Computer and Information Science; Vol. 9, No. 4; 2016
ISSN 1913-8989 E-ISSN 1913-8997
Published by Canadian Center of Science and Education

Home Thermal Modeling: Cooling Energy Consumption and Costs in Saudi Arabia

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Received: September 2, 2016 Accepted: September 16, 2016 Online Published: October 25, 2016

doi:10.5539/cis.v9n4p22 URL: http://dx.doi.org/10.5539/cis.v9n4p22

Abstract

Objectives: The consumption of electricity and its costs are expected to be increased in Saudi Arabia due to its rapid growth in population. As the Kingdom is characterized by extreme hot climate, a massive amount of electricity consumed by the residential sector goes to power air conditioners. To control this huge amount of energyconsumedin homes, thermal models have been generated with two or more parameters. **Methodology:** The households' surveys have been conducted in order to collect the data. The Non-linear regression analysis has been carried out to obtain the outcomes of study. Moreover, household surveys have been conducted for data collection. The grid algorithm and the non-linear regression have been used to learn the parameters in the model to simulate the weather in Saudi Arabia. The temperature loggers have been placed in the houses to observe the behavior of residents of using cooling system. The web forecast has been used to analyze the temperature of cities on hourly basis. **Results:** Simple thermal model has been built using two parameters by applying the grid and non-linear regression methods for data fitting. Then the thermal model with envelope has also been created using four parameters by applying non-linear regression method for data fitting. **Conclusion:** It has been evaluated through outcomes that thermal model with envelope is better as compared to simple thermal model. Moreover, the data fitting by non-linear regression method has also been observed to perform better than data fitting by grid method.

Keywords: cooling energy, electricity, population, thermal model

1. Introduction

Energy consumption has been enhancing throughout the world, as a result of which, majority of the countries are facing unprecedented expansion in electricity infrastructure. A stable agriculture and irrigation system also tends towards a great need of energy consumption. It has been evaluated that the modern agricultural techniques are widely helpful for retrieving outcomes related to the severe energy related complications. A past study indicated that the implementation of modern irrigation system can easily improve the energy consumption aspects in an effective way (Valipour, 2015a). Residential sector is the third-largest major consumer of energy in the world, which represents almost 27% of total consumption (Lausten, 2008). During the time span of 2010, the electricity expansion has been made in residential sector with 426 Mtoe (17.84 EJ). This expansion of electricity has experienced almost 29% of dramatic increase in the last decade. Thus, the enhancement in energy efficiency of electrical equipments is not only influential for the conservation of energy in residential areas, but it also helps in reducing the load on electrical generators (Nejat, Jomehzadeh, Taheri *et al.,* 2015). There are many challenges regarding engineering structures that can influence the future needs of energy consumption. For example, many factors within a region can affect the overall energy consumption of that region such as weather, population etc, also energy efficiency and incorporation of energy resources with transmission of electricity (Valipour, 2015b). Taking into consideration the context of Saudi Arabia, the consumption of electricity and its costs are expected to enhance due to its growing population year by year (World Population Statistics, 2013). Saudi Arabia lies in the tropics between 16°N and 32°N latitudes and 37 to 52°E longitudes, due to which it is one of the hottest countries with low humidity in the world. The climate of Saudi Arabia comprised of extreme heat and aridity (Krishna, 2014). Due to extreme heat and hot climate of Saudi Arabia, the residential sector has been observed to consume a massive amount of electricity to power air conditioning (Saudi Electricity Company, 2016). It is important to find solutions to minimize the consumption of air conditioners or cooling systemsin the Kingdom of

Saudi Arabiain order to save the energy consumption. Moreover, these solutions involve saving the overstated costs, which are expected to be spent by Saudi Arabia.

In order to minimize and control the consumption of cooling and costs in residential homes, the first step is to study their environment thermal parameters that affect the work of cooling systems. The thermal models for residential homes have been established to further perform the study. Thermal modeling helps to understand the generation or loss of cooling and heating in buildings. The flows of cooling or heating throughout a building can be related to temperature variations inside the building. Therefore, in order to minimize cooling or heating energy consumption in home, the thermal model of that home must be built (Ryder-Cook, 2009).

Home thermal model is a mathematical formula that describes internal temperature variations according to the effect of home thermal parameters. There are several parameters that affect the cooling or heating in home. Some of these parameters are thermal production power, thermal leakage rate, home envelope, i.e. the thickness of home walls and solar heat. The power of thermal production depends on the cooling or heating system brand, capacity, and engines. The thermal leakage rate depends on wall envelope thickness and ventilations. Leakage through ventilations can occur in different ways such as leakage through windows, wall gaps, and deliberate ventilations (Rogers, Maleki, Ghosh *et al.,* 2011). The effect of solar heat depends on the orientation of outside facade and the position of sun (Nassiopoulos, Kuate, & Bourquin, 2014). Besides this, some other parameters, such as thermal capacity of room air and heat power generated by internal sources can be also considered in thermal models. Internal sources include heating provided by cooking and other energy use, as well as the heat generated by people (Guo, Li, Poulton *et al.,* 2008; Nassiopoulos, Kuate, & Bourquin, 2014). Here, the thermal models are categorized on the basis of parameters involved in modeling formula. First, there is simple thermal model, which has been created according to thermal production power and thermal leakage rate parameters. Different thermal models can be created by adding the effect of any or many thermal parameters to simple thermal model formula. The effect of home envelope parameters is added to produce thermal model with envelope. According to the situation, adding applicable thermal parameters would give more precise thermal models (Rogers, Maleki, Ghosh *et al.,* 2011).

