Finally, which kind of Multi-layered Installation Is the Best?

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Abstract

The aim of the research presented in this paper was to develop the features of a Genetic Algorithm (GA) to optimise the external-wall insulation in residential buildings.

In this paper, a new optimal design method is proposed for saving energy in buildings. This method provides the most efficient energy consumption for building external shell and it will be useful to reduce CO_2 emission in the future all over the world. Specifically for this paper, the authors applied this method for a sample building as a case study. The GA optimization method, which can resolve nonlinear optimization problems, is adopted for this optimization analysis. In addition, its applicability is analysed in a case study. In order to validate the accuracy of this method, all results are simulated by E.S.A.M software and the results can certify the validity of this method. The results show that the proposed method is sufficiently capable of determining the optimal insulation for external walls. This paper reviews the basics of GAs, emphasizing on making a new synthetic insulation.

Keywords:

Genetic Algorithm, Optimization, Energy Consumption, Building, R-Value, E.S.A.M software

1. Introduction

1.1. Energy consumption in building

In these days, energy conservation is a popular topic in building industry all over the world. It is now attracting a great deal more attention throughout the world with regard to environmental preservation of the Earth [6]. In recent decade, a number of high-energy efficiency equipment have been developed for example, triple-effect absorption refrigerators, cogeneration systems, etc. [3]. In addition, the operation culture has changed especially in developed country and most people know that energy consumption is highly dependent on the combination and operation of the equipment used [5]. Therefore, the best result for saving energy in building can be achieved by suitable construction and good operation as well [23]. There are a lot of researches on making a solution for energy consumption by external walls in building and in order to resolve these problems many researchers around the world tried to present some offers on building insulation.

Over the recent few years, greenhouse gas reduction and energy consumption have become climactically a worldwide challenge [7]. Apart from the domestic buildings, commercial and industrial sectors make a significant contribution to the climbing levels of energy consumption and greenhouse gas emissions.

Since over 40% of the energy used in most countries is used to heat or cool buildings [9], and the major part of this energy is consumed as heat loss of external walls [15], the prediction of building energy consumption has, therefore, played an very important role in national energy use in each country and building energy

efficiency is of prime concern [22]. Identifying energy savings is becoming an increasingly important yet challenging task [16].
In order to improve the energy efficiency of buildings, architects, building designers and facility managers require effective tools for designing, analysing and maintaining the building energy configurations.

Simulating building energy consumption especially in external wall element is a key to the study of energy efficiency in buildings [8]. Conventionally, building energy consumption patterns have been modelled in terms of mathematical/empirical equations which are obtained through rigorous building energy simulations [20]. This typically involves a thorough study of the critical system parameters and their effects on the annual energy consumption [11].

1.2. R-Value

The R-value is a measure of thermal resistance used in the building and construction industry. Under uniform conditions, it is the ratio of the temperature difference across an insulator (ΔT) and the heat flux[1] [19].

In most countries, R-values are given in ***SI*** units, typically square-metre kelvins per watt or $m^2 . K/W$ (or equivalently, $m^2 . °C/W$) [19].

Increasing the thickness of an insulating layer increases the thermal resistance.

The R-value is a measure of an insulation sample's ability to reduce the rate of heat flow under specified test conditions. The primary mode of heat transfer impeded by insulation is conduction, but insulation also reduces heat loss by all three heat transfer modes: *conduction*, *convection*, and *radiation* [19].

In calculating the R-value of a multi-layered installation, the R-values of the individual layers are added, which is illustrated as follow:

$$\begin{aligned}\textbf{R-value (total)} &= \text{R-value (outside air film)} + \text{R-value (body)} + \text{R-value (sheathing)} \\ &+ \text{R-value (insulation)} + \text{R-value (plasterboard)} + \text{R-value (inside air film)}\end{aligned} \quad \textbf{(1)}$$

An important subject to R-value calculation is humidity; commonly there is a reverse relationship between R-value and humidity. In other words, when humidity increases R-value decreases.

1.3.Different insulation types

The maximum thermal performance or R-value of insulation is very dependent on proper installation. In order to select a suitable insulation we should consider several forms of insulation, their R-values, and the thickness needed.
There are four types of insulations:

1.3.1. Rolls and batts

Blanket insulation comes in the form of batts or rolls. They are flexible products made of mineral fibbers, including fiberglass or rock wool. They are available in different widths suited to standard spacing of wall studs and attic[2] or floor joists. Batts with a special flame-resistant facing are available in various widths for basement walls where the insulation will be left exposed. Figure (1)

1.3.2. Loose-fill

Blown-in loose-fill insulation includes cellulose, fiberglass, or rock wool in the form of loose fibbers or fibber pellets that can be used by pneumatic equipment, usually by professional installers. This form of

[1] Heat transfer per unit area, $\dot{Q}_A$ through it or $R = \Delta T / \dot{Q}_A$
[2] section of a house below the roof; low wall at the top of a classical building which hides the roof;

insulation can be used in wall cavities. It is also appropriate for unfinished attic floors, for irregularly shaped areas, and for filling in around obstructions. Figure (2)

1.3.3. Rigid foam

Rigid insulation is made of fibrous materials or plastic foams and is produced in board-like forms and melded pipe coverings. These provide full coverage with few heat loss paths and are often able to provide a greater R-value where space is limited. Such boards may be faced with a reflective foil that reduces heat flow when it is next to an air space. Rigid insulation is often used for foundations. Figure (3)

1.3.4. Foam-in-place

Foam-in-place insulation can be blown into small areas to control air leaks, like those around windows, or can be used to insulate an entire house. Foam insulation can be applied by a professional using special equipment to meter, mix, and spray the foam into place. Figure (4)

Figure (1) Roll and Batts[3]

Figure (2) Loose-Fill[4]

Figure (3) Rigid Foam[5]

Figure (4) Foam-in-place[6]

The different forms of insulation can be used together. For example, we can add batt or roll insulation over loose-fill insulation. Usually, material of higher density[7] should not be placed on top of lower density insulation that is easily compressed. Doing so will reduce the thickness of the material underneath and thereby lower its R-value.

1.4.Genetic Algorithm

Genetic Algorithm (GA) provides a method for solving optimization problems by imitating the evolutionary process based on the mechanics of Darwin's natural selection [1]. GAs are the search methods based on principles of natural selection and genetics. Goldberg described the usual form of genetic algorithm; GA has been applied to a diverse range of scientific, engineering and economic problems [21].
A genetic algorithm (GA) is a search technique used in computing to find solutions for optimization problems. Genetic algorithms can be categorized as Meta heuristics with global perspective [1].
Recently, genetic algorithms have received considerable attention regarding their potential as an optimization technique for complex problem and have been successfully applied in the area of industrial engineering [10]. Genetic algorithms are implemented as a computer simulation to find better solutions. GAs encode the decision variables of a search problem into finite-length strings of alphabets of certain cardinality. The strings which are candidate solutions to the search problem are referred to as chromosomes. The alphabets are referred to as genes and the values of genes are called alleles. In contrast to traditional optimization techniques, GAs work with coding of parameters, rather than the parameters themselves [13]. To evolve good solutions and to implement natural selection, we need a measure for distinguishing good

[3] **Source:** http://www.goodrichlumber.com
[4] **Source:** http://www.archiexpo.com
[5] **Source:** http://www.diyexplore.com
[6] **Source:** http://www.buildipedia.com

[7] Weight per unit volume (ρ)

solutions from bad solutions. The measure could be an objective function that is a mathematical model or a computer simulation, or it can be a subjective function where humans choose better solutions over worse ones [14]. In essence, the fitness measure must determine a candidate solution's relative fitness, which will subsequently be used by the GA to guide the evolution of good solutions. Another important concept of GAs is the notion of population. Unlike traditional search methods, genetic algorithms rely on a population of candidate solutions [18]. The population size, which is usually a user-specified parameter, is one of the important factors affecting the scalability and performance of genetic algorithms. Once the problem is encoded in a chromosomal manner and a fitness measure for discriminating good solutions from bad ones has been chosen, the evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

1.4.1. Genetic Algorithm Vocabulary

Since genetic algorithms are rooted in both natural genetics and computer science, the terminologies used in genetic algorithm literature are mixture of the natural and the artificial science [2]. The correspondence of genetic algorithm terms and optimization terms is summarized in Table (1).

