Improved Optimization Scheme based on Rule for Energy Efficiency and Multiple Users Comfort Environment in Smart Home

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A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Computer Engineering

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Nomenclature	
T	Temperature
L	Illumination
A	Air-quality
USP	User Set Parameters
AP	Adjusted Power
CP	Consume Power
RP	Required Power
Ω	No of generations
μ	Few successive generations
$\beta_1, \beta_2, \beta_3$	User defined factors [0, 1]
e_T, ce_T, e_L, e_A	Error in (Temperature, Change in Temperature, Illumination, Air-quality)
T_{set}, L_{set},A_{set}	(User set parameters for temperature, illumination and air-quality)
J_1, J_2, J_3	Small values between '0' and '1'
$P(k)$	Sum of required power

Abstract

Smart homes and residential buildings are becoming one of the interesting and challenging research topics in order to satisfy what occupants' need in the certain building environment. At the same time, the total amount of energy consumption in smart home and building environment has been increasing rapidly since last few years. Therefore, many scientific researchers have been given huge attention to the energy control and management in smart home and residential building environment. Several proposals based on optimization algorithms and other technologies exist in literature that has been tried to solve the challenge between energy consumption and occupant's comfort index. In this thesis, we proposed rule based optimization scheme for reducing power consumption, an optimization scheme based on dynamic user setting for multi-users, and optimization scheme based on prediction of indoor environment parameters in order to increase user comfort index and consume less energy in the smart home area. Previously, we have already implemented optimization algorithms such as Ant colony optimization and Incremental genetic algorithm in order to increase user satisfaction level and energy efficiency. The energy control system using algorithms aimed to find highest optimal set points and increase the occupant's overall satisfaction in building environment. It gives a high overall comfort index and less power consumption results. However, there are still ways to get higher comfort index results with less energy consumption. Therefore the purpose of this thesis is aimed to increase occupant's comfort index and consume less power through optimal environment set points which is using rule based optimization. In addition, we considered multi user set point setting for every members of the home. Thus every user is able to customize their comfort condition ranges by dynamic user set point settings for multi-users. The third proposed idea is about predicting indoor environment parameters to consume less power. As a result, RBO reduced power consumption by 24.32% as compared to GA, 10.26% as compared to IGA, and 25.72% as compared to ACO. To satisfy multi users' comfort in smart home, we proposed dynamic user set points setting by three methods. Among the three methods, max-min based user set point setting consumed highest power. Average based user set point setting reduced power by 4.28% as compared to max-min based user set point

setting and min-max based user set point setting reduced power by 8.74% as compared to max-min based user set point setting. Finally, we compared predicted indoor environment parameters and unpredicted indoor parameters. For illumination and air quality control, the results were almost similar. But, the prediction of indoor parameters, for temperature control, ABS, and RBO based system reduced power consumption by 2% as compared to unpredicted indoor parameters, ABS, and RBO based system. Prediction of indoor parameters, for temperature control Max-min, and RBO based system reduced power consumption by 0.71% as compared to unpredicted indoor parameters, Max-min, and RBO based system. Similarly, prediction of indoor parameters, for temperature control Min-max, and RBO based system reduced power consumption by 3.28% as compared to unpredicted indoor parameters, Min-max, and RBO based system.

Acknowledgement

I would like to express deepest thank and gratitude to my supervisor Professor DoHyeun Kim for his full support, expert guidance, understanding and encouragement throughout my study and research. Without his incredible patience and timely wisdom and counsel, my thesis work would have been a frustrating and overwhelming pursuit.

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1. Introduction

The usage of energy has been increased worldwide since last decade. People have been spending most of their time in building environment. Because of this reason, too much energy has been consumed in smart and intelligent building areas. At the same time, energy resource that we have is an expensive and certain limit. Therefore, we need solutions that consume less power with occupants' high satisfaction or comfort level in the smart buildings, thus spending less money on energy consumption. In order to overcome those issues researchers have been paying their attention to this topic. Increasing the occupants' overall comfort index and decreasing energy consumption is still a big challenge in energy management and control systems.

Why we need to implement energy efficient system? We have already mentioned about issues that we have been facing related to usage of energy in smart home and building. In order to improve the occupants' overall satisfaction level with consume less energy. Also to overcome financial issues, we need an energy efficiency system. The fundamental purpose of implementing energy efficient system is improve to make occupants comfort index and consume less power in the smart home.

What are the energy control and management system in smart home? Basically, according to the basic definition that energy management and control system is a system of computer-aided tools utilized by operators of electric utility grids to monitor, control, and optimize the performance of the generation and transmission system. Therefore, inside the smart home area, we can manage, control, and optimize the usage of the generation using energy management and control system.

What is optimization algorithm? Optimization algorithms, try to find the minimum values of mathematical functions, are used commonly. Among other things, they're used to evaluate design tradeoffs, to assess control systems, and to find patterns in data. One way to solve a difficult optimization problem is to first reduce it to a related but much simpler problem, then gradually add complexity back in, solving each new problem in turn and using its solution as a guide to solving the next one. This approach seems to work well in practice, but it's never been characterized theoretically. What is optimization and optimization problem? Mathematics, computer science and operations research, mathematical optimization is the selection of the best elements from some set of available alternatives. Basically, optimization algorithms aim is that maximizing or minimizing a real function by systematically choosing input values from an allowed set and estimate the value of the function. Generally, an optimization issue is the problem of finding the fittest solution from all possible solutions. An optimization issue can be divided into two sections depending on whether the variables are continuous or discrete.

Why do we need to use energy optimization? Optimization has been used by an energy management system to find optimal parameters. There is two major elements in this system are current indoor parameters and user set points. The current indoor parameters indicate the environmental conditions in the smart home area. The user set points indicate the demand comfort level of the occupants in the smart home area. To express user's comfort, we consider three parameters, such as temperature, illumination, and air quality. Then current indoor environment and user set points consist of those basic three parameters. The difference between user set points and current indoor parameters is called error difference. In our thesis, error difference is the input to the fuzzy controller in order to calculate required power consumption. So here is an important point that the minimum error difference can achieve minimum power consumption. In this way, it is obvious that we need to use energy optimization in order to minimize the error difference between the user set points and current indoor parameters. As a result of those concepts, we can minimize the error difference between the two parameters using optimization. At the same time we can achieve minimum energy consumption in a smart home.

Figure 1.1 shows the conceptual design of overall proposed ideas. Each concept is described below. We propose three ideas in this work. Firstly, the rule based optimization scheme for reducing power is proposed. The rule based optimization targets to satisfy of the user's requirement along with minimal energy consumption with improved performance in terms of computation. The ranges of user set parameters are optimized using rule based optimization. Then the optimal parameters from rule based optimization and indoor environment parameters from sensors are input to fuzzy controller.

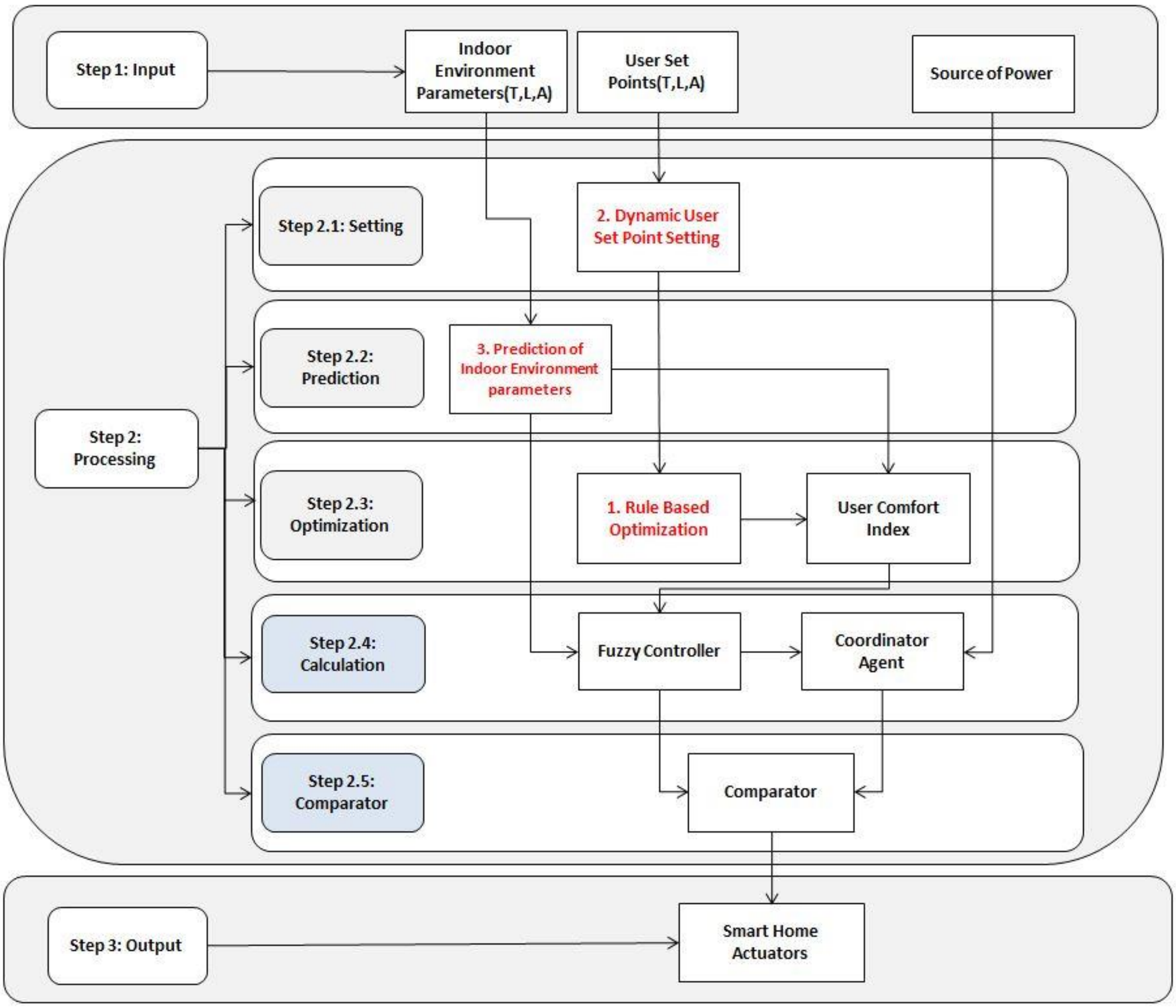

Figure 1.1 Conceptual design of overall proposed ideas

Then minimum required power is output of a fuzzy controller which is passed to control actuators for temperature, illumination, and air quality. Coordinator agent takes as input required power and optimal parameters. The coordinator agent adjusts the input power of the smart home on the basis of available power, required power. The adjusted power compared with the required power to get the actual consume power. The consumed power is used by the actuators. Secondly, optimization scheme based on dynamic user set point setting for multi-users is proposed. The dynamic user set point setting is considered for comfort condition of every member of the home. Every member is able to choose their comfort ranges which are minimum and maximum between certain ranges. Then minimum and maximum ranges are input to dynamic user set point setting and system level comfort ranges for temperature, illumination, air quality are calculted according to all members comfort ranges. We use three met hods to calculate actual user set point which is average based setting, maximum-minimum based setting, and minimum-maximum based setting. The actual user set points from dynamic user set point setting is input to rule based optimization to get optimal parameters. Then the optimal parameters from rule based optimization and indoor environment parameters from the sensors are input to fuzzy controller. Minimum required power is output of fuzzy controller for controls which are temperature, illumination, air quality. Coordinator agent takes as input required power and optimal parameters. The coordinator agent adjusts the input power of the smart home on the basis of available power, required power. The adjusted power compares with the required power to get the actual consume power. The consumed power is used by the actuators. Thirdly, optimization scheme based on prediction of indoor environment paremeters. We use Kalman filter prediction for predicting indoor environment parameters from the sensor. We observe small reduction in actual power consumption by using prediction of indoor environment parameters.

The rule based optimization idea is inspired by comfort index calculation. The goal of optimizing user set points is in order to maximize comfort index and at the same time consuming less energy. Therefore, getting optimal parameter is the key of the system. If we can get optimal parameters with highest comfort index, we can get minimum power consumption. For this reason, rule based optimization considered on minimizing the error difference between current indoor environmental parameters and user set points based on some rules. Users can define their own ranges of each set point. So, user defined set point ranges, and current environment parameters are input to the rule based optimization. We optimize temperature, illumination, and air quality parameters separately. Current environmental parameters such as temperature, illumination, and air quality and user set point ranges are input to the rule based optimization.

User set points define comfortable maximum and minimum ranges of users. In smart home, comfort environment is important to every family member. Therefore, we suggest that all people in the smart home are able to set their comfortable user set points. Then the system user set point is calculated by user set point setting. Thus, we can make a comfortable environment for every member in a smart home. The adjusted user set points are input of the rule based optimization. Actually the user set points are parameters which have maximum and minimum value. It indicates that user's comfort zone.

Optimization scheme based on prediction of indoor environment parameters uses Kalman filter to predict indoor environment parameters from sensors. Then predicted indoor environment parameters are input to rule based optimization to get optimal parameters and also it is input to the fuzzy controller to calculate required power. We consume less energy using Kalman filter prediction of indoor environment parameters.

2. Related works

2.1. Optimization approaches in energy consumption

In this section we are going to discuss about the related work optimization and prediction algorithms which are applied to the energy management system and schemes. Since people spend most of their time in building, the environment comfort conditions of buildings are highly related to occupants' satisfaction. Therefore, in the literature many works have been proposed to energy savings and energy management control system. Those works have been applied optimization algorithms to address the problem. In particular genetic algorithm (GA) is used by an energy management system in many ways. Optimizing the input parameters of fuzzy logic using GA and predict using Kalman filter. The parameters we optimized are temperature, illumination, and air-quality which reflects the occupant's comfort index in the building environment. The proposed GA based optimized model produces over all improved comfort indexes as compare to our previous work PSO based system [3]. Adaptive learning algorithm based on genetic algorithms GA for automatic tuning of proportional, integral and derivative (PID) controllers in Heating, ventilating, and air conditioning (HVAC) systems to achieve optimal performance. Genetic algorithms which are search procedures based on the mechanics of Darwin's natural selection, are employed since they have proven to be robust and efficient in finding near-optimal solutions in complex problem spaces. The modular, dynamic simulation software package HVACSIM has been modified and incorporated in the genetic algorithm-based optimization program to provide a complete simulation environment for detailed study of controller performance. Three performance indicators overshoot, settling time, and mean squared error are considered in the objective function of the optimization procedure for evaluation of controller performance [4]. Genetic algorithm optimization techniques are applied to shift properly the membership functions of the fuzzy controller in order to satisfy the occupants' preferences while minimizing energy consumption. The implementation of the system integrates a smart card unit, sensors, actuators, interfaces, a programmable logic controller (PLC), local operating network (LON) modules and devices, and a central PC which monitors the performance of the system. The communication of the PLC with the smart card unit is performed using an RS 485 port, while the PLC-PC communication is performed via the LON network [10]. Energy savings potential for using MPC with weather predictions for the investigated building heating system were between 15% and 28%, depending on various factors, mainly insulation level and outside temperature [12].

In the literature many works have been proposed in the area of energy savings and some valuable energy management control systems have been proposed. Approaches based on conventional control systems have been introduced in prior works [22, 23]. These conventional controllers consist of classical controllers [22]. The classic controller has the temperature overshoot problem. The other problem with this approach is that, it does not consider user set parameters and the model is not user friendly. It also does not address the energy efficiency and the model was not energy efficient. To overcome the overshoot problem designer proposed PID controllers [23]. These controllers improve the situation, but the improper choice of the gains in PID controllers could make the system unreliable and unstable. Therefore, designers give attention to the optimal controller and adaptive controller respectively [24, 25]. The problems of conventional controllers are addressed in the optimal and adaptive controls. The optimal controller based approach improves the thermal comfort. Adaptive controllers have the capability to adapt to the environmental conditions. It is reported as most promising controllers in the context of adaptation to the climate conditions. Although optimal and adaptive controllers addressed the problems of classical controllers, but these approaches also have problems. These approaches need a building model which makes it difficult to implement for each and every building. The use of elements of bioclimatic architecture confuses the process of minimization of the cost function and if such a minimization is acquired, the results are not valid in practice. Another problem with techniques is that, they don’t consider occupants comfort index. These approaches are also not user friendly because they did not consider user set parameters. The last and most important point is that, these approaches don’t consider energy efficiency and consumed more energy.

