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OPTIMIZATION OF AN HVAC SYSTEM WITH A PARTICLE SWARM OPTIMIZATION ALGORITHM

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Abstracts:

Air pollution is strongly affected by building's energy consumption. In this thesis we address the problem of reducing the building energy consumption while providing comfort levels for the inhabitants. We tackle this problem by adopting an information-driven approach to optimize the use of HVAC systems, (heating, ventilation and air conditioning systems), both in terms of high indoor comfort levels and in low energy consumption. More specifically, we consider a real case study, namely an office building in Verona, where the mentioned objectives depend on a large set of variables which include temperature, humidity, presence of people, building location and etc…In this research we derive an algorithmic approach based on Particle Swarm Optimization (PSO) procedure and statistical models to achieve the best configuration of variables for the optimization of the system. The results of this study show a good performance of the approach and detect future relevant developments.

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INTRODUCTION

Heating, Ventilating, and Air Conditioning (HVAC) system are advanced technologics for the control of environmental comfort. These systems are mainly introduced on huge scale buildings with the uses of offices, grocery stores, healing facilities, or schools. In this thesis we will address the issue of the reduction of energy consumption in building which providing comfort levels for inhabitants this prolem depends on a set of controllable variables such as blinds, dimmers, and fan coil and a set of uncontrollable variables such as room temperature, humidity luminosity. Our ambition is to find the best configuration of controllable variables to minimize energy consumption and maintaining optimal comfort levels. This theme has a for environmental problems, which pushed world's government to question about environmental consequences due to the excessive use of nonrenewable energies. In particular, energy expenditure due to buildings seems to account for the 30% of the total world energy consumption. As a result, HVAC performance can be improved by setting the best configurations to minimize the energy consumption.

Our study is aims to contribute the scientific research on energy consumption through a statistical approach variables. We will build time series model to predict the behavior of most problems in this study and then we will drive a PSO algorithm structure for the optimization of these problems. Two well-known indicators with the purpose of testing the indoor comfort of the user in research building are represented the PMV and DGI indexes[1] that are in use to measure thermal comfort and glare at daytime. The main goal is to find out the best configuration of dimmers, blinds, and fan coil to derive a set of low energy consumption while ensuring the basic comfort in the acceptability range of the users. The two main procedures we use in this case study are prediction modeling and optimization algorithm.

The prediction modeling is performed through Random Forest models to predict the behavior of HVAC variables. For the optimization phase, a Particle Swarm Optimization algorithm has been

[1] Ashrae. (2004). *ANSI/ ASHRAE Standard 55-2004, Thermal Comfort Conditions for Human Occupancy.* American Society of Heating, Air-Conditioning,and Refrigeration Engineers,Inc.

implemented to obtain the best configuration of the controllable variables. The thesis is organized in four chapters: in the first, we will shortly present a description of the pollution problem and building energy efficiency; the second chapter presents the methodology that we chose to solve the problem. The third is dedicated to the case study we choose for developing our methodology, and finally the fourth chapter reports some conclusions with possible future developments.

CHAPTER 1

PROBLEM STATEMENT

1. The problem statement

1.1 Air pollution problem and building energy consumption

In the climate change conference in Paris[2] represent about the necessary commitments aimed at minimizing global climate pollution. Commitment to a national scope is significantly reduce emissions, with the goal to keep the global temperature rise below two degrees Celsius. The city and buildings are where the majority of the world's population may play a significant role in controlling energy waste. Through many statistics show that the pollution from transportation and energy use in buildings is significant, and are the two most important area of global climate change. By Organisation for Economic Co-operation and Development(OECD), total power of the World rises year by year

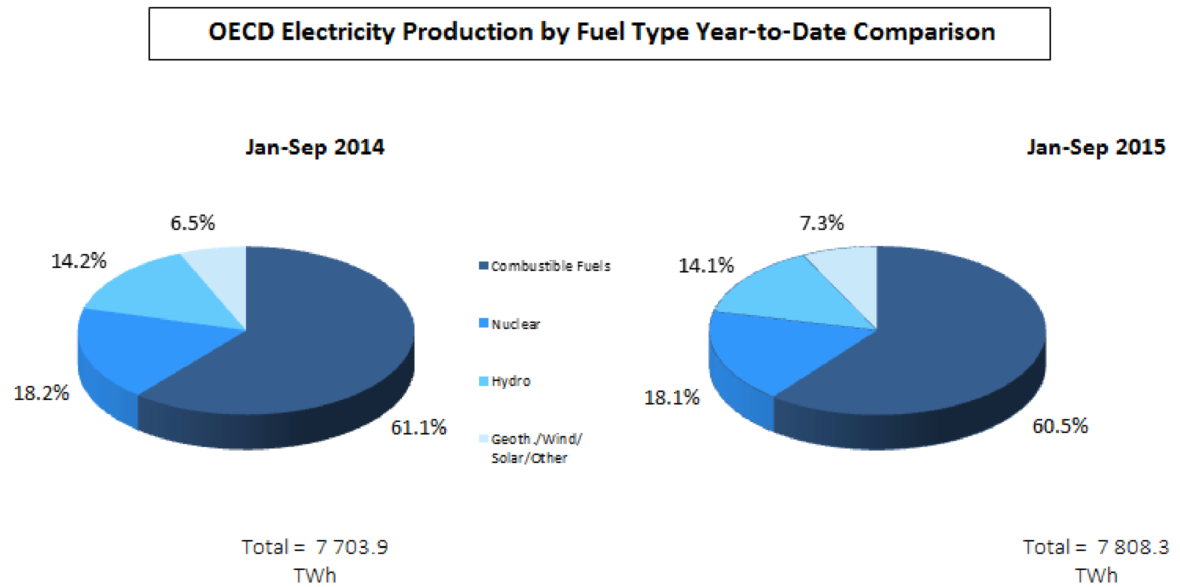


Figure 1.1. OECD Electricity productions by fuel in 2014 and 2015[3]

[2] Paris Climate Change Conference – 30 November 2015 to 11 December 2015, in Paris, France.
[3] Agency, I. E. (September 2015). *Monthly electricity statistics*. Freepublication.

As we can see from the figure above, aggregate OECD electricity production are accomplished 7 808.3 TWh, an increase of 1.4% or 104.5 TWh over the same time of the previous year. The power creation from Combustible Fuels, Hydro, and Nuclear fell by 0.6, 0.1 and 0.1 percent focuses separately while that of Geoth./Solar/Wind/Others developed by 0.8 percent concentrations. Plus, as indicated by factual of Organization for Economic Co-operation and Development(OECD), the power of Europe additionally increase.

OECD Europe

	Last 3 months			Year-to-Date			Past Year
	Sep-15	Aug-15	Jul-15	Jan-Sep-15	change[1]	share[2]	2014
+ Combustible Fuels	130.6	124.7	131.5	1 151.7	1.2%	45.6%	1 565.1
+ Nuclear	61.0	62.2	63.1	599.1	-2.2%	23.7%	830.8
+ Hydro	42.5	46.1	49.0	454.5	1.0%	18.0%	588.9
+ Geoth./Wind/Solar/Other	32.3	32.4	36.9	321.7	18.9%	12.7%	363.3
= Indigenous Production	**266.4**	**265.4**	**280.6**	**2 527.0**	**2.2%**	**100.0%**	**3 348.1**
+ Imports	33.7	34.4	36.0	309.6	5.6%		397.0
- Exports	34.3	34.9	36.0	305.9	4.4%		395.4
= Electricity Supplied	**265.8**	**265.0**	**280.6**	**2 530.6**	**2.4%**		**3 349.7**

Figure 1.2. OECD Europe [4]

In September 2015, Indigenous production was 266.4 TWh. Contrasted with September 2014 figure, this was greater by 5.5 TWh or 2.1%, Contrasted with the earlier month, it was an expansion of 0.4%. Contrasted with the prior month, flammable Fuels creation developed by 4.8%, an expansion of 6.0 TWh. All out generation for the year-to-date was 2 527.0 TWh. This with the same period a year ago demonstrates that: aggregate creation was greater by 55.2 TWh, or 2.2% and burnable Fuels generation developed by 1.2%, an ascent of 13.1 TWh. Next to, Geoth./Wind/Solar/Other generation demonstrated a produce of 18.9% or 51.2 TWh and Trade volume ascends by 29.3 TWh or 5%.

[4] Agency, I. E. (September 2015). *Monthly electricity statistics*. Freepublication.

1.2 HVAC systems

1.2.1 Building energy efficiency

Around the world, buildings represent a vast offer of energy utilization and greenhouse gas (GHG) emanations. For instance, a lessening of only five percent in worldwide energy use would spare what might as well be called more than 10 million barrels of oil for each day. In the United States Buildings are considered as the biggest local energy efficiency, and outflows can be permanently lessened by a method for energy use by buildings. Building productivity can have a relative impact in the European Union as well.Industrialized nations confront an enormous employment of retrofitting existing buildings while creating nations that are quickly urbanizing have a unique chance to coordinate low-carbon advancement in their urban arranging. For instance, China- one of the most polluted city by using too much energy has set up measures for enhancing building productivity, broadening the quality and life ranges of buildings, and escalating energy preservation for existing buildings and the offer of green buildings in new development is relied upon to achieve 50 percent by 2020. The term HVAC is the acronym for Heating, Ventilation, and Air Conditioning. The context HVAC, it is very extensive because at the moment when one considers a system of this type. Evidence exists to show that we may have to do with a simple wood stove, used for heating of comfort, as well as an extremely reliable system of overall air conditioning used in submarines and spacecraft. Considering the cooling equipment, they vary from the small domestic unit to the refrigeration machinery used in industrial processes.

The main objective of an HVAC system is to ensure a certain real comfort to the spaces of the users in which they are constructed. However, an efficient system is a determining factor for the reduction of energy consumption in the environments to a decrease in carbon dioxide emissions. It is statistically proven that more than 30% of CO_2 emissions in the atmosphere are produced by the buildings in which we live.

Among the personal factors is the level of activity, since the human body continually it produces heat through a process called metabolism and increases the activity of the person this heat increases (someone sitting it produces less heat of an individual who runs). The clothing is a significant factor in that it acts as an insulator, slowing down the loss of heat from the body. To achieve the comfort, we need to evaluate what could be the clothing of the occupants and, because of the wide variety of materials, weights and textures of fabrics can be considered only rough estimates.

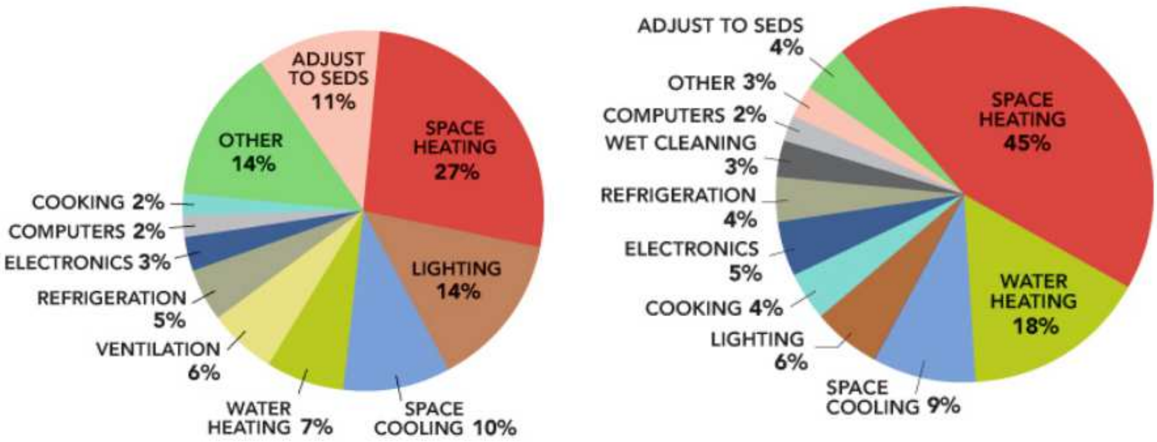
In the characteristics of the person is also part of the expectation factor, since it affects the perception of comfort about the type of room in which it is (a person who enters into a prestigious hotel has different expectations than to one that enters a building or loss).

Lastly, but no less important for this, there are the environmental factors. The air temperature, i.e., the temperature of the room in which the person is located. The radiant temperature, heat is transmitted from a hot body to a colder body without effect on intermediate space (for example, solar radiation). The moisture that has effects on humans but also to the environment itself, in fact for some people a moisture too low can cause problems and on the contrary extremely high levels in the air can cause serious problems of mold building and its content;

Finally, the air velocity that affects the temperature perceived by human, since the greater the speed of the body of a person, the greater the cooling effect perceived; also too fast air can be annoying.

The energy-saving concept is closely related to HVAC systems. In fact, considering the use of energy in commercial buildings in the US in 2012, has emerged as about a quarter of total consumption Primary energy consumption is due to the heating, cooling and lighting and engage each about one-seventh of the total. If we also consider ventilation with its 6% of energy, the HVAC become a complete the largest user of energy in commercial buildings Figure 1.2.1

Considering the use of energy in residential buildings emerges as the heating engages about half the energy consumption (Figure 1.2.1), followed by water heating (18%) and from the cooling of the environments (9%).



(a) The commercial construction sector (b) The residential construction sector

Figure 1.3. Building energy consumption in the US in 2012

In a situation of this type, it is easy to understand how the electric energy, it is a constant source of consumption of commercial and residential buildings. To confirm this, a study in 2007 in the 27 states EU member showed that the electricity consumption of HVAC was about 313 TWh, about l11% of the total (2800 TWh) of that year

1.2.2 Control strategies of HVAC system

Heating, Ventilating, and Air Conditioning (HVAC) system are advanced technologics for the control of environmental comfort. These systems are mainly introduced on huge scale buildings with the uses of offices, grocery stores, healing facilities, or schools. As a conclusion, we could recognize the importance of HVAC systems.