Table (1) Explanation of Genetic Algorithm Terms

Genetic Algorithms	Explanation
Chromosome (String, Individual)	Solution (Coding)
Genes (Bits)	Part of solution
Locus	Position of gene
Alleles	Values of gene
Phenotype	Decoded solution
Genotype	Encoded solution

1.4.2. Genetic Algorithm Terminology

This paragraph explains some basic terminologies for genetic algorithm:

- *Fitness Function*

The fitness function is the function you want to optimize. For standard optimization algorithms, this is known as the objective function.

- *Individuals*

An individual is any point to which you can apply the fitness function. The value of the fitness function for an individual is its score. An individual is sometimes referred to as a genome and the vector entries of an individual as genes.

- *Populations and Generations*

A population is an array of individuals. At each iteration, the genetic algorithm performs a series of computations on the current population to produce a new population. Each successive population is called a new generation.

- *Diversity*

Diversity refers to the average distance between individuals in a population. A population has high diversity if the average distance is large; otherwise, it has low diversity.

- *Fitness Value*

The fitness value of an individual is the value of the fitness function for that individual.

- *Parents and Children*

To create the next generation, the genetic algorithm selects certain individuals in the current population, called parents, and uses them to create individuals in the next generation, called children. Typically, the algorithm is more likely to select parents that have better fitness values.

1.4.3. Genetic Algorithms' steps

We can start to evolve solutions to the search problem using the following steps:

- *Initialization*

The initial population of candidate solutions is usually generated randomly across the search space. However, domain-specific knowledge or other information can be easily incorporated.

- *Evaluation*

Once the population is initialized or an offspring population is created, the fitness values of the candidate solutions are evaluated [1].

- *Selection*

Selection allocates more copies of those solutions with higher fitness values and thus imposes the survival-of-the-fittest mechanism on the candidate solutions. The main idea of selection is to choose better solutions out of worse ones, and many selection procedures have been proposed to accomplish this idea, including roulette-wheel selection, stochastic universal selection, ranking selection and tournament selection, some of which are described in the next section [1].

- *Recombination*

Recombination combines parts of two or more parental solutions to create new, possibly better solutions (i.e. offspring). There are many ways of accomplishing this (some of which are discussed in the next section), and competent performance depends on a properly designed recombination mechanism. The offspring under recombination will not be identical to any particular parent and will instead combine parental traits in a novel manner [1].

- *Mutation*

While recombination operates on two or more parental chromosomes, mutation locally but randomly modifies a solution. Again, there are many variations of mutations, but it usually involves one or more changes being made to an individual's trait or traits. In other words, mutation performs a random walk in the vicinity of a candidate solution [1].

- *Replacement*

The offspring population created by selection, recombination, and mutation replaces the original parental population. The algorithm usually selects individuals that have better fitness values as parents. The genetic algorithm creates three types of children for the next generation [21]:

- Elite children are the individuals in the current generation with the best fitness values. These individuals automatically survive to the next generation.

- Crossover children are created by combining the vectors of a pair of parents.

- Mutation children are created by introducing random changes, or mutations, to a single parent.

The following schematic diagram illustrates the three types of children.

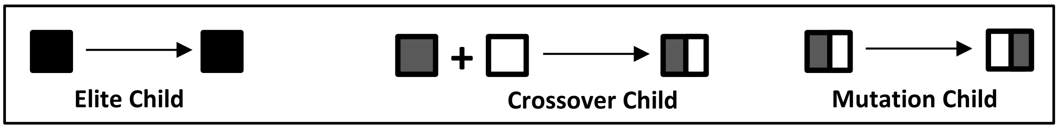


Figure (5) Three types of children for the next generation

1.4.4. Stopping Conditions for the Algorithm

The genetic algorithm uses the following five conditions to determine when to stop [21]:

- *Generations*
  The algorithm stops when the number of generations reaches the value of Generations.

- *Time limit*
  The algorithm stops after running for an amount of time in seconds equal to Time limit.

- *Fitness limit*
  The algorithm stops when the value of the fitness function for the best point in the current population is less than or equal to Fitness limit.

- *Stall generations*
  The algorithm stops if there is no improvement in the objective function for a sequence of consecutive generations of length Stall generations.

- *Stall time limit*
  The algorithm stops if there is no improvement in the objective function during an interval of time in seconds equal to stall time limit.

The algorithm stops as soon as any one of these five conditions is met. The searching procedure of GA is shown in Figure (6).

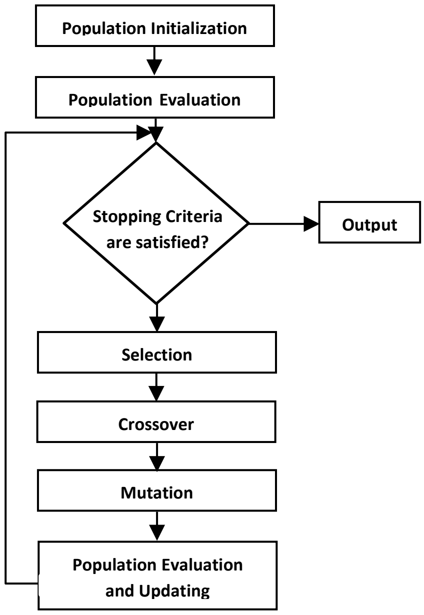


Figure (6) The flow diagram of a GA optimization model

1.4.5. Differences of Genetic Algorithm

Genetic algorithms differ from conventional optimization and search procedure in several fundamental ways as follows [17]:

- GAs work with a coding of solution set, not the solutions themselves.
- GAs search from a population of solutions, not a single solution
- GAs use payoff information (Fitness Function), not derivative or other auxiliary knowledge
- GAs use probabilistic transition rules, not deterministic rules

1.4.6. Major Advantages of GAs

Genetic algorithms have received considerable attention regarding their potential as a novel optimization technique. There are three major advantages when applying genetic algorithms to optimization problems [24].

- GAs do not have much mathematical requirements about the optimization problems. Due to their evolutionary nature, genetic algorithms will search for solutions without regarding the specific inner workings of the problem. GAs can handle any kind of objective functions and any kind of constraints (i.e., linear or nonlinear) defined on discrete, continuous or mixed search spaces.
- The periodicity of evolution operators makes genetic algorithms very effective at performing global search (in probability).
- GAs provide us a great flexibility to hybridize with domain dependent heuristics to make an efficient implementation for a specific problem.