A comparison of different control mechanisms for energy consumption and occupants comfort index in building environment is carried out in [26]. During comparisons, user set parameters were not considered. So the main disadvantage of their work is that, their models are not user friendly because users are not involved in deciding the occupants comfort index. A control strategy is proposed in [27] to maintain energy consumption and occupants comfort index, but user set parameters does not consider in deciding occupants comfort index. User set parameters plays a vital role in deciding occupants comfort index. In one of the previous work attention is made towards the occupants comfort index [28]. This work also did not consider the user participation in deciding occupants comfort index. Predictive and adaptive controllers using artificial neural network to allow the adaptation of the control model to the environmental conditions, building characteristics and user behaviors is proposed in [29]. This approach not only lack of user set parameters, but also did not consider occupants comfort index. Another predictive control strategy using a system method for overall system environment and energy performance to the changes of control settings of VAV air-conditioning system is proposed and developed in [30]. To optimize the parameters GA algorithm has been used. This system also lack of user set points and occupants comfort index. The approach only considers energy efficiency in the building. A reinforcement learning controller to achieve occupants comfort index with minimal energy consumption is described in [31]. The method succeeded in accomplishing occupants comfort index, but failed to provide energy efficiency. Another robust reinforcement learning control for building power systems is proposed in [32]. The main drawback of this system is energy efficiency because the system could not achieve the desired results in minimized energy consumption. An optimized fuzzy controller applied for the control of environmental parameters at the building zone level has been proposed in [33]. In this method the occupants' preferences are monitored via a smart card unit. Other proposals in this connection are predictive control approaches [34, 35], where weather predictions have been applied to heating, ventilating and air-conditioning system.

2.2. Optimization scheme approach based on the IGA

In this approach, we use an optimization scheme approach based on an Incremental genetic algorithm (IGA). The aim of this approach is to achieve maximum user comfort with less power consumption as compared to GA based system.

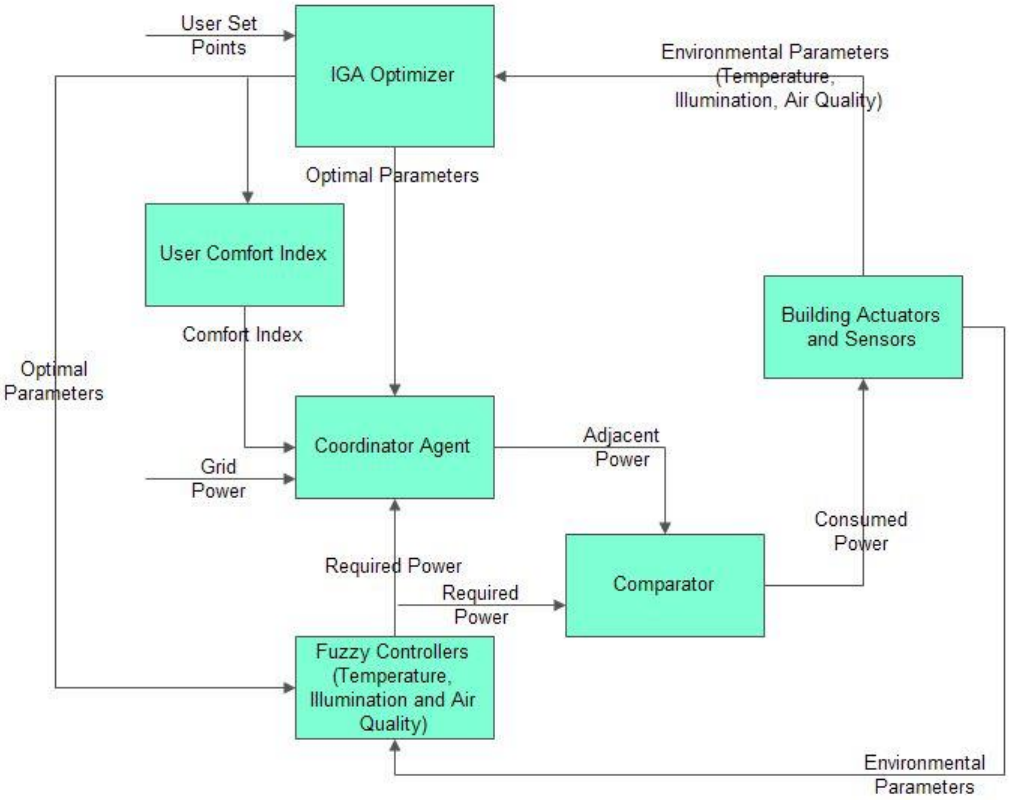

Figure 2.1 Optimization scheme approach based on the IGA

Figure 2.1 illustrates the optimization scheme approach based on IGA in the building environment. In particular the system scheme consists of six basic components which are IGA optimizer, user comfort index, coordinator agent, fuzzy controllers, comparator, building actuators and sensors. IGA optimizer takes environmental parameters and user set points as input. Then the optimal parameters from IGA are input to the user comfort index in order to calculate the comfort index. Then the optimal parameters and environmental parameters are input to the fuzzy controller in order to estimate required power. Then the required power from fuzzy controller and grid power are input to the coordinator agent in order to get adjusted power. Then the required power and adjusted power are input to the comparator in order to get actual consumed power. Finally, the consumed power is input to building actuators.

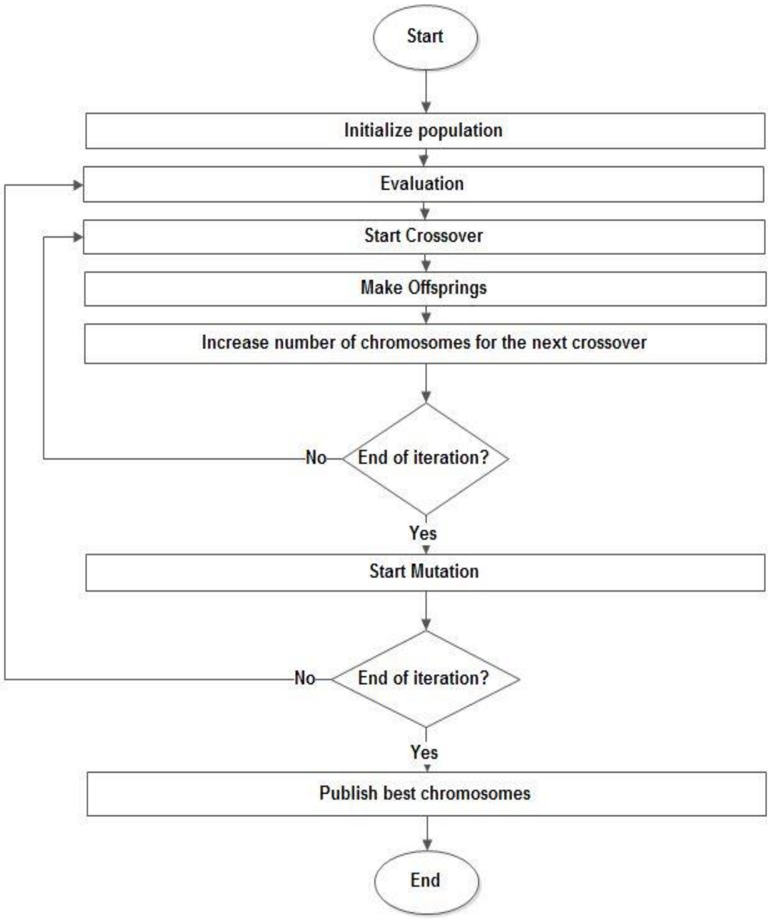

Figure 2.2 Incremental genetic algorithm

The idea of IGA for optimizing modified problems is simple. Instead of starting with a randomly generated population of chromosomes, start by using the information saved from running an initial population on the initial problem. IGA has given focus in two major directions. First is that a modification made to a problem does not shift optimal and good sub-optimal solution points much in the solution space. Second is that the information saved during the application of a GA for the initial problem will be useful for subsequent application of a genetic algorithm to modified versions of a problem. The aim is to reduce evolution time, measured in number of generations of a genetic algorithm used for re-optimizing modified problem. Then the proposed system provides improved results. Figure 2.2 illustrates work sequence of IGA which is used by the system. First of all, initial population of chromosomes is created. Then it is evaluated by some fitness function. Then crossover is started. The crossover makes offspring. Then we need to increase the number of chromosomes and update chromosomes for the next iteration of crossover. After finishing crossover, mutation process is started. Then end of the mutation, we got best chromosomes.

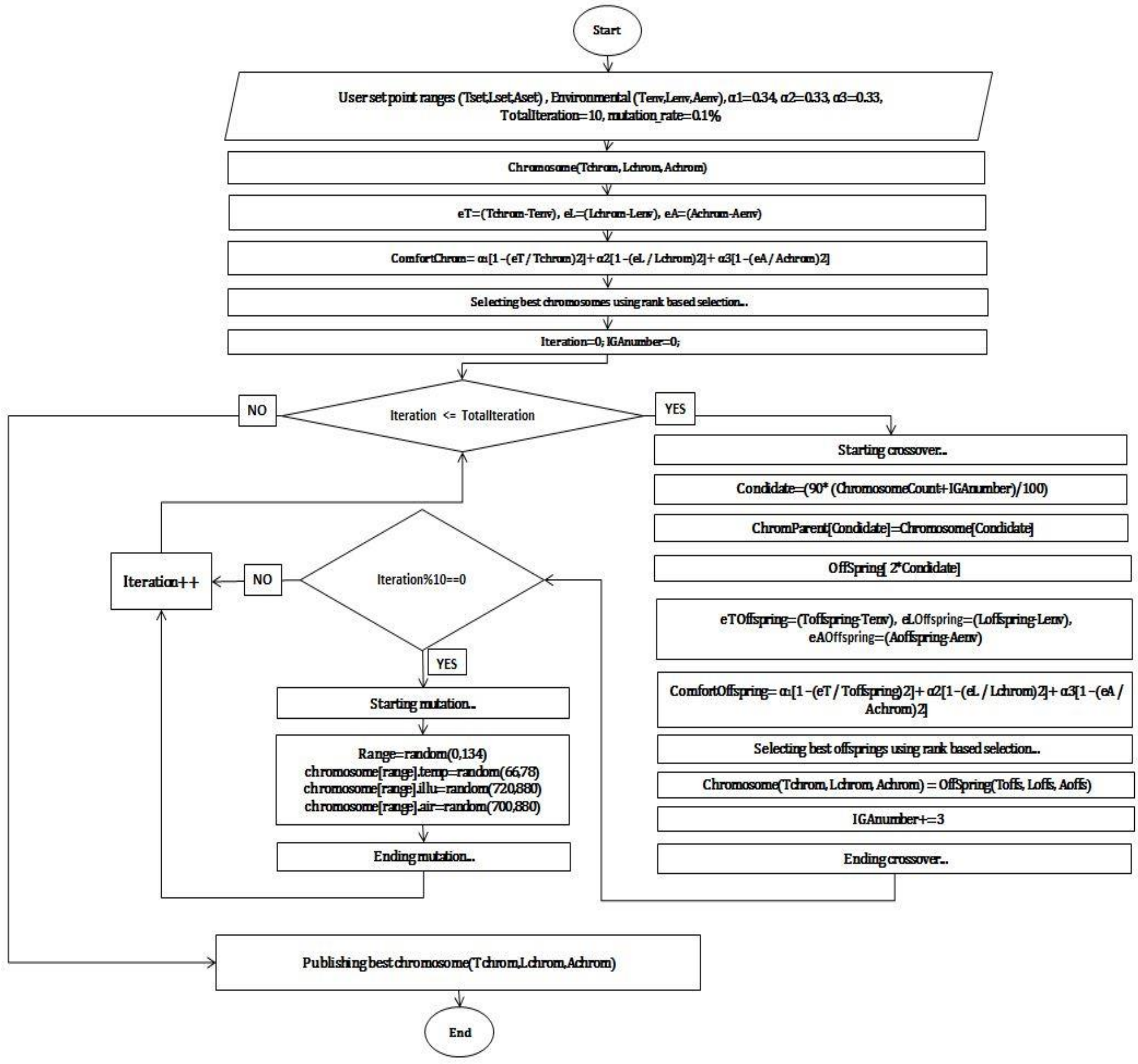

Figure 2.3 Detailed flow chart of IGA

The figure 2.3 illustrates detailed flow chart of incremental genetic algorithm. We get user set ranges, environmental parameters, mutation rate, user defined factor, and iteration count as input. Then random chromosomes are created. Then error differences are calculated from chromosomes and environmental parameters. Then the comfort index is calculated by following equation [1.1] using error differences and environmental parameters. Then best chromosomes are selected by the rank based selection. After that, the crossover is started and we calculate the candidate number in order to make parent chromosomes. Then offspring is created from parent chromosomes. Then we estimate the error difference for each offspring and comfort index. Then the best offspring is selected by the rank based selection. The offspring is given to chromosomes from next iteration. Then, if the mutation rate is met, we perform the mutation. End of the mutation, iteration will be increased for the next iteration. Similarly iteration will repeat until certain numbers of iterations are finished.

2.3. Optimization scheme approach based on ACO algorithm

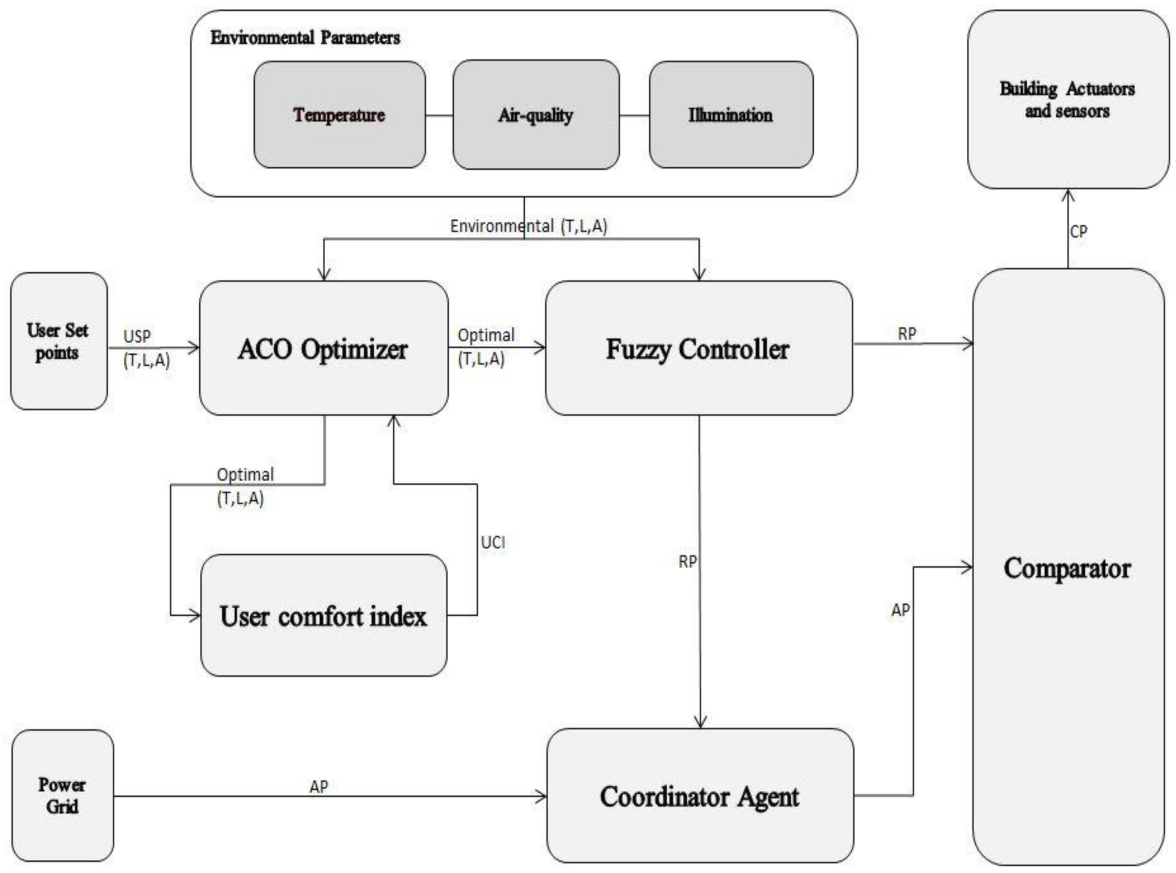

Figure 2.4 Block model optimization method based on ACO algorithm

In this approach, we proposed that optimization method based on Ant Colony Optimization algorithm. We implemented different algorithms in order to get optimal parameter and increase comfort index. Therefore the figure 2.4 shows the block model consists of basic eight concepts which are environmental parameters, user set points, power grid, ACO optimizer, fuzzy controller, coordinator agent, comparator, and actuators and sensors. User set points and environmental parameters are input to the ACO optimizer. The output of ACO optimizer is called trails. The trails are solutions. So, user comfort indexes are calculated for each trail. Then the optimal parameters from ACO optimizer are input to fuzzy controller. Then required power from the fuzzy controller is an input to coordinator agent and comparator. Adjusted power from coordinator Agent is input to the comparator. Then consumed powers are estimated by the comparator and input to the building actuators and sensors.

