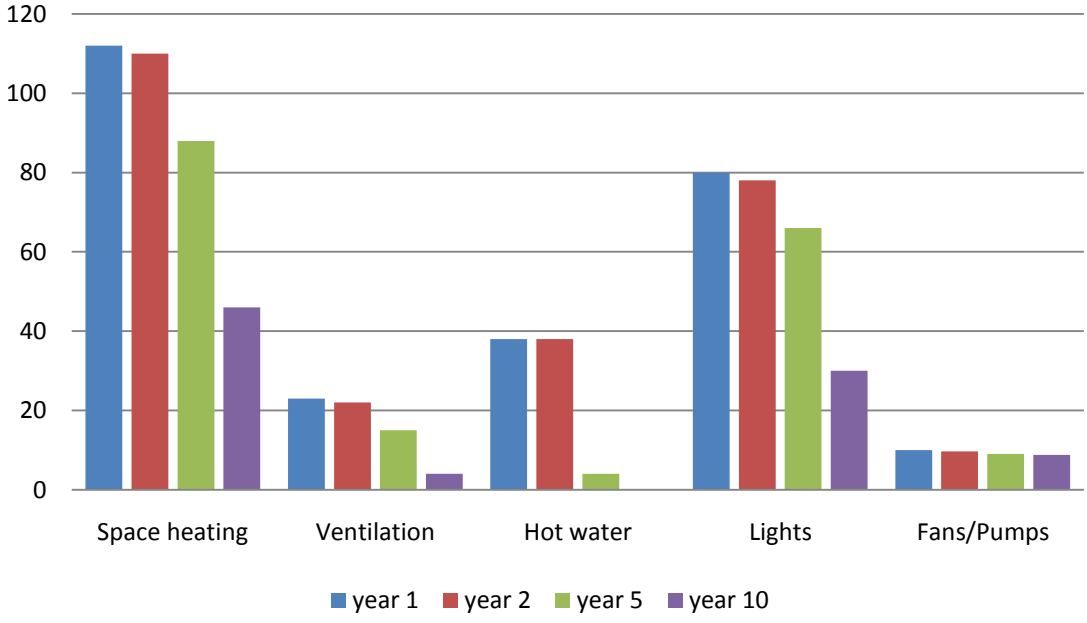

Figure 4-8. Energy consumption (kW-hr/m^2/year) with different simulation periods.