1.5. E.S.A.M Software

E.S.A.M 2.1is an up-to-date, computer program that simulates the hourly energy usage of a building given hourly weather information and a description of the building. It requires an input text file featuring all the necessary parameters and details that describe the building and its systems; and readable by E.S.A.M 2.1. This software is linked to AutoCAD Software and it can read building data from CAD files. The first version of this software was created by SAMAN energy Co in 2002 and it has been developed and completed until now. The last version of this software (E.S.A.M 2.1) can simulate all building energy parameters in different conditions. In this project we could simulate energy consumption by different kinds of external-wall materials. That computer software was used for calculation heat loss in a real case study. All results compared with other software (Carrier and DOE 2.2) and the errors were eliminable.

2. Previous Studies

GA is well suited to handle complicated optimization problems with nonlinear, discrete and constrained search spaces.

- Huang and Lam [2] and also Fong et al. [3] adopted GA (or evolutionary programming) to solve heating, ventilating and air-conditioning (HVAC) control problems.
- Obara and Kudo [4] applied this GA method to control problems of energy systems consisting of fuel cells, thermal storage, heat pumps, etc.
- Write et al. [5] applied GA to investigate multi objective problems to identify the optimal building materials.
- Hongwei et al. [25] applied GA to mix integer and nonlinear programming problems in an energy plant in Beijing, and made a detailed economic investigation by changing the economic and environmental legislative contexts.

Since some researchers focus on both equipment selection (type of equipment, capacity size, etc.) and system operational control planning [12], in this paper, a new optimal design method to control energy consumption in external walls is proposed. This method optimizes the thickness of material to make a multilayer insulation. This method will be helpful for engineers who design external shells for buildings.

3. Experimental Setup

In order to do this project a series of planned experiments was run in the energy laboratory at the Isfahan Construction Engineering Organization. The experiments made use of the NECH Germany and Starbucks Switzerland insulation laboratory units. The thermal conductivity indicator machine is also equipped with the digital monitor to show the temperature and heat flux. This device has linked with a computer and this allows accurate digital temperature and heat flux reading to three decimal places to be recorded in real time by the attached data logger and supplied computer software.

Figure (7) Energy laboratory devices

In order to do this research project four types of insulation were used. Some of these insulation materials usually are used in external walls in buildings. The technical details of those are illustrated in Table (2).

Table (2) Technical details of insulation materials

Insulation Material	Density (ρ) kg/m3	Thermal Conductivity (λ) W/(m.°C)
Polyurethane Rigid Panel	30	0.030
Polystyrene Board (HCFC)	35	0.035
Phenolic Rigid Panel	100	0.400
Rock Wool	20	0.047
Glass Wool	10	0.054

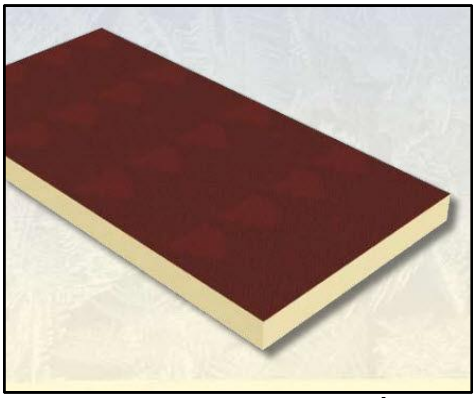


Figure (8) Polyurethane[8]

Figure (9) Polystyrene-Foam-Board[9]

Figure (10) Phenolic[10]

Figure (11) Rock-Wool-Board[11]

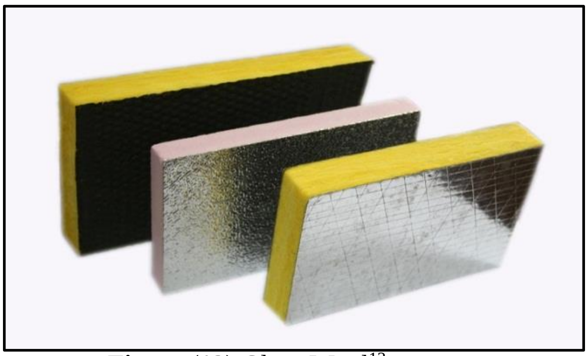


Figure (12) Glass-Wool[12]

4. Results and discussions

4.1. Error Analysis

The graph in Figure (13) clearly shows the error analysis in this project. As is shown by the graph, the difference temperature (ΔT) has remained constant with some fluctuations.

When we started collecting data, the difference temperature increased to reach a peak of nearly 3°C in the first 10 minute. Afterwards it fluctuated at around 3^{o}C for approximately 40 minutes. In that period the heat flux was 0.81 Watt constantly.

This graph can show that we can analyse data easily and the mean value of data in the period is 3 ^{o}C and another statistic parameter (standard deviation) is 0.06.

[8] **Source:** http://www.archiexpo.com

[9] **Source:** http://www.artgrafix.com

[10] **Source:** http://www.diytrade.com

[11] **Source:** http://www.tradeindia.com

[12] **Source:** http://www.dahongchem.com

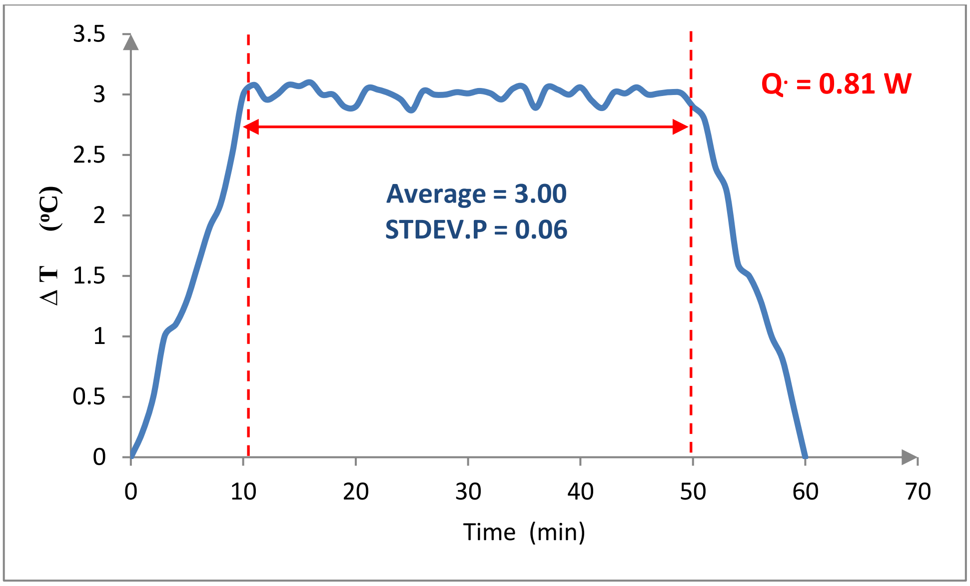


Figure (13) Difference Temperature Error Analysis

4.2.Calibration

As it mentioned before, for doing the tests a thermal conductivity indicator machine was used. For calibration we used two types of glass wool. One of them named original insulation was tested by Department of Energy that is a reference of standard documents and insulation materials in country. Another material was normal glass wool available in insulation materials markets.