HVAC system has to maintain air pollution within acceptable limits, for example, high level of CO2 in a building. Besides, it can remove moisture from the air. Therefore, this system include many components to support thermal control in buildings. To explain HVAC system, we can see a list the essential elements:

- fans
- supply/return air duct
- supply outlets and return air inlets
- filters

- boiler
- chiller
- pumps
- heating/cooling coils
- damper

The figure 1.4 is the mechanism of cooling or heating of an indoor building

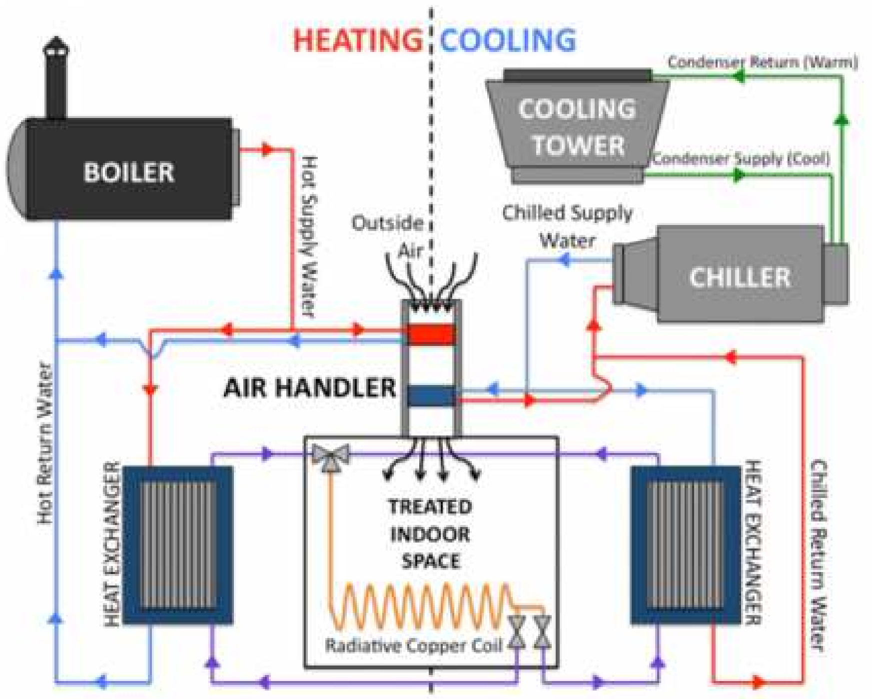


Figure 1.4. HVAC systems

There is the cooling zone (figure 1.4) in that the chiller produces cold water with the help of a condenser. Condenser utilizing a vapor-compression method support to lose heat in the outside air and to distribute in the cold water system. Then the water moves to the AHU (air handling unit), especially in the cooling coil (see figure below). The latter is cooled and diffuse in the indoor environment. Besides, the boiler has to produce hot water then passed to the AHU to heat the air that passes through it.

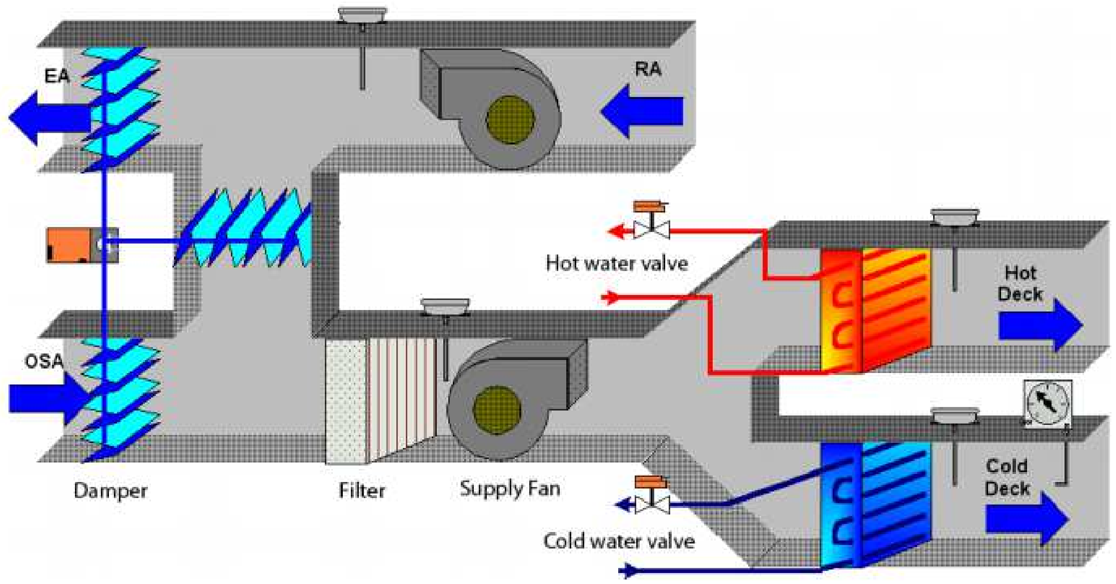


Figure 1.5. AHU system

1.3 The optimization problem for an office building

In this part, we address the issues of optimization from a mathematical point of view. Optimization is a field of the applied mathematics, which studies theory and methods to Individuate maximum or minimum points of a function. Let's define a function f as:

$$f: X \subseteq R^p \to Y \subseteq R$$

Where the set X is called decision space and the set Y is called criteria space. Given f which depends on $x \in X$ (that can be composed of one or more variables), optimize f means mathematically:

$$\min_{x \in X} f(x)$$

To find the points x that minimize our function f. Optimization means minimization, and also maximization:

$$\max_{x \in X} f(x)$$

This kind of optimization is even known as unconstrained optimization, but it can also be constrained to some equations (constraints):

$$\min_{x \in X} f(x) \textit{ subject to } \quad g_j(x) \leq h_j \quad \textit{with } j=1,\dots,n$$

Similarly for maximization:

$$\max_{x \in X} f(x) \textit{ subject to } \quad g_j(x) \leq h_j \quad \textit{with } j=1,\dots,n$$

So far we have considered single-objective optimization problems, now I can introduce those called Multi-Objective problems. The term objective indicates the statement minimizing/maximizing a function. Follow an unconstrained multi-objective problem:

$$\min_{x \in X} f_i(x) \quad \textit{with} \quad i=1,\dots,m$$

It has the purpose to optimize more functions that could be completely different among them. A very common problem in Economics and Statistics is the constrained multi-objective optimization problem, which is described by the following notation:

$$\min_{x \in X} f_i(x) \quad \textit{with} \quad i=1,\dots,m \textit{ subject to } g_i(x) \leq h_i \textit{ with } i=1,\dots,n$$

The constrained multi-objective optimization problem will be the one that we will use to solve the Str.a.t.e.g.a problem. The other issue which was mentioned in the next lines is a full scenario to what relates optimization. Firstly we can distinguish two kinds of problems based on the search zone in which we are working on

- Combinatorial problems
- Continuous problems

To explain them will be sufficient to describe the first category, which contains those problems to determine an optimal solution from a finite set of solutions, in other words, we are talking about problems that own a discrete search zone. We remember that the famous ”traveling salesman”: given a set of cities and their distances, finds the shortest path so as to reach each city and go back to the beginning, it belongs to the class of combinatorial problems. In continuous problems, variables in the model can get continuous values, commonly real values. To solve continuous optimization problems, convexity which is some general methods require the cost function (objective function) to satisfy some properties. In combinatorial problems are often solved through metaheuristics capable of providing nearly optimal solutions. According to literature, metaheuristic methods are abundantly implemented, so we will spend some time talking about them. To mention some of them: Tabu Search (TS), Simulated Annealing (SA), Particle Swarm (PSO), Genetic Algorithms (GA) and Ant Colony (AC). As identified by their names, their algorithms are inspired by nature, for instance, PSO emulates bird flocking, and AC reproduces the ant's collaboration. Even though these methods were born to work out combinatorial problems, they were extended to face continuous ones. On the contrary to what happen with other algorithms such as descent algorithm or gradients methods, they do not need to calculate derivatives to get near the maximum/minimum points. With the purpose to understand the power of the metaheuristics, let's consider to look for the global minimum of an objective function, such that owns the following shape:

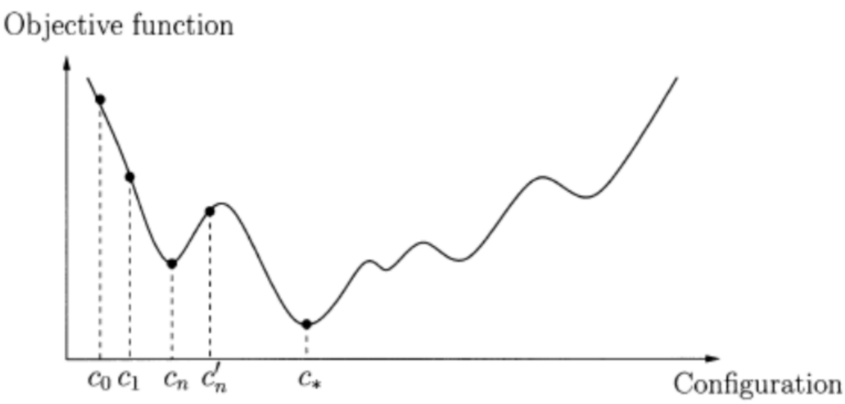


Figure 1.6. Shape of an objective function depending on configurations, source from[5]

A naive iterative algorithm would choose a point randomly, let's say c_1, and other two points one smaller and the other one greater (respectively c_0 and c_n) and would select the point that minimizes the objective function between c_0 and c_n. Suppose c_n minimizes the function, it would take the role of c_1, at the next iteration. This algorithm certainly would produce a local minimum, but it would be the case that it is not a global minimum. This problem results from a wrongly initial selection of c_1, which causes the algorithm to get trapped in a local minimum. Similarly it would happen in the most famous first-order gradient descent optimization algorithm which exploits gradients to get a local minimum. Nevertheless, metaheuristics are structured such that they can get out from a local minimum; this property is based on the idea to degrade the solution some time to time graphically can be thought as to climb the mountain next to the local point.

[5] Collette, Y. (2003). Multiobjective optimization: principles and case studies. *Phd thesis,*, 6.

Starting from continuous problems, they can be divided into linear and non-linear problems whether their objectives functions and constraints are linear or are not on decision variables. The linear ones are solved using simple linear programming [6]. On the other hand, nonlinear problems can be solved in two ways depending on the quantity of local minimum presented by the cost function. Local approaches perform an optimal work on local search, yet they risk to get trapped in local minimum when the number of local minimum points is high. Earlier introduced, the global methods can be discerned in classical methods and metaheuristic algorithms. The latter can be further branched in distributed and neighborhood classes.

GA and PSO are considered distributed since they are population-based, this implies that a set of solutions is managed at each iteration, whereas SA belongs to neighborhood class since it can deal with only one solution at each iteration. To what concern combinatorial problems, we can distinguish approximate method and the exact one, the latter can find the global optimum, but they cannot be applied when the size of the search zone is too high. Heuristics and metaheuristics can be then placed in approximate methods of getting near optimal solutions. Recently a new class has been introduced; it is composed of a mix of metaheuristics and local search to exploit the advantages of metaheuristics in global search and the benefits of local search, that algorithm has been defined as hybrids.

[6] Gass, S. (2003). *Linear Programming: Methods and Applications* (5th ed.). Newyork, USA: McGraw-Hill.

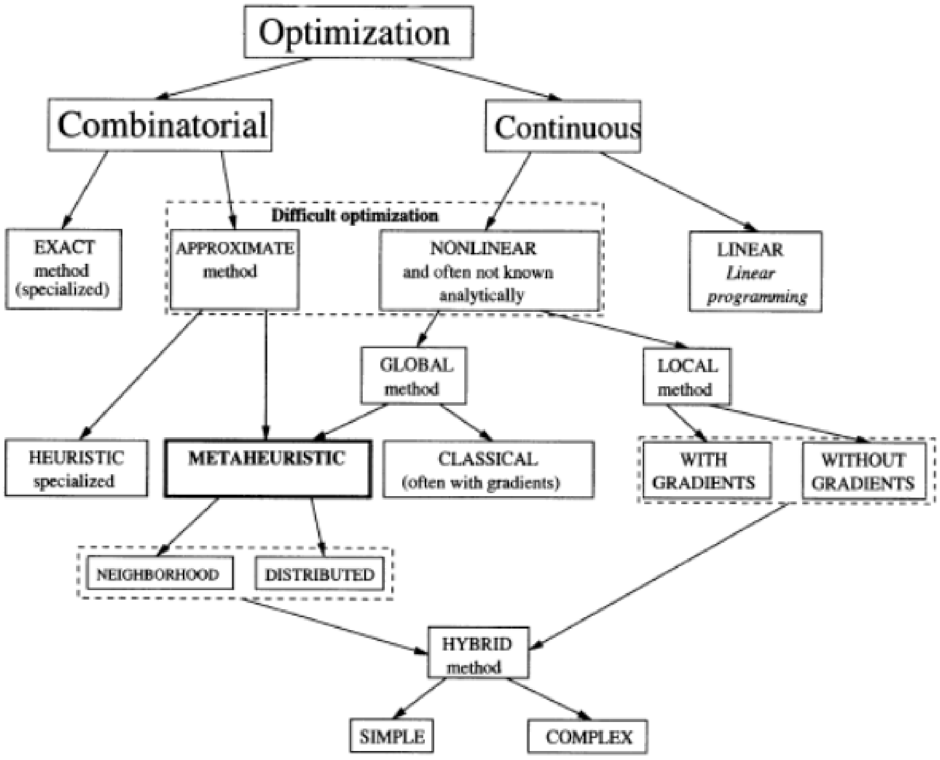


Figure 1.7. Taxonomy of optimization solver, source from [7]

[7] Collette, Y. (2003). Multiobjective optimization: principles and case studies. *Phd thesis,*, 6.

CHAPTER 2

METHODOLOGY FOR THE HVAC OPTIMIZATION

2. Methodology for the HVAC optimization

2.1. General methodology structure

In this chapter, we will introduction the method that we chose to consider for addressing the problem of optimal of an HVAC system that will reduce energy consumption and providing comfort levels for inhabitants.

In the part, we will build linear stochastic Random Forest model to predict the behavior of most problems in this study and then we will apply PSO algorithm for the optimization of these problems.

2.2. The stochastic models

To solve a problem that with a large and complex dataset, it means that has the high dimension that datasets present. For example, in bioinformatics field, energy saving field those data sets with millenary of parameters (variables) has displayed a characteristic. Therefore, in modeling variable selection is the first step. It reduces the number of dimensions, among the entire variable, that will using in our problem. Therefore, selection variable is so necessary can be easily explained: it reduces unnecessary data, increase the data quality, fatter algorithms that will apply in future, simplify and improve the correctness of the models. The technique used for selection variables is Random Forest (RF) method. We have Boosting Tree[8], Bagging[9] and the most recent one Random Forest introduced in 2001 by Breiman[10]. Random Forest could apply for regression and classification, and prevents the overfitting problem. The step of Random forest works:

[8] Breiman, L. (2003). *The Boosting Approach to Machine Learning: An Overview, NonlinearEstimation and Classification.* Springer.

[9] Breiman, L. (1996). Bagging predictors. *Machine Learning, 21*, 123-140.

[10] Breiman, L. (2001). Random Forests. *Machine Learning, 45*, 5-32.

1. The dataset divides two parts such as train set and test set

2. Selection n bootstrap units from the train set.

3. Create binary regression tree for every bootstrap unit and during the splitting phase instead of choosing the best split node among all the p variables, it determines the best split variable choosing among m variables randomly (m < p).