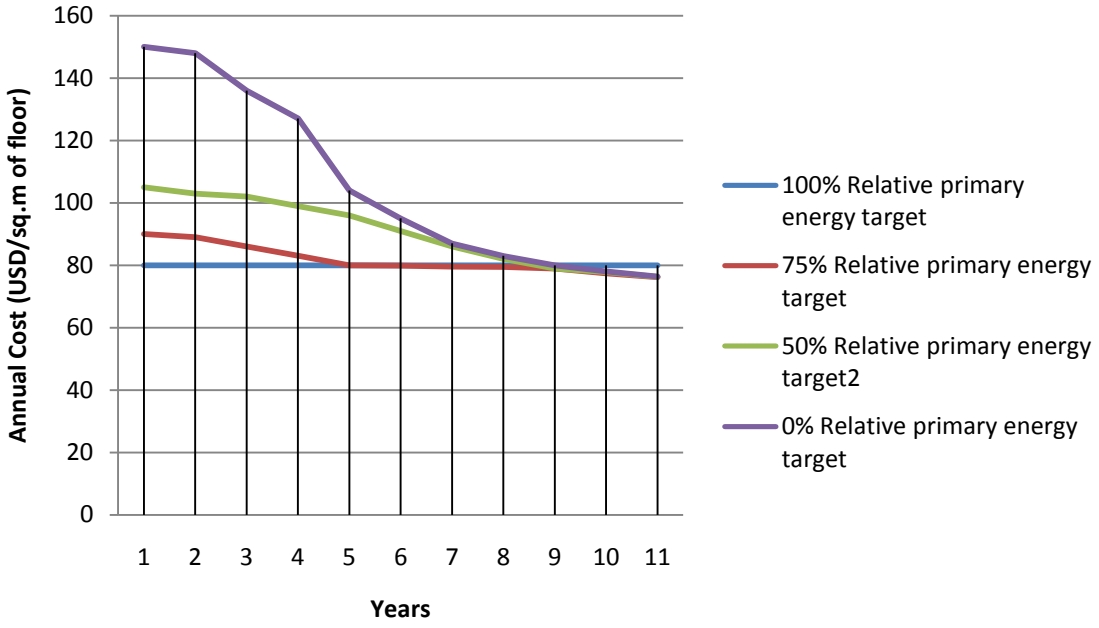

Figure 4-9. Cost of operating the building. Break-even point is at 9.4 years

Table 4-1. Hourly load and usage patterns

Load/Usage	Hour	
	8am to 6pm	7pm to 7am
Occupancy	$N \sim (10,1)$	0
Lighting (lx)	500	0
Minimum temperature (^{0}C)	20	17
Maximum temperature (^{0}C)	25	25
Air change (l/h)	1	0.2
Hot water (l/m_f^2)	0.05	0

Table 4-2. Describing the output values when the simulation is run for one year

Output	Values at four different relative auxiliary primary energy targets			
Relative auxiliary primary energy target	100%	75%	50%	0%
Relative annual total cost	100%	112%	131%	187%
Building aspect ratios$s_h : s_v$	1.8:1.8	9.1:11	12:8.8	14.1:11
Wall to floor area ratio	0.45	1.0	1.0	1.0
Insulation U value (W/m^2K)	0.19	0.19	0.06	0.06
Window type	3	4	4	4
South window to floor area ($m_w^2 : m_F^2$)	1.0%	6.6%	6.6%	6.6%
East window to floor area ($m_w^2 : m_F^2$)	1.5%	0.09%	0.09%	0.09%
West window to floor area ($m_w^2 : m_F^2$)	1.2%	0.09%	0.09%	0.09%
North window to floor area ($m_w^2 : m_F^2$)	1.5%	7%	7%	7%
Total window area of floor area ($m_w^2 : m_F^2$)	5.2%	13.78%	13.78%	13.78%
Collector and PV array tilt (^{0})	54	54	54	54
Collector area of floor area ($m_c^2 : m_F^2$)	0.4%	1.5%	4.0%	4.0%
PV capacity per floor area ($w_p : m_F^2$)	0	6	35	86
Thermal storage (l/m_f^2)	3.9	10.8	10.9	11.1
Lighting control	Top up	Top up	Top up	Top up
Battery Capacity(kW hr)	0	12	24	35
Auxiliary Lighting load (MJ_{el}/m_F^2)	80	45	42	32
Hot water heating load (MJ_{th}/m_F^2)	38	39	36	38
Space heating load (MJ_{th}/m_F^2)	112	46	46	46
Appliances load (MJ_{el}/m_F^2)	246	246	246	246
Solar fraction of thermal load	9.5%	15%	20%	50%
PV generation/electricity load	0	8.3%	39%	106%
Daylight contribution of lighting load	30%	66%	76%	78%
Purchased thermal energy (MJ_{fuel}/m_F^2)	107	71	66	65.5
Purchased gross electricity (MJ_{el}/m_F^2)	352	258	171.5	131
Surplus of gross PV generation	0	0	20.5%	51%
Net auxiliary primary energy (MJ_{prim}/m_F^2)	1120	840	560	0
Annual total cost (USD/m_F^2)	80	90	105	150