The graph illustrated in Figure(14), showes changes in the amount of heat flux between two insulation materials.

While X-axis in this graph showes the difference temprature (ΔT), Y-axis represents heat flux. As it can be seen by the graph, after starting point , there was an up-ward trend and the graph of original glass wool has gone up significantly and and the line of tested glass wool has followed the previous graph as well. All neccesary equations are shown in this figure.

As a whole, using this calibration method will be very easy in this project and the result of this calibration is shown in Figure (15).

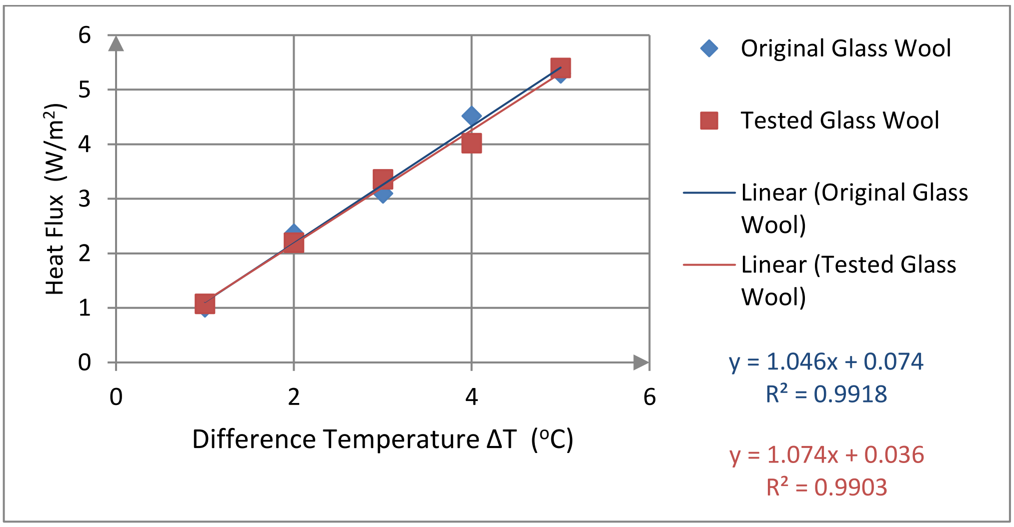
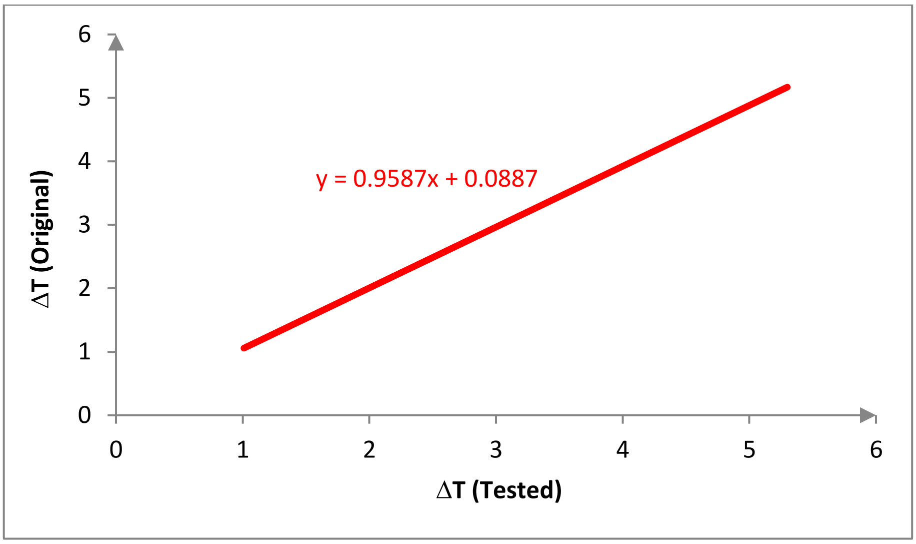


Figure (14) Calibration (Glass Wool)

As is illustrated by the Figure (15), we can use a linear trendline to calibrate indicator machine.
In this graph, it can be seen that, there is a linear relationship between difference temperature measured by using tested insulation and original material, therefor, by using this relationship and calibration equation , we can calibrate all data and use correct information for calculation.
The trendline in this excrement was an upward trend with using data from calibration area Figure (14).



Figure(15) Calibration trendline and equation

4.3.R-Value calculation for single layer Insulation

All types of insulation materials in this project are tested by laboratory unit and all results are illustrated in Figure (16) and Figure (17). It should be mentioned that the thickness of all samples were 20 cm. As it can be seen in the following figures, we can calculate the R-value for all samples[13] by using trendline equations. All results are placed in Table (3).