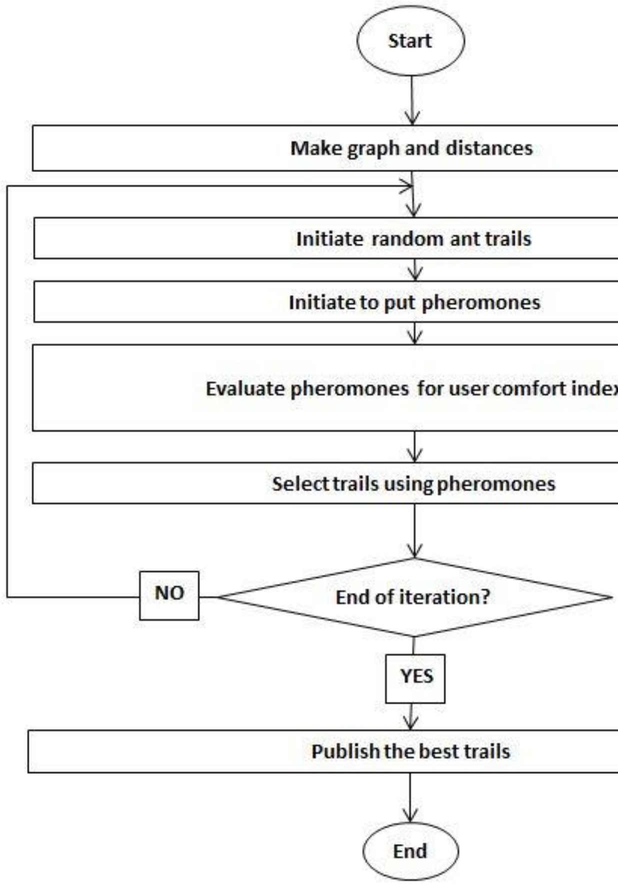

Figure 2.5 Ant colony optimization algorithm flowchart diagram

2.4. Sensor data

Sensor data are input to the system which indicates the condition of the smart home. We have three sensor data which are temperature, illumination, and air quality. We use real temperature sensor data from January 2010 and June 2010. Then for illumination and air quality, we use simulation linear data.

2.5. Comfort index and condition

Comfort condition is the quality of life in an intelligent and smart home or building area. It is important because of the reason that people spend their most of time in the building environment. Then occupants' comfort environment directly impacts on their satisfaction and productivity. We can determine the occupants' comfort index by three basic factors which are thermal comfort, visual comfort, and indoor air quality. Temperature is utilized to indicate the thermal comfort in a smart home. The auxiliary heating and cooling system are deployed to preserve the temperature in the comfort zone range. The illumination level is utilized to indicate the visual comfort in the building environment, which is measured in Lux [0, 1]. The electrical lighting system is utilized to manage visual comfort. CO_2 concentration is utilized as an index to measure the air quality in the building environment, and the ventilation system is utilized to preserve the low CO2 concentration.

Comfort index using Eq. (1.1).

$$\text{Comfort} = \alpha 1\ [1-(e_T/T_{set})^2] + \alpha 2\ [1-(e_L/L_{set})^2] + \alpha 3\ [1-(e_A/A_{set})^2] \qquad (1.1)$$

The range of comfort index is between [0, 1]. The comfort index varies between '0' and '1'. '0' means lowest or minimum comfort index and '1' means highest or maximum comfort index. α1, α2, α3 are the user defined factors which solve any possible conflict between the three comfort factors which are temperature, illumination and air-quality. Overall comfort is $\alpha1+\alpha2+\alpha3 = 1$. In (Eq. 1.1) e_T is the error difference between optimal parameter of rule based optimization (temperature in this case) and actual sensor temperature [0, 1]. The minimum error difference, the maximum will be the comfort index. Therefore, comfort index and error difference are opposite parameters to each other. As a result of that the error difference is an actual input to the fuzzy controller. e_L is the error difference between optimal parameter of rule based optimization (illumination in this case) and actual sensor illumination. e_A is the error difference between optimal parameter of rule based optimization and actual sensor air-quality. T_{set}, L_{set}, A_{set} are the user set parameters of temperature, illumination and air-quality.

2.6. Fuzzy logic and controllers

Fuzzy controller is a control system based on fuzzy logic. We use fuzzy controllers for temperature, illumination, and air quality. The proposed schemes use fuzzy controllers to get required power consumption. Error difference e_T and change in error ce_T (difference between current and previous error) between optimal parameters and indoor environment parameters are input to the fuzzy controller for temperature. The terms NB, NM, NS, ZE, PS, PM, and PB have been abbreviated for negative big, negative medium, negative small, zero, positive small, positive medium, and positive big. The input to the fuzzy controller for illumination is the error difference between the optimal parameter and real environmental illumination parameter.

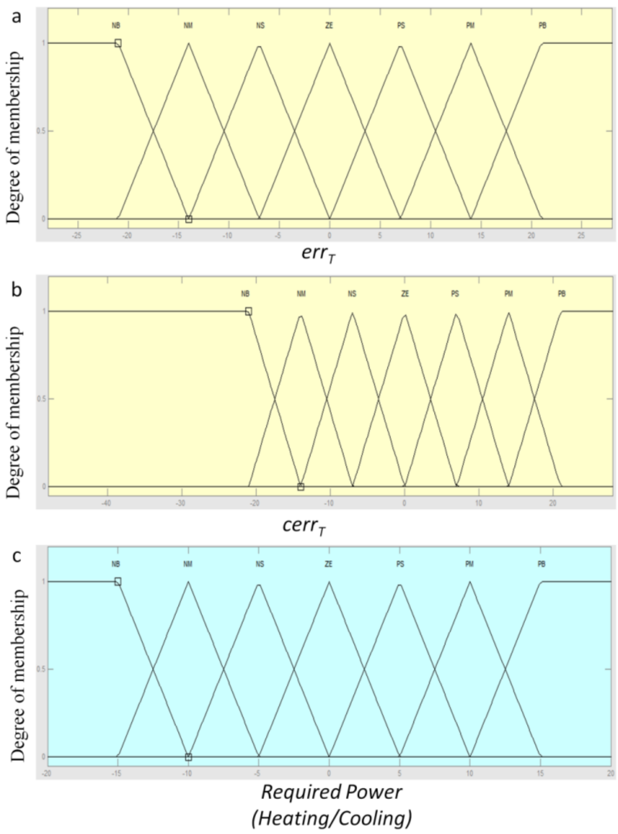

Figure 2.6 Input and output membership functions for temperature. (a) Input membership function of e_T , (b) Input membership function of ce_T , (c) Output membership function.

The input membership function is for the error which is the only input. If the input error is High Small the required output power would be OLittle. For error Medium Small (MS) the output power would be OMS. For Basic Small (BS) the required power would be OBS. For OK the output power would be OOK. For SH the required output power is OSH while for High, the required power is OH. The input to the fuzzy controller for air-quality is the error difference between optimized air-quality parameter and real environmental air-quality parameter.

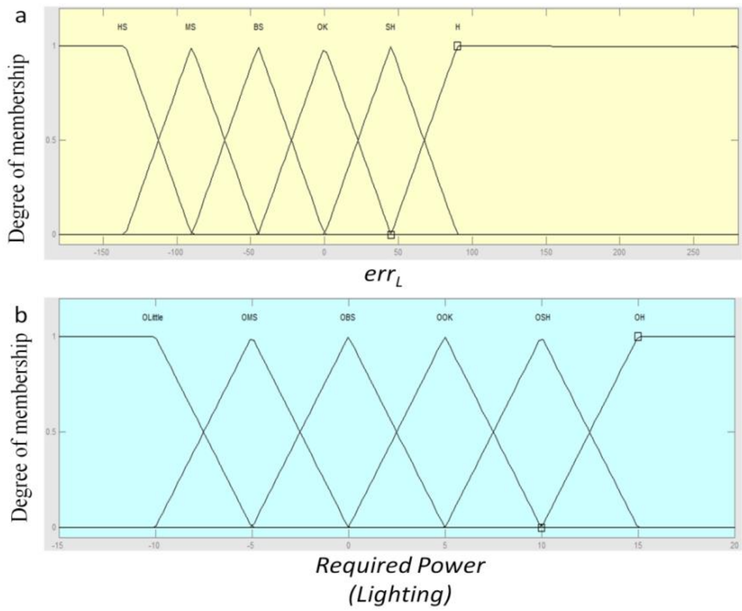

Figure 2.7 Input and output membership functions for illumination. (a) Input membership function of err_L (b) Output membership function

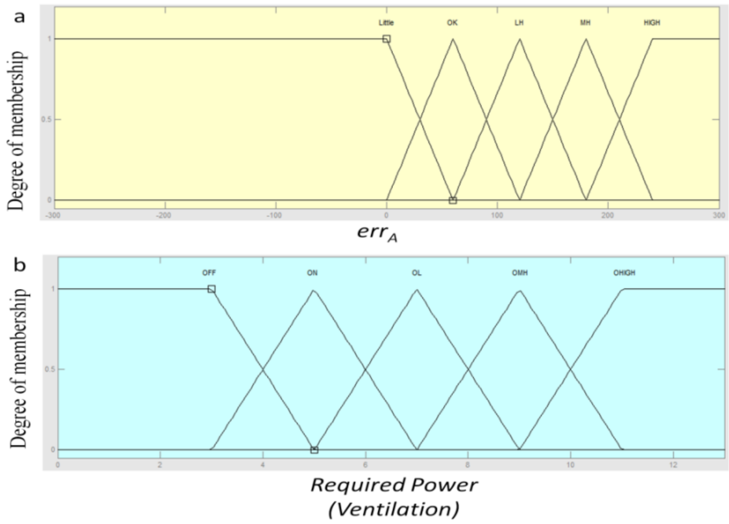

Figure 2.8 Input and output membership functions for air quality. (a) Input membership function of e_A (b) Output membership function

The input membership function is for the error which is the only input to the air quality fuzzy controller. If the input error is little, the required output power would be OFF. For OK, the output power would be ON. For LH the required power will be OL. For MH, the required power would be OMH, and for HIGH the required would be OHIGH. The output of the fuzzy controllers is the required power for each of the temperature, illumination and air-quality. The required power is input to the coordinator agent and comparator components.

Table 2.1 Fuzzy controller rules for temperature controller

Required Power		err_T						
		NB	NM	NS	ZE	PS	PM	PB
	NB	NB	NS	PS	PB	PB	PB	PB
	NM	NB	NM	ZE	PM	PM	PB	PB
	NS	NB	NM	NS	PS	PM	PB	PB
$cerr_T$	ZE	NB	NM	NS	ZE	PS	PM	PB
	PS	NB	NB	NM	NS	PS	PM	PB
	PM	NB	NB	NM	NM	ZE	PM	PB
	PB	NB	NB	NB	NB	NS	PS	PB

Table 2.2 Fuzzy controller rules for illumination control

Error	HS	MS	BS	OK	SH	H
Required Power	OHS	OMS	OBS	OOK	OSH	OH

Table 2.3 Fuzzy controller rules for air-quality control

Error	Little	OK	LH	MH	HIGH
Required Power	OFF	ON	OL	OMH	OHIGH

2.7. Coordinator agent

Required power from fuzzy controller and available power from source of power are input to the coordinator agent. Adjusted power is calculated for each temperature, illumination, and air-quality control. Figure 2.9 shows flowchart of coordinator agent. Required powers for temperature, illumination, and air quality are input to the coordinator agent. We calculate the total required power for the system. After checking the total power, whether less than the available power source or more than an available power source. If the total power is less than available power, take required power as adjusted power. Otherwise, customize adjusted power and finally we get adjusted powers for each temperature, illumination, air quality control.

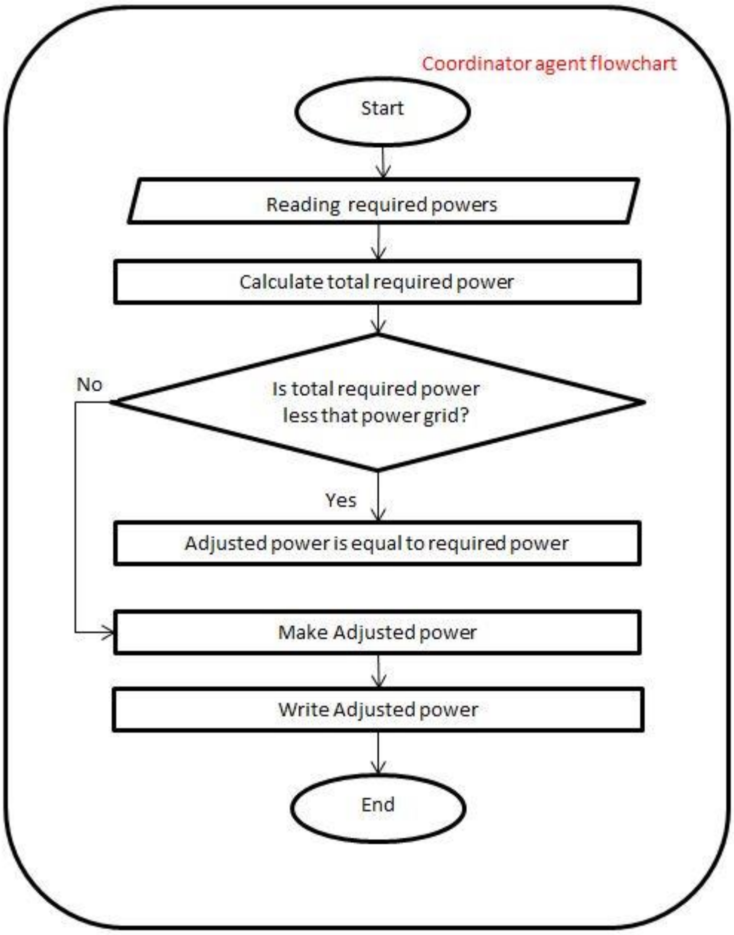

Figure 2.9 Flowchart of coordinator agent

2.8. Comparator

Required power from fuzzy controller and adjusted power from coordinator agent are input to the comparator to get actual consume power for each temperature, illumination, and air quality control. Finally, the actual consumed powers are input to the smart home actuators. Figure 2.10 shows a flow chart of comparator. It takes adjusted power and required power as input. Then checking condition, whether to adjust power is less than required power or not. If the condition is yes, take adjusted power as consumed power. If the condition is no, take required power as consumed power. Then write consumed power as a result.

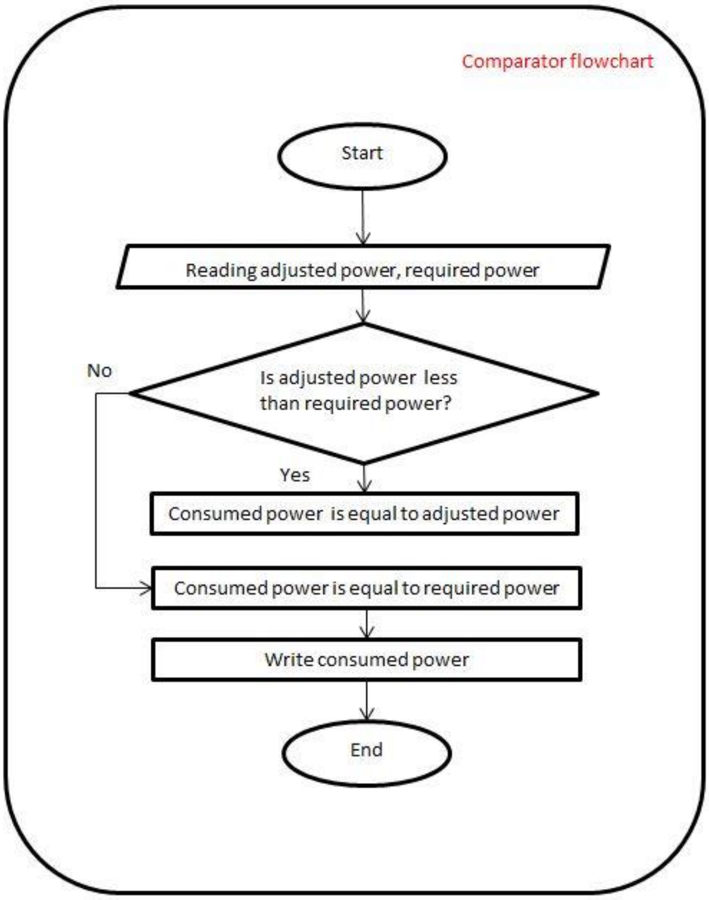

Figure 2.10 Flowchart of comparator

2.9. Smart home actuators

Smart home actuators are the devices which utilize the power in the smart home. The actuators are AC used for cooling, heater for heating in the home, and light for visual comfort and fan for providing air quality comfort. The consumed power calculated by comparator is given to the actuators to set its operational level in order to maintain user comfort in building environment.