Table 4-3. Describing the output values when the simulation is run for two years

Parameters	Values at four different relative auxiliary primary energy targets			
Relative auxiliary primary energy target	100%	75%	50%	0%
Relative annual total cost	99.5%	111%	125%	185%
Building aspect ratios $s_h : s_v$	11.3:13.1	9.1:11	10:8.3	192.1:181
Wall to floor area ratio	0.415	1.0	1.0	1.0
Insulation U value (W/m^2K)	0.19	0.18	0.06	0.06
Window type	3	4	4	4
South window to floor area ($m_w^2 : m_F^2$)	1.2%	6.6%	6.6%	6.8%
East window to floor area ($m_w^2 : m_F^2$)	1.7%	0.09%	0.09%	0.1%
West window to floor area ($m_w^2 : m_F^2$)	1.3%	0.09%	0.09%	0.1%
North window to floor area ($m_w^2 : m_F^2$)	1.7%	7%	7%	6.9%
Total window area of floor area ($m_w^2 : m_F^2$)	5.9%	13.78%	13.78%	14.0%
Collector and PV array tilt (^{0})	54	54	54	54
Collector area of floor area ($m_c^2 : m_F^2$)	0.4%	1.5%	4.0%	4.1%
PV capacity per floor area ($w_p : m_F^2$)	1	8	39	84
Thermal storage (l/m_f^2)	4	10.6	10.9	11.0
Lighting control	Top up	Top up	Top up	Top up
Battery Capacity (kW hr)	10	26	30	35
Auxiliary Lighting load (MJ_{el}/m_F^2)	78	44	41	32
Hot water heating load (MJ_{th}/m_F^2)	38	39	36	38
Space heating load (MJ_{th}/m_F^2)	112	46	46	46
Appliances load (MJ_{el}/m_F^2)	246	246	246	246
Solar fraction of thermal load	14%	20%	25%	50%
PV generation/electricity load	2%	9%	47%	109%
Daylight contribution of lighting load	32%	62%	75%	77%
Purchased thermal energy (MJ_{fuel}/m_F^2)	96	70	69	66
Purchased gross electricity (MJ_{el}/m_F^2)	235	160	192	132
Surplus of gross PV generation	0%	0%	22%	60%
Net auxiliary primary energy (MJ_{prim}/m_F^2)	1096	824	549	0
Annual total cost (USD/m_F^2)	79.6	89	100	148

Table 4-4. Describing the output values when the simulation is run for five years

Parameters	Values at four different relative auxiliary primary energy targets			
Relative auxiliary primary energy target	100%	75%	50%	0%
Relative annual total cost	97%	100%	120%	130%
Building aspect ratios $s_h : s_v$	1.0:1.8	8.1:12.3	60:52.1	16:13.3
Wall to floor area ratio	0.5	1.0	1.0	1.0
Insulation U value (W/m^2K)	0.19	0.10	0.06	0.06
Window type	4	4	4	4
South window to floor area ($m_w^2 : m_F^2$)	1.1%	6.6%	6.9%	7.3%
East window to floor area ($m_w^2 : m_F^2$)	3.3%	0.09%	0.1%	0.2%
West window to floor area ($m_w^2 : m_F^2$)	4.4%	0.09%	0.1%	0.5%
North window to floor area ($m_w^2 : m_F^2$)	1.6%	7%	7%	7.0%
Total window area of floor area ($m_w^2 : m_F^2$)	10.4%	13.78%	14.1%	15.0%
Collector and PV array tilt (^{0})	54	54	54	54
Collector area of floor area ($m_c^2 : m_F^2$)	0.4%	1.6%	4.0%	4.1%
PV capacity per floor area ($w_p : m_F^2$)	25	35	60	90
Thermal storage (l/m_f^2)	6	10.5	10.9	10.9
Lighting control	Top up	Top up	Top up	Top up
Battery Capacity (kW hr)	36	35	36	35
Auxiliary Lighting load (MJ_{el}/m_F^2)	66	43	40	32
Hot water heating load (MJ_{th}/m_F^2)	38	39	36	38
Space heating load (MJ_{th}/m_F^2)	88	46	46	46
Appliances load (MJ_{el}/m_F^2)	246	246	246	246
Solar fraction of thermal load	20%	24%	37%	50%
PV generation/electricity load	56%	67%	81%	109%
Daylight contribution of lighting load	52%	64%	71%	78%
Purchased thermal energy (MJ_{fuel}/m_F^2)	89	67.7	66	65
Purchased gross electricity (MJ_{el}/m_F^2)	203	147	137	132
Surplus of gross PV generation	10%	15%	24%	58%
Net auxiliary primary energy (MJ_{prim}/m_F^2)	700	525	349	0
Annual total cost (USD/m_F^2)	78	80	96	104