4. The prediction for every tree, in terms of regression it uses average among the results of n tree.

2.3. Particle Swarm Optimization(PSO) Algorithm

2.3.1. The structure of the PSO algorithm

A first develop to the complex non-linear optimization issue by following the action of swam flocks are built up by Kennedy and Eberhart. The method of a particle swarm generates the concept of function optimization them. The formula of a global optimum of an n-dimensional function is

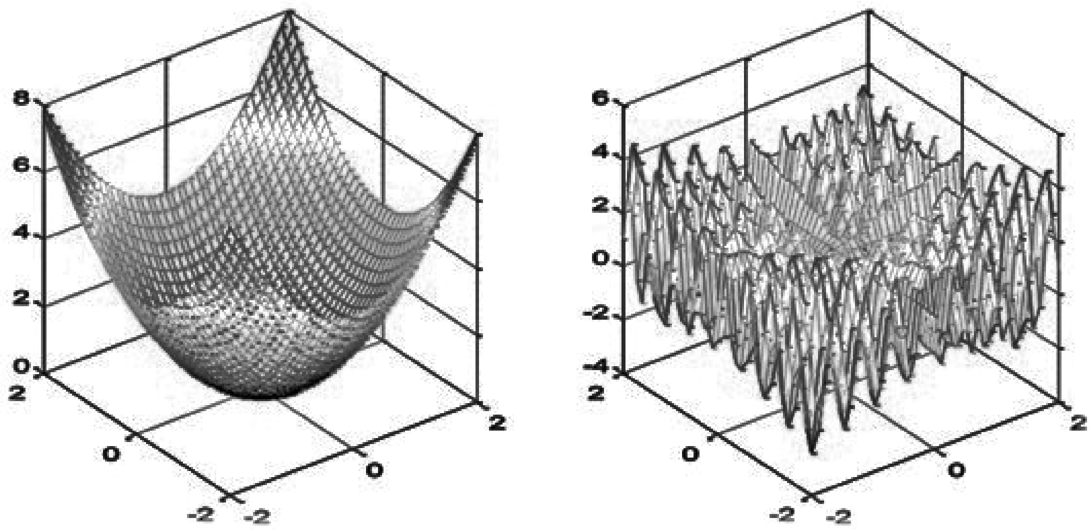
$$f(x_1, x_2, x_3, \dots, x_n) = f(X) \qquad (2.3.1)$$

Where x_i is the search variable. The aim is to find a value x^* subject to the function $f(x^*)$ is a maximum function or a minimum function in the search zone.

The formulas given by

$$f_1 = x_1^2 + x_2^2 \qquad (2.3.2)$$

and $f_2 = x_1 \sin(4\pi x_2) - x_2 \sin(4\pi x_1 + \pi) + 1$ (2.3.3)



(a) Unimodel (b) Multi-model

Figure 2.1: the functions unimodel and multi-model

From figure 2.1(a), it is the global minimum of the function f_1 is at $(x_1, x_2) = (0,0)$, i.e. at the start of function f_1 in the search zone that is a *unimodel* function, which has only one smallest. However, finding the global optimum is difficult for *multi-model* function. Figure 2.1(b) presents the function f_2 which has a pursuit space with various crests, such a variety of specialists need to begin from various primary areas and keep investigating the hunting space until no less than one operators come to the worldwide ideal position. Amid this procedure, all operators can convey and share their data among themselves.

The PSO algorithm keeps up a swarm of particles and every each particle speaks to a future solution in the swarm. Every particles fly through a multi-dimensional pursuit space where every molecule is modifying its position as per its specific experience and that of neighbors. In the multi-dimensional search zone($i.e. R^n$), suppose x_i^t denote the position vector of molecule at time step t, then updating the position of each molecule in the search zone

$$x_i^{t+1} = x_i^t + v_i^{t+1} \text{ with } x_i^0 \sim U(x_{min}, x_{max}) \qquad (2.3.4)$$

Where,

v_i^t is the particle velocity vector that makes the optimization method and displays experience information and the social experience learning from every particle; The

x_{min} is a minimum value and x_{max} is a maximum values because $U(x_{min}, x_{max})$ is the uniform distribution.

Accordingly, all particles are initiated randomly and estimated to measure global best and fitness together with determining the personal best.

Global Best

The global best is a method where the best suitable particle affects the state of each particle. It will use a star network structure to get the information from all particles in the entire swarm. In this way, every single particle, $i \in [1, \dots, n]$ where $n > 1$, has a current state in search zone x_i, a current velocity, v_i, and a best position in search zone, $P_{best,i}$. The objective function$f(.)$ will determine the best position $P_{best,i}$corresponds to the position of particle i had the smallest value, analyzing a minimization issue. Besides, the position allowing the smallest value among all the personal $P_{best,i}$ is position of the global best G_{best}. The following equations (2.3.5) and (2.3.6) updating the personal and global best values are.

Considering minimization problems, and then position of the personal best $P_{best,i}$ at the next time step, $t + 1$, where $t \in [0, \dots, N]$, is:

$$P_{best,i}^{t+1} = \begin{cases} P_{best,i}^{t} if\ f(x_i^{t+1}) > P_{best,i}^{t} \\ x_i^{t+1} if\ f(x_i^{t+1}) \leq P_{best,i}^{t} \end{cases} \qquad (2.3.5)$$

Where $f: \mathbb{R}^n \to \mathbb{R}$ is the fitness function. The global best position G_{best} at time step t is calculated as

$$G_{best} = \min\{P_{best,i}^{t}\}, \text{ where } i \in [1, \dots, n] \text{ and } n > 1 (2.3.6)$$

In this way, it is vital to note that the best $P_{best,i}$ is the best position which the individual particle i has visited since the first time step. On the other hand, the global best position G_{best} is the best position discovered by any of the particles in the whole swarm.

For gbest of the algorithm method, the velocity of particle i is computed:

$$v_{id}^{t+1} = v_{id}^{t} + c_1 r_{1d}^{t} \left[P_{best,i}^{t} - x_{id}^{t}\right] + c_2 r_{2d}^{t} [G_{best} - x_{id}^{t}] \qquad (2.3.7)$$

Where

v_{id}^t is the velocity vector of particle i in dimension d at time t;

x_{id}^{t} is the position vector of particle i in dimension d at time t;

$P_{best,i}^{t}$ is the personal best position of particle i in dimension d found from initialization through time t;

G_{best} is the global best position of particle i in dimension d found from initialization through time t;

c_1 and c_2 are positive constants;

r_{1d}^{t} and r_{2d}^{t} are random numbers from uniform distribution $U(0,1)$ at time t.

The following Figure 2.2 shows the *gbest* algorithm.

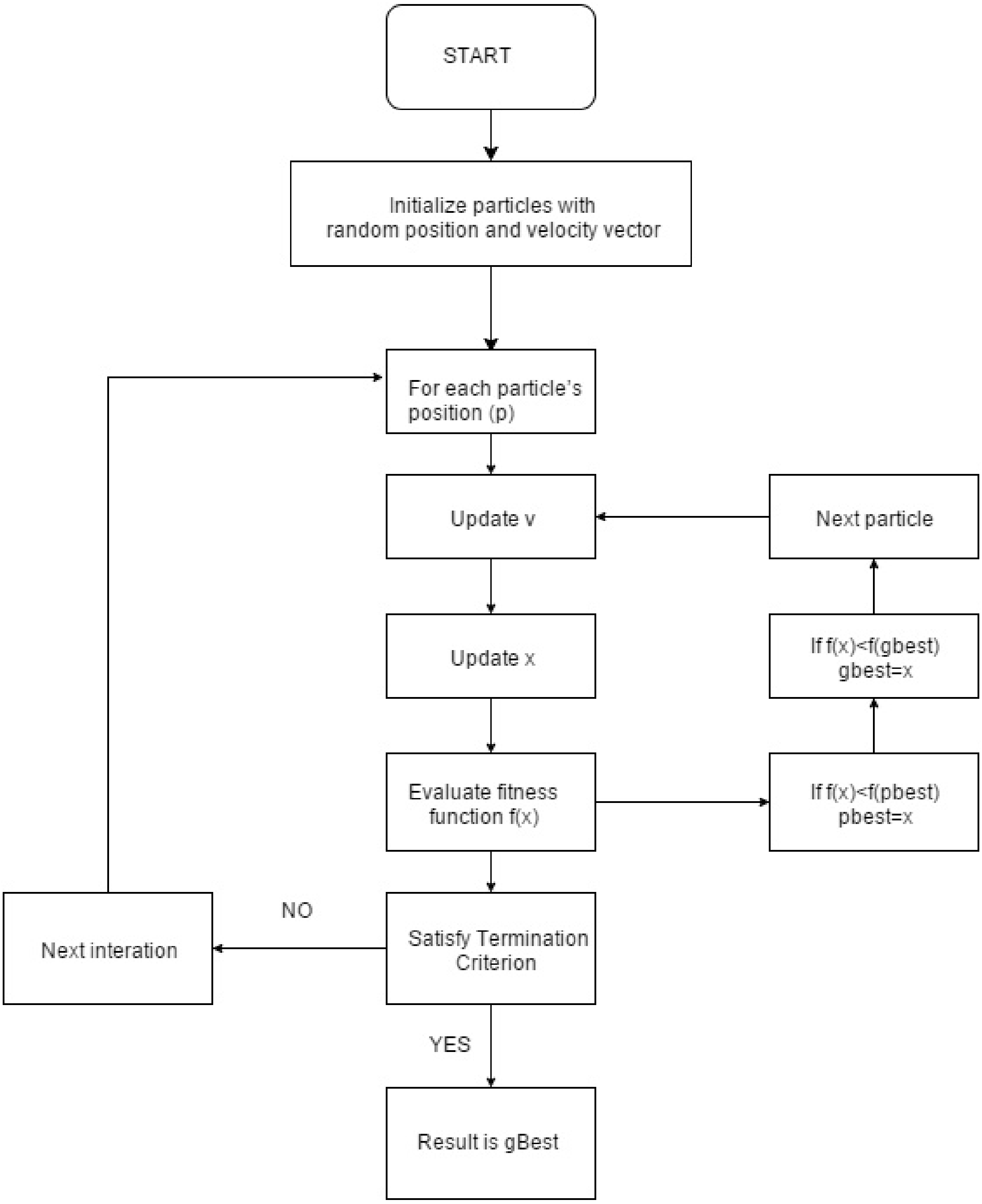


Figure 2.2 gbest PSO

2.3.2. The parameters of PSO Algorithm

PSO algorithm has some parameters that could affect its performance. The basic parameters of PSO are swarm size, iteration number, velocity component, and acceleration coefficient presented below.

Size of swarm

The number of particles is called swarm size or/and population. Per iteration covers a vast swarm generates bigger parts of the search zone. A significant number of particles might decrease the number of iteration want to achieve an optimization result well. In opposition, important measures of particles rise the computational difficulty by iteration, and more time. From some observational studies, most of the algorithm implementations apply an interval for the size of swarm is $n \in [30,70]$.

Iteration

The number of iterations to achieve a result well is also concerns. A too big iteration have the some computational complexity is useless and more time while too small iterations can finish the search method early.

Velocity Component

These components are imperative for updating the particle velocity. There are three phases in formulas (2.3.7) and (2.3.8):

- The term v_{id}^{t} gives a memory of the previous flying way that involves action in the ready-to-use past. These elements the similar a momentum that stops drastically change the way of the particle and bias via the current way.
- The term $c_1 r_{1d}^{t}\left[P_{best,i}^{t} - x_{id}^{t}\right]$ is calculating the performance of the particle i about past performances. This component resembles an individual memory of the best position for the particle.
- The term $c_2 r_{2j}^{t}\left[P_{best,i}^{t} - x_{ij}^{t}\right]$ for *gbest* is the social component and computing the achievement of the particle i about an association of particles or neighbors. Each particle flies to the best position determined influence to the social component.

a) Coefficients

The coefficients c_1, c_2 are constant and r_1 and r_2 are random values, keep up the stochastic impact of the psychological and social segments of the particle's speed individually. When $c_1 = c_2 = 0$, all particles remain flying at their current velocity until they hit the inquiry zone's limit. Accordingly, from the formula (2.3.7) and (2.3.8), the velocity renew formula is:

$$v_{id}^{t+1} = v_{id}^{t} \qquad (2.3.9)$$

When $c_1 > 0$ and $c_2 = 0$, all particles are independent. The velocity renew formula will

$$v_{id}^{t+1} = v_{id}^{t} + c_1 r_{1d}^{t} \left[P_{best,i}^{t} - x_{id}^{t}\right] \qquad (2.3.10)$$

On the opposite, when $c_2 > 0$ and $c_1 = 0$, every particle are seduced to an individual point$(i.e. G_{best})$ in the whole herd and the velocity will be updated by:

$$v_{id}^{t+1} = v_{id}^{t} + c_2 r_{2d}^{t} [G_{best} - x_{id}^{t}] \qquad (2.3.11)$$

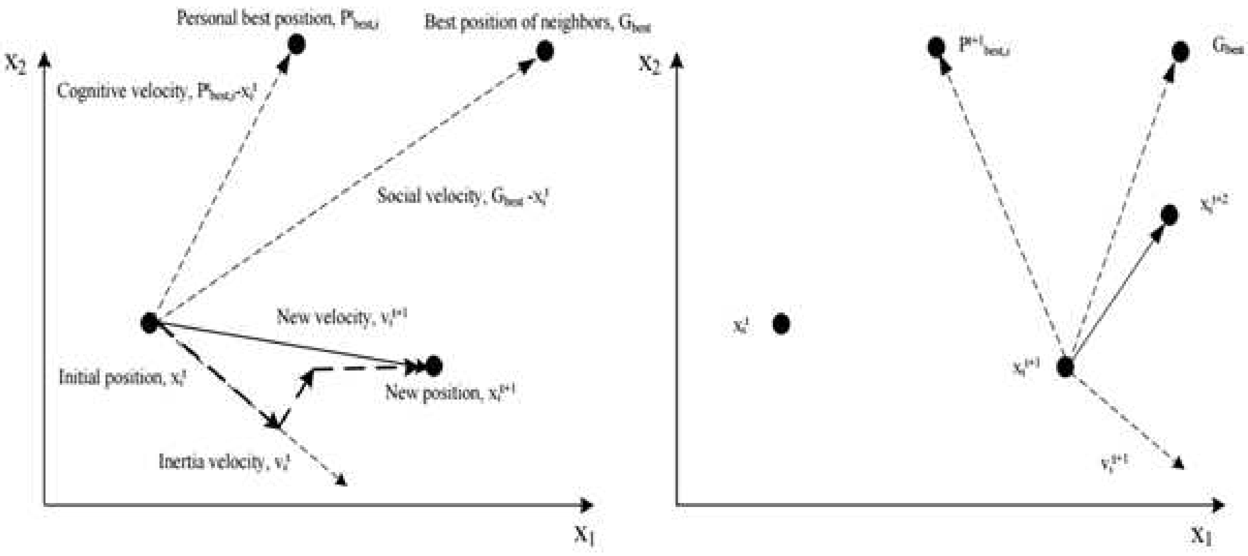
When $c_1 = c_2$, every particle are seduced to the mean of $P_{best,i}^{t}$ and G_{best}.

When $c_1 \gg c_2$, each particle is more strongly influenced by its personal best position, bringing about inordinate meandering. In opposite, when $c_2 \gg c_1$ every particle is much more affected by the gbest position, which is causes every particle to move early to the best result.

Normally, c_1 and c_2 are constant, with trial and error to find their best values. Incorrect initialization of c_1 and c_2 might lead to conflicting or loop behavior. From the diverse factual inquiries about, it has been suggested that the two constants ought to be $c_1 = c_2 = 2$.