Over the last few years, thermal models of buildings have been studied by different scientists and institutions to provide appropriate solutions to save the energy. An intelligent agent has been introduced by Rogers, Maleki, Ghosh *et al.* (2011) at the University of South Hampton in UK, in which the primary objective is to control a home heating system within a smart grid.The agent has been established with the task of learning thermal properties of home. It uses Gaussian processes to predict environmental parameters over the next 24 hours. The agent then provides real-time feedback to householders concerning the cost and carbon emissions of their heating preferences.

Hagras, Packham, Vanderstockt *et al.,* (2008) proposed a novel agent-based system for the management of energy in commercial buildings. This system has been entitled as Intelligent Control of Energy (ICE). In order to learn inside/outside conditions of thermal as well as to control the cooling/heating system, different techniques have been used by the researchers. Some of these techniques are fuzzy systems, neural networks, and genetic algorithms, which are beneficial in minimizing the costs associated with energy and also to maintain customer comfort. Moreover, a Gaussian Adaptive Resonance Theory Map (gARTMAP) has been presented by Mokhtar, Liu, & Howe (2014) for the management of heat system in buildings. The proposed model is an artificial neural network, which helps to predict and categorize the required control output by using non-linear regression. Therefore, the step towards saving energy in all previous works has been observed to occur by learning thermal characteristics of building, creating the appropriate thermal models, and predicting user consumption behavior, and then adjusting the heating/cooling system dependently.

Previous literature is mainly focused on diversified algorithms and traditional irrigation method, which could be helpful for fulfilling the consumption related aspects. However, the energy consumption rate is continuously increasing at a constant rate across the globe. Therefore, it is necessary to know about the impact of modern agricultural and irrigation systems for resolving energy demands. The significance of home thermal modeling should be identified for reducing the complications related with energy consumptions.

2. Methodology

2.1 Building the Simple Thermal Models

In order to build thermal models, the mathematical formulations are required to be generated. In this case, the standard thermal model has been considered, in which the day is divided into a set of discrete time slots $t \in Time$. As this work is about minimizing the energy consumption of cooling systems, it has been assumed that air conditioner cools the home. The thermal production power of air conditioners measured in Kilo Watts is given

by *CP*. The variable $COOLon \in \{1, 0\}$ is defined for every $t \in Time$, such that $COOLon = 1$, if the air conditioner is actively producing cool, and otherwise 0. The value of *COOLon* in any time slot *t* is given by:

$$COOLon^t = \begin{cases} 1, if\ air\ conditioner\ actively\ producing\ cool \\ 0, otherwise \end{cases} \tag{1}$$

On the basis of aforementioned equation, the amount of cooling energy *COOLrate* has been measured in C˚ that delivered by the cooling system in any time slot *t*.

$$\mathrm{COOLrate}^t = (\mathrm{CP} * \mathrm{COOLon}^t) + \alpha\,(\mathrm{T}_{ext}^t - \mathrm{T}_{int}^t) \tag{2}$$

Where, α is the value of thermal leakage rate, T_{ext}^t is external temperature in the time slot *t*, and T_{int}^t is internal temperature in the time slot *t*. Thus, the internal temperature in any time slot *t* after delivering this cooling energy is given by:

$$\mathrm{T}_{int}^{t+1} = \mathrm{T}_{int}^t - \mathrm{COOLrate}^t \tag{3}$$

Assuming that the air conditioner is controlled by a timer and thermostat, the variable that represents the air conditioner timer value is defined, $TIMERon^t \in \{1, 0\}$ for *every* $t \in Time$ and given by:

$$\mathrm{TIMERon}^t = \begin{cases} 1, if\ Timer\ set\ on \\ 0, if\ Timer\ set\ off \end{cases} \tag{4}$$

For all $t \in Time$ and $TIMERon^t = 1$, the thermostat acts to keep internal temperature T_{int} of homes at the set point of thermostat T_{set} by:

$$\mathrm{COOLon}^t = \begin{cases} 1, \mathrm{T}_{int}^{t-1} > \mathrm{T}_{set} + \Delta\mathrm{T} \\ 0, \mathrm{T}_{int}^{t-1} < \mathrm{T}_{set} - \Delta\mathrm{T} \end{cases} \tag{5}$$

Where, ΔT induces hysteresis, due to which thermostat cannot cycle on continuously at the set point (Rogers, Maleki, Ghosh *et al.,* 2011; Lin, Middelkoop, & Barooah, 2012; Ma, Borrelli, Hencey *et al.,* 2012).

2.2 Simple Thermal Model

The simple thermal model seems to be dependent on air temperature, which generally increases over the time slot due to cooling system thermal production power and decreases due to home thermal leakage:

$$\overline{\mathrm{T}}_{int}^{t+1} = \overline{\mathrm{T}}_{int}^t - (\mathrm{CP} * \mathrm{COOLon}^t) + \alpha\,(\mathrm{T}_{ext}^t - \overline{\mathrm{T}}_{int}^t) \tag{6}$$

Where, $\overline{T}_{int}^t$ denotes internal temperature in the time slot *t* that is predicted by thermal model (Rogers, Maleki, Ghosh *et al.,* 2011). The simple thermal model presented above is primarily depending on two parameters: the thermal production power of air conditioner *CP* and thermal leakage rate of home α. Before the creation of thermal model, it is necessary to learn *CP* and α *since these two parameters are not measured, so they have to be estimated*. The process of learning parameters is called data fitting. Generally, the data fitting is aimed at describing the data by a simpler mathematical principle that is as close as possible to the real data. Then, the fit yields the parameters in corresponding mathematical formula. Commonly, the root mean squared errors used as a measure for deviation between observed and predicted data. Thus, the data fitting means to find a minimum for root mean squared error (Betzler, 2003). The root mean squared error (*RMSE*) is given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_{obsrv}^i - X_{pre}^i\right)^2} \tag{7}$$

Where, X_{obsrv} is the real observed value and X_{pre} is the predicted value by a model at time unit *i* (Brennan, 2013).