Table 4-5. Describing the output values when the simulation is run for ten years

Parameters	Values at four different relative auxiliary primary energy targets			
Relative auxiliary primary energy target	100%	75%	50%	0%
Relative annual total cost	96%	95%	95%	96%
Building aspect ratios $s_h : s_v$	45.0:40.8	1.2:2.2	18:15	17:14.1
Wall to floor area ratio	1	1.0	1.0	1.0
Insulation U value (W/m^2K)	0.07	0.06	0.06	0.06
Window type	4	4	4	4
South window to floor area ($m_w^2 : m_F^2$)	7.2%	7.3%	7.3%	7.3%
East window to floor area ($m_w^2 : m_F^2$)	0.2%	0.2%	0.2%	0.2%
West window to floor area ($m_w^2 : m_F^2$)	0.4%	0.5%	0.4%	0.5%
North window to floor area ($m_w^2 : m_F^2$)	7.1%	7.0%	7.0%	7.0%
Total window area of floor area ($m_w^2 : m_F^2$)	14.9%	15.0%	14.9%	15.0%
Collector and PV array tilt (^{0})	54	54	54	54
Collector area of floor area ($m_c^2 : m_F^2$)	4%	4%	4.1%	4.1%
PV capacity per floor area ($w_p : m_F^2$)	90	91	92	91
Thermal storage (l/m_f^2)	11.4	11.5	11.1	11.1
Lighting control	Top up	Top up	Top up	Top up
Battery Capacity (kW hr)	36	36	35	35
Auxiliary Lighting load (MJ_{el}/m_F^2)	30	32	31	32
Hot water heating load (MJ_{th}/m_F^2)	38	39	36	38
Space heating load (MJ_{th}/m_F^2)	46	46	46	46
Appliances load (MJ_{el}/m_F^2)	246	246	246	246
Solar fraction of thermal load	50%	50%	51%	52%
PV generation/electricity load	107%	107%	106%	109%
Daylight contribution of lighting load	78%	77%	76%	77%
Purchased thermal energy (MJ_{fuel}/m_F^2)	65	66	66	66
Purchased gross electricity (MJ_{el}/m_F^2)	131	132	131	132
Surplus of gross PV generation	60%	59%	58%	58%
Net auxiliary primary energy (MJ_{prim}/m_F^2)	0	0	0	0
Annual total cost (USD/m_F^2)	77	76.4	76.8	76.9

Table 4-6. Design variables and annual energy consumption data for minimum cost and low energy designs

Parameters	Minimum cost design (For 1 year simulation run)	Low(zero) energy design (For 10 year simulation run)
Wall U value (W/m^2K)	0.19	0.06
Window U value (W/m^2K)	1.8	1.0
Total window area (m^2)	53.1	135
Heat lost through windows (GJ_{th})	98.9	49.2
Exhaust air heat recovery	Yes	Yes
Lighting control	No	Yes
Solar thermal collectors(m^2)	3.6	37
Battery capacity ($kw\ hr$)	0	36
PVs (kW_p)	0	24
Space heating load (GJ_{th})	100.9	41.2
Water heating load (GJ_{th})	29.3	0
Lighting load (GJ_{el})	70.5	26.9
Appliance load (GJ_{el})	45	45
Annual total cost (USD)	69300	69210

CHAPTER 5
CONCLUSION

In this study an economic analysis was done by summing up all the costs for running the systems in the building for a given number of years. Energy efficient resources such as solar panels, PVs systems, daylighting measures were employed in order to reduce energy drawn from the electricity grid. A set of 18 variable parameters were used to formulate the total cost. The problem formulated in this manner was first optimized using simulated annealing algorithm. Since SA algorithm didn't converge to a solution, information guided simulated algorithm was used. The results obtained were compared with the existing literature and were found to be in good agreement. Furthermore the results showed a 4.8% improvement over the previous research work done in this field.

While much promise is shown by the present work, a lot remains unexplored. For example, more work will be required to develop the model for incorporating detailed study of HVAC systems, ventilation and daylighting measures. The maintenance and repair aspects of various systems need to be incorporated. A more refined cost structure would be helpful simulating a more realistic design of the building. A different research direction would explore how the model of the building may be further modified. This model did not include the staircases and the elevators. Further research is required for an improved performance of the optimization procedure and faster convergence.