2.3.3. Geometrical representation

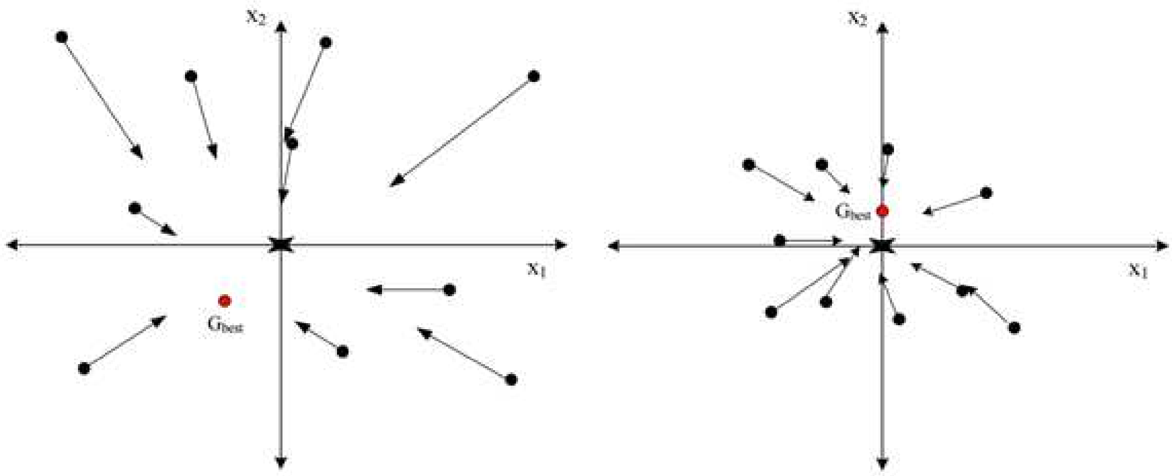
The updated velocity for particles includes three parts in formula (2.3.7) and (2.3.8) respectively. Consider a journey of an individual particle in a search zone.



(a)Time step t *(b)Time step t+1*

Figure 2.3 updating position and velocity for a particle.

The figure 2.3 represents the three velocity elements give to moving the particle to the gbest[11] position at time steps t and $t + 1$.



(a) time $t = 0$ (b) time $t = 1$

Figure 2.4 Updating position and velocity

[11] Global best

The figure 2.4 displays the position of more particle in search zone is updated. The point of the figure is the best position.

Figure 2.4 (a) presents the original situation of every particle with a gbest position. The cognitive basis is 0 at t=0, and the best position for the popular segment will attract all particles. The gbest position does not replace.

Figure 2.4 (b) presents the new points of every particulate matter and a new gbest position after the initial iteration at t=1.

2.3.4. Neighborhood Topologies

An area must be characterized for every molecule. This area decides the degree of social association inside of the swarm and impacts a development of specific particles. The convergence is slower for the little neighborhood. However, it could develop the performance of resolutions. The convergence is quicker if neighborhood is bigger, yet the danger that occasionally convergence happens prior. Address this issue, the search process begins with little neighborhoods size and afterward the little neighborhoods size is expanded over time.

This algorithm is social communication amongst the particles in the whole herd. Each particle in the herd exchanging knowledge by particles connects with each other. A particle in the whole herd gets a better situation, and entire particles will pass through this particle. The neighborhood of the particles determines this performance of the particles. Nowadays, neighborhood structures are developed by researchers. Some structures of neighborhood or topologies are:

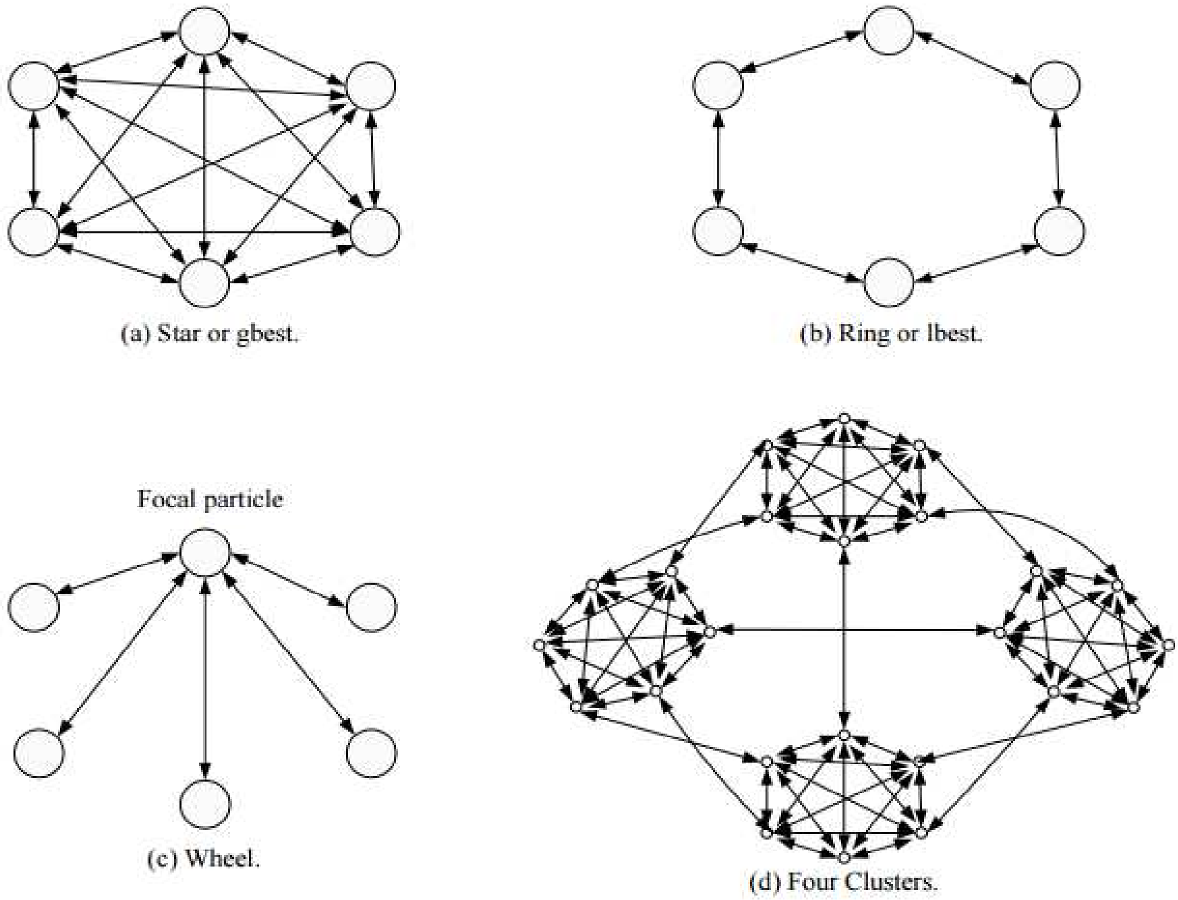


Figure 2.5: Neighborhood topologies

Figure 2.5(a) explains each point connects with every other point (star structure). This structure is fast convergence than different structures; however, local minima problem can appear.

Figure 2.5(b) explains each point is combined only with its next neighbors. In this structure, at one point detects a better performance, the point will pass it to its next neighbors, and these two next neighbors give it to their next neighbors until it arrives the ending point. Therefore, the optimum result is propagated slowly throughout the circle at all points. It is bigger components of the search zone that are covered them with a star structure, and convergence is slower the star structure.

Figure 2.5(c) explains only one point combine to the others, and communicating all information through this point. That mean the focal point will adjust its position to moving the best achievement point and compare with the best achievement of all points. And then all the points notify the new location of the focal point.

Figure 2.5(d) explains two sides of neighboring groups and one side between different groups connect with four groups. There is not the best topology known to obtain the best for all characters of optimization problems.

2.3.5. Comments on the methodology

This algorithm is a standout amongst the most efficient techniques for determining the global optimization issues, and there are a few benefits and drawbacks.

The advantages and drawbacks of PSO are talked about beneath:

Advantages:

- It is a derivative-free algorithm.
- It is simple to perform.
- PSO has a finite amount of parameters, the effect of parameters are small.
- The calculation is exceptionally straightforward.
- There are a few methods guarantee convergence and the best value of the issue effortlessly inside of a brief time frame.
- It is conceptually exceptionally basic.

Drawbacks:

- To degrade the control of its direction and velocity are difficult.
- There are the problems with the non-coordinate system.

CHAPTER 3

THE OPTIMIZATION PROCEDURE FOR AN OFFICE BUILDING

3. The optimization procedure for an office building

The goal is to determine the optimal configures to reduce total electric power (y) maintain inhabitant comfort through PMV(x1) and DGI(x2). Firstly, I describe an Explorative Data Analyses (EDA) method that describes the behavior of the system. In the second part, I will present the way choose the variables by Random Forest (RF) model. Finally, the PSO algorithm is used to determine the optimal configures combination.

3.1. Exploratory data analysis

Exploratory data analysis defines an approach to studies numerically and graphically a set of data for performing inference on it. Tukey used the term firstly to explore data since from Exploratory data analysis is probable to detect outliers, recognize patterns, install hypotheses and validate assumptions. Exploratory data analysis can use many tools such as max, min, mean, median values for descriptive analysis that to explain the relations among variables. Regarding the problem, I named as the most suitable tools:

- time series
- boxplot
- density distribution plot

3.1.1. Descriptive analysis

The optimization approach is constructed and tested on a set of data chosen as a case study, and related to a building located in Verona (Italy). In this building, an office is selected for the experimentation, and a set of sensors are installed to record the most relevant variables that can affect the energy consumption and the thermal and lighting comfort levels.

Specifically, we record the following time series, consisting of 29,435 observed values with a constant time interval of 5 minutes:

- Indoor Comfort levels: temperature, humidity, air velocity, central mean radiant temperature, luminosity, CO_2 concentrations, occupancy, window sensor, door sensor, corridor temperature;

- User habits;

- Weather condition variables: temperature, illuminance, radiation and humidity;

- Electric and thermal consumption variable: thermal power and electric power.

For the optimization process, a set of actuators are specified and codified: the power of the fan coil, the position of the blinder and two dimmable lights. The response variables to optimize are the energy consumption represented by the total electric power (y_1) - which includes thermal and electric consumptions - and two comfort indices for the office user: the Predictive Mean Vote (PMV, y_2) and the Daylight Glare Index (DGI, y_3) [20, 22]. The Predictive Mean Vote variable measures the level of satisfaction of the office user on the thermal environment and is mostly influenced by the temperature, the humidity, the air velocity and the central mean radiant temperature observed in the considered room. PMV has an optimal value of comfort equal to 0 and within $\pm$ 0.5 is deemed acceptable by criterion ASHRAE-55[12]. The Daylight Glare Index expresses discomfort glare due to the lighting system and depends on the luminosity inside the room and the electromagnetic radiation given off by the sun. DGI is considered optimal when its values are lower than or equal 22. All the variables recorded in this case study are presented in Tab. 1.

[12] Ashrae. *ANSI/ ASHRAE Standard 55-2004, Thermal Comfort Conditions for Human Occupancy*. American Society of Heating, Air-Conditioning, and Refrigeration Engineers, Inc., 2004

Table 1. The set of variables recorded by Building Automation System

	Variables	Notation
Indoor Comfort variables	Internal Temperature	v_1
	Humidity	v_2
	Air Velocity	v_3
	Central mean radiant Temp	v_4
	West luminosity	v_5
	East luminosity	v_6
	CO2	v_7
User habits	Occupancy	v_8
Weather Condition	Outside Temperature	v_9
	Outside Illuminance	v_{10}
	Outside Radiation	v_{11}
	Outside Humidity	v_{12}
Other Comfort requirements	Window sensor	v_{13}
	Door sensor	v_{14}
	Corridor temperature	v_{15}
Electric and thermal consumption variable	Fan Coil thermal power	y_{load}
Actuator Variables	Dimmer 1	d_1
	Dimmer 2	d_2
	Blinds	b
	Fan Coil Device	f_c
System response variables	Total Electric Power	y

	Predicted Mean Vote (PMV) Daylight Glare Index (DGI)	x_1 x_2

The multi-objective optimization process is realized by deriving a prediction for each response variable in all the experimental space through Random Forest models and then using PSO algorithm to identify the best combination of actuator levels that optimize the comfort responses and simultaneously minimize energy consumption. The experimental space is composed of 36 actions representing all the possible level combinations of the actuators variables. The actuator levels are summarized in Table 2.

Table 2. The actuator levels.

Actuator Variables	Notation	Levels
Dimmer 1	d_1	{0, 1}
Dimmer 2	d_2	{0, 1}
Blinds	b	{0, 0.5, 1}
Fan Coil Device	f_c	{0, 0.5, 1}

The uncontrollable variables are all those variables that are due to the state of the system in the moments before since the system does not react instantly to a change but is also reflected in the detected values in the periods next. In particular, the variables temperature, humidity and mean radiant temperature Central are influenced by past values of the HVAC system. Other variables, such as brightness in the east and west, the air velocity, and CO2 are influenced more by values close to time. Also, there is a variable which shows the presence or absence of individuals in the room. Finally, variables that are not affected at all by the past values of the system are those relating to external weather conditions.

Two indices constitute the variables of comfort for the assessment of thermal comfort and bright room (allow to synthesize quality comfort through a unique numeric value).

The Predicted Mean Vote (PMV) is the result of an equation that relates functions of clothing the person (clothing insulation and ratio of surface covered and bare surface), activity duties of the person (metabolic heat production and metabolic production of free energy), environment variables (temperature air, mean radiant temperature, relative speed of the air and the water vapor pressure) and also considers if the skin is wet. The optimal value of the index is 0, moving away increases the sensation of warmth perceived up to the value of -3, moving away positively increases the feeling of cool up to the value of +3 (cold)[13]

$$PMV = (0{,}303e^{-2{,}100*M} + 0{,}028) * [(M - W) - H - E_c - C_{res} - E_{res}]$$

Where the different terms represent, respectively:

M- The metabolic rate, in Watt per square meter(W/m^2);

W- The effective mechanical power, in Watt per square meter(W/m^2);

H- The sensitive heat losses;

E_c- The heat exchange by evaporation on the skin;

C_{res}- Heat exchange by convection in breathing;

E_{res}- The evaporative heat exchange in breathing.

The Daylight Glare Index (DGI) or glare index is calculated for each piece of source view through the window (sky, obstructions, land,...) Moreover, relates the illumination source, the average illumination of the background, the angular size of the source in steradians as perceived by the eye and the solid angle of the source, the effect of modifying the observer's position about the source in steradians[14]. Concerning DGI, it is metric which measures discomfort due to glare; it developed by Hopkinson[15] in 1972:

$$DGI = 10 \cdot log \sum_{i=1}^{n} G_i$$

[13] Ashrae. *ANSI/ ASHRAE Standard 55-2004, Thermal Comfort Conditions for Human Occupancy*. American Society of Heating, Air-Conditioning, and Refrigeration Engineers, Inc., 2004.
[14] The steradian (symbolized sr) is the Standard International (SI) unit of solid angular measure.
[15] Hopkinson R.O. worked at the Building research station, Garston, Watford, England

Where the glare index G_i represents the glare due to each source (our case of study presents only windows) and it is calculated through the formula:

$$G_i = 0.478 \cdot \left(\frac{L_s^{1.6} \cdot \Omega_i^{0.8}}{L_b + (0.07 \cdot \omega^{0.5} \cdot L_w)} \right)$$

Let's define one by one the parameters used:

L_s: is the luminance of each part of the source (cd/m^2)

L_b: average luminance of the surfaces in the environment, within the field of view(cd/m^2)

L_ω: the weighted average luminance of the window(cd/m^2)

ω: the solid angle of window (sr stands for steradians)

Ω: the solid angle of source (sr)

To expatiate more on those variables I put forward you to give a glance at[16]. DGI a discomfort metric the higher is its value more annoying is the glare. Nevertheless light glare can be considered acceptable for value 22, inferior values are irrelevant.