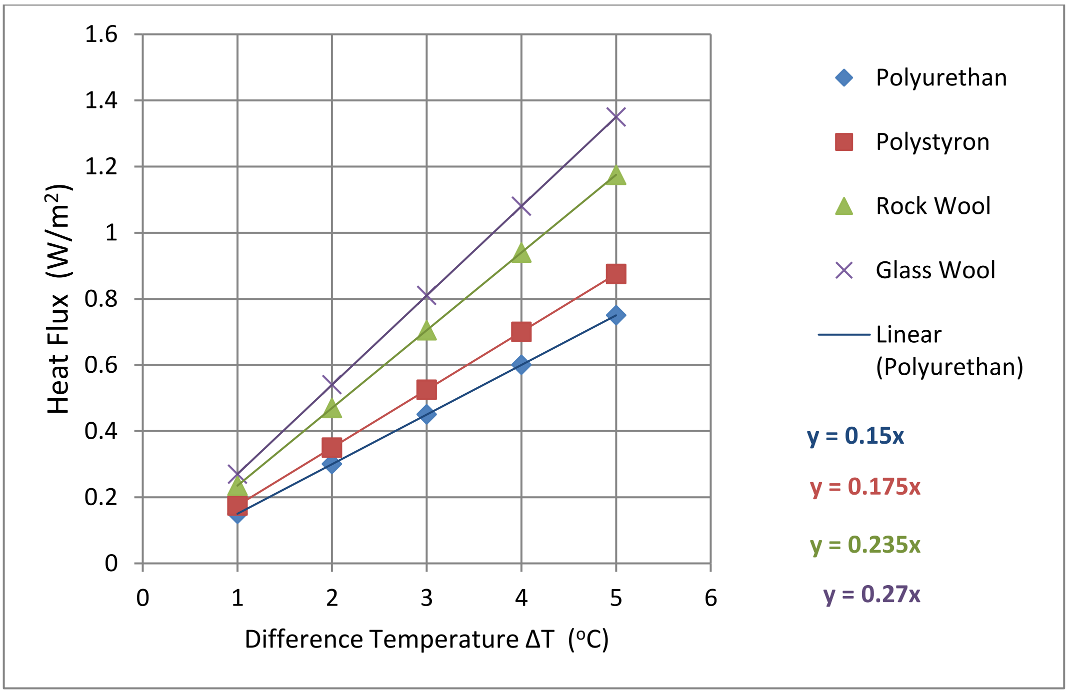


Figure (16) R-Value Results

[13] Heat flux (q)=ΔT/R-value

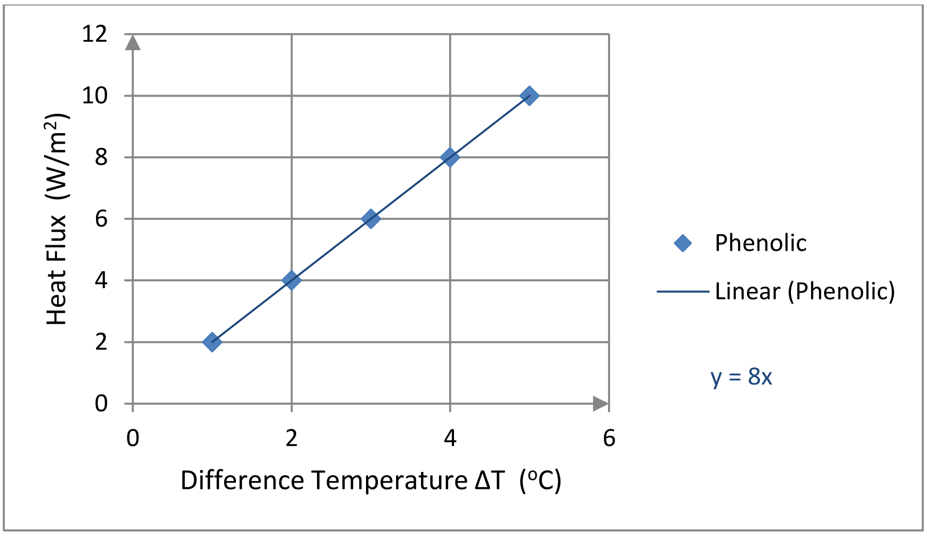


Figure (17) R-Value Result for Phenolic

Table (3) The Results of R-Value

Insulation Type	R-Value[14] (m^2. °C/W)
Polyurethane Rigid Panel	6.667
Polystyrene Board (HCFC)	5.714
Phenolic Rigid Panel	0.500
Rock Wool	4.255
Glass Wool	3.704

4.4.The effect of humidity on R-Value

A major source of decreasing R-Value in external walls is humidity. Water can influence on insulation materials and increases the thermal conductivity in humid weather condition. This issue usually is occurred in winter and increases the heat loss.

To survey the effect of humidity on R-Value in insulation material six steps of humidity condition were simulated and the results are illustrated in Table (4) and Figure (18).

Table (4) The effect of humidity on R-Value

Weight of water (gr)	0	30	50	70	100	150	GRADIENT
Insulation Type							
Polyurethane Rigid Panel	6.667	5.017	3.917	2.817	1.167	-1.583	-0.055
Polystyrene Board (HCFC)	5.714	4.214	3.214	2.214	0.714	-1.786	-0.050
Phenolic Rigid Panel	0.500	0.410	0.350	0.290	0.200	0.050	-0.003
Rock Wool	4.255	3.055	2.255	1.455	0.255	-1.745	-0.040
Glass Wool	3.704	2.654	1.954	1.254	0.204	-1.546	-0.035

[14] Thickness = 20 cm

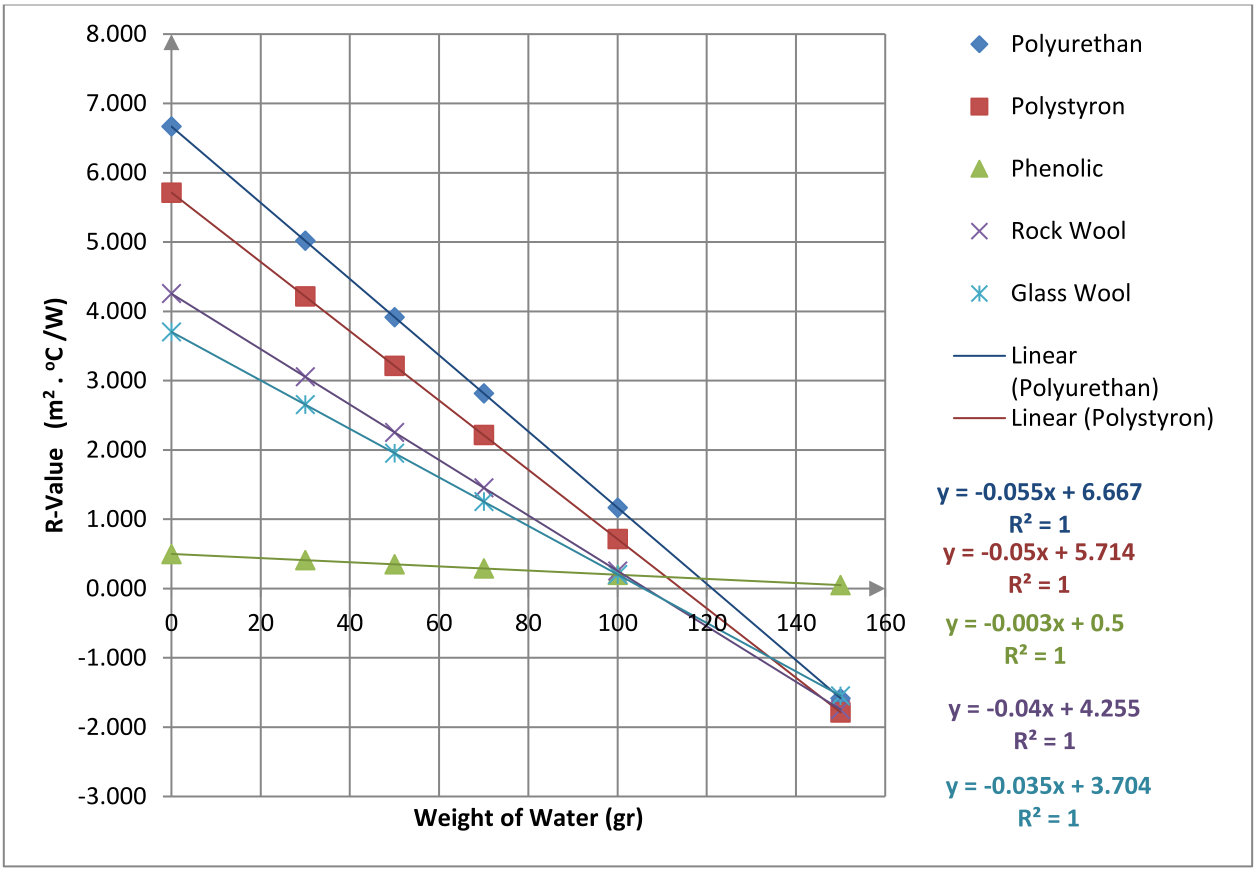


Figure (18) The effect of humidity on R-Value

As it can be shown by Figure (18), all gradients are negative; therefore, R-Value for all materials in this project decreased when the humidity increased.

Improving the quality of R-Value in multilayer insulation in humid condition is a major aim of this research.