APPENDIX
NOMENCLATURE

1	a	Uniform capital recovery factor
2	A	Area (m^2)
3	c	Specific cost (USD/unit)
4	COP	Coefficient of performance
5	d	Depth (m)
6	d^*	Estimated distance
7	E	Energy (J)
8	G	Solar Irradiance (W/m^2)
9	h	Height (m)
10	I	Illuminance (lx)
11	k	Feedback gain term
12	n	Number of samples
13	PV	Photovoltaics (s)
14	Q	Heat gains and losses (W)
15	r	Real interest rate
16	s	Aspect ratio; annual energy price increase
17	t	Time (s)
18	T	Temperature (^oC)
19	T_g	Guided Temperature (^oC)
20	U	Collector heat loss factor ((W/m^2K)
21	w	Width (m)
22	x	The degree that a design option is deployed ; variable
23	$\bar{x}$	Vector variable ($x_1, x_2, x_3, ..., x_n$)
24	Y	Variable
Subscripts		
1	0	Zero loss
2	a	Annual
3	amb	Ambient

4	A	Area based
5	B	Building
6	C	Collector
7	curr	Current
8	d	Indoor horizontal daylight
9	el	Electricity
10	F	Floor
11	fuel	Heating fuel
12	g	Guided
13	h	Horizontal
14	i	Design option ; index variable
15	max	Maximum
16	min	Minimum
17	new	New Value
18	opt	Optimum
19	OV	Outdoor vertical
20	p	Peak capacity
21	prim	Primary energy
22	R	Room
23	sp	Surplus
24	th	Thermal
25	v	Vertical
26	W	Window
Greek characters:		
1	ε	Luminous efficacy (lm/W)
2	η	Efficiency
3	λ	Energy price escalation factor
4	μ	Primary energy to electricity conversion factor
5	ρ	Reflectance
6	τ	Transmittance

7	δ	Difference
8	γ	Cooling Schedule
9	α	Information effectiveness parameter

LIST OF REFERENCES

[1] K. Peippo, P.D. Lund and E. Vartiainen, Multivariate optimization of design tradeoffs for solar low energy buildings, Energy and Buildings, vol. 29, pp. 189-205, 1999.

[2] R. Hooke and T.A. Jeeves, “Direct search” solution of numerical and statistical problems, Journal of the ACM, vol. 8, no. 2, pp. 212-229, 1961.

[3] N. Bouchlaghem, Optimising the design of building envelopes for thermal performance, Automation in Construction, vol. 10, pp. 101-112, 2000.

[4] J.A. Nelder and R. Mead, A simplex method for function minimization, Computer Journal, vol. 7, pp. 308-313, 1965.

[5] R.A. Mitchell and J.L. Kaplan, Non linear constrained optimization by a non-random complex method, J. Res. Natl. Bur. Stand. C72, 24-258, 1969.

[6] L.G. Caldas, L.K. Norford, A design optimization tool based on a genetic algorithm, Automation in Construction, vol. 11, pp. 173-184, 2002.

[7] D. Goldberg, Genetic algorithms in search, optimization and machine learning, Addison-Wesley Publishing, 1989.

[8] H. Jedrzejuk and W. Marks, Optimization of shape and functional structure of buildings as well as heat source. Basic theory, Building and Environment, vol. 37, pp. 1379-1383, 2002.

[9] H. Jedrzejuk and W. Marks, Optimization of shape and functional structure of buildings as well as heat source utilisation. Partial problems solution, Building and Environment, vol. 37, pp. 1037-1043, 2002.

[10] H. Jedrzejuk and W. Marks, Optimization of shape and functional structure of buildings as well as heat source. Utilisation example, Building and Environment, vol. 37,pp. 1249-1253, 2002.

[11] T.R. Nielsen and S. Svendsen, Life cycle cost optimization of buildings with regard to energy use, thermal indoor environment and daylight, International Journal of Low Energy and Sustainable Buildings, vol. 2, pp. 1-16, 2002.

[12] L. Gonzalez-Monroy and A. Cordoba, Optimization of energy supply systems with simulated annealing: continuous and discrete descriptions, Physica A, vol. 284, pp. 433-447, 2000.

[13] J.A. Wright, H.A. Loosemore and R. Farmani, Optimization of building thermal design and control by multi-criterion genetic algorithm, Energy and Buildings, vol. 34, pp. 959-972, 2002.

[14] W. Wang, R. Zmeureanu and H. Rivard, Applying multi-objective genetic algorithms in green building design optimization, Building and Environment, vol. 40, pp. 1512-1525, 2005.