In this study, different information should be known for data fitting. Observations over 24 hours of internal temperatures T_{int}^t and external temperatures T_{ext}^t have been collected. The time periods when air conditioner timer is on and thermostat set points are needed to find the time periods when the air conditioner provides active cooling, a mentioned in Formula (5). These 24 hours observations are used by Formula (6) to predict the evolution of internal temperature over the same period initializing at $\overline{T}_{int}^1 = T_{int}^1$; where T_{int}^1 is observed internal temperature in the time slot $t = 1$. Then, the error in this prediction *E* is given by:

$$E = \sqrt{\frac{1}{Time}\sum_{t \in \mathrm{Time}}(\mathrm{T}_{int}^t - \overline{\mathrm{T}}_{int}^t)^2} \tag{8}$$

Thus, the values which minimize this error are considered as the best estimates of *CP* and α (Rogers, Maleki, Ghosh *et al.,* 2011).

2.3 Thermal Model with Envelope

Thermal model provides a detailed description for the components of phase change materials of building envelope for the calculation of building thermal field (Guichard, Miranville, Bigot *et al.,* 2014). The home envelope parameter represents the wall thickness, which reduces thermal leakage from inside to outside and vice versa (Rogers, Maleki, Ghosh *et al.,* 2011). To involve the effect of home envelope in simple thermal model presented by Formula (6), two more parameters are considered. These parameters represent the coefficients of thermal transmission through the home wall from outside to inside and from inside to outside the home. As shown in Figure 1, Beta β parameter is the coefficient of heat transmission through home wall from outside to inside the home and the Gamma γ parameter is the coefficient of cooling transmission through home wall from inside to outside the home.

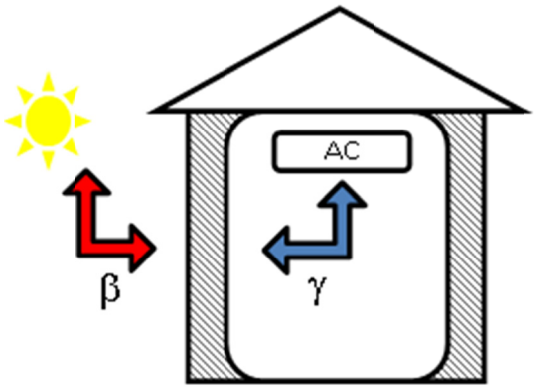

Figure 1. Home envelope parameters Source: Perera & Sirimanna (2014)

The temperature of envelope in any time slot *t* should be given by:

$$T_{env}^{t+1} = T_{env}^{t} + \left(\beta(T_{ext}^{t} - T_{env}^{t})\right) + \left(\gamma(\overline{T}_{int}^{t} - T_{env}^{t})\right) \quad (9)$$

Moreover, simple thermal model in Formula (6) will be modified to the following:

$$\overline{T}_{int}^{t+1} = \overline{T}_{int}^{t} - (CP * COOLon^{t}) + \alpha\,(T_{env}^{t} - \overline{T}_{int}^{t}) \quad (10)$$

Where, T_{env}^{t} is the envelope temperature at time slot *t* (Rogers, Maleki, Ghosh *et al.,* 2011; Perera & Sirimanna, 2014). The parameters that are attached with home envelopeare Beta β parameter and the Gamma γ parameter. These parameters can be learned and estimated in the same way as *CP* and αparameters are learned, where the best estimates are the ones that minimize error *E* in Formula (8)(Rogers, Maleki, Ghosh *et al.,* 2011).

2.4 Data Collection and Preparation

The Royal Commission for Yanbu (RCY) province of the Kingdom of Saudi Arabia has been selected to conduct the present study. The reason to select this province is that it has same style homes and cooling systems. Ten homes have been randomly selected and included as the sample of study, which were denoted by alphabets from A to K. The data required to perform the study include observations of external and internal temperature, thermostat set points and timer settings of home cooling system, and the cooling capacity of air conditioners.

In order to take the reading of internal temperatures, the temperature loggers (Note 1) have been placed in each home during the 24 hours of the day. The loggers have been set to read current temperature every 1 minute. Each logger can only hold 5 days of data. Accordingly, loggers had to be taken to download the data and place them back. So, data collected for 3 periods, 5 days long each during the summer. In order to find the time periods in which the air conditioner produces active cooling, the technique the algorithm below (1) has been used.

Algorithm (1)
TIME ←#one-day time slots
TIMERon [TIME] ← Array of collected timer settings

```
SET ← Thermostat set point
BAND ← 0.1 // induces hysteresis in thermostat
// Find COOLon values (i.e. time slots in which air conditioner is actively producing cool)
for t = 1:Time
// if timer set to ON in the current time slot t
ifTIMERon(t)= 1 thenDELTA = int_temp(t) - SET
if DELTA > BAND thenCOOLon(t) = 1
else if DELTA < BAND thenCOOLon(t) = 0
elsethenCOOLon(t) = 0
end
```

2.5 Creating Simple Thermal Model

The simple thermal model has been created on the basis of system parameters, which include thermal production power CP and thermal leakage rate of the home α. Data fitting has been done to learn these parameters as previously described. The methods of grid and non-linear regression have been used for data fitting.