4.5.Optimization of thermal resistance by using GA

The insulation equation for optimization is given as follows:

$$Max\ R\,(X_1, X_2, X_3, X_4, X_5) = \frac{x_1}{\lambda_1} + \frac{x_2}{\lambda_2} + \frac{x_3}{\lambda_3} + \frac{x_4}{\lambda_4} + \frac{x_5}{\lambda_5} \qquad (2)$$

$0.02 \leq x_1 \leq 0.05$, $0.02 \leq x_2 \leq 0.06$, $0.02 \leq x_3 \leq 0.05$, $0.03 \leq x_4 \leq 0.05$, $0.02 \leq x_5 \leq 0.06$

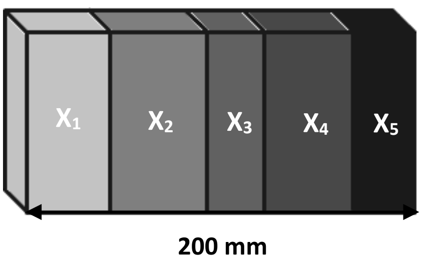


Figure (19) Multilayer Insulation

- **Representation**

First, we need to encode decision variables into binary strings. The length of the string depends on the required precision. For this project, the unit of variables in main equation is meter and for more accuracy in Genetic algorithm's process, we changed the unit in to millimetre. Each variable in this paper needs six bits in chromosome string to convert from decimal to binary code then the total length of chromosome is 30 bits which can be represented as follows:

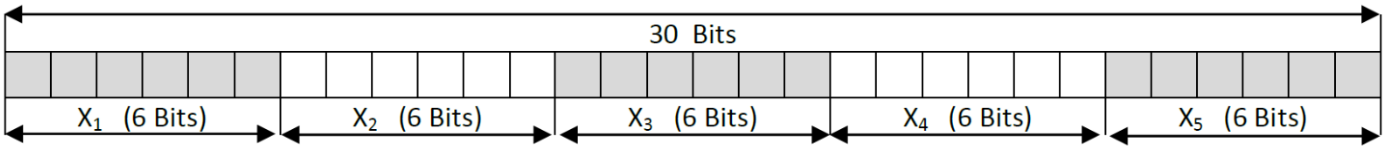


Figure (20) Chromosome

- **Initial Population**

Initial population is randomly generated and illustrated in Table (5).

Table (5) Initial Population elements in Barney mode

X_1	X_2	X_3	X_4	X_5
011110	011110	101000	110010	110010
110010	110010	011110	101000	011110
101000	011110	101000	101000	110010
010100	101000	011110	110010	111100
011110	101000	011110	101000	111100
110010	010100	110010	011110	110010
101000	111100	011110	011110	101000
101000	011110	011110	110010	110010
011110	101000	011110	101000	111100
011110	010100	110010	101000	111100

According to Table(5), all chromosomes as an initial population is shown below:

V1= [011110011110101000110010110010];

V2= [110010110010011110101000011110];

V3= [101000011110101000101000110010];

V4= [010100101000011110110010111100];

V5= [011110101000011110101000111100];

V6= [110010010100110010011110110010];

V7= [101000111100011110011110101000];

V8= [101000011110011110110010110010];

V9= [011110101000011110101000111100];

V10= [011110010100110010101000111100].

Table (6) Initial Population decimal values

	X_1 (mm)	X_2 (mm)	X_3 (mm)	X_4 (mm)	X_5 (mm)
V_1 (x_1, x_2, x_3, x_4, x_5)	30	30	40	50	50
V_2 (x_1, x_2, x_3, x_4, x_5)	50	50	30	40	30
V_3 (x_1, x_2, x_3, x_4, x_5)	40	30	40	40	50
V_4 (x_1, x_2, x_3, x_4, x_5)	20	40	30	50	60
V_5 (x_1, x_2, x_3, x_4, x_5)	30	40	30	40	60
V_6 (x_1, x_2, x_3, x_4, x_5)	50	20	50	30	50
V_7 (x_1, x_2, x_3, x_4, x_5)	40	60	30	30	40
V_8 (x_1, x_2, x_3, x_4, x_5)	40	30	30	50	50
V_9 (x_1, x_2, x_3, x_4, x_5)	30	40	30	40	60
V_{10} (x_1, x_2, x_3, x_4, x_5)	30	20	50	40	60

- **Evaluation**

The process of evaluating the fitness of a chromosome consists of the following three steps:

- **Step1.** Convert the chromosome's gene type to its phenotype. Here, this means converting binary string into relative real values.

- **Step2.** Evaluate the objective function.

- **Step3.** Convert the value of objective function into fitness. For the maximization problem, the fitness is simply equal to the value of objective function.

The fitness function values of chromosomes are as follows:

Table (7) Fitness function values

Chromosomes	Fitness Function Value (R-Value) m2.k/W
V_1	3.95
V_2	4.58
V_3	4.07
V_4	4.06
V_5	4.18
V_6	3.93
V_7	4.50
V_8	4.26
V_9	4.18
V_{10}	3.66

It is clear that chromosome V_2 is the strongest one and that chromosome V_{10} is the weakest one.

- **Selection**

In most practices, a *Roulette Wheel is* used for selection procedure; it can select a new population with respect to the probability distribution based on fitness values. The roulette wheel can be constructed as follows;

1. Calculate the total fitness value *eval* (V_k) for each chromosome V_k:

$$eval\ (V_k) = f(x), \qquad k=1, 2, \ldots, pop\text{-}size \tag{3}$$

2. Calculate the total fitness for the population:

$$F = \sum_{k=1}^{pop-size} eval\ (V_k) \tag{4}$$

3. Calculate selection probability p_k for each chromosome V_k:

$$p_{\boldsymbol{k}} = \frac{\text{eval}\ (V_k)}{\text{F}}\ , \qquad \text{K} = 1, 2, \ldots, \text{pop} - \text{size} \tag{5}$$

4. Calculate cumulative probability q_k for each chromosome V_k:

$$q_k = \sum_{j=1}^{k} p_j \qquad \text{k} = 1, 2, \ldots, \text{pop} - \text{size} \tag{6}$$

The selection process begins by spinning the roulette wheel *pop-size* times; each time, a single chromosome is selected for a new population in the following way;

Step 1.
Generate a random number from the range [0,1].

Step 2.
If $r \leq q_1$, then select the first chromosome V_1 ; otherwise, select the K^{th} chromosome

$$V_k\ (2 \leq K \leq pop\text{-}size)\ such\ that\ q_{k-1} < r < q_k\ .$$

The total fitness F of the population is

$$\text{F} = \sum_{k=1}^{10} eval\ (V_k) = 41.27 \qquad \frac{m^2.k}{W} \tag{7}$$

The probability of a selection p_k for each chromosome V_k (k=1, 2, …, 10) is shown in Table(8).

Table (8) P-factor for chromosomes

P-factor	Value
P_1	0.095443
P_2	0.110676
P_3	0.098358
P_4	0.098165
P_5	0.101080
P_6	0.094969
P_7	0.108858
P_8	0.102899
P_9	0.101080
P_{10}	0.088471

The cumulative probabilities q_k for each chromosome V_k (k=1, 2, …, 10) is shown in Table(9).