[15] C.M. Fonseca and P.J. Flemming, Multiobjective optimization and multiple constraint handling with evolutionary algorithms – part 1: a unified formulation, IEEE Transactions on Systems, Man and Cybernetics, Part A, vol. 28, no. 1, pp. 26-37, 1998.

[16]J.A. Lynes, P.J. Littlefair, Lighting energy savings from daylight: estimation at the sketch design stage, Lighting Res. Technol. 22 (1990) 129–137.

[17] D.H.W. Li and J.C. Lam, Vertical solar radiation and daylight illuminance data for Hong Kong, Lighting Research and Technology 2000 32: 93 DOI: 10.1177/09603271000206

[18] February 5, 2012, from http://rredc.nrel.gov/solar/old_data/nsrdb/

[19] T.B. Johansson, B. Bodlund, R.H. Williams Eds., Electricity: Efficient End-Use and New Generation Technologies and Their Planning Implications, Lund Univ. Press, Lund, Sweden, 1989.

[20] S. Carpenter, Learning from experiences with advanced houses of the world, CADDET Analysis Series 14, Centre for the Analysis and Dissemination of emonstrated Energy Technologies, Sittard, The Netherlands, 1995.

[21] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi.Optimization by Simulated Annealing. Science, Number 4598, 220:671{680, May 1983.

[22] V. Cerny. Thermodynamical Approach to the Traveling Salesman Problem: an Efficient Simulation Algorithm. Journal of Optimization Theory and Applications, 45(1):41{51, 1985.

[23] Nicholas Metropolis and S Ulam, The Monte Carlo Method, Journal of American Statistical Association, Vol. 44 No. 247. Sept 1949, pp. 335-341.

[24]Harold Szu and Ralph Hartley, Fast Simulated Annealing, Physics Letters A(1987), Volume: 122, Issue: 3, Publisher AIP, pp: 157-162.

[25] AmitTalapatra, Implementing Energy Efficiency in Building Codes Based on the American Clean Energy and Security Act of 2009, Federation of American Scientists,1725 DeSales Street, NW 6th Floor, Washington, DC 20036.

[26] Youssef Bichiou, MoncefKrarti, Optimization of envelope and HVAC systems selection for residential buildings, Energy and Buildings, Elsevier 43 (2011) 3373-3382.

[27]NatasaDjuric and Vojislav Novakovic, Identifying important variables of energy use in low energy office buildings by multivariate analysis, Energy and Buildings, Elsevier 45 (2012) 95-98.

[28] HasanKarbay, MuslumArici, Multiple pane window applications in various climatic regions of Turkey, Energy and Buildings, Elsevier 45 (2012) 67-71.

[29] James C. Spall, Introduction to stochastic search and optimization Estimation Simulation and Control, Wiley Interscience, pp: 14.

[30] Steffen Petersen and SvendSvendsen, Method and simuation program informed decisions in the early stages of building design, Energy and Buildings, Elsevier, 42 (2010) 1113-1119.

[31] ChanghaiPeng, Ying Huang and Zhishen Wu, Building-integrated photovoltiacs (BIPV) in architectural design in China, Energy and Buildings, Elsevier 43 (2011) 3592-3598.

[32] January 23, 2012, BP Solar to expand its solar cell plants in Spain and India, http://www.renewableenergyworld.com/rea/news/article/2007/03/bp-solar-to-expand-its-solar-cell-plants-in-spain-and-india-47861.

[33] OrhanEkren and Banu Y. Ekren, Size optimization of a PV/wind hybrid energy conversion system with battery storage using simulated annealing, Applied Energy, Elsevier 87 (2010) 592-598.

[34] V. Aro-Heinila and M. Suvanen, Simuation program for energy analysis of multi room houses for solar energy studies, Report TKK-F-A436, Helsinki University of Technology, Espoo, Finland, 1980.

[35] RiikkaKyro, JukkaHeinonen, AnttiSaynajoki and SeppoJunnila, Occupants have little influence on the overall energy consumption in district heated apartment buildings, Energy and Buildings, Elsevier 43 (2011) 3484-3490.

[36] T.D. Pettersen, Variation of energy consumption in dwellings due to climate, building and inhabitants, Energy Build. 21 (1994) 209-218.