3. Optimization scheme based on rule for reducing power consumption

3.1. Conceptual design of optimization scheme based on rule for reducing power consumption

In this section, we propose an optimization scheme based on rule for reducing power consumption approach in order to reduce power consumption.

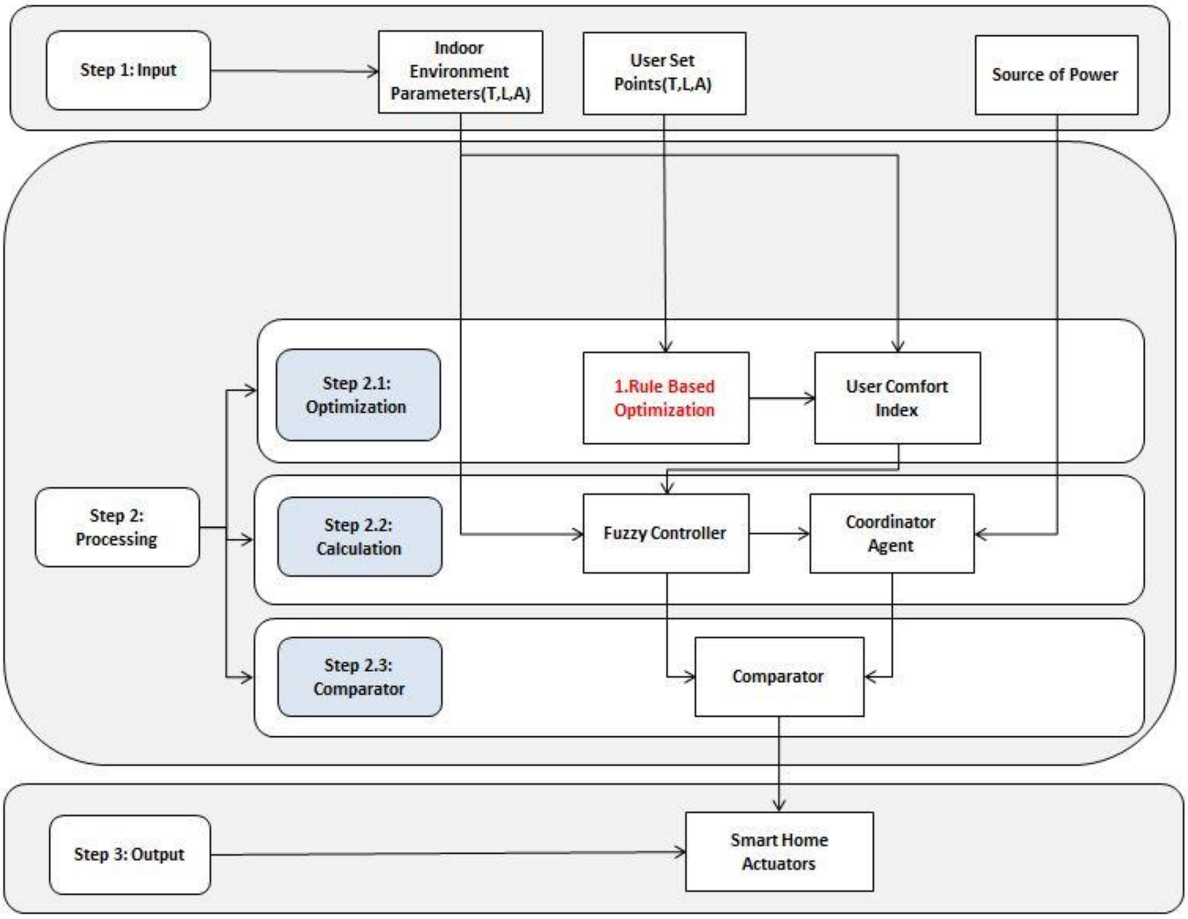

Figure 3.1 Conceptual design of an optimization scheme based on rule for reducing power consumption

Figure 3.1 shows conceptual design of optimization scheme based on rule which illustrates concepts of the rule based optimization scheme for reducing power consumption. Conceptual design includes three basic steps which are input, processing, and output. In step1, we have indoor environment parameters (temperature, illumination, and air-quality), user set points (temperature, illumination, and air-quality), and source of power. In step2, it includes three sub steps which are optimization, calculation, and comparison. In step2.1, it includes rule based optimization and user comfort index. In step2.2, it includes fuzzy controller and coordinator agent. In step 2.3, it includes comparator. Then, in step3, it includes smart home actuators.

3.2. Block diagram of optimization scheme based on rule for reducing power consumption

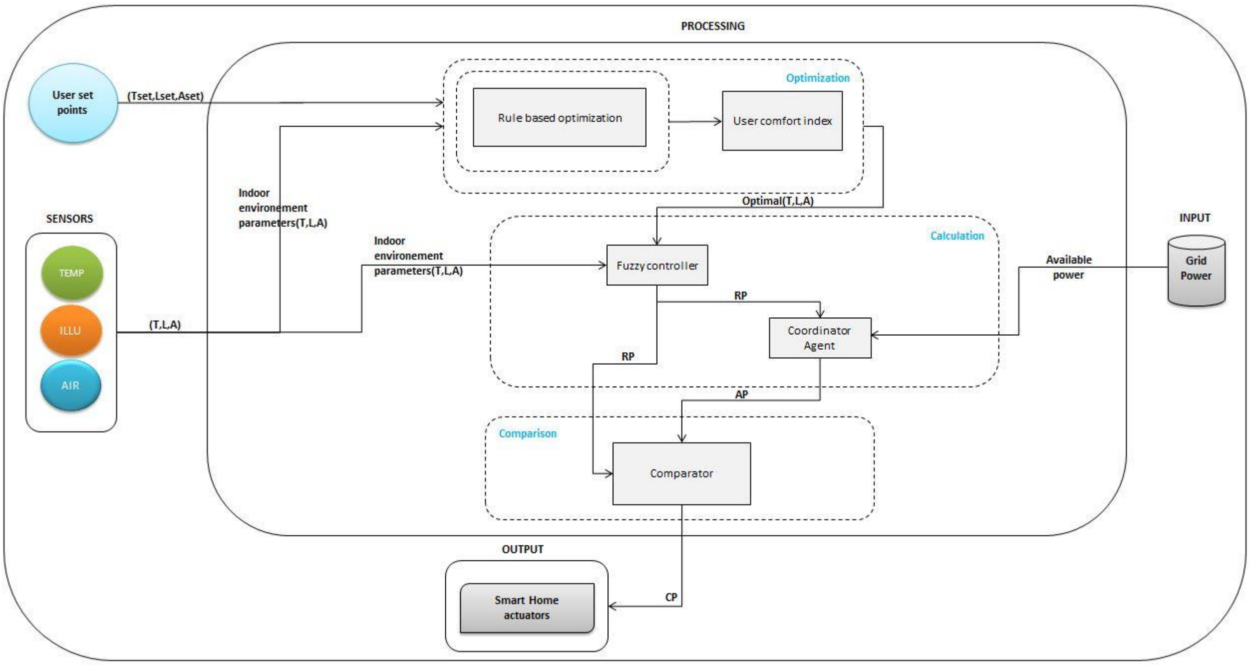

Figure 3.2 Block diagram of optimization scheme based on rule for reducing power consumption

Figure 3.2 shows block diagram of optimization scheme based on rule for reducing power consumption. Indoor environment parameters (temperature, illumination, and air quality) from sensors and user set points are input to the RBO optimizer for optimization. Then the optimized parameters are input to user comfort index to calculate the user comfort index.

Figure 3.3 shows overall architecture of rule based optimization scheme. Minimum and maximum set point ranges of temperature, illumination, and air quality are input to the rule based optimization. Also current home temperature, illumination, and air quality are input to the rule based optimization.

Then optimal parameters for temperature, illumination, and air quality are calculated separately. Each part is described below.

3.3. Optimization scheme based on rule

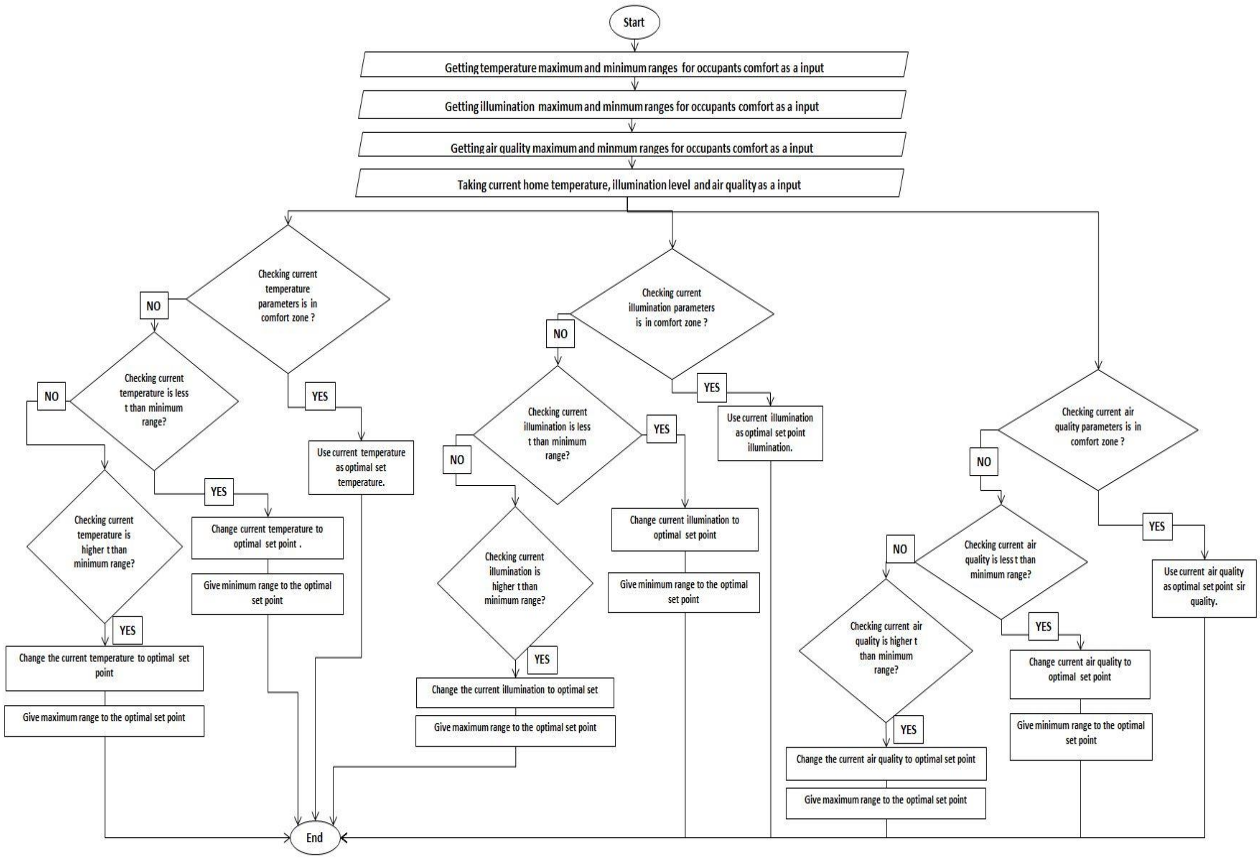

Figure 3.3 Flowchart design of optimization scheme based on rule

Figure 3.4 illustrates rule based optimization for temperature set point. We take temperature user set maximum, minimum ranges, and current environment parameter as input. Then checking current temperature parameter is whether in comfort zone or not. If the current temperature is in the comfort zone, we use current temperature parameter as a user set temperature point. If the current temperature as not in the comfort zone, If current temperature is not in comfort zone, we check current temperature is less than minimum range of temperature and if it is true, take the minimum range value as the user set point temperature.

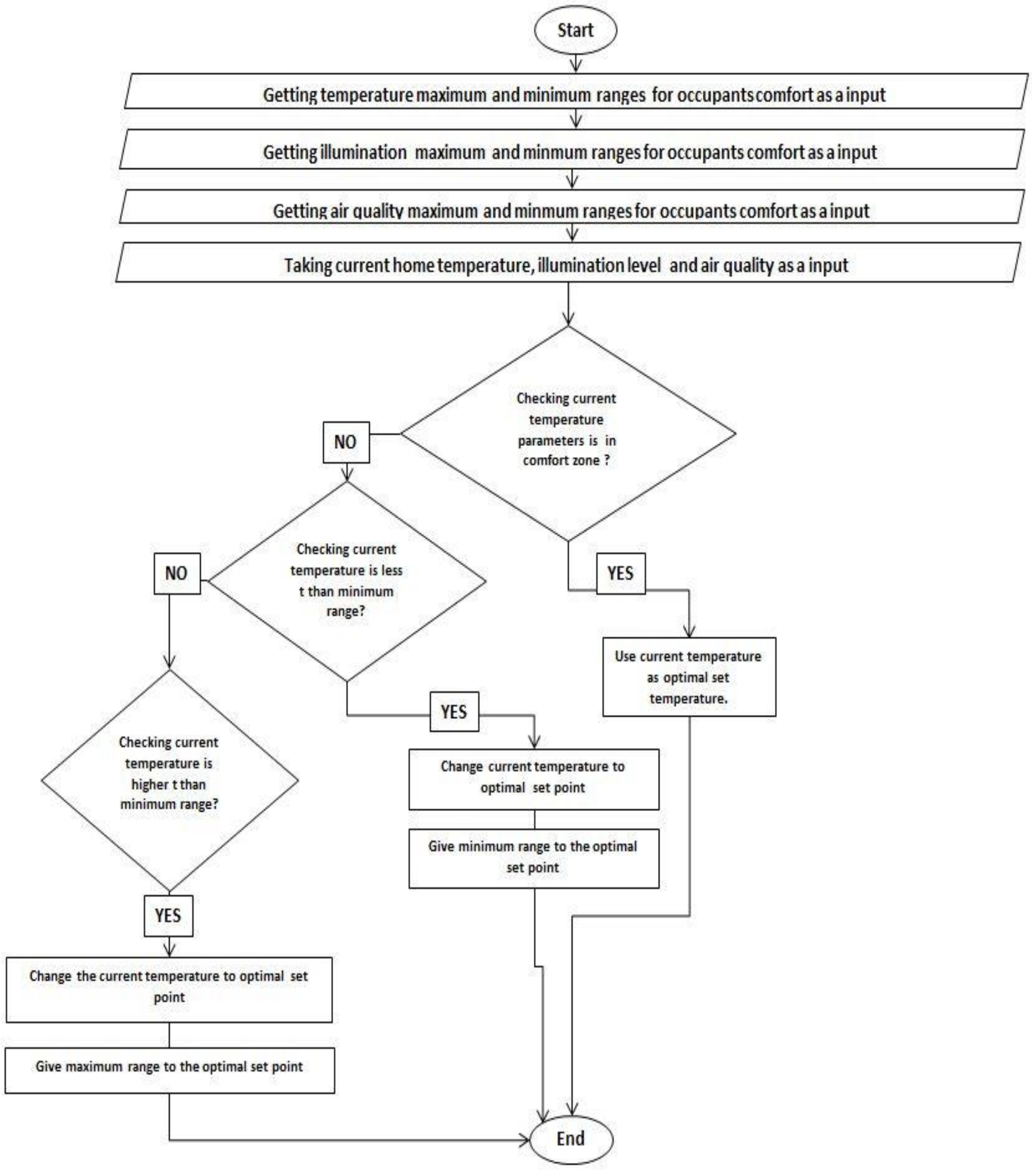

Figure 3.4 Optimization scheme based on rule for temperature set point

If the current temperature is less than minimum range condition is false, we check another condition to find optimal temperature set point. The condition is that the current temperature is higher than the maximum range of temperature, if the condition is true, we take the maximum range value as the user set point temperature.