Table (9) Q-factor for chromosomes

q-factor	Value
q_1	0.095443
q_2	0.206119
q_3	0.304477
q_4	0.402642
q_5	0.503722
q_6	0.598692
q_7	0.707550
q_8	0.810448
q_9	0.911529
q_{10}	1.000000

Now we are ready to spin the roulette wheel 10 times, and each time we select a single chromosome for a new population. The results of that action is as follows:

Table (10) Roulette Wheel Results

R	Value
R_1	0.301431
R_2	0.322062
R_3	0.766503
R_4	0.881893
R_5	0.350871
R_6	0.583392
R_7	0.177618
R_8	0.343242
R_9	0.032685
R_{10}	0.197577

The first number R_1=0.301431 is greater than q_2 and smaller than q_3, meaning that the chromosome V_3 is selected for the new population; the second number R_2= 0.322062 is greater than q_3 and smaller than q_4, meaning that the chromosome V_4 is selected for new population; and so on. Finally, the new population consists of the following chromosomes:

V’1 = [101000011110101000101000110010] (V3);

V’2 = [010100101000011110110010111100] (V4);

V’3 = [101000011110011110110010110010] (V8);

V’4 = [011110101000011110101000111100] (V9);

V’5 = [010100101000011110110010111100] (V4);

V’6 = [110010010100110010011110110010] (V6);

V’7 = [110010110010011110101000011110] (V2);

V’8 = [010100101000011110110010111100] (V4);

V’9 = [011110011110101000110010110010] (V1);

V’10 = [110010110010011110101000011110] (V2);

- **Crossover**

Crossover used here is one-cut-point, which randomly selects one cut-point and exchanges the right parts of two parents to generate offspring. Consider two chromosomes as follows, and the cut-point is randomly selected after the 15th gene:

V1 = [011110011110101 000110010110010]

V2 = [110010110010011 110101000011110]

The result of offspring by exchanging the right parts of their parents would be as follows:

V’1 = [011110011110101110101000011110]

V’2 = [110010110010011000110010110010]

The probability of crossover is set as $P_c = 0.25$, so we expect that, on average, 25% of chromosomes undergo crossover. Crossover is performed in the following way:

begin

k=0;

while (k≤10) **do**

rk =random number from [0, 1];

if (r_k <0.25) **then**

select Vk as one parent for crossover;

end

k=k+1:

end

end

In this project the sequence of random numbers is:

0.625721, 0.266823, 0.288644, 0.295114, 0.163274, 0.567461, 0.085940, 0.392865, 0.770714, 0.548656

This means that the chromosomes V'_5 and V'_7 were selected for crossover. We generate a random integer number *position* from the range [1, 29] (because 30 is the total length of a chromosome) as cutting point or in other words, the position of the crossover point.

- **Mutation**

Mutation alters one or more genes with a probability equal to the mutation rate. Assume that the 18th gene of the chromosome V1 is selected for a mutation. Since the gene is 0, it would be flipped into 1. Thus the chromosome after mutation would be

$$V_1 = [01111001111010100\ \boxed{0}\ 110010110010]$$
$$\downarrow$$
$$V'_1 = [01111001111010100\ \boxed{1}\ 110010110010]$$

The probability of mutation is set as $P_m = 0.01$, so we expect that, on average, 1% of total bit of population would undergo mutation. There are m × *pop-size* = 30 × 10 = 300 bits in the whole population; we expect 3 mutation per generation. Every bit has an equal chance to be mutated. Thus we need to generate a sequence of random numbers r_k(k=1,… ,300) that is illustrated in Table (11).

Table (11) Mutation randomize

Bit Position	Chromosome Number	Bit Number
105	4	15
164	6	14
201	7	21

After mutation, we get the final population as follows:

V”1 = [011110101000011110110010110010];

V”2 = [110010111100010100101000011110];

V”3 = [110010011110011110101000110010];

V”4 = [011110101000010100110010111100];

V”5 = [101000011110010100110010111100];

V”6 = [110010010100101000101000110010];

V”7 = [110010111100010100011110101000];

V”8 = [101000101000010100110010110010];

V”9 = [011110110010010100110010110010];

V”10 = [011110011110101000101000111100];

The corresponding decimal values of variables [X1, X2, X3, X4, X5] and fitness are as follows:

R_1 (30, 40, 30, 50, 50) = 4.21 m^2.°C /W

R_2 (50, 60, 20, 40, 30) = 4.84 m^2.°C /W

R_3 (50, 30, 30, 40, 50) = 4.38 m^2.°C /W

R_4 (30, 40, 20, 50, 60) = 4.37 m^2.°C /W

R_5 (40, 30, 20, 50, 60) = 4.42 m^2.°C /W

R_6 (50, 20, 40, 40, 50) = 4.12 m^2.°C /W

R_7 (50, 60, 20, 30, 40) = 4.81 m^2.°C /W

R_8 (40, 40, 20, 50, 50) = 4.52 m^2.°C /W

R_9 (30, 50, 20, 50, 50) = 4.47 m^2.°C /W

R_{10} (30, 30, 40, 40, 60) = 3.92 m^2.°C /W

Table (12) Selected GA Parameters

Parameter	Selected Value
Population size (individuals)	10
Number of Generations	1000
Crossover Probability	0.25
Mutation Probability	0.01

Now we just completed one iteration of genetic algorithm. Running of the test is terminated after 1000 generation. We have obtained the best chromosome in 536th generation as follows:

V*=[110010111100010100110010010100]

$$eval\ (V^*) = R(5, 6, 2, 5, 2) = 4.87\ m^2.°C/W$$

X*1 = 50 mm;
X*2 = 60 mm;
X*3 = 20 mm;
X*4 = 50 mm;
X*5 = 20 mm;

4.6.GA Insulation test Results

After calculations, a sample of multilayer insulation that was suggested by GA made and it was tested in humid condition. The results are illustrated in Table(13) and Figure(13).

Table (13) GA insulation test results

Weight of water (gr) / Insulation Type	0	30	50	70	100	150	GRADIENT
G.A Insulation	4.87	3.97	3.37	2.77	1.87	0.37	-0.03

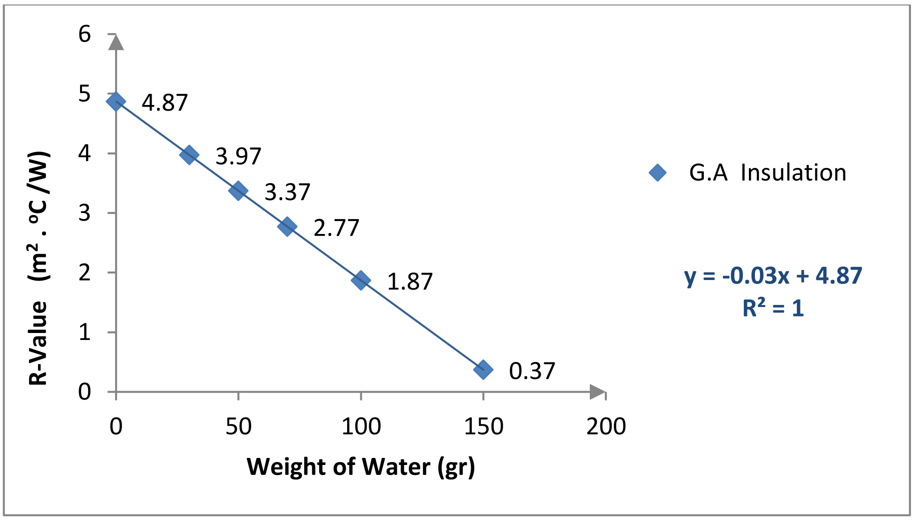


Figure (21) GA insulation test results

All previous tests were repeated for new generation of external wall insulation material. The results can show that GA method has improved the quality of insulation especially in humid condition.