[37] Trine Dyrstad Pettersen, Variation of energy consumption in dwellings due to climate building and inhabitants, Energy and Buildings, Elsevier 21 (1994) 209-218.

[38] February 9, 2012, http://www.climate-charts.com/Locations/u/US72315003103001.php#data

[39] K. Peippo, A numerical multivariate approach to optimization of photovoltaic solar low energy building designs, Report TKK-F-A770, Department of Engineering Physics and Mathematics, Helsinki University of Technology, Espoo, Finland, 1997.

[40] Minister of Natural Resources, Canada 2001-2004, Solar water heating project analysis chapter, Clean energy project analysis: RETScreen Engineering and cases textbook, ISBN 0-622-35674-8, catalogue no: m39-101/2003e-pdf

[41] Guilherme Carrilho da Graca, Andre Augusto and Maria M. Lerer, Solar powered net zero energy houses for southern Europe: Feasibility study, Solar Energy, Science Elsevier, article in press(9th Feb 2012).

[42]D.H.W. Li and J.C. Lam, Predicting vertical luminous efficacy using horizontal solar data, Lighting Research and Technology 2001 33:25. DOI: 10.1177/136527828010330-0107.

[42] David H. Wolpert and William G. Macready, No free lunch theorems for optimization, IEEE transactions on Evolutionary Computation, Vol. 1, No. 1, 1997.

[43] J. Rust, “Using randomization to break the curse of dimensionality,” Econometrica, vol. 65, no. 3, pp. 487–516, 1997.

[44] M. A. Styblinski and T.-S. Tang, “Experiments in non-convex optimization: Stochastic approximation with function smoothing and simulated annealing,” Neural Networks, vol. 3, pp. 467–483, 1990.

[45] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, “Optimization by simulated annealing,” Science, vol. 220, no. 4598, pp. 671–680, 1983.

[46] S. P. Brooks and B. J. T. Morgan, “Optimization using simulated annealing,” Journal of the Royal Statistical Society. Series D (The Statistician), vol. 44, no. 2, pp. 241–257, 1995.

[47] B. Hajek, “Cooling schedules for optimal annealing,” Mathematics of Operations Research, vol. 13, pp. 311–329, 1988.

[48] Masayuki Terada and Hisaaki Takabayashi, Industrial storage device for low carbon society, Hitachi Review Vol. 60 (2011) No. 1.

[49] February, 21 2012. http://cs.adelaide.edu.au/~paulc/teaching/montecarlo/node139.html

[50] Hwang C L, Masud ASM Multiple objective decision making methods and applications—a state-of-art-survey. Lecture notes in economics and mathematical systems. Berlin: Springer, 1979.

[51] Jendo S, Marks W. On multicriteria optimization of structures. Archives of Civil Engineering 1984;30(1):3–21 [in Polish].

[52] February, 25 2012. http://www.iccsafe.org/Store/Pages/Product.aspx?id=3000X12

[53] February, 25 2012. http://en.wikipedia.org/wiki/Building_envelope

[54] MrinalKumar, “An Information Guided Framework for Simulated Annealing,” American Control Conference, Jun 27-29, 2012, Montreal, Canada.

[55] February, 29 2012. http://openpub.realread.com/rrserver/browser?title=/ASHRAE_1/ashrae_90_1_2010_IP_1024

[56] February, 29 2012. http://resourcecenter.pnl.gov/cocoon/morf/ResourceCenter/article//103

[57] February, 29 2012. http://www.wattsun.com/misc/photovoltaic_tilt.html

[58] March, 7 2012. http://solarpowerrocks.com/north-carolina/

BIOGRAPHICAL SKETCH

Diwakar Sinha was born in the city of Patna, India. He lived in the city till he completed his high school in 2005. In 2006 he was enrolled as a full time student in Mechanical Engineering at the Jadavpur University, Kolkata. He studied over there for 4 years in pursuit of an undergraduate degree in mechanical engineering. During his undergraduate years, he came in close contact with his professors and the research work they were involved in at that time. Within the course of the next 3 years, he co-authored a number of publications. After his graduation in July 2010, he was admitted to University of Florida, Gainesville, Florida in order to pursue a master's degree in mechanical engineering.