Zone	Feeling	DGI Level
Discomfort zone	intolerable	>28
	just intolerable	28
	uncomfortable	26
	just uncomfortable	24
Discomfort zone	comfortable	22
	just acceptable	20
	noticeable	18
	just perceptible	16

Table3: Zone Comfort DGI

[16] Bellia, L. C. (2011). Energy. *Daylight glare: a review of discomfort indexes, 36,* 5935-5943.

The statistics analysis will display general characteristics of our dataset. Our dataset has quality variables: d1, d2, b, fc, v8, v13, v14 and others. They are summarized:

```
       d1              d2               b               fc         
 Min.   :0.0000   Min.   :0.000   Min.   :0.0000   Min.   :0.00000  
 1st Qu.:0.0000   1st Qu.:0.000   1st Qu.:0.0000   1st Qu.:0.00000  
 Median :0.0000   Median :0.000   Median :1.0000   Median :0.00000  
 Mean   :0.2446   Mean   :0.244   Mean   :0.6921   Mean   :0.09666  
 3rd Qu.:0.0000   3rd Qu.:0.000   3rd Qu.:1.0000   3rd Qu.:0.00000  
 Max.   :1.0000   Max.   :1.000   Max.   :1.0000   Max.   :1.00000  
       v1              v2              v3          v4       
 Min.   :17.09   Min.   :10.36   Min.   :0   Min.   :15.94  
 1st Qu.:22.27   1st Qu.:32.92   1st Qu.:0   1st Qu.:21.49  
 Median :23.51   Median :41.13   Median :0   Median :22.77  
 Mean   :23.03   Mean   :39.70   Mean   :0   Mean   :22.25  
 3rd Qu.:24.61   3rd Qu.:48.30   3rd Qu.:0   3rd Qu.:23.89  
 Max.   :26.75   Max.   :65.02   Max.   :0   Max.   :26.22  
       v5               v6               v7               v8        
 Min.   : 16.26   Min.   : 14.62   Min.   : 321.8   Min.   :0.0000  
 1st Qu.: 17.45   1st Qu.: 15.81   1st Qu.: 383.4   1st Qu.:0.0000  
 Median : 17.75   Median : 16.26   Median : 411.8   Median :0.0000  
 Mean   : 22.68   Mean   : 19.77   Mean   : 430.7   Mean   :0.2581  
 3rd Qu.: 23.71   3rd Qu.: 21.32   3rd Qu.: 455.6   3rd Qu.:1.0000  
 Max.   :156.17   Max.   :215.47   Max.   :1424.0   Max.   :1.0000  
       v9                v10                 v11         
 Min.   :-10000000   Min.   :-10000000   Min.   :  0.60  
 1st Qu.:-10000000   1st Qu.:-10000000   1st Qu.:  2.60  
 Median :-10000000   Median :-10000000   Median :  4.80  
 Mean   : -6408908   Mean   : -6408915   Mean   : 45.76  
 3rd Qu.:       18   3rd Qu.:        0   3rd Qu.: 38.20  
 Max.   :       18   Max.   :        0   Max.   :741.20  
      v12                v13                 v14         
 Min.   :-10000000   Min.   :-10000000   Min.   :0.00000  
 1st Qu.:-10000000   1st Qu.:        0   1st Qu.:0.00000  
 Median :-10000000   Median :        1   Median :0.00000  
 Mean   : -6408893   Mean   :     -679   Mean   :0.04773  
 3rd Qu.:       61   3rd Qu.:        1   3rd Qu.:0.00000  
 Max.   :       61   Max.   :        1   Max.   :1.00000  
       x1                 x2                 y         
 Min.   :-1.65816   Min.   :-49.3009   Min.   :  0.00  
 1st Qu.:-0.21380   1st Qu.: -0.8440   1st Qu.: 15.90  
 Median : 0.12604   Median : -0.5607   Median : 60.00  
 Mean   :-0.01601   Mean   :  2.6279   Mean   : 63.02  
 3rd Qu.: 0.41551   3rd Qu.:  2.9227   3rd Qu.:105.60  
 Max.   : 1.04988   Max.   : 33.0361   Max.   :146.60  
     y_load             v15       
 Min.   :-0.4493   Min.   :17.02  
 1st Qu.: 0.1040   1st Qu.:22.29  
 Median : 0.1393   Median :23.56  
 Mean   : 0.2880   Mean   :22.97  
 3rd Qu.: 0.2570   3rd Qu.:24.54  
 Max.   : 2.3134   Max.   :27.38  
```

We can see that outside temperature (v9), Air Velocity (v3), illuminance (v10) and humidity (v12) variables did not run well as established where collected the data. Therefore, our dataset will remove these variables.

3.1.2. Graphical analysis

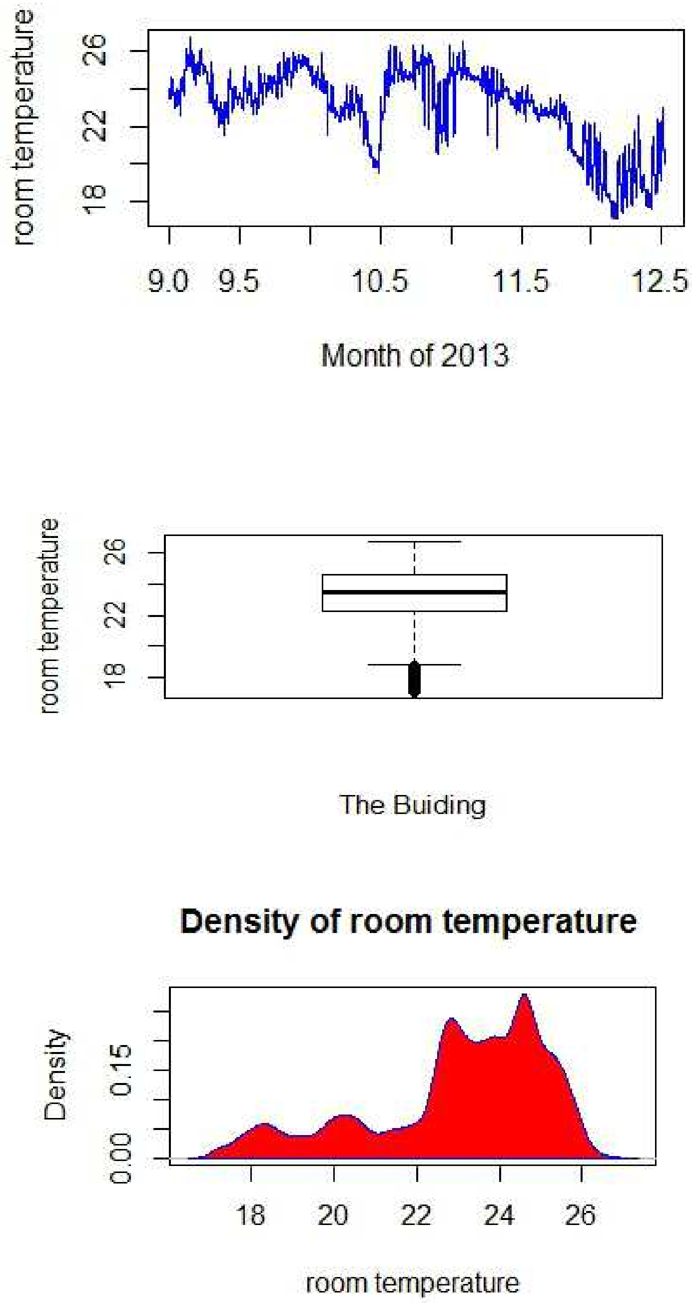


Figure 3.1 Time series, density distribution, and boxplot of Room temperature (v1) in 2013

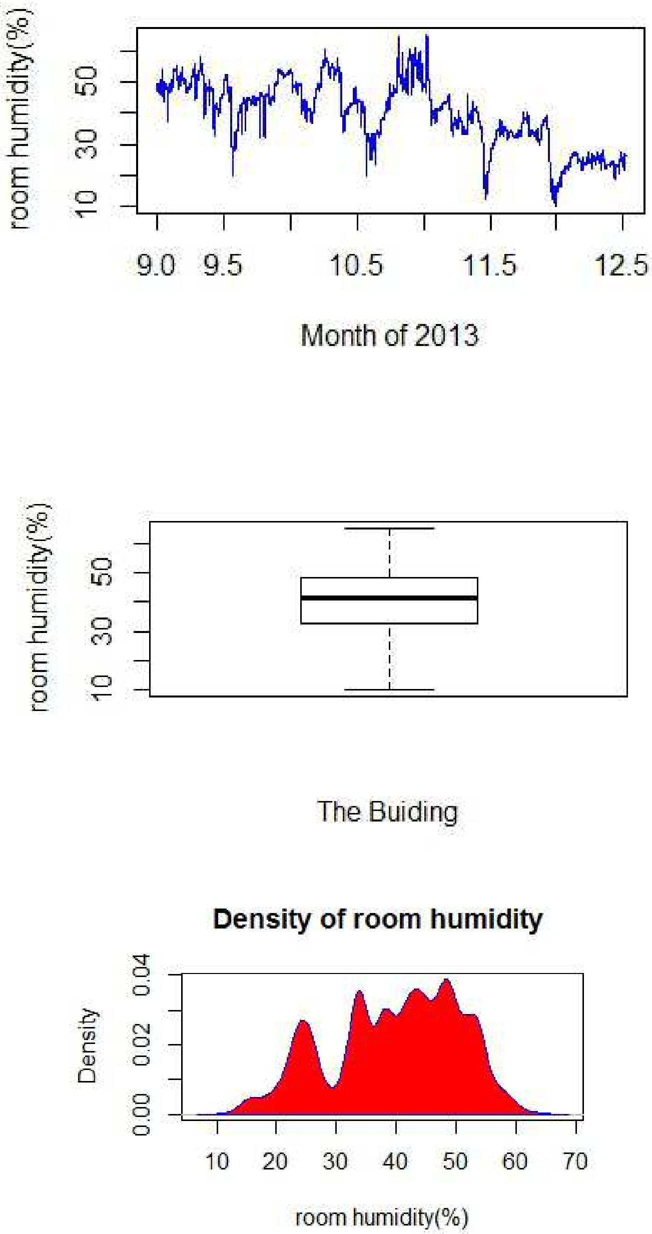


Figure 3.2 Time series, density distribution, and boxplot of room humidity (v2) in 2013

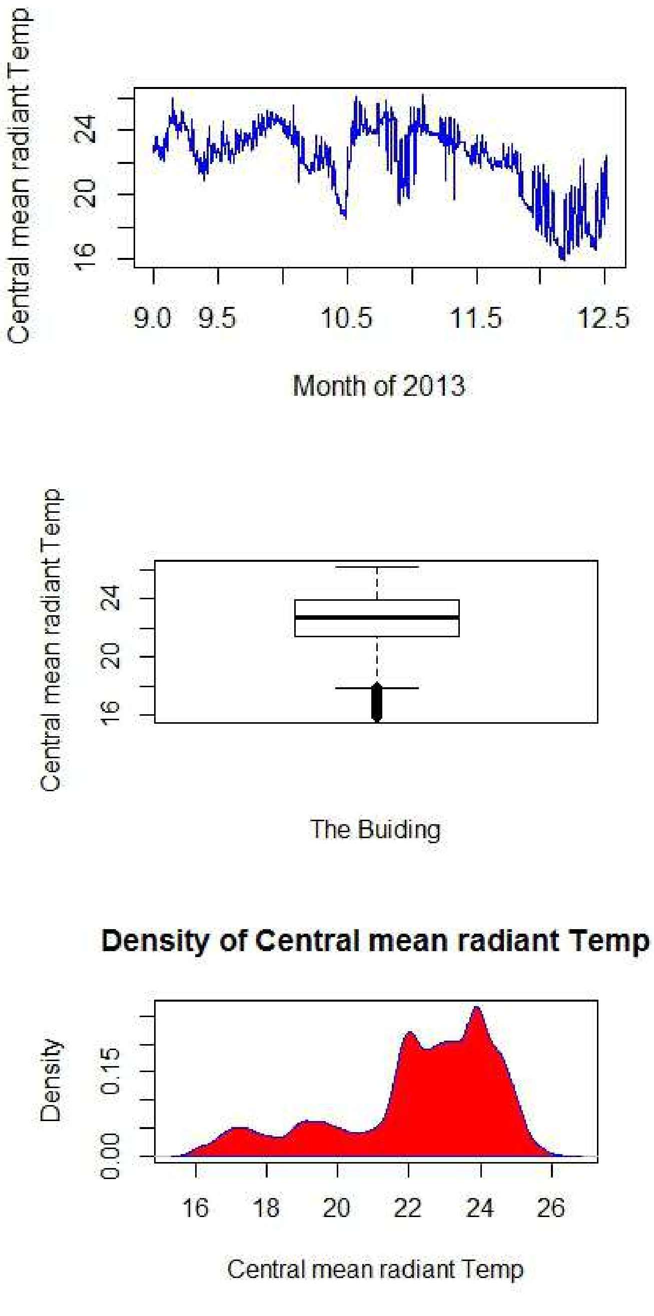


Figure 3.3 Time series, density distribution, and boxplot of Central mean radiant temp (v4) in 2013