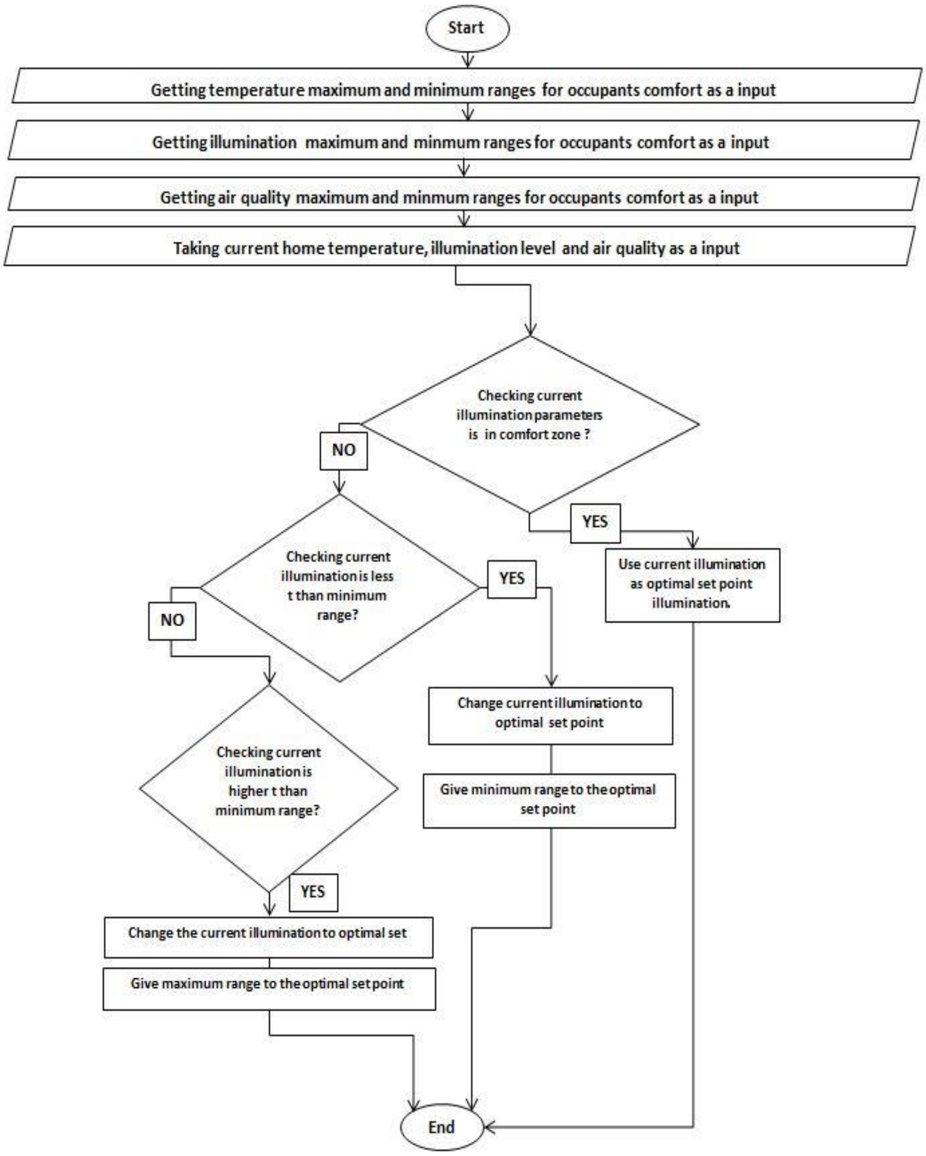

Figure 3.5 Optimization scheme based on the rule for illumination set point

Figure 3.5 illustrates rule based optimization for illumination set point. For illumination optimal set point, we do similar actions to find optimal user set point. Therefore, checking current illumination parameter is whether in comfort zone or not. If the current illumination is in the comfort zone, we use the current illumination parameter as a user set illumination point. If current illumination is not in comfort zone, we check current illumination is less than minimum range of illumination and if it is true, take the minimum range value as the user set illumination point. If the current illumination is less than minimum range condition is false, we check another condition to find optimal illumination set point. The condition is that current illumination is higher than the maximum range of illumination, if the condition is true, we take the maximum range value as the user set illumination point.

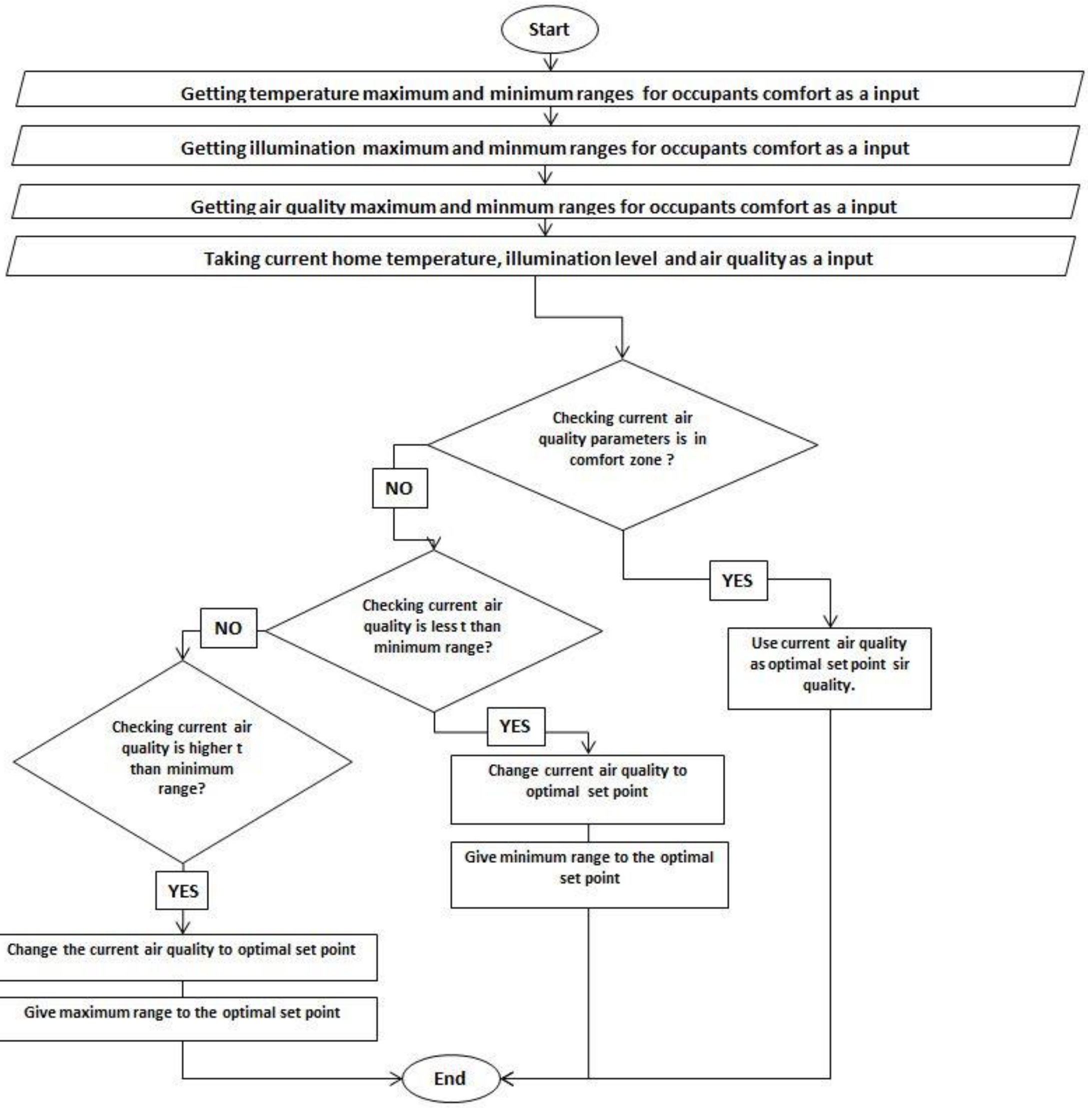

Figure 3.6 Optimization scheme based on rule for air quality set point

Figure 3.6 illustrates rule based optimization for air quality set point. For air quality optimal set point, checking current air quality parameter is whether in comfort zone or not. If the current air quality is in the comfort zone, we use the current air quality parameter as a user set air quality point. If current air quality is not in comfort zone, we check current air quality is less than minimum range of air quality and if it is true, take the minimum range value as the user set air quality point. If the current air quality is less than minimum range condition is false, we check another condition to find optimal air quality set point. The condition is that current air quality is higher than the maximum range of air quality, if the condition is true, we take the maximum range value as the user set air quality point.

3.4. Simulation result of optimization scheme based on rule for reducing power consumption

In order to evaluate performance of our proposed Rule based optimization scheme, we have developed and simulator in Visual Studio 2013 using c#. User preference set parameters range was Tset = [66, 78] (Kelvin), Lset = [720, 880] (lux), and Aset = [700, 880] (ppm). Brief detail of system configuration is given in Table 3.1.

Table 3.1 Simulation Environment

Module	Hardware	Software	Remark
Virtual sensing data for temperature, illumination, and air-quality	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7
Optimization of user set parameters (temperature, illumination, and air-quality)	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7
Dynamic user set point settings for multi-users	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7
Prediction of indoor environment parameters for temperature, illumination, and air-quality	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7

The environmental configuration remains the same for all the experiments. The uniform configuration helps in the comparison of results with existing techniques. We developed the simulator by using .Net programming environment with the configuration shown in Table 3.1.

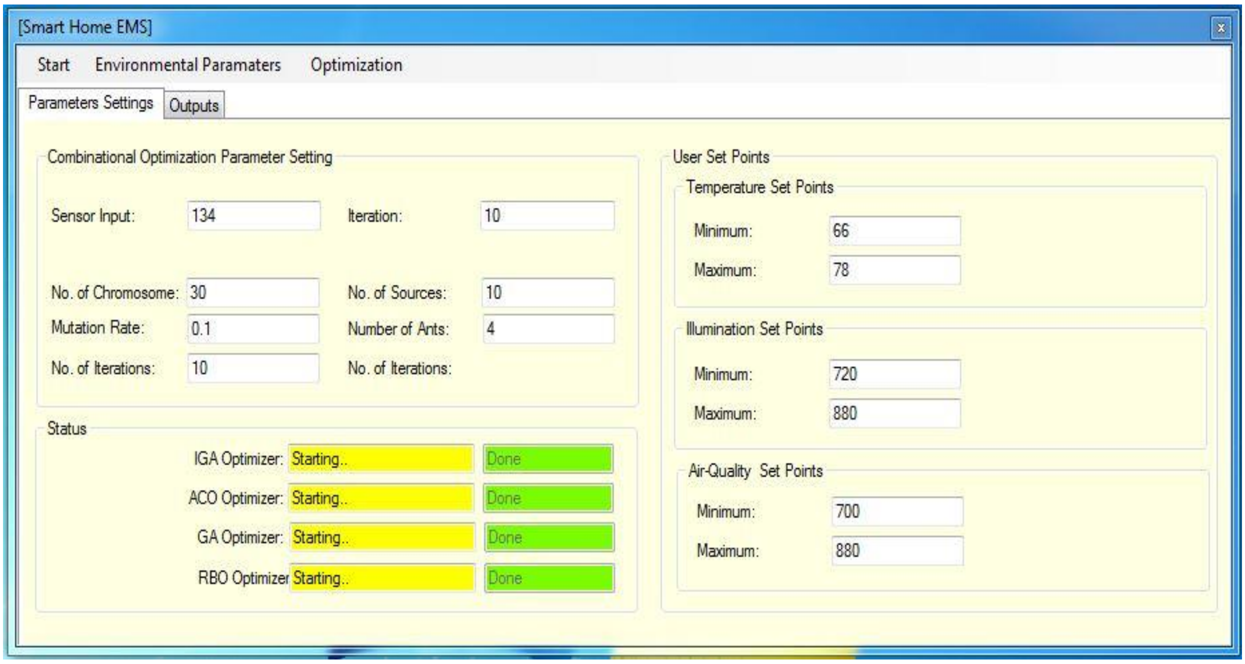

Figure 3.7 Simulation of optimization algorithms

Figure 3.7 shows a simulation of optimization algorithms which are incremental genetic algorithm (IGA), ant colony optimization (ACO), genetic algorithm (GA), and rule based optimization (RBO). 134 simulation sensor inputs input to the system. Chromosomes, mutation rate and number of iterations are input to the system in order to perform GA, and IGA. Then number of sources, number of ants, and iteration are input to the system in order to perform ACO. Then user set points are input to the system for temperature, illumination, and air quality. For temperature, the minimum range is 66 and maximum range is 78. For illumination, the minimum range is 720 and maximum range is 880. For air quality, the minimum range is 700 and maximum range is 880.

Figure 3.8 shows a comparison of rule based optimization power consumption and genetic algorithm based power consumption for temperature. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. From the graph, we can see that the system using rule based optimization consumed less power each hour compared than a system using GA. RBO based power consumption starts from 11.6075kwt at 1o'clock. Then GA based power consumption starts from 13.3kwt at the same time. Therefore, this due to the fact that optimized parameters for temperature control based on RBO are more efficient and consuming less power compared as GA.

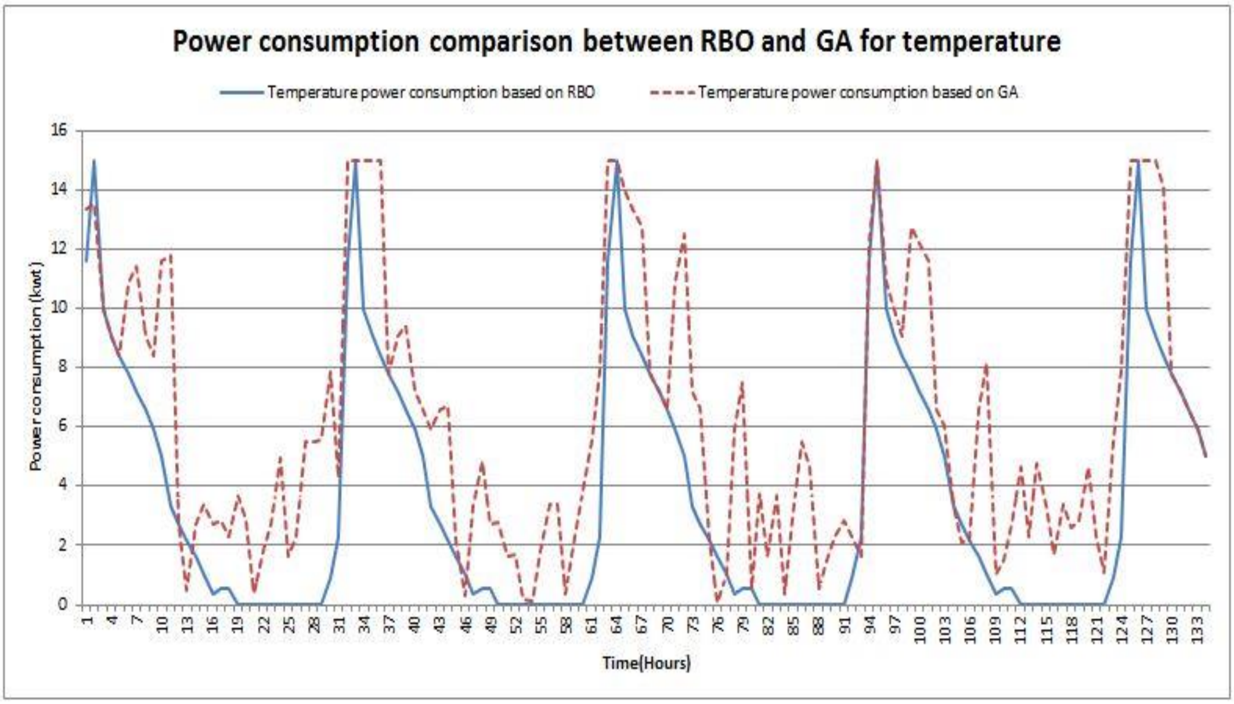

Figure 3.8 Power consumption comparison between RBO and GA for temperature

Figure 3.9 shows a comparison of rule based optimization power consumption and genetic algorithm based power consumption for illumination. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. From the graph, we can see that the system using rule based optimization consumed less power each hour compared than a system using GA. RBO based power consumption starts from 14.9kwt at 2o'clock. Then GA based power consumption starts from 15kwt at the same time. Therefore, this due to the fact that optimized parameters for illumination control based on RBO are more efficient and consuming less power compared as GA.