2.5.1 The Grid Method

The grid method depends on the exhaustive search. It is used to build a grid of points (x,y), while x and y values represent all possible values of the parameters to be estimated. These parameters are thermal production power CP and thermal leakage rate α in this work case, and the possible combinations of x and y have been looped together. At each loop, simple thermal model Formula (6) has been applied to find the predicted internal temperatures. Then, the error E defined by Formula (8) has been computed between the observed and predicted internal temperatures. At last, the (x,y) combination, that produces the minimum error E, has been identified as the best estimate of CP and α. The pseudo code for grid method can be observed from Algorithm (2), mentioned as follows:

```
Algorithm (2)
EXT ← Load external temperatures
DATA ← Observed internal temperatures
FindCOOLon (Algorithm (4.1))
// Generate grid of points for CP and α
Leakage [max] ← Array (0.001:0.1)//array values range
CP [max] ← Array (0.001:0.1)
ERROR [max,max]←2 DimensionalArray of Zeros
// Loop through all possible combination to find values which minimize theerror between predicted and observed
internal temperatures
fori = 1:max
for j = 1:max
Predicted_INTERNAL_T = Run Simple ThermalModel(CP(j),Leakage(i),EXT,COOLon)
ERROR(i,j) = sqrt(mean((DATA - Predicted_INTERNAL_T)^2))
end
end
BEST_ESTIMATES = min(ERROR)
```

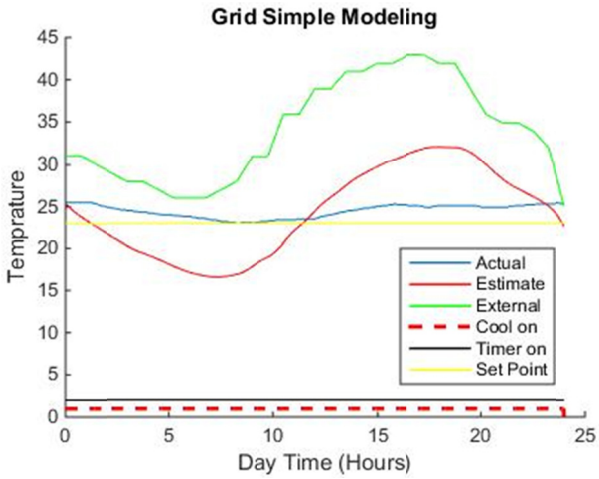

Figure 2. Home simple thermal model created by grid method of data fitting

In Figure 2, X-axisrepresents the time slots for one day from 12:00 am to 11:59 pm, and Y-axis represents the temperature values. The green line is the plot of collected external temperature data. The blue line is the plot of observedinternal temperaturedata by the energy loggers. The red line is the plot of predicted internal temperature data by the applied thermal model formula. The yellow line indicates the air conditioner set point. The black and dotted red lines at the bottom are time periods, in which the timer is on and time periods, in which the air conditioner produces more cooling. It can be noticed from Figure 2 that data does not fit the data well. The grid method depends on the inclusion and accuracy of search space or the grid. But, using complicated grid will increase the costs and the time of search implementation.

2.5.2 Non-Linear Regression Method

The non-linear regression is a method for data fitting to any selected formula (Motulsky & Ransnas, 1987). It represents the relationship between a continuous response variable and one or more continuous predictor variables (MathWorks, 2014). The relationship between responses and predictors can be described by a formula that includes one or more parameters. The primary objective of non-linear regression method is to minimize the error between observed responses and the responses predicted by selected formula (Motulsky & Ransnas, 1987). The minimized error is given by Formula (7).

The non-linear regression method has been observed to fit the data iteratively. First, any initial estimate of the value of each parameter must be provided. Then, the non-linear regression method adjusts these values to improve the fit to data. It continues the adjustment of new values to improve the fit time after another until no valuable improvement occurs (Motulsky & Ransnas, 1987). The non-linear regression method has been performed in the form:

$$Y = f(X, beta) \tag{11}$$

Where f is any function of X and *beta* evaluates each row of X along with the vector *beta* to compute the prediction for corresponding row of Y.X is n-by-p matrix of p predictors at each of n observations. Y is n-by-1 vector of observed responses; whereas, the *beta* is vector of parameters (MathWorks, 2014). Following is the psuedo code for non-linear regression method:

```
Algorithm (3)
EXT ← Load external temperatures
DATA ← Observed internal temperatures
N ← # of parameters to learn
FindCOOLon (Algorithm (4.1))
Learnt_Parameters [N] = Non_Linear_Regression(DATA,EXT,COOLon,Thermal_Model)
Predicted_INTERNAL_T = RunThermalModel(Learnt_Params,Ext,COOLon)
```

In current study, *Time* has been divided into n time slots t. Then, X is n-by-p matrix, while p is the *COOLon* value corresponding to each collected external temperature at any time slot $t \in Time$. Y is n-by-1 vector of observed internal temperatures. f is simple thermal model given by Formula (6). *beta* specifies the parameters to be estimated *CP* and α. Simple thermal model created by non-linear regression method of data fitting for House G on June 8th is shown in Figure 2. The following Figure 3 shows better data fitting as compared to the grid method, due to the reasons that actual and estimated temperatures are almost same.