5. Case Study

In order to examine the applicability of this optimal design method, we used the intentional wall insulation in a residential building. In order to achieve new results of this condition we simulated all parameters by E.S.A.M software. The technical details are illustrated in Table (14) and Table (15). To clear the local situation two Figures (22) and (23) can be useful.

Table (14) Technical details

The Maximum height (Floor to Ceiling)	4 m
Area	300 m^2
Floor	1
Thickness of wall Materials	35 cm

Table (15) Technical details of external walls

External Walls	Wall Direction	Length (m)	Facing material
1	south	15	Brick
2	west	20	Brick
3	North	15	Brick

Figure (22) The view of case study

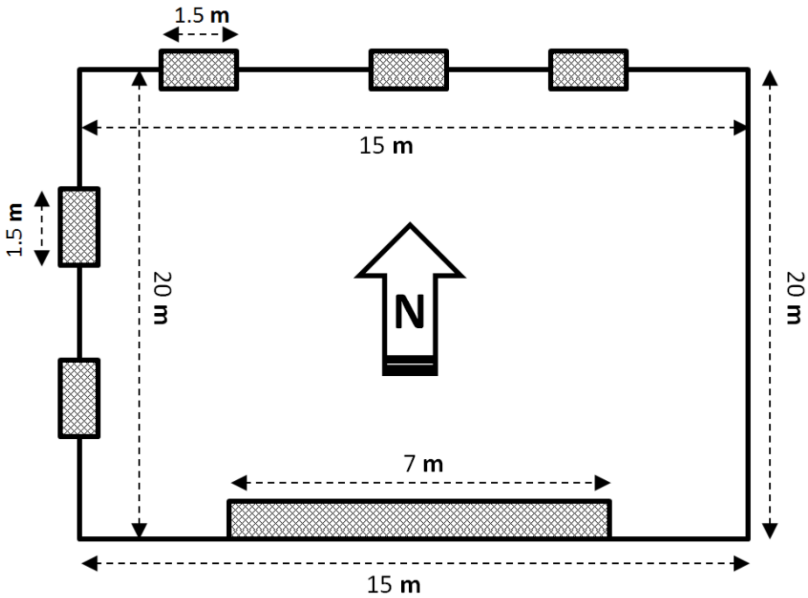


Figure (23) The plan of case study

Since, the details of external walls material are the aim of this research , all technical parameters for building external shell are placed in Table (15),(16) and (17). In this project three types of external wall were simulated:

- External wall without insulation material. Table(15)
- External wall with normal insulation material. Table(16)
- External wall with GA insulation material. Table(17)

Table (15) The details of external wall without insulation

layer	Material & Description	Thickness (mm)	Thermal Conductivity (W/m.k)	Density (kg/m^3)
1	Facing brick	50	0.80	2000
2	Air Cavity	20	0.13	-
3	Concrete Block	100	1.11	1700
4	Mortar between Block	15	0.46	1500
5	Plaster	15	0.50	1200
Expected Thermal transmittance (W/m^2.K)			0.542	
Thermal Resistance (m^2.k/W)			0.369	

Table (16) The details of external wall without insulation

layer	Material & Description	Thickness (mm)	Thermal Conductivity (W/m.k)	Density (kg/m^3)
1	Facing brick	50	0.80	2000
2	Air Cavity	20	0.13	-
3	Normal Insulation	200	0.05	10
4	Concrete Block	100	1.11	1700
5	Mortar between Block	15	0.46	1500
6	Plaster	15	0.50	1200
Expected Thermal transmittance (W/m^2.K)			0.092	
Thermal Resistance (m^2.k/W)			4.369	

Table (17) The details of external wall without insulation

layer	Material & Description	Thickness (mm)	Thermal Conductivity (W/m.k)	Density (kg/m^3)
1	Facing brick	50	0.80	2000
2	Air Cavity	20	0.13	-
3	GA Insulation	200	0.04	29
4	Concrete Block	100	1.11	1700
5	Mortar between Block	15	0.46	1500
6	Plaster	15	0.50	1200
Expected Thermal transmittance (W/m^2.K)			0.075	
Thermal Resistance (m^2.k/W)			5.369	

To calculate the total energy consumption in each building we used the E.S.A.M software and all results are illustrated in Table(18). It is clear that by using normal insulation we can save a large amount of energy in this case study but an important result is that by using GA method we could increase the saving from 31% to 50%.

Table (18) E.S.A.M Software results

	Total Energy Consumption (MJ)	Total Difference Consumption (MJ)	Saving percentage
Non Insulation	45,154	0	0%
Normal Insulation	31,218	13,936	31%
GA Insulation	22,511	22,643	50%

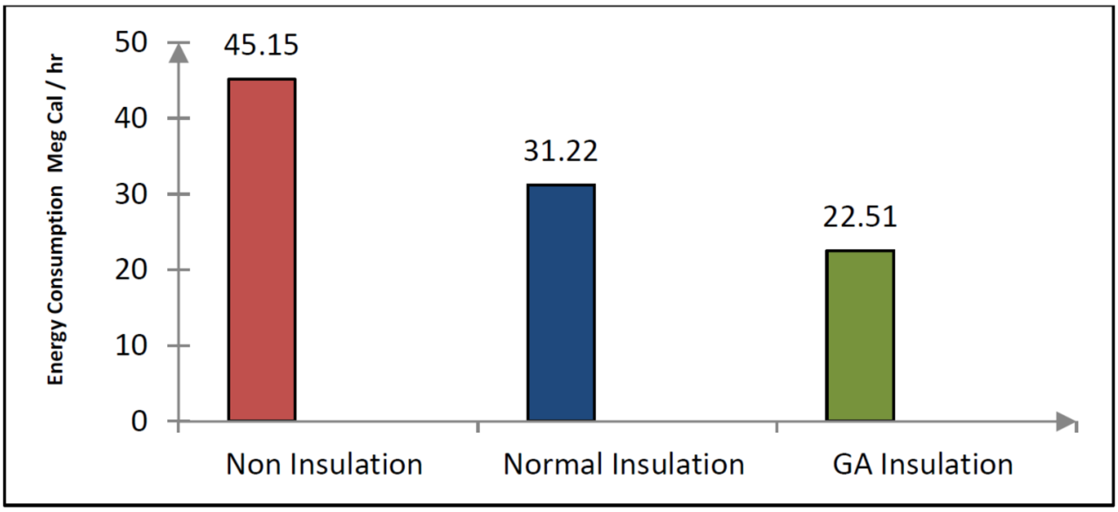


Figure (24) The effect of insulation on energy consumption

6. Conclusions

By doing this project we could show that GA method not only improve the insulation quality, but also it can help building managers and architects to design and construct new generation of green houses. GA could increase R-Value and it could improve the insulation quality in humid condition as well. This paper introduced the new approach to make multilayer insulation for external walls and the validity of using this method tested by a case study. All process in that project followed an academic trend and all stages completed by error analysis and calibration. The first aim of this research was the development of Genetic Algorithm method in construction industry and the results can be clearly shown that using this method in future can be useful for saving energy and it can help governments to reduce gas emission.

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