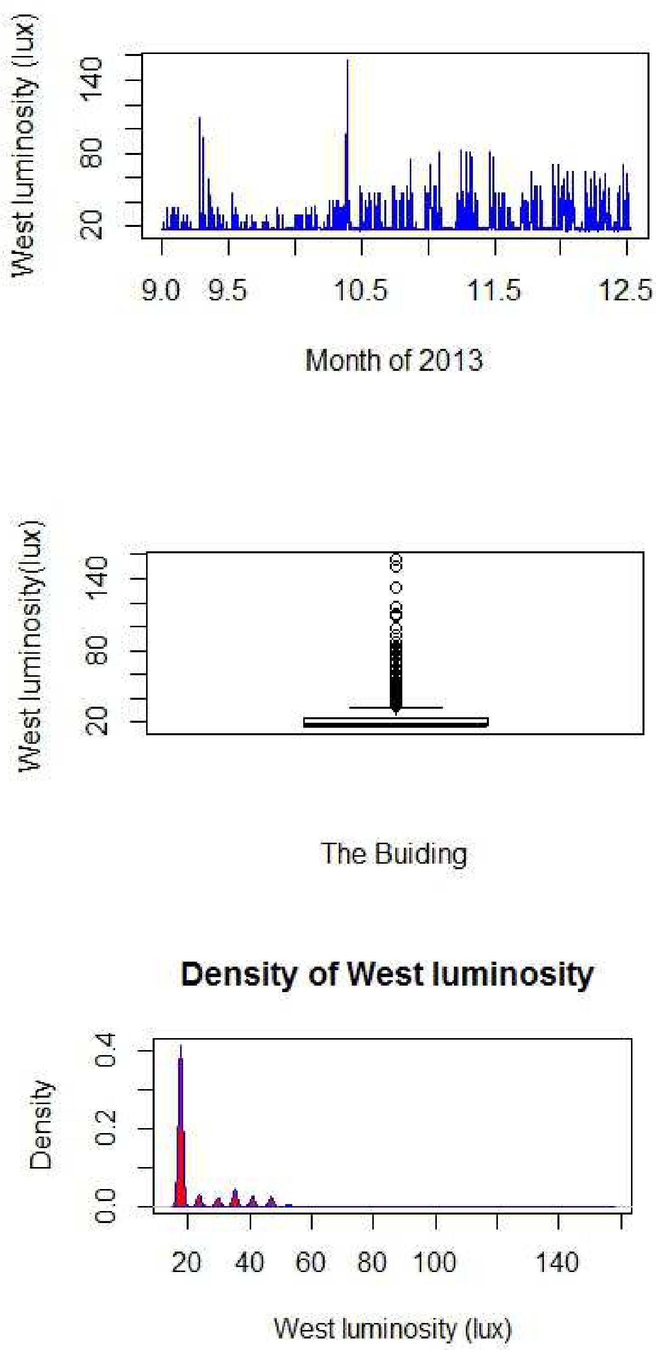


Figure 3.4 Time series, density distribution, and boxplot of West luminosity (v5) in 2013

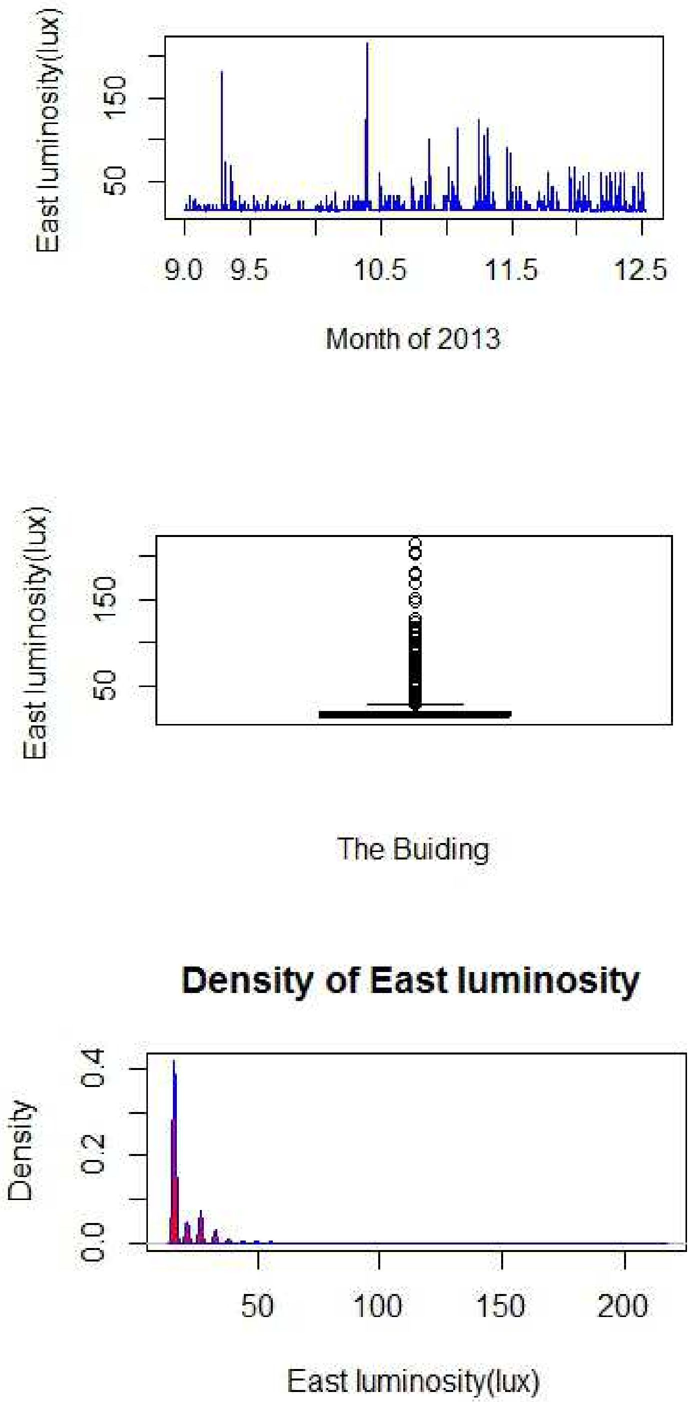


Figure 3.5 Time series, density distribution, and boxplot of East luminosity (v6) in 2013

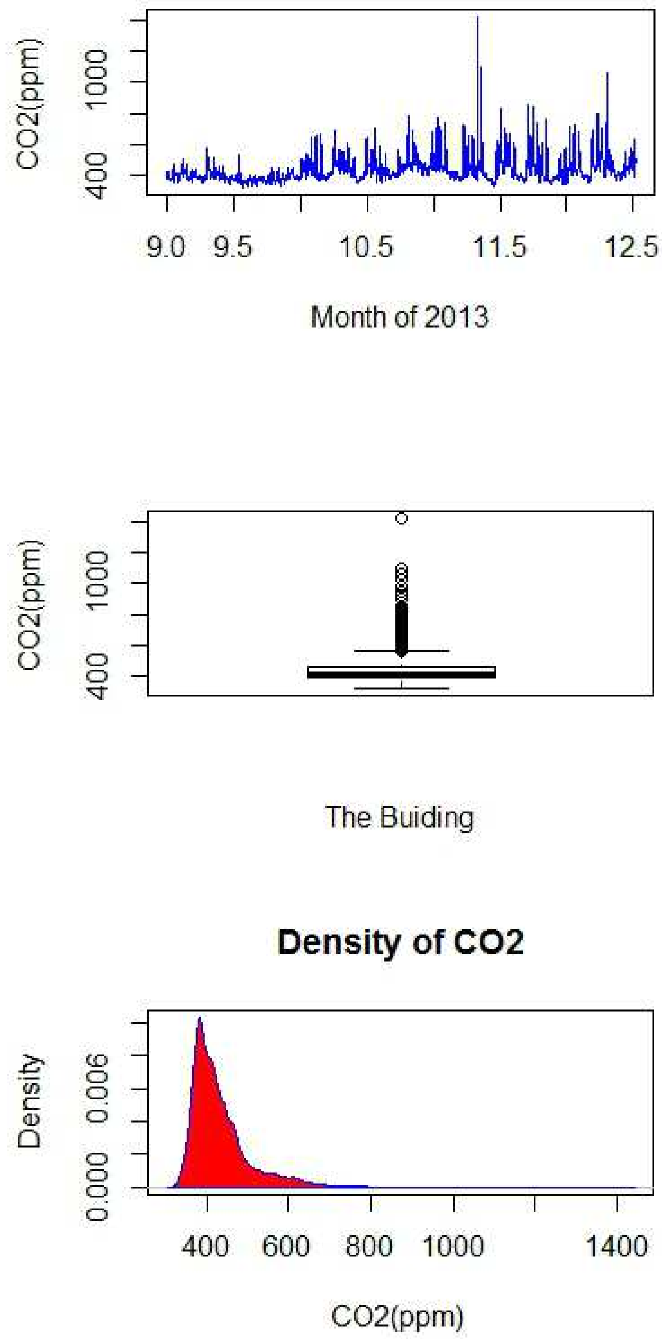


Figure 3.6 Time series, density distribution, and boxplot of CO2 (v7) in 2013

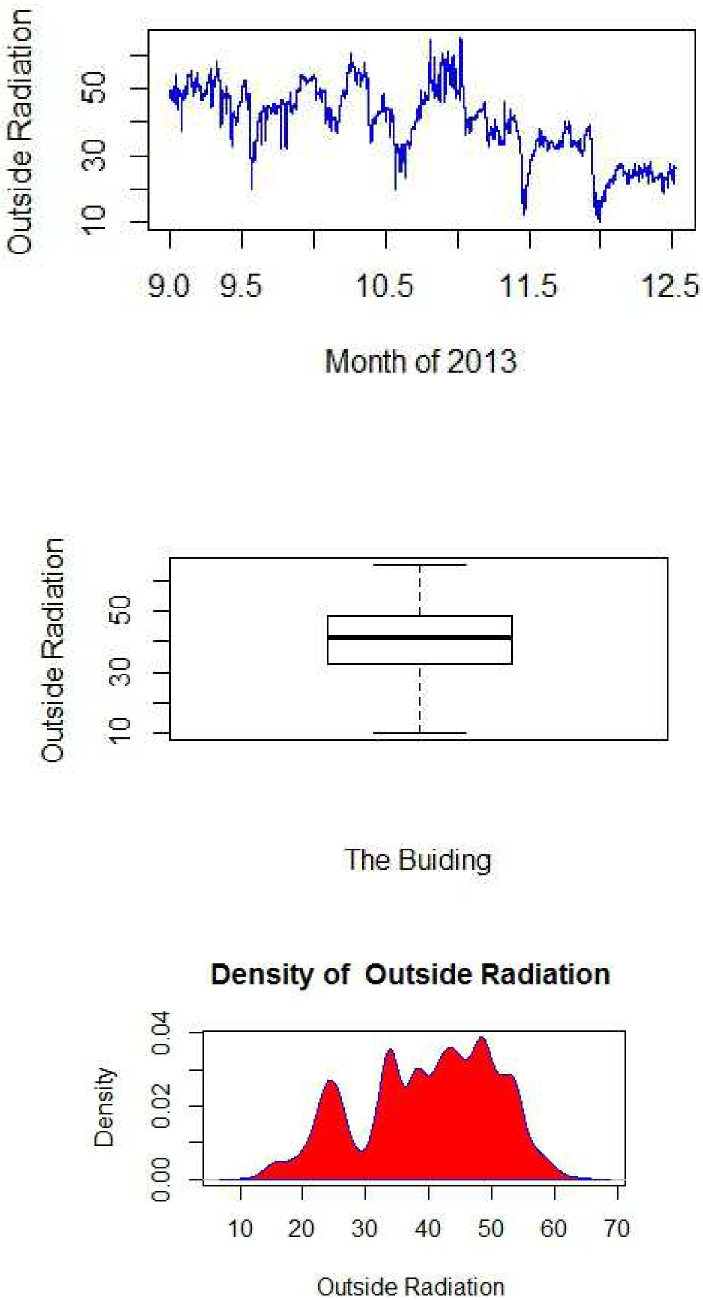


Figure 3.7 Time series, density distribution, and boxplot of outside radiation (v11) in 2013

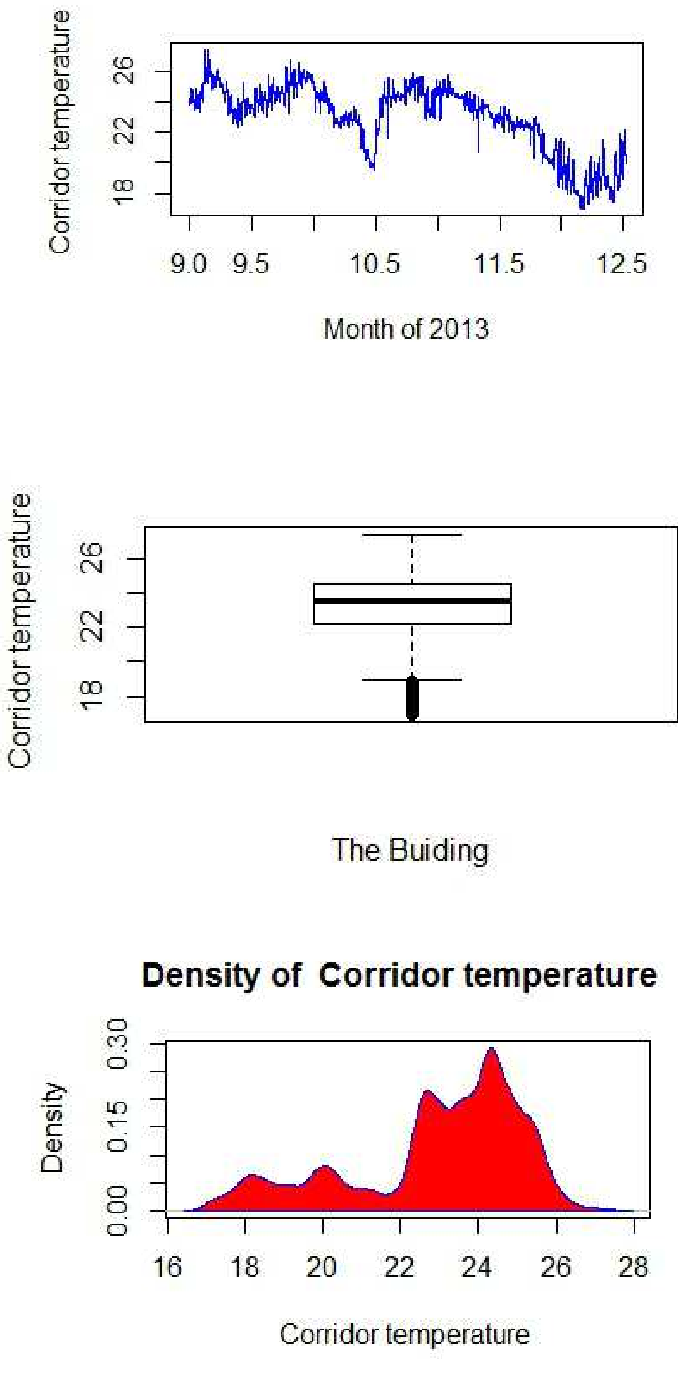


Figure 3.8 Time series, density distribution, and boxplot of corridor temperature (v15) in 2013