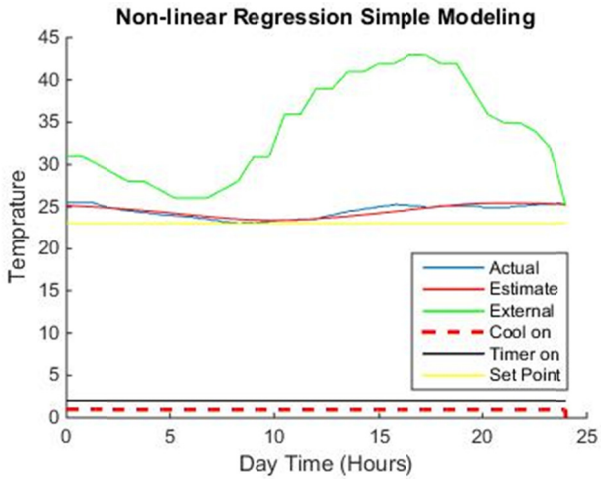

Figure 3. Home simple thermal model created by non-linear regression method of data fitting

2.6 Creating the Thermal Model with Envelope

Here, the home thermal model has been built on the basis of four parameters, which are thermal production power *CP*, thermal leakage rate of home α, and envelope parameters which are Beta β and Gamma γ parameters. For the fitting of data, non-linear regression method has been used. The Formula (10) that represents thermal model with envelope has been used as model function f in the implementation of non-linear regression Formula (11). The non-linear regression method has been used here for data fitting because the evaluation illustrates that it is better method than the grid method. Figure 3 is a thermal model with envelope created by the non-linear regression method of data fitting for House G on June 8th.

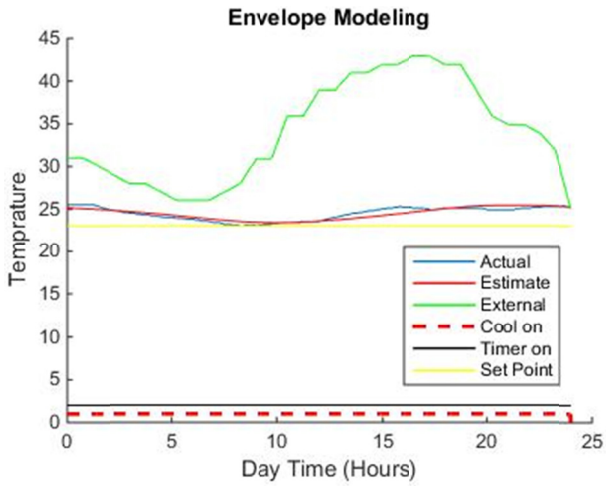

Figure 4. Home thermal model with envelope created by non-linear regression method of data fitting

From the above figure, it can be observed that there is good data fitting according to actual and estimated temperatures plot lines.

2.7 Computation of Cooling Cost

The costs associated with the consumption of air conditioner can be estimated by developing thermal models. According to the Saudi Electricity Company (Note 2), air conditioners consume 60% of total monthly consumption by the householders of Saudi Arabia. Also, given that each air conditioner consumes 1.6 Kilo Watt per Hour (KWh) per ton of its cooling capacity (Saudi Electricity Company, 2016). The consumption of air conditioner $AC_{consumption}$ in KWh is given by:

$$AC_{consumption} = 1.6 * CAPCTY \tag{12}$$

Where, *CAPCTY* is the air conditioner capacity measured in tons. The pricing method of Saudi Electricity Company depends on certain consumption segments, because each segment has its own price. If a customer reaches a higher consumption segment, the price rises. Table 1clarifies the residential consumption segments along with their prices (Saudi Electricity Company, 2016).

Table 1. Residential consumption prices according to Saudi Electricity Company

Consumption Segments (KWh)	Residential (Halalah **(Note 3)**)
2000 – 1	**5**
4000 – 2001	**10**
6000 – 4001	**12**
7000 – 6001	**15**
8000 – 7001	**20**
9000 – 8001	**22**
10000 – 9001	**24**

More than 10000	**26**

Note: The consumption cost calculated each 30 days.

For the computation of cooling cost of air conditioners, the pseudo code has been given below:

```
Algorithm (4)
input C ← # air conditioner cooling capacity
input B ← # specific hours budget
// Compute air conditioner consumption by Kilowatt for one hour
// Each Ton of cooling capacity consume 1.6 Kilowatt/Hour
consumption = 1.6 * C
// Compute the cooling cost for one month
// Only 60% of each consumption segment considered because that the air conditioner consumption represents 60%
of Saudi homes bills
cost← 0
sum← 0
for c = 1:30 // loop through month days
for k = 1:B // loop through each day cooling hours
sum = sum + consumption
ifsum<= 60% of 1st segment
then cost = cost + (1st segment cost * consumption)
else ifsum<= 60% of 2nd segment
then cost = cost + (2nd segment cost * consumption)
elseif .
else ifsum>60% of highest segment
then cost = cost + (highest segment cost * consumption)
end
end
monthly_cost = cost / 100; // convert from Halalah to Riyals
```

The estimated air conditioner consumption cost has been calculated for House G on June 8th from thermal model developed in Figure 4. The outcomes demonstrate a consumption cost of 160.96 Riyals per month, considering that the air conditioner capacity is equal to 2 Tons. Many researches have used these regression practices which have been used in this paper, Valipour, (2015c) utilized the transfer-based models and evaluate the data by regression analysis in his study related to crop evapotranspiration. Khoshravesh *et al*., (2015) has propsed different regression models to analyze the monthly reference evapotranspiration. Similarly, Valipour, (2014a; 2014b; 2012) has also used these models to analyze the results.