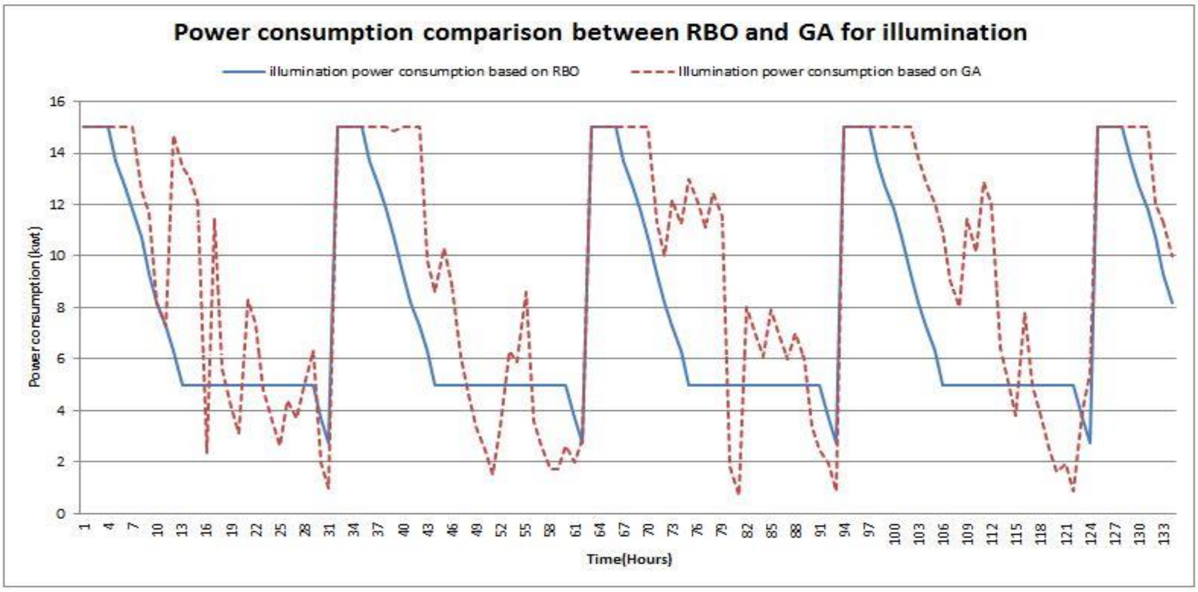

Figure 3.9 Power consumption comparison between RBO and GA for illumination

Similarly, Figure 3.10 shows a comparison of rule based optimization power consumption and genetic algorithm based power consumption for air quality. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. From the graph, we can see that the system using rule based optimization consumed less power each hour compared than a system using GA. RBO based power consumption starts from 2.66kwt at 1o'clock. Then GA based power consumption starts from 3.33kwt at the same time. Therefore, this due to the fact that optimized parameters for air quality control based on RBO are consuming less power compared as GA.

Table 3.2 shows a comparison of total power consumption for each control. For temperature control, RBO based power consumption consumed total 494.907kwt power. At the same time, GA based power consumption consumed 834.593kwt power. As a result, we can see the huge power consumption difference between RBO based power consumption and GA based power consumption. Then we can see that RBO based power consumption is way better than GA based power consumption in this system. For illumination control, RBO based power consumption consumed total 1052.34kwt power. At the same time, GA based power consumption consumed 1261.57kwt power. As a result, we can see the big power consumption difference between RBO based power consumption and GA based power consumption.

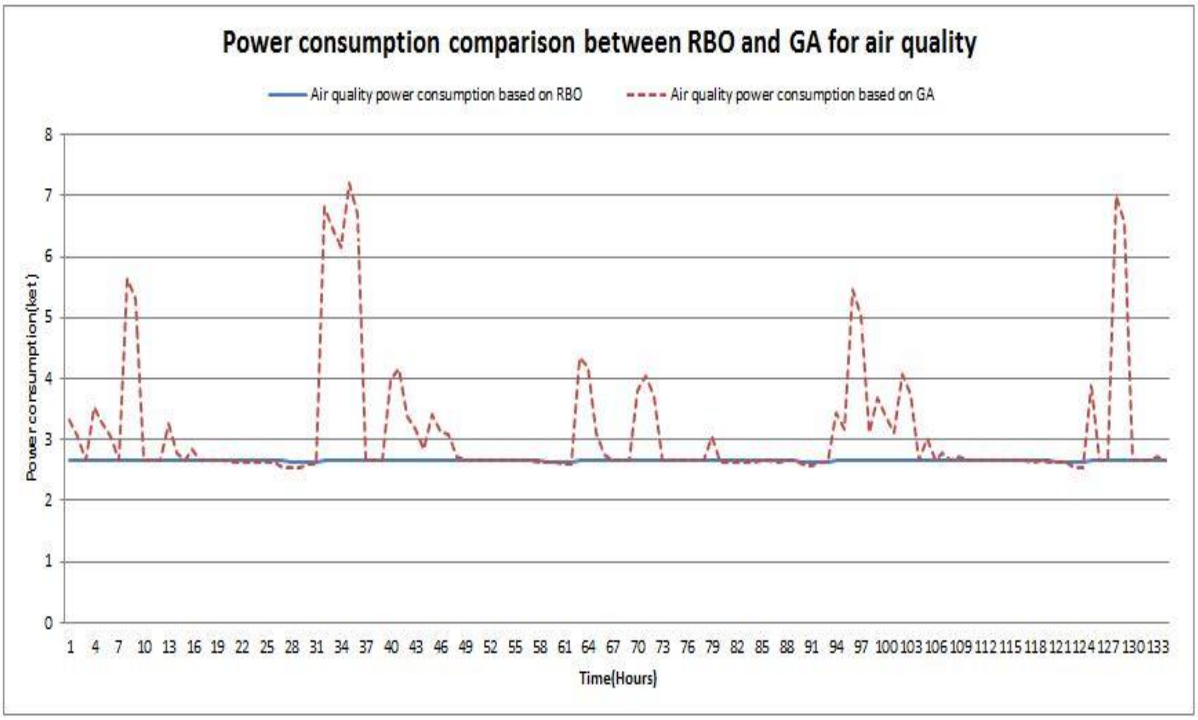

Figure 3.10 Power consumption comparison between RBO and GA for air quality

Table 3.2 Total power consumption comparison of RBO and GA

	Temperature	Illumination	Air quality	TOTAL
RBO based power consumption	494.907	1052.34	365.663	1903.91
GA based power consumption	834.593	1261.57	419.65	2515.82

This due to the fact that RBO based power consumption consumes less power than GA based power consumption in this system. Similarly, for air quality control, RBO based power consumption consumed total 365.663kwt power. At the same time, GA based power consumption consumed 419.65kwt power. As a result, we can see the much power consumption difference between RBO based power consumption and GA based power consumption. Then we can see that for air quality, RBO based power consumption consumes less power than GA based power consumption in this system. Finally, we have total consumed power from each power consumption scheme using RBO and GA. Then total power consumption of RBO was 1903.91kwt and total power consumption of GA was 2515.82kwt. Therefore, we can conclude that RBO based power consumption consumed less power compared as GA based power consumption.

Figure 3.11 shows a comparison of rule based optimization power consumption and incremental genetic algorithm based power consumption for temperature. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. From the graph, we can see that the system using rule based optimization consumed less power each hour compared than a system using IGA. RBO based power consumption starts from 10kwt at 3o'clock. Then IGA based power consumption starts from 10.9kwt at the same time. Therefore, this due to the fact that optimized parameters for temperature control based on RBO are more efficient and consuming less power compared as IGA.

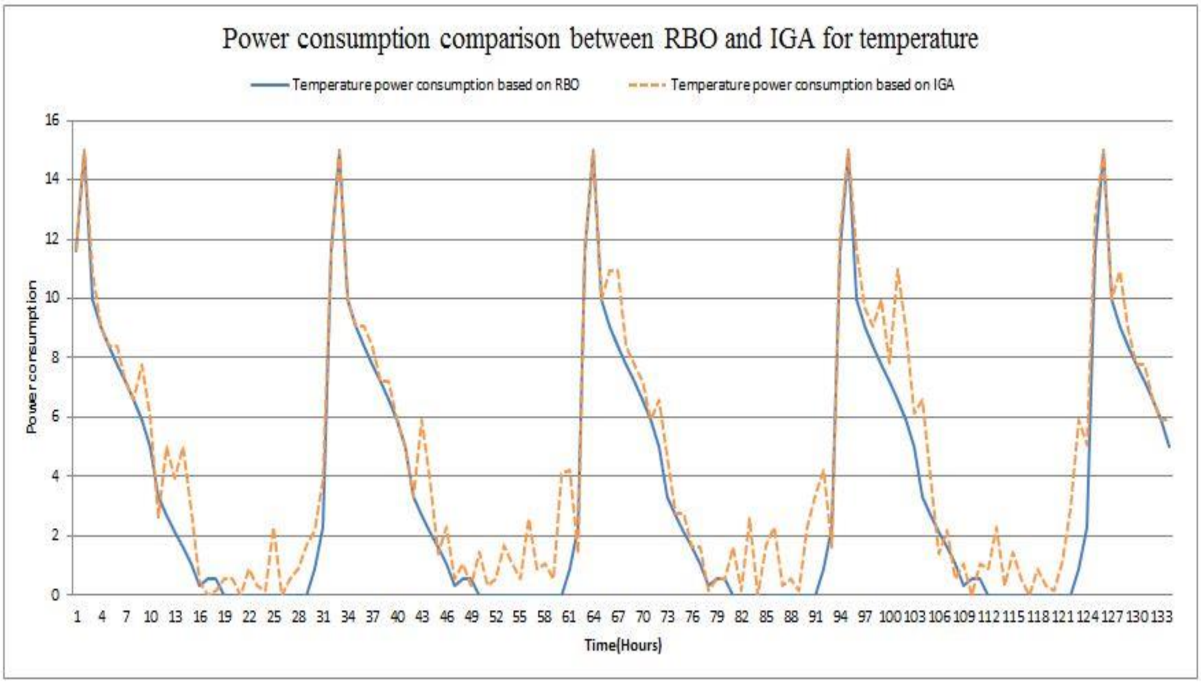

Figure 3.11 Power consumption comparison between RBO and IGA for temperature

Figure 3.12 shows a comparison of rule based optimization power consumption and incremental genetic algorithm based power consumption for illumination. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. From the graph, we can see that the system using rule based optimization consumed less power each hour compared than a system using IGA. RBO based power consumption starts from 14.9kwt at 2o'clock. Then IGA based power consumption starts from 15kwt at the same time. Then we can see that for illumination, RBO based power consumption consumes less power than IGA based power consumption in this system.

Similarly, Figure 3.13 shows a comparison of rule based optimization power consumption and incremental genetic algorithm based power consumption for air quality. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts.

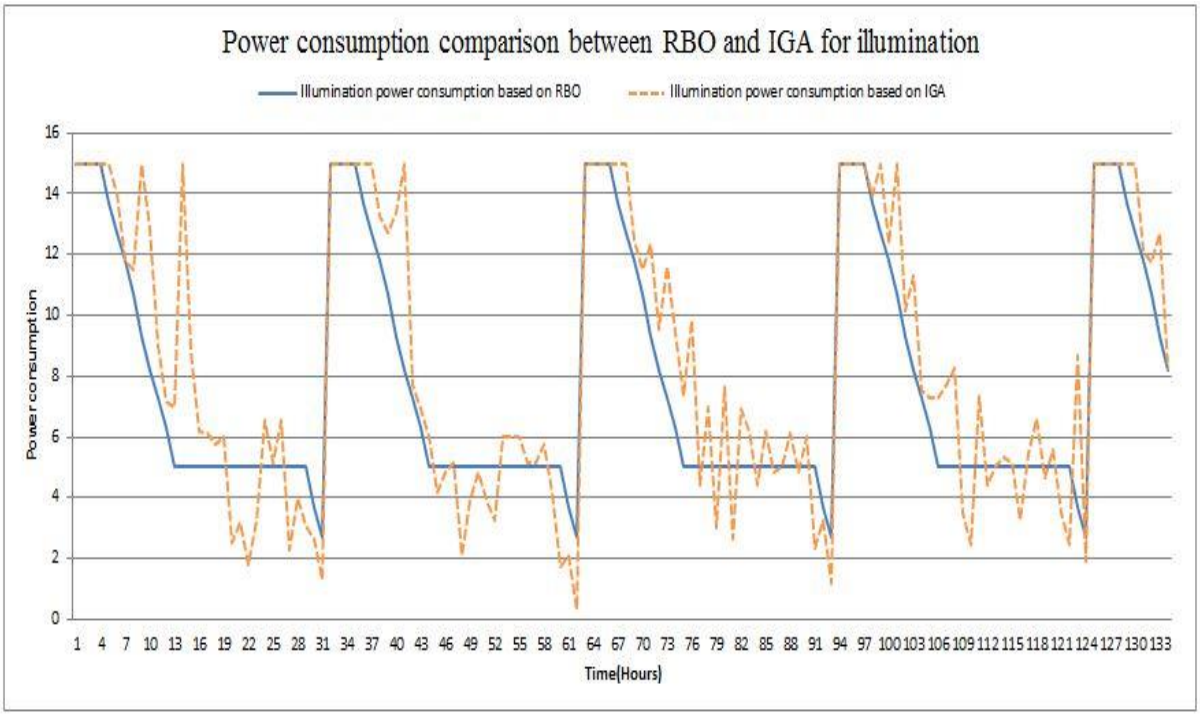

Figure 3.12 Power consumption comparison between RBO and IGA for illumination

From the graph, we can see that the system using rule based optimization consumed less power each hour compared than a system using IGA. RBO based power consumption starts from 2.66kwt at 1o'clock. Then IGA based power consumption starts from 3.07kwt at the same time. From the result we can see that power consumption based on RBO consumes less power compared as IGA.

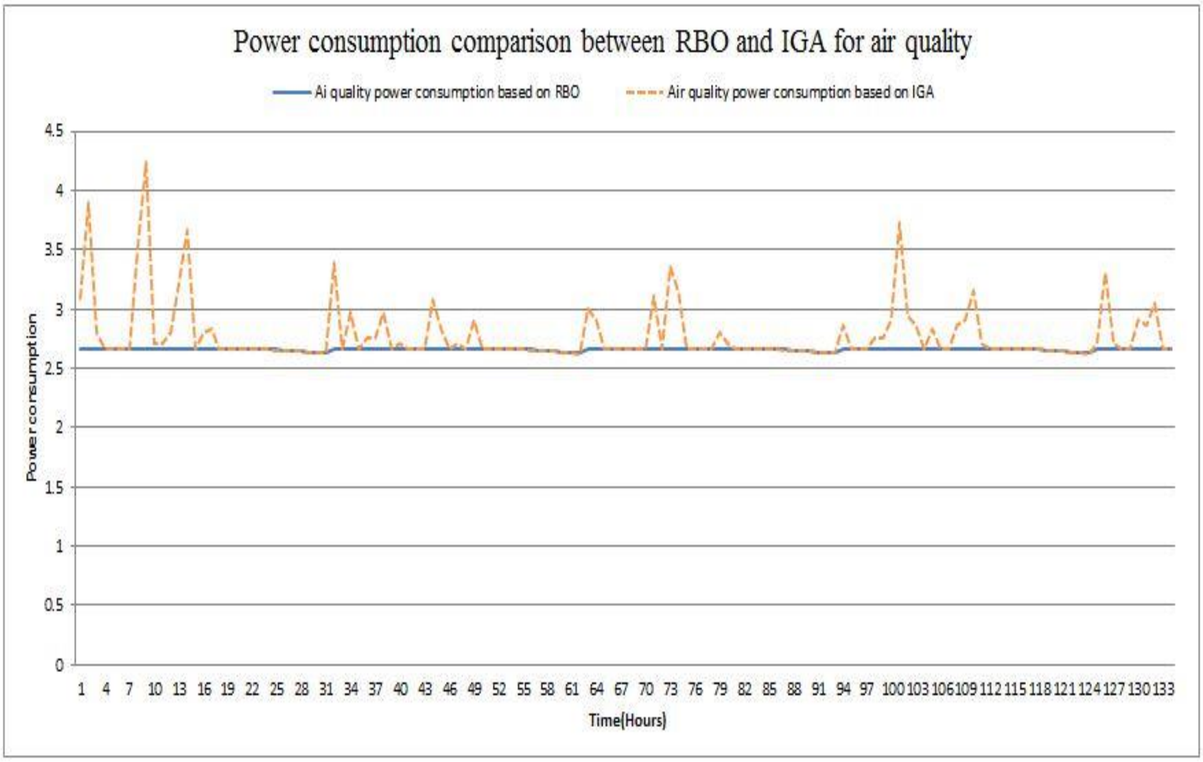

Figure 3.13 Power consumption comparison between RBO and IGA for air quality

Table 3.3 Total power consumption comparison of RBO and IGA

	Temperature	Illumination	Air quality	TOTAL
RBO based power consumption	494.907	1052.34	365.663	1903.91
IGA based power consumption	614.214	1135.18	372.416	2121.81

Table 3.3 shows a comparison of total power consumption for each control. For temperature control, RBO based power consumption consumed total 494.907kwt power. At the same time, IGA based power consumption consumed 614.214kwt power. As a result, we can see that power consumption difference between RBO based power consumption and IGA based power consumption. Then we can

see that RBO based power consumption is consuming less power compare than IGA based power consumption in this system. For illumination control, RBO based power consumption consumed total 1052.34kwt power. At the same time, IGA based power consumption consumed 1135.18kwt power. As a result, we can see the much power consumption difference between RBO based power consumption and IGA based power consumption. This due to the fact that RBO based power consumption consumes less power than IGA based power consumption for illumination control in this system. Similarly, for air quality control, RBO based power consumption consumed total 365.663kwt power. At the same time, IGA based power consumption consumed 372.416kwt power. As a result, we can see the much power consumption difference between RBO based power consumption and IGA based power consumption. Then we can see that for air quality, RBO based power consumption consumes less power than IGA based power consumption in this system. Lastly, we have total consumed power from each power consumption scheme using RBO and IGA. Then total power consumption of RBO was 1903.91kwt and total power consumption of GA was 2121.81kwt. As a conclusion, we can say that RBO based power consumption consumed less power compared as IGA based power consumption.