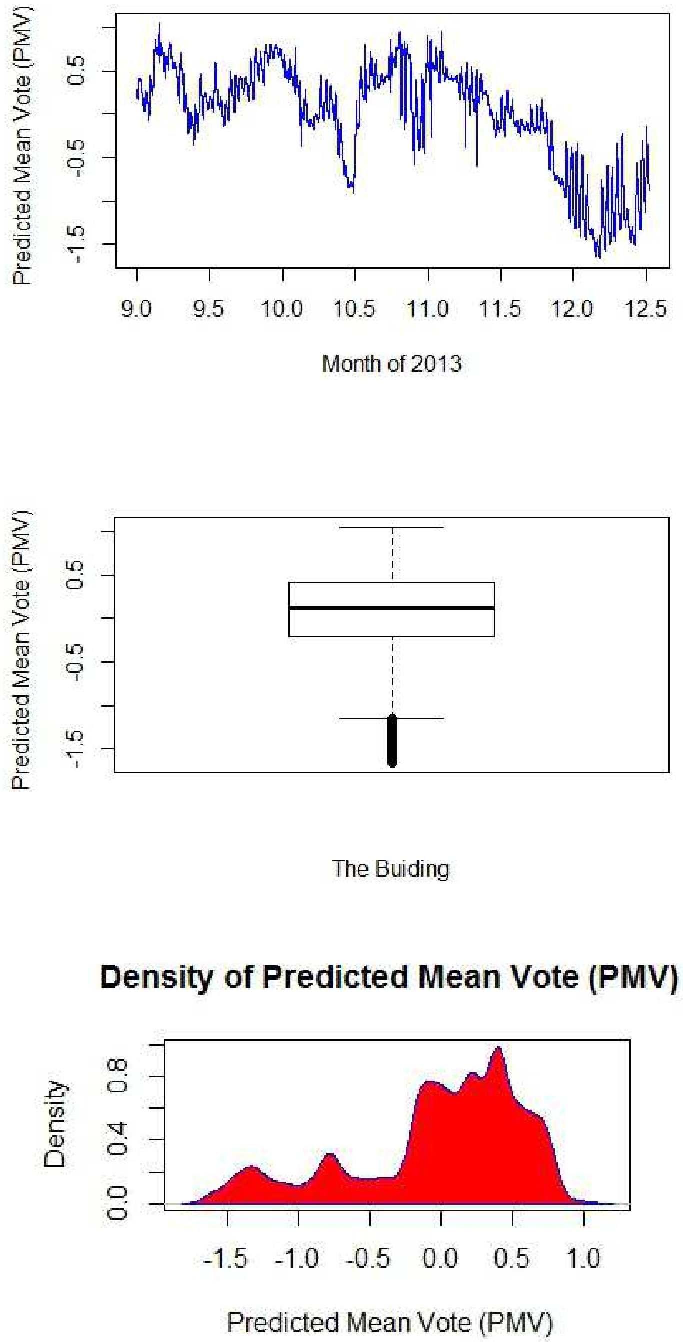
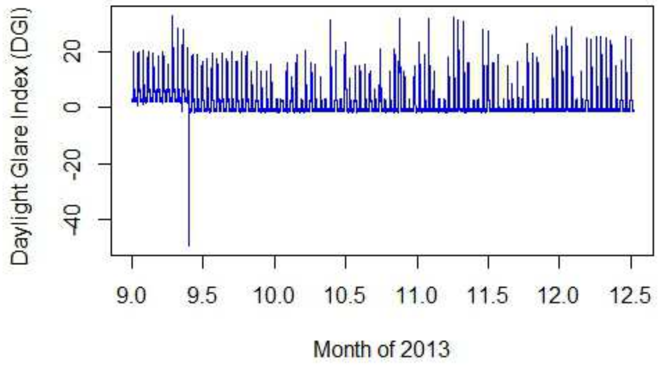
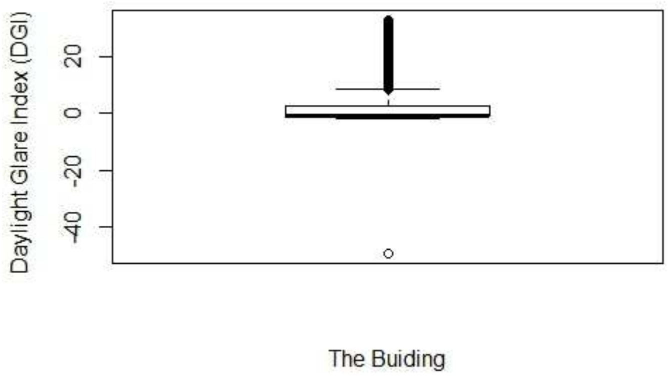


Figure 3.9 Time series, density distribution, and boxplot of predicted mean vote (x1) in 2013





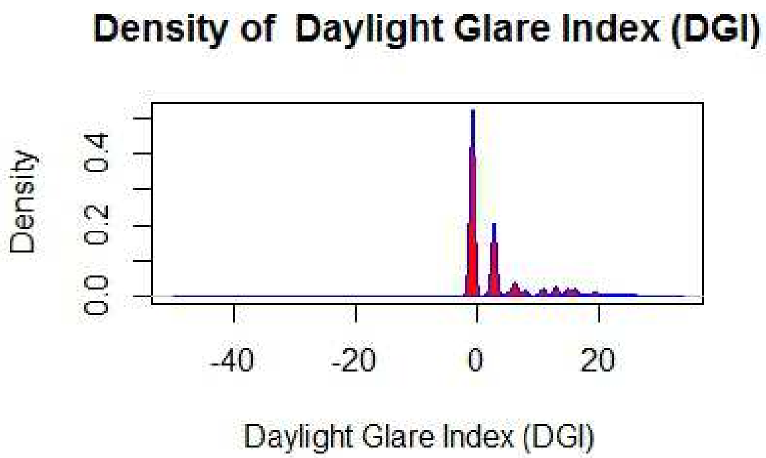


Figure 3.10 Time series, density distribution, and boxplot of daylight glare index(x2) in 2013

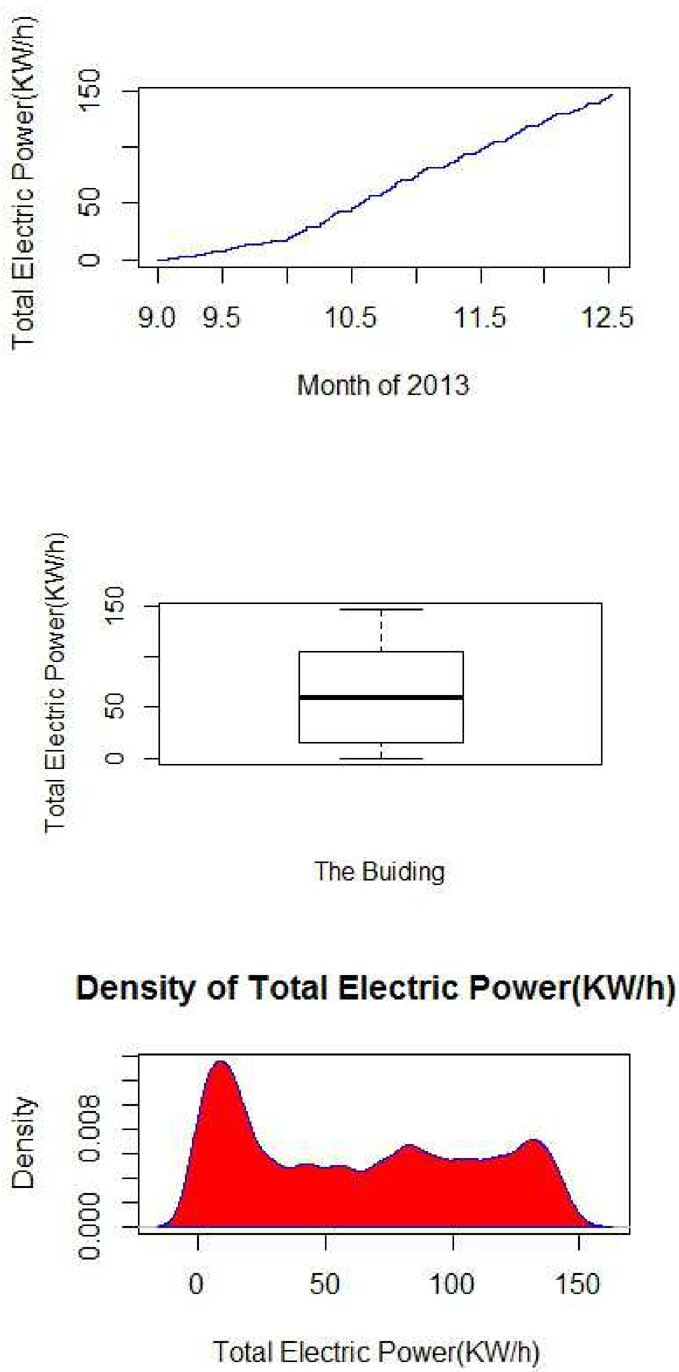


Figure 3.11 Time series, density distribution, and boxplot of total electric power (y) in 2013

The internal temperature (v1) is distributed with median around 24 and presents behavior for the building. Their distributions (figure 3.1) exhibit a longer left tail (visible in figure 3.1) due to the presence of outliers (evident in the boxplots) that can be temporarily speaking individuated in two periods from October and from November to the end of the detection period. Humidity (v2) is distributed in the building (figure 3.2), the medians are slightly greater than 40% of humidity, however a big variability is shown in figure 3.2 since the min and the max values are respectively at 10% and 70%, as a result PMV (x1) will be surely affected by this strong variability. Looking at the time series plot (figure 3.2) a decreasing trend can be easily observed, but it is quite normal since in winter season a lower humidity is expected. Regarding the mean radiant temperature (v4) is expected just a slight difference with respect to internal temperature, in fact the medians are lower than v1. Besides, v1 and v4 present a similar trend over the time and also the peaks of minimum are situated in the same time points.

To what concern EAST and WEST luminosity in the room (respectively v6 and v5), high peaks are evident daily in the morning (figures 3.5 and 3.4). CO_2 (v7) from the 21st October 2013 is high peaks and PMV depends on internal and radiant temperature, and the PMV trend follows a very similar pattern over the time. Concerning the daylight glare index (figure 3.10) is sometimes the DGI sensor gets blocked and returned those minimum values. About total electricity power (figure 3.11) which slight increase from September to October and rise from October to the middle December. Thus, they tend to grow over time that is precisely the problem that we need to optimize while maintaining comfortable for the persons in the building.

3.2. Features Selection

Regarding feature selection, some considerations need to finish. Our final purpose is to detect the best configuration of the controllable variables (d1, d2, b, fc), they will be surely present as explanatory variables of each model therefore we do not need to implement them in the features selection process. Moreover, some categorical variables have been purposely removed from our final models such as v8, v13, v14. This arguably choice has been taken since their effects can be detect paying more attention to some uncontrollable variables, for example, the occupancy (v8) could be observed by an increment on CO_2 emissions (v7). We will show the results of feature selection via Random Forest:

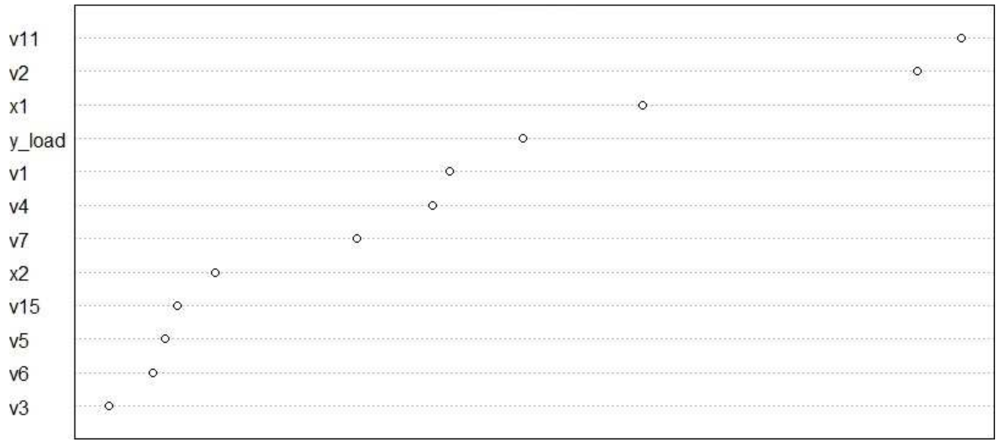


Figure 3.12. Variable importance for total electric power model(y)

Regarding energy consumption are considered by Random Forest the following features: room temperature (v1) and humidity (v2), mean radiant temperature (v4) influence the total electric power. Besides, our attention is the high score of CO2 emissions (v7) which influence the total electric power, because increasing of CO2 is a sign of occupancy in the room, and then CO2 warms the around the room consequently relaxing the heater. The last variable to enter the model is the outside corridor temperature (v15), we could imagine the door is often open, so being a corridor normally a bit colder than the temperature of a room; the system needs more energy to heat the entire room. Surely predictors as room temperature and humidity, mean radiant temperature affect PMV. An impressive result has been achieved by the outside radiations (v11), then reasonably the position of the building well

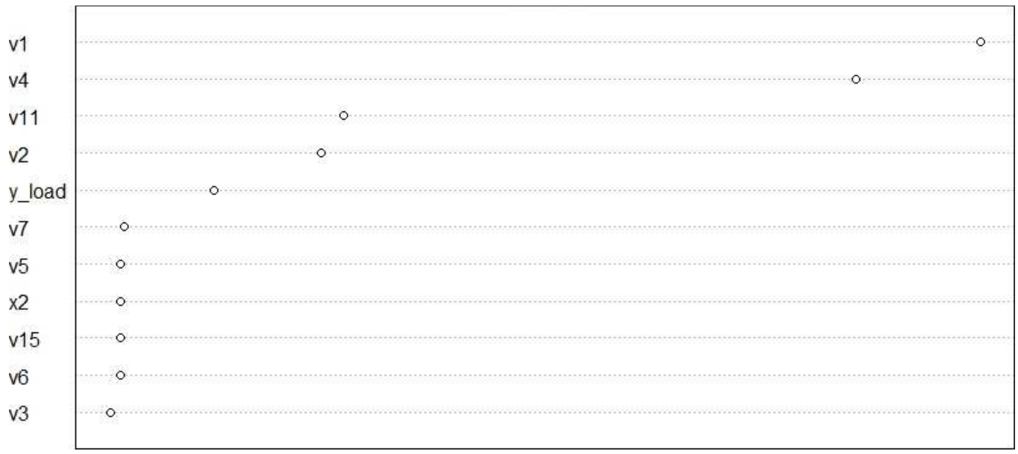


Figure 3.13: Variable importance for PMV model

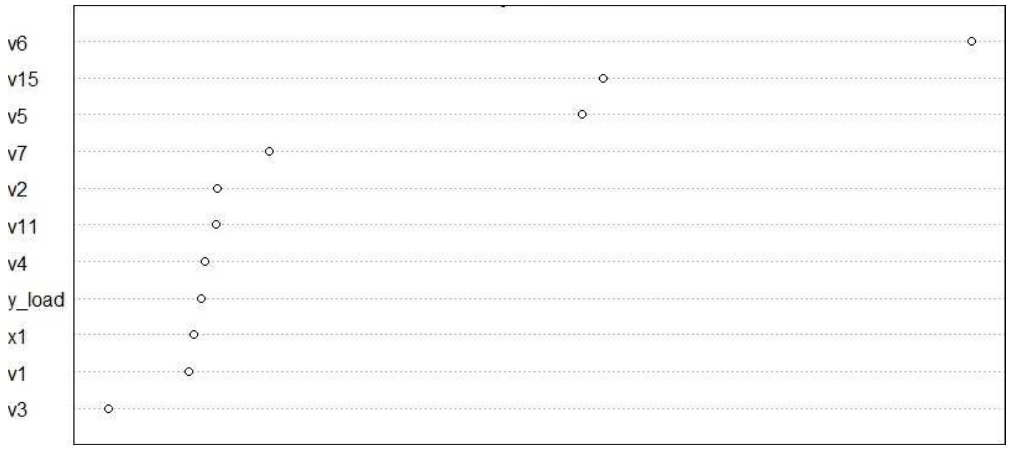


Figure 3.14: Variable importance for DGI model

The DGI model will enter the EAST and WEST luminosity (v5, v6) and the outside radiations (v11) and internal humidity (v2), corridor temperature (v15), thermal load (y load) and CO2 emissions (v7) get high scores; Correlation Analysis will compare the results obtained between variables and a Correlation Analysis is applied to response variables. Given two variables X and Y which invented by Pearson, the most known correlation coefficient:

$$P_{X,Y} = \frac{COV(X,Y)}{\sigma_X \sigma_Y} \qquad (3.1)$$

Where $COV(X, Y)$ is the covariance between X and Y. The $P_{X,Y}$ coefficient can assume $-1 \leq P_{X,Y} \leq 1$.