3. Results

Statistical measurements are needed to evaluate the efficiency of thermal modeling and data fitting to be accurate and authentic. The residuals and norm of residual analysis is a measure, which is often used for the efficiency of data fit for the comparison of different data fits. The residuals are the differences between the observed data and corresponding predicted fit data. The residuals plot can give insight into the efficiency of a fit by examining it visually (MathWorks, 2014). If the model fit to the data is correct, the residuals will approximate only experimental errors that exhibit random arrangement of positive and negative residuals. This is helpful in generating a statistical relationship among the observed and predicted values. But if the model fit to data is inappropriate, the positive residuals may tend to cluster together at some parts of graph; whereas, negative residuals cluster together at other parts. Such clustering indicates that the observed values differ systematically from the predicted values (Motulsky & Ransnas, 1987).Therefore; if the residuals appear to behave randomly, it suggests that the model fits the data well. On the other hand, if non-random structure is evident in residuals, it is a clear sign that the model fits the data poorly. However, the more the residuals are randomly distributed; the best is the fit (Féménias, 2003). The norm of mathematical object is a quantity that describes the length, size or extent of this object. Mathematically, a more precise vector *t* has been denoted as:

The norm of *t*ies defined as:

$$t = [t_1, t_2, t_3, t_4, \dots t_n]$$
$$Norm\ of\ t = \sqrt{(|t_1|^2 + |t_2|^2 + \dots + |t_n|^2)} \quad (13)$$

Thus, the norm of residuals is square root of the sum over squared residuals. The norm of residuals varies from 0

to infinity with smaller numbers, which indicates better fit; whereas, zero indicates a perfect fit (Betzler, 2003).

3.1 Evaluating Results of Simple Thermal Model

A model of simple thermal model has been created by the grid and non-linear regression methods of data fitting have been used. The norm of residuals has been calculated for each thermal model data fit. The outcomes obtained through these calculations are shown in Table 2 and Table 3 (Note 4).

Table 2. Norm of residuals values for simple thermal models created by grid method of data fitting

		Days														
		June 2013												**July 2013**		
		5	**6**	**7**	**8**	**9**	**15**	**16**	**17**	**18**	**19**	**29**	**30**	**1**	**2**	**3**
Homes	**A**	118	99	203	174	189	207	178	202	170	162	198	188	156	190	183
	B	184	101	227	269	269	329	326	361	332	289	276	231	202	240	219
	C	191	126	263	298	298	342	338	358	323	298	241	215	189	235	231
	D	133	133	157	193	210	203	198	211	192	181	136	178	144	159	144
	E	170	254	400	233	158	212	208	244	182	151	147	122	114	136	135
	F	196	170	314	232	234						412	178	152	229	214
	G	138	138	158	177	209	238	234	254	167	144	219	270	210	201	150
	I	122	122	156	192	206	206	204	221	201	186	138	194	155	163	151
	J	258	186	156	207	226	161	145	158	169	185	142	222	195	206	203
	K	153	92	212	188	177	314	313	282	230	191	203	159	119	141	133

Table 3. Norm of residuals values for simple thermal models created by non-linear regression method of data fitting

		Days														
		June 2013												**July 2013**		
		5	**6**	**7**	**8**	**9**	**15**	**16**	**17**	**18**	**19**	**29**	**30**	**1**	**2**	**3**
Homes	**A**	63	45	36	47	31	32	26	26	26	25	28	28	29	29	29
	B	33	29	29	30	30	29	30	29	30	29	30	30	33	30	31
	C	31	31	30	30	30	29	30	29	29	30	32	29	31	29	29
	D	26	26	25	24	25	25	26	25	26	24	26	25	25	26	25
	E	51	34	36	52	32	37	35	38	38	39	29	46	36	35	32
	F	41	33	62	30	34						61	36	50	42	38
	G	50	50	26	29	26	31	35	31	31	26	20	31	34	29	39
	I	26	26	26	25	26	24	25	24	24	24	24	24	24	24	24
	J	30	27	30	25	27	25	22	26	32	34	31	33	29	41	38
	K	36	32	34	33	35	32	34	69	29	39	31	41	36	44	36

The norm of residual values has been observed to be resulted by using the grid method range of 92-412, and the overall average of calculated values is 203.01, as shown in Tables 2 and 3. However, the norm of residuals values resulted from using the non-linear regression range between 20-69 and the average of overall calculated values is 32.04. According to the resulted averages, the method of non-linear regression provides better fits than using the grid method for data fitting.

3.2 Evaluating Thermal Model with Envelope Results

It has been evaluated through outcomes that the method of non-linear regression is much better than the grid method for data fitting. Thermal model with envelope is built here by the non-linear regression method of data fitting using the collected data for this study. In Table 4, the norm of residuals is calculated for these thermal models data fit to be compared with the norm of residuals values calculated for simple thermal model data fit created by non-linear regression method, which are shown in Table 3.