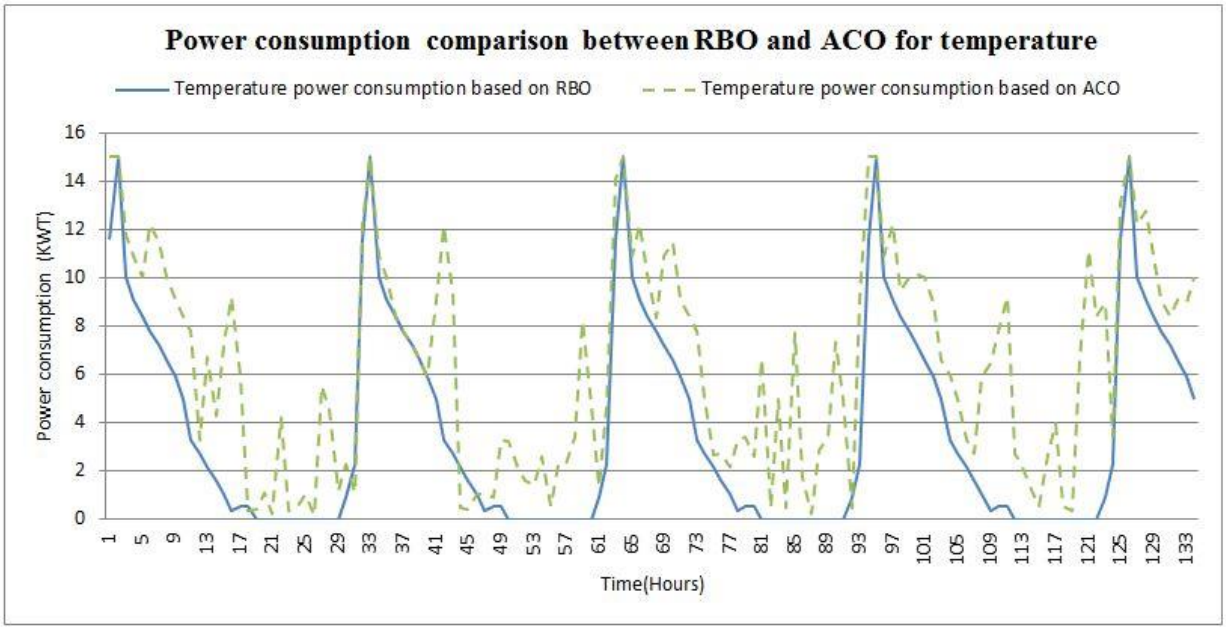

Figure 3.14 Power consumption comparison between RBO and ACO for temperature

Figure 3.14 shows a comparison of rule based optimization power consumption and ant colony optimization algorithm based power consumption for temperature. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. From the graph, we can see that the system using rule based optimization consumed less power each hour compared than a system using ACO. RBO based power consumption starts from 11.6075kwt at 1o'clock. Then ACO based power consumption starts from 15.0056kwt at the same time. Therefore, this due to the fact that optimized parameters for temperature control based on RBO are more efficient and consuming less power compared as ACO.

Figure 3.15 shows a comparison of rule based optimization power consumption and ant colony optimization algorithm based power consumption for illumination. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. From the graph, we can see that the system using rule based optimization consumed less power each hour compared than a system using ACO. RBO based power consumption starts from 14.994kwt at 2o'clock. Then ACO based power consumption starts from 14.999kwt at the same time. Therefore, this due to the fact that optimized parameters for illumination control based on RBO are more efficient and consuming less power compared as ACO.

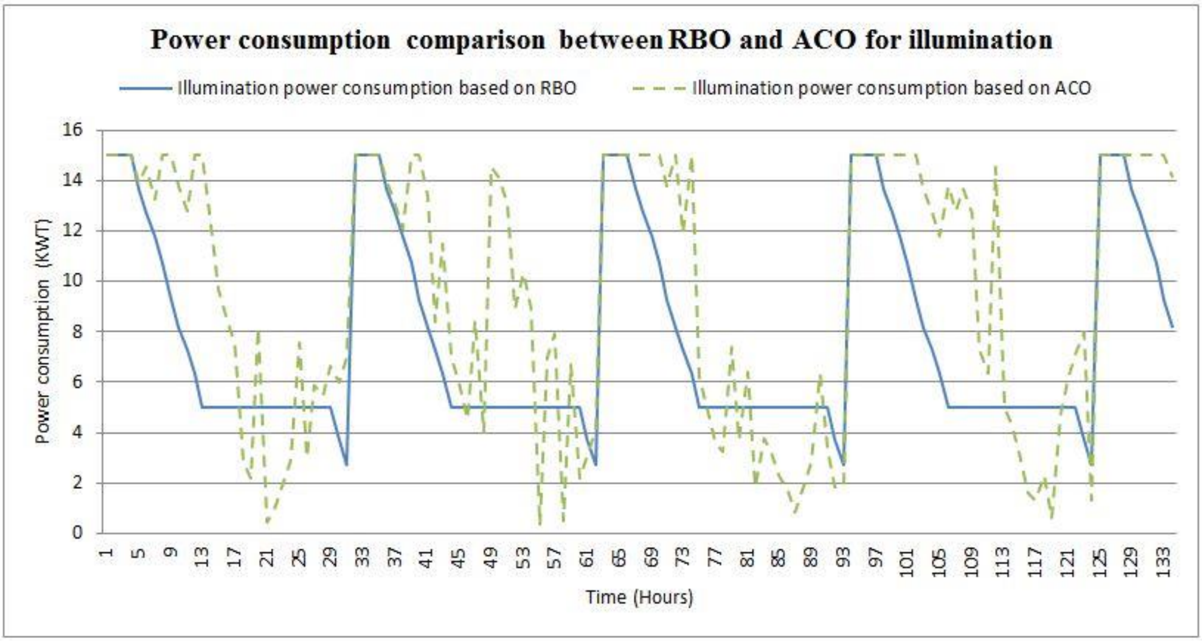

Figure 3.15 Power consumption comparison between RBO and ACO for illumination

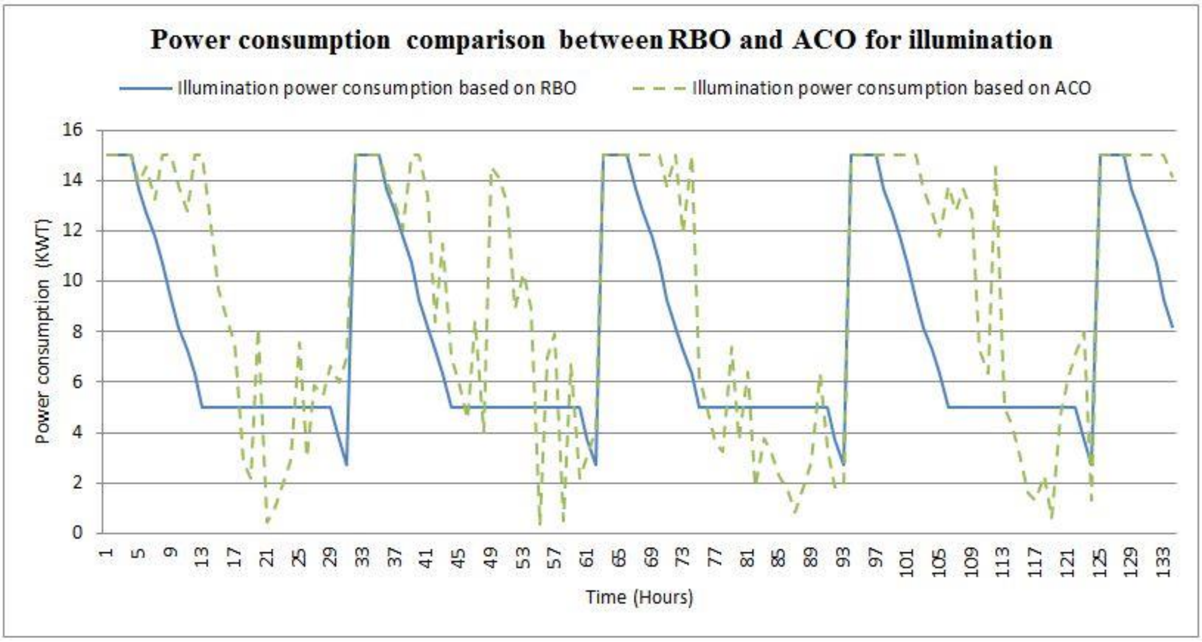

Figure 3.16 Power consumption comparison between RBO and GA for air quality

Similarly, Figure 3.16 shows a comparison of rule based optimization power consumption and ant colony optimization algorithm based power consumption for air quality. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. From the graph, we can see that the system using rule based optimization consumed less power each hour compared than a system using ACO. RBO based power consumption starts from 2.66kwt at 1o'clock. Then ACO based power consumption starts from 3.61kwt at the same time. Therefore, this due to the fact that optimized parameters for air quality control based on RBO are consuming less power compared as ACO.

Table 3.4 shows a comparison of total power consumption for each control. For temperature control, RBO based power consumption consumed total 494.907kwt power. At the same time, ACO based power consumption consumed 848.524kwt power. As a result, we can see the huge power consumption difference between RBO based power consumption and ACO based power consumption. Then we can see that RBO based power consumption is way better than ACO based power consumption in this system. For illumination control, RBO based power consumption consumed total 1052.34kwt power. At the same time, ACO based power consumption consumed 1273.39kwt power. As a result, we can see the big power consumption difference between RBO based power consumption and ACO based power consumption.

Table 3.4 Total power consumption comparison of RBO and ACO

	Temperature	Illumination	Air quality	TOTAL
RBO based power consumption	494.907	1052.34	365.663	1903.91
ACO based power consumption	848.524	1273.39	441.574	2563.49

This due to the fact that RBO based power consumption consumes less power than ACO based power consumption in this system. Similarly, for air quality control, RBO based power consumption consumed total 365.663kwt power. At the same time, ACO based power consumption consumed 441.574kwt power. As a result, we can see the much power consumption difference between RBO based power consumption and ACO based power consumption. Then we can see that for air quality, RBO based power consumption consumes less power than ACO based power consumption in this system. Finally, we have total consumed power from each power consumption scheme using RBO and ACO. Then total power consumption of RBO was 1903.91kwt and total power consumption of ACO was 2563.49kwt. Therefore, we can conclude that RBO based power consumption consumed less power compared as ACO based power consumption.

4. Optimization scheme based on dynamic user setting for multi-user

4.1. Conceptual design of optimization scheme based on dynamic user setting for multi-user

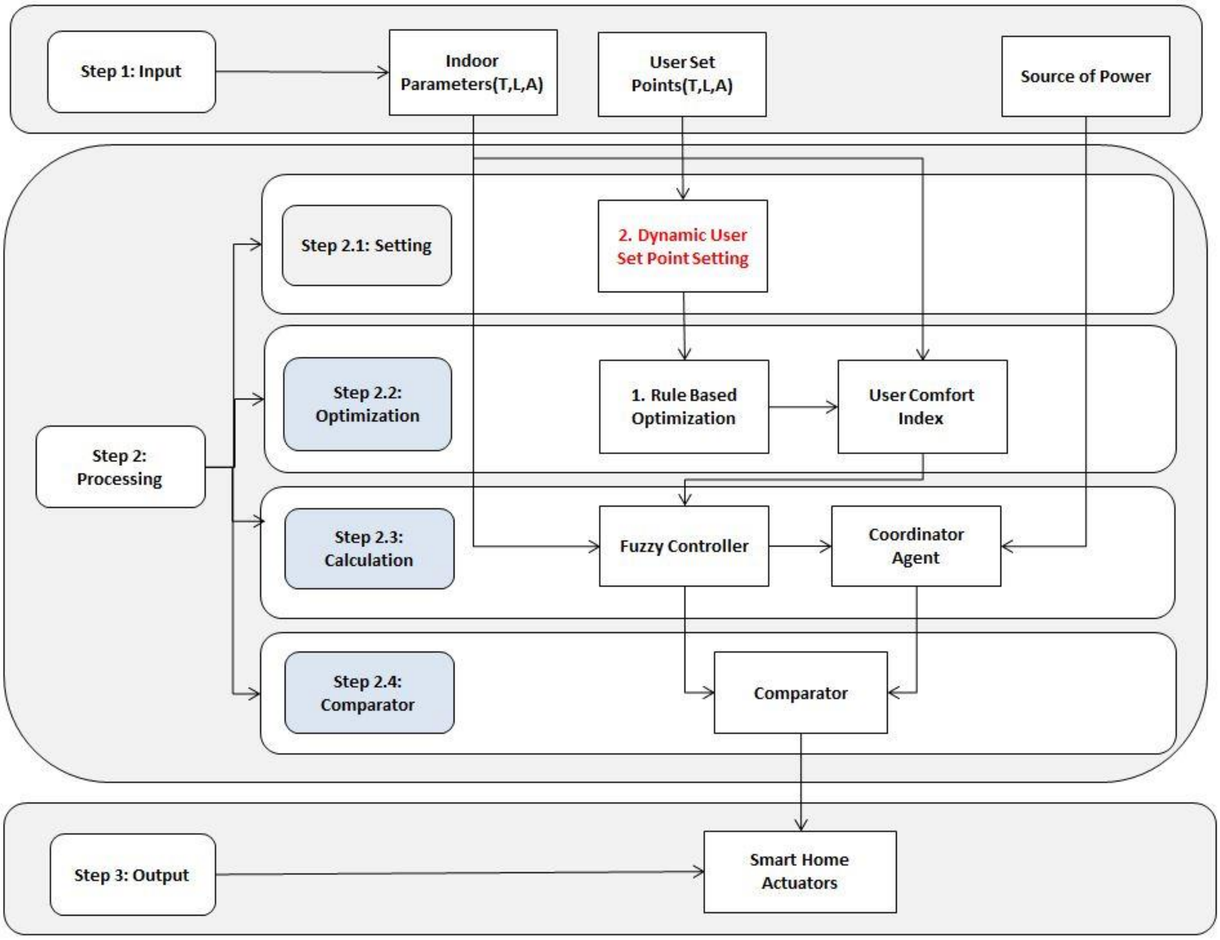

Figure 4.1 Conceptual design of optimization scheme based on dynamic user setting for multi-user

Figure 4.1 shows the conceptual design of an optimization scheme based on dynamic user setting for multi users. Conceptual design includes three basic steps which are input, processing, and output. In step1, we have indoor environment parameters (temperature, illumination, and air-quality), user set points (temperature, illumination, and air-quality), and source of power. In step2, it includes four sub steps which are setting, optimization, calculation, and comparison. In step2.1, it includes dynamic user set point setting. In step 2.2, it includes rule based optimization and user comfort index. In step2.3, it includes fuzzy controller and coordinator agent. In step 2.4, it includes comparator. Then, in step3, it includes smart home actuators.