- $P \approx 1$ is strong linear positive correlation
- $P \approx 0$ no correlation between X and Y
- $P \approx -1$ is strong linear negative correlation.

Random Forest support the choices of these correlations done (see the figure 3.15)

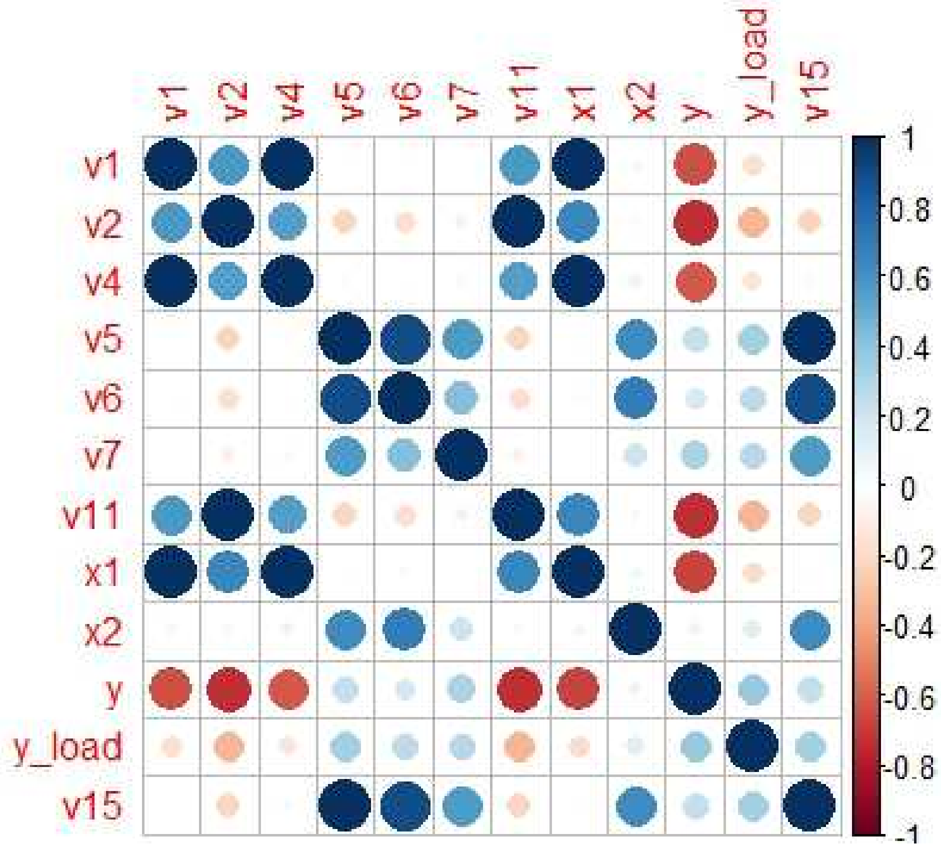


Figure 3.15: Spearman correlation matrix

3.3. Modeling

The model would like to explain the real meaning of the system and help ours understand better how it works. We will use models to predict the behavior of 3 components: total electric power (function y), predicted mean vote (function x1) and daylight glare index (function x2) that we need three continuous response variables (regression problem). Therefore, we set the cost functions:

$$y=f(d1, d2, b, fc, v1, v2, v4, v15, yload, x1, x2) \quad (3.2)$$

$$x1= f(d1, d2, b, fc, v1, v2,v4, v7, v11, yload) \quad (3.3)$$

$$x2= f(d1, d2, b, fc, v5, v6, v11, yload) \quad (3.4)$$

Likewise Kusiak's work[17], we decided to extent the three models adding also the previous lag of the response variable itself in order to take into account the previous state of the model, now the cost functions take the following shapes:

y=f(d1, d2, b, fc, v1, v2, v4, v15, yload, x1, x2, lag(y,1)) (3.5)

x1= f(d1, d2, b, fc, v1, v2,v4, v7, v11, yload, lag(x1,1) (3.6)

x2= f(d1, d2, b, fc, v5, v6, v11, yload, lag(x2,1)) (3.7)

To determine the accuracy degree of a model with respect to the real system and select the best model among several ones, the one which better fits our data we have to evaluation model. These are the result of Random Forest model validation

	MAE	Std_AE	MAPE	Std_APE
Total electric power	1.77453931	0.618466976	0.015279428	0.00502064
PMV	0.007848672	0.006675412	0.013594595	0.00954175
DGI	0.01711764	0.048516133	0.082578091	0.59135364

Table.4. Performance metrics of Total electric power, PMV, DGI on 6 hours predictions

We obtain the quite good predictions are achieved by Random Forest. The next part we will optimal these objective.

3.4. The system optimization

We will formula mathematically as a constrained problem of multi-objective:

$$\min_{(d1,d2,b,fc)} y$$

Subject to

y=f(d1, d2, b, fc, v1, v2, v4, v15, yload, x1, x2, lag(y,1))

x1= f(d1, d2, b, fc, v1, v2,v4, v7, v11, yload, lag(x1,1)

x2= f(d1, d2, b, fc, v5, v6, v11, yload, lag(x2,1))

[17] Kusiak, A. X. (2012). Energy. *Modeling and optimization of HVAC systems using a dynamic neural network*, *42*, 241-250.

where the lag variables represent the variable values at the previous time, in our case 5 minutes before. The formulation describes our final objective perfectly that to avoid misunderstanding. The purpose is to find the best future configuration settings of (d1, d2, b, fc) that allow me to minimize the energy consumption (y), and at the same time maintaining good levels of comfort as PMV and DGI (x1, x2) expressed mathematically as constraints.

Optimization Results

The multi-objective optimization with the Pareto front combined with PSO algorithm allows us to identify the actions that are considered optimal for the two comfort variables. Optimization algorithm predicts the comfort response variable for all possible action in time t+1 and selects the set of non-dominated solutions that simultaneously optimize PMV and DGI variables. Among these solutions we choose one that corresponds to the minimum energy consumption predicted by the model. This procedure is iterated for each t+d, d=2,…T, where T=70 (6 hours).

Figure 3.16 presents the predicted values of comfort variables for set of non-dominated solution identified by optimization procedure for t+1. The red point identifies the selected solution.

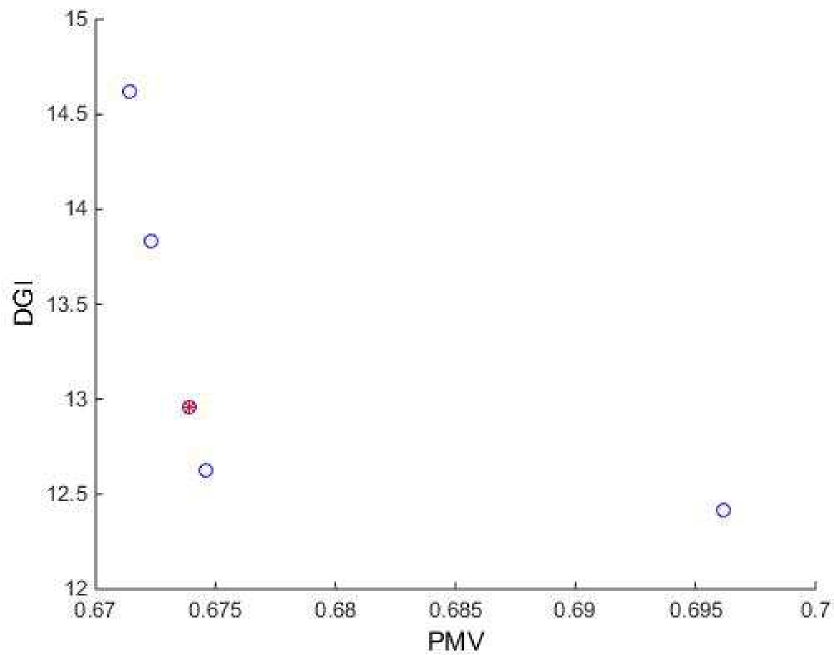


Figure 3.16. The Pareto front at time t +1

We optimize response value of x1 (PMV) and x2 (DGI) and compare the optimize responses with observed response values. The figure 3.17 and 3.18 are represented the comparison of the optimized and observed behaviors of the comfort values. As can be seen from the figure, we provide higher comfort values for PMV, the PMV achieved values much closer to 0 (0 is optimal value for PMV) with respect to the observed values.

The behavior of the visual comfort variable DGI is also enhanced as presented in the figure 3.18. The optimal value for DGI is 21 and the optimized values are closer to the optima in comparison to the observed values.

The behavior of the total electric power is presented in Figure 3.19. We can see that setting the optimal action obtained with the optimization procedure the large amount of energy can be saved. At the end of the period (70 time points) we measure a reduction of the energy consumption of about 19%.

The results can be improved by enchasing the predicting model identification. The optimization procedure combined with predictive statistical model can be proposed as an efficient system for reducing the energy consumption of the building while maintaining the high comfort level.

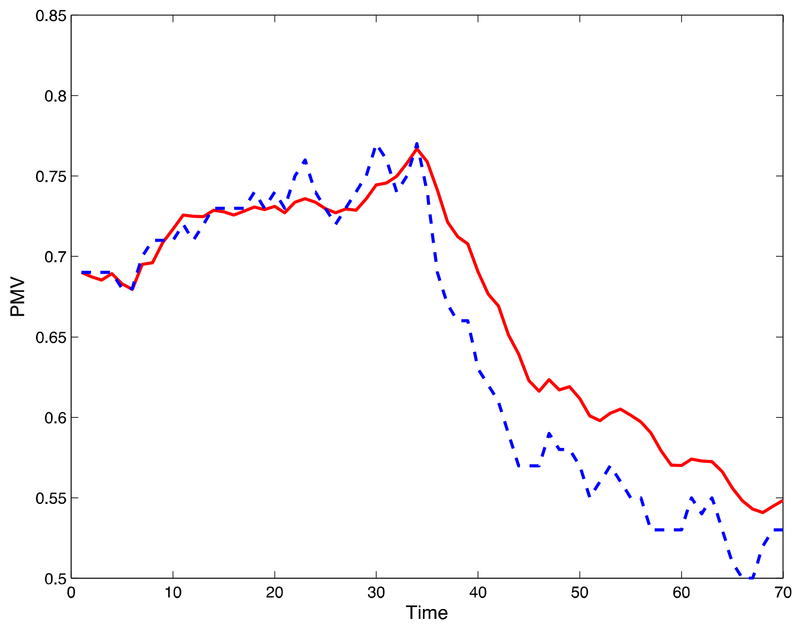


Figure 3.17. Optimal mean vote (PMV) value in 6 hours

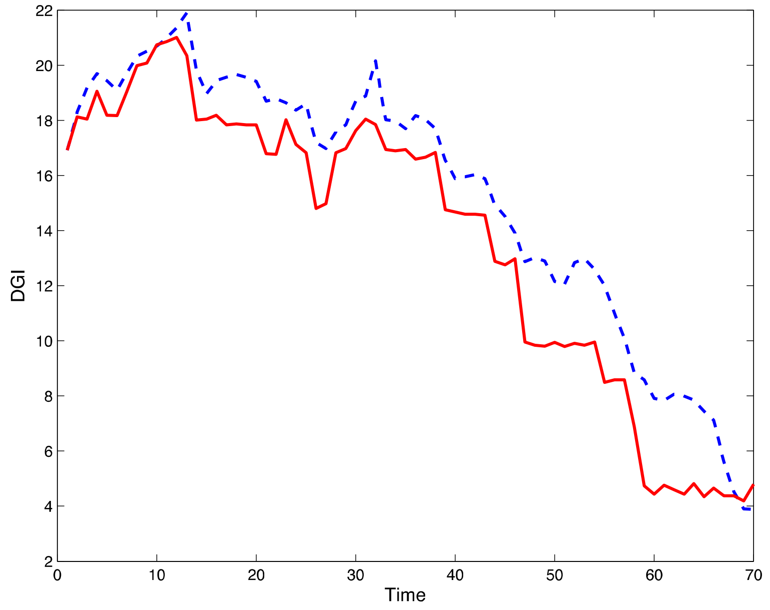


Figure 3.18. Optimal Daylight glare index (DGI) value in 6 hours

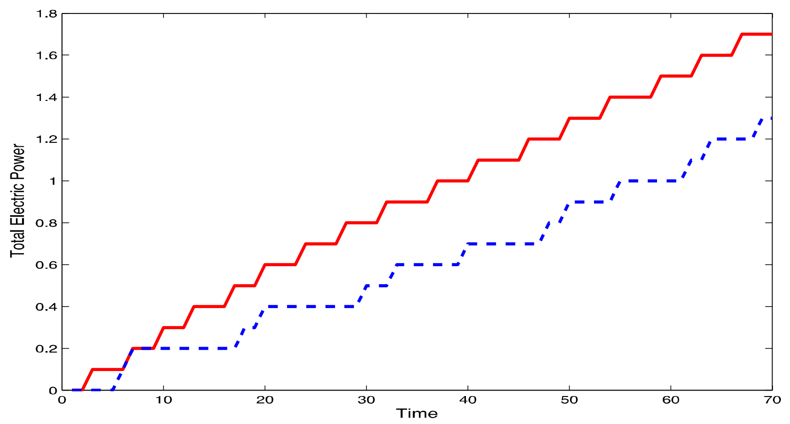


Figure 3.19. Optimal Energy value in 6 hours

We note that blue line is optimal value and red line is observation value. We can see that we have optimal value of total electric power well while maintain two values predicted mean vote (PMV) and daylight glare index (DGI).

CHAPTER 4

CONCLUSIONS AND FUTURE DEVELOPMENTS

4. Conclusions and further research suggestions

In this thesis, we address the problem of the optimization of the HVAC system. We developed research focusing on the real case study, the office building with HVAC system which was designed to be completely automatic.

The objective of this study is to identify the optimal combination of controlled variables (actuators) in order to reach the required thermal and visual control taking care of minimizing the energy consumption of the building.

We applied the correlation analysis to select the most significant variables to construct three prediction models for each of the response variables: PMV, DGI and total electric power.

To build the model we train the Random forest with a training set of 13000 observations and validate the model for all three responses (objectives).

The PSO optimization algorithm was adopted to the multi-objective problem and implemented in order to find the best combination of controlled variable for each 5 minutes of the prediction period.

This optimization procedure can be proposed as efficient predictive algorithm for automatic HVAC system in order to reduce energy consumption of the building

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