Table 4. Norm of residuals values for thermal models with envelope created by non-linear regression method of data fitting

		Days														
		June 2013												**July 2013**		
		5	**6**	**7**	**8**	**9**	**15**	**16**	**17**	**18**	**19**	**29**	**30**	**1**	**2**	**3**
Homes	**A**	30	34	30	32	25	27	24	24	25	24	28	28	28	29	28
	B	31	28	29	30	30	29	30	29	29	29	30	30	33	30	32
	C	31	31	30	30	30	29	30	29	29	29	31	29	30	29	29
	D	25	25	25	24	25	25	25	25	26	24	25	25	25	25	25
	E	39	34	36	52	32	31	32	31	33	39	28	32	29	35	32
	F	41	30	37	31	32						46	28	50	42	40
	G	39	39	26	29	26	31	35	29	27	23	20	21	22	23	23
	I	26	26	25	25	25	24	24	24	24	24	24	24	24	24	24
	J	26	27	25	25	27	23	22	23	24	34	31	31	29	22	38
	K	32	30	30	33	35	29	30	38	29	39	30	41	36	44	35

The norm of residuals values range between 20-52 and the average value is 29.48. Results of the thermal model with envelope are close to, but smaller in comparison with the results of simple model. The plot of residuals for previous models has been examined visually, and it exhibits random behavior in the cases of simple thermal and thermal with envelope models by non-linear regression method of data fitting. However, in the case of simple model by the grid method of data fitting, it is close to making a pattern. It has been observed from earlier sections that if residuals appear to behave randomly, then the model fits the data well. So, this examination proves that the method of non-linear regression is better as compared to the grid method for data fitting. Figures 5, 6 and 7 clarify plots of residuals for different thermal models described above for House G on June 18th. Each figure shows thermal model and the residuals of its plot.

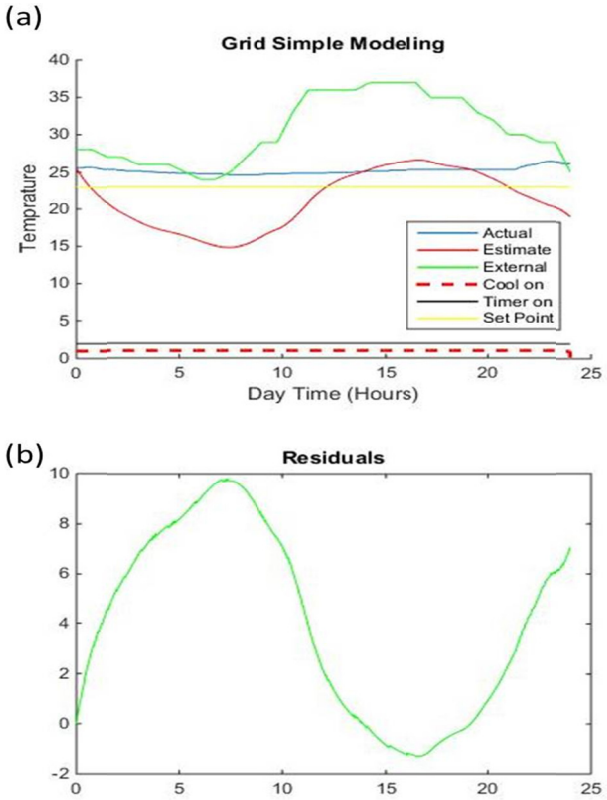

Figure 5. Simple thermal model by grid method of data fitting: (a) the thermal model, and (b) its plot of residuals (Pattern behavior)

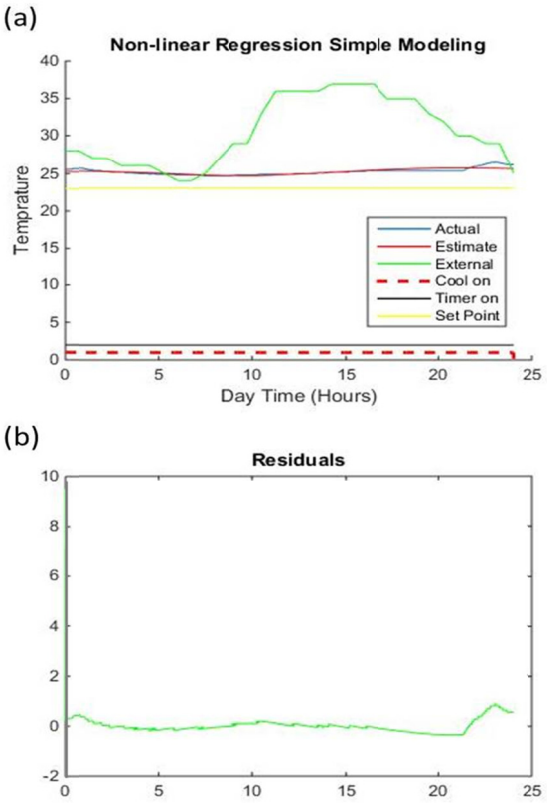

Figure 6. Simple thermal model by non-linear regression method of data fitting: (a) the thermal model, and (b) its plot of residuals (Random behavior)

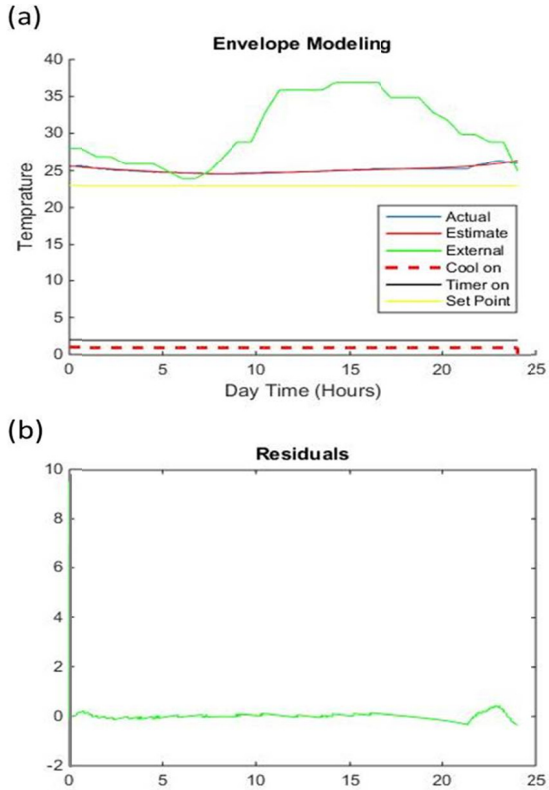

Figure 7. Thermal model with envelope by non-linear regression method of data fitting: (a) the thermal model, and (b) its plot of residuals (Random behavior)

For previous models, the plot of residuals has been examined visually, which exhibits random behavior in the cases of simple thermal and thermal with envelope models by non-linear regression method of data fitting. However, in the case of simple model by the grid method of data fitting, it is close to making a pattern. Figures 5, 6, and 7 clarify plots of residuals for different thermal models described above for House G on June 18th. Each Figure shows the thermal model and its plot of residuals.

3.3 Thermal Models Comparison

The comparison of thermal models comprised of two stages. First, data fitting methods, which are the grid and non-linear regression, are applied to simple thermal model and then their comparison has been made. Second, the method that exhibit better data fit is applied to simple thermal model and thermal model with envelope to be compared. The comparison is based on evaluation of the norm of residuals values, in which the smaller numbers are indicating better fits and zero indicates the perfect fit. The comparison stages have been summarized in Table 5.

In first stage, the average norm of residuals for simple thermal model by grid method is 203.01; however, through non-linear regression method, the average value is 32.04. Thus, a major difference has been observed among these two values. So, the first stage of comparison result with that of the non-linear regression is a better method as compared to the grid for data fitting. The second stage makes a comparison among simple thermal model and thermal model with envelope by applying non-linear regression for data fitting. The average value of the norm of residuals average for simple thermal model is 32.04, while it is 29.48 for thermal model with envelope. These values indicate that the thermal model with envelope provides more accurate results as compared to simple thermal model.

Table 5. Summary of the comparison of thermal models

Thermal Model Type	Data Fitting Method	Norm of Residuals Avg.	Comparison Stage
Simple	Grid	203.01	Stage 1
Simple	Nonlinear Regression	32.04	Stage 2
With Envelope	Nonlinear Regression	29.48	

The algorithms used in this study are helpful in analyzing the results. Grid technique has also been introduced for assessing the outcomes. Similarly, Mallick (2014) applied algorithm technique in analyzing the results of weather conditions in Saudi Arabia, which not only estimated the heterogeneous areas but also focused on homogenous areas. It can be said that energy consumption is directly proportional to the weather conditions, hot weather tend to consume more energy in the form of different appliances. This study can be compared by the study of Foucquier et al. (2013), who described the energy consumption majorly in buildings in European Union.

4. Conclusion

The concepts of thermal modeling and data fitting have been discussed in the present study. It has been argued that thermal models can be created with two or more parameters. Also, different methods for data fitting can be applied. First, simple thermal model has been developed with the help of two parameters by applying two methods for data fitting. These methods include non-linear regression and grid methods. Second, thermal model with envelope has been created using four parameters by applying non-linear regression method for data fitting. Moreover, different thermal models have been tested, and the evaluation and comparison of results have been made. From the comparison of results, it has been observed that thermal model with envelope functions more appropriately as compared to simple thermal model. Besides this, the outcomes also revealed that the method of non-linear regression of data fitting provides more appropriate results in contrast with data fitting by the grid method. Also, the method for computation of estimated cost of cooling from thermal model has been introduced and implemented. The results related to the other regions under similar or different climates can only be assessed through diverse collection of data. The results of this study cannot be extended for other regions because of territory differences.

The research has been limited to the energy consumption for a small number of households. However, there is still a space for more studies regarding commercial and residential buildings situated in Saudi Arabia. There are many options that are being utilized in other states like microCCHP, vacuum insulation, LHTES, etc. Therefore this tends to the research related to test the feasibility in the built environment in Saudi Arabia. Moreover, the study has been restricted to the thermal models of buildings in Saudi Arabia for only a province. The study could be conducted in some major areas of energy consumption within Saudi Arabia or other major energy-consumed regions in the world. The future studies have the space to follow the increased solar energy projects within Saudi Arabia and the energy management processes. Aside from solar projects, the future researches can follow the geothermal, wind and biomass alternatives proposed for buildings. There are many solutions existing can be useful as free of cost or less expensive, such as by designing the building by taking in account the incorporating passive design aspects which have a vital effect on the consumption of energy.

Acknowledgements

The author is very thankful to all the associated personnel in any reference and special thanks to the royal commission of Yanbu that contributed for the purpose of this research. Further, this research holds no conflict of interest and is not funded through any source.

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Notes

Note 1. LogTag® Temperature recorders are used in this study.

Note 2. The Saudi Electricity Company is the main supplier of electricity in the Kingdom of Saudi Arabia.

Note 3. Saudi Riyal = 100 Halalah

Note 4. Some data are missing because of reading errors.