4.2. Block diagram of optimization scheme based on dynamic user setting for multi-user

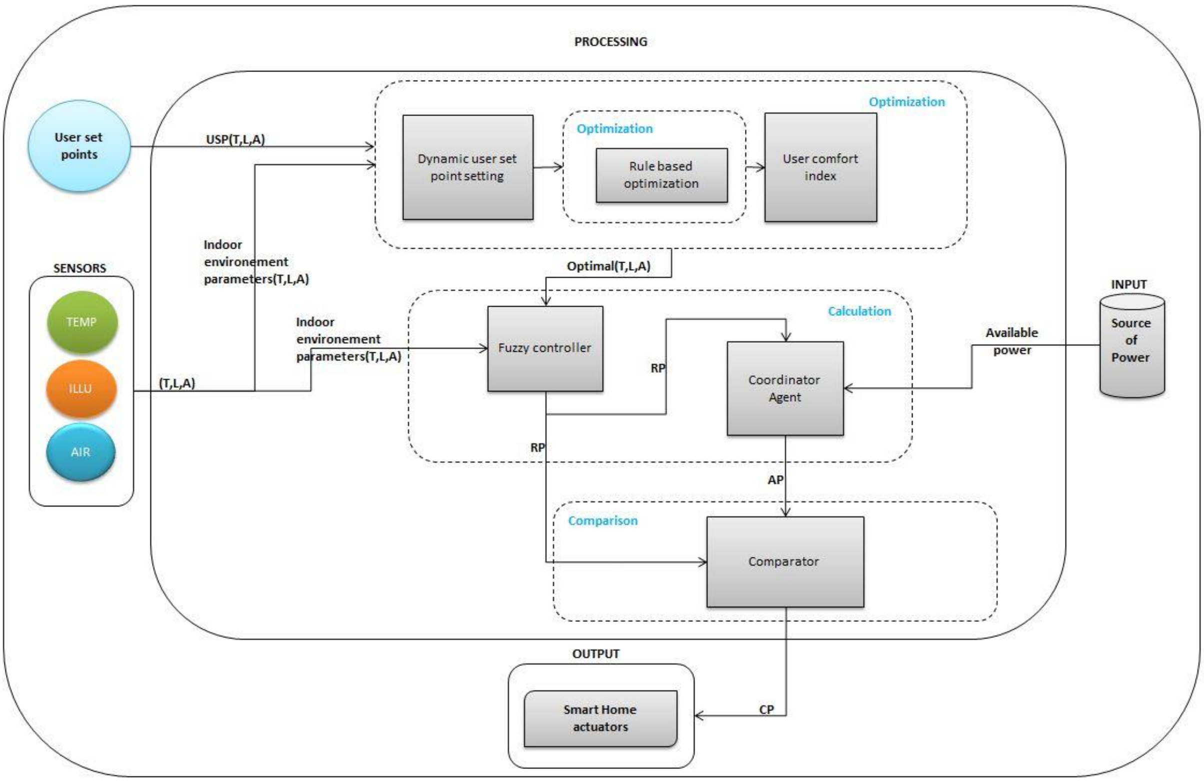

Figure 4.2 Block diagram of optimization scheme based on dynamic user setting for multi-user

Figure 4.2 shows a block diagram of an optimization scheme based on dynamic user setting for multi-user. User set points of multi user are input to the dynamic user set point setting. Then indoor environment parameters (temperature, illumination, and air quality) from sensors and multi user set points from dynamic user set point setting are input to the RBO optimizer for optimization. Then the optimized parameters are input to user comfort index to calculate the user comfort index. Then optimized parameters from RBO and predicted indoor environment parameters are input to the fuzzy controller to calculate required power for temperature, illumination, and air quality. Then the coordinator agent adjusted the power, according to the required power from the fuzzy controllers and available power from the source of power. Then comparator takes required power from fuzzy controller and adjusted power from coordinator agent. Then consumed power from the comparator is input to smart home actuators which are devices utilized the power inside the smart home.

4.3. Design of optimization scheme based on dynamic user setting for multi-users in smart home

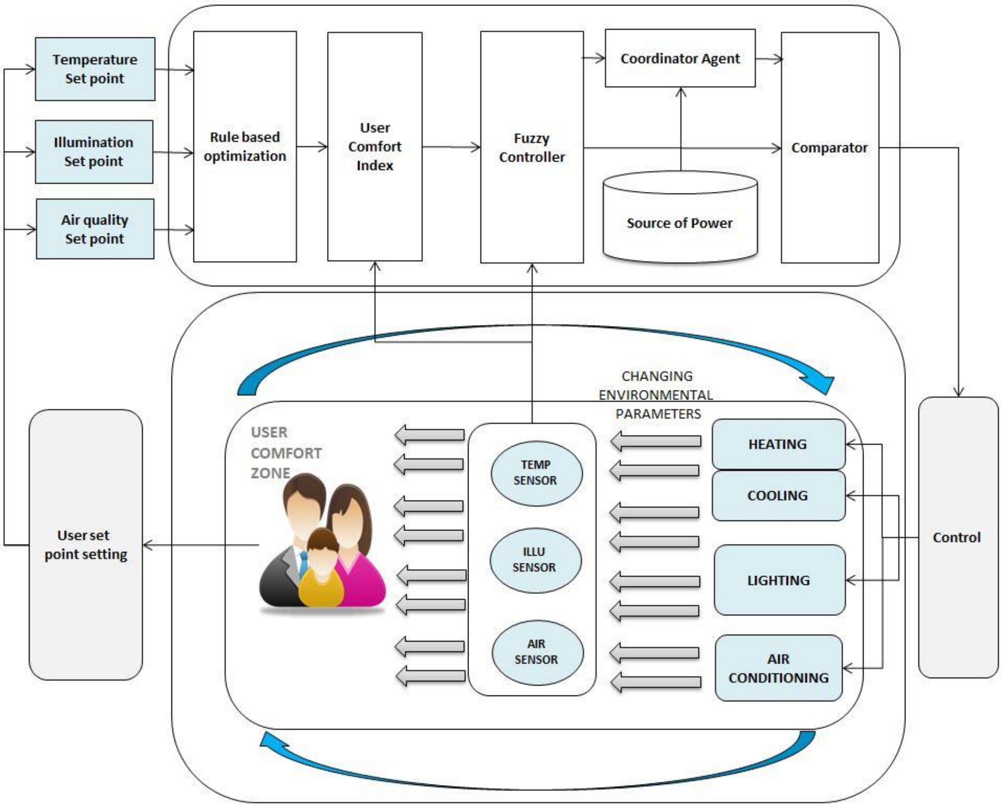

Figure 4.3 Design of optimization scheme based on dynamic user setting for multi-users in smart home

Figure 4.3 illustrates the optimization scheme based on dynamic user setting for multi-user in a smart home. Users indicate family members in a smart home. When users feel uncomfortable with certain environment, they can set user set points by themselves. Then the user set points are input to the rule based optimization. Then we calculate user comfort index of each optimal parameters. Then the optimal parameter and current environment parameters are input to the fuzzy controller. Then required power from fuzzy controller is input to the coordinator agent in order to get adjusted power. Then the required power from fuzzy controller and adjusted power of coordinator agent are input to the comparator. Then, using the consumed power from comparator, we control the heater, cooler, lighting, and air conditioning in a smart home. The sensor parameters are changed after control the actuators in a smart home. Then the all users can be in a comfortable environment.

4.4. Design of dynamic user set point setting for multi-users

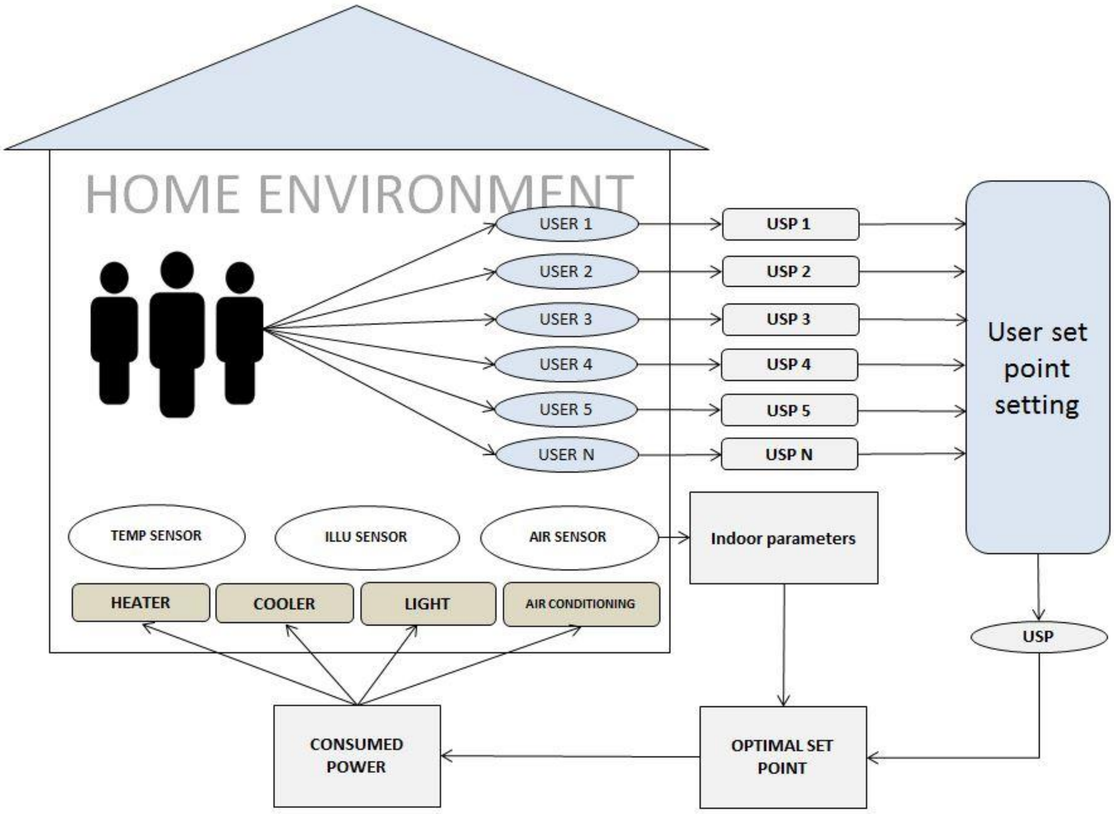

Figure 4.4 Dynamic user set point settings for multi-users

Figure 4.4 illustrates user set point setting in a home environment. We suppose n numbers of users in smart home are able to set their own comfortable user set ranges. Then all user set points are input to the user set point setting. We get user set point which is calculated by user set point setting. Then the optimal parameter is calculated based on user set point and indoor parameters from the sensors in a home environment. Consumed power is given to home actuators such as heater, cooler, lighting, and air conditioning.

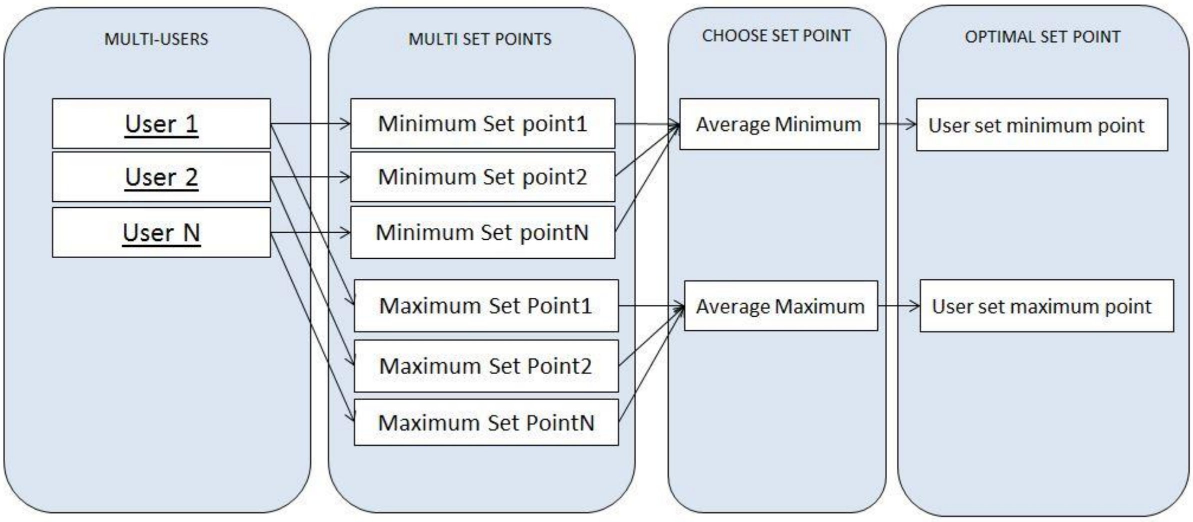

Figure 4.5 Average based setting for multi-users

Figure 4.5 illustrates user set point setting based on average parameters. Maximum and minimum user set points of each user are input to the user set point setting. Then we will calculate average minimum and maximum parameters based on each user set point. Then we get user set points as user set point which comfortable for everyone in a smart home.

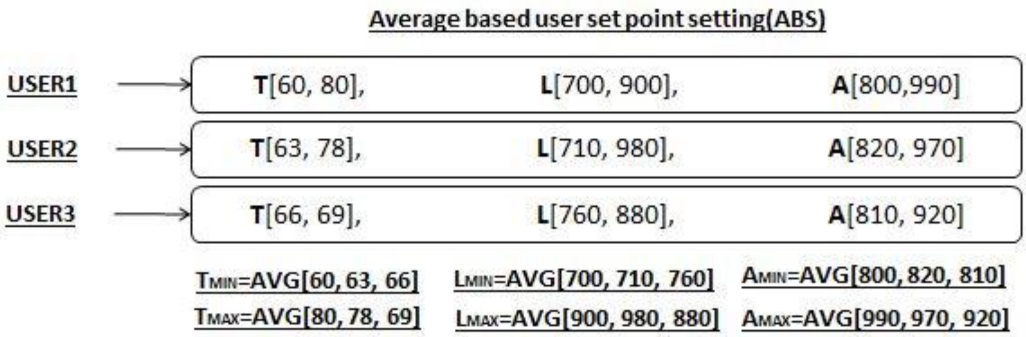

Figure 4.6 Calculation of average based setting for multi-users (Example)

Figure 4.6 illustrates the calculation of average based setting for multi users. We suppose that we have three users and each user set their own user set points for each control, such as temperature, illumination, and air quality. For temperature, it takes minimum user set points and maximum user set points as input from each user in order to calculate actual Tmin and Tmax. Then it calculates Tmin among the user set points by average calculation and Tmax among the user set points by average calculation.

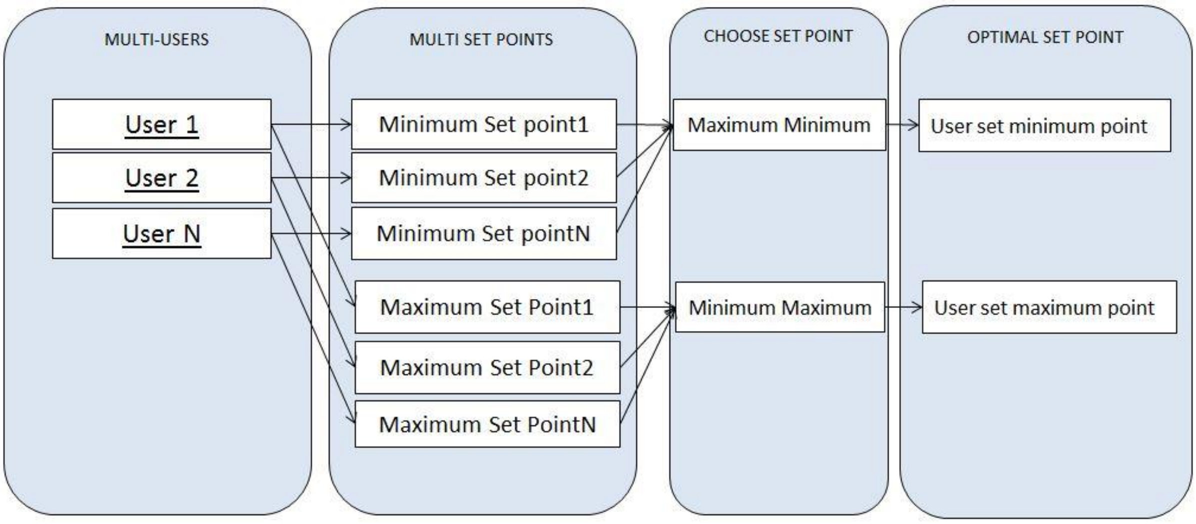

Figure 4.7 Max-min based setting for multi-users

Figure 4.7 illustrates user set point setting based maximum and minimum parameters. Minimum and maximum user set points of each user are input to the user set point setting. Then user set minimum point is calculated by rank based selection which choose maximum parameter among all minimum set points from each user. Similarly, user set maximum point is calculated by rank based selection which choose minimum parameter among all maximum set points from each user.

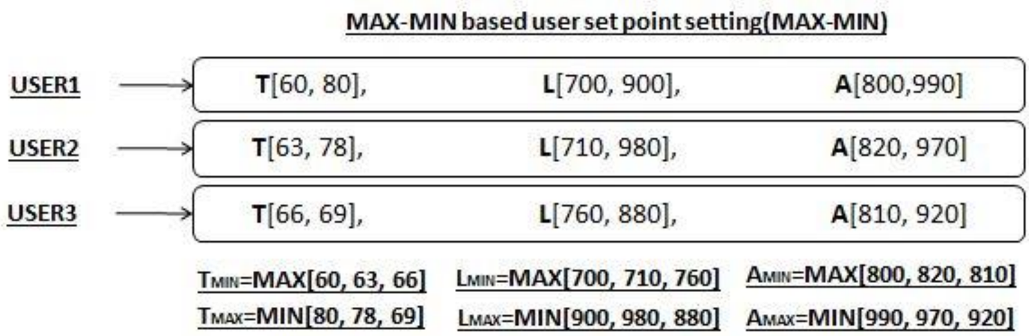

Figure 4.8 Calculation of Max-min based setting for multi-users (Example)

Figure 4.8 illustrates the calculation of Max-min based setting for multi users. We suppose that we have three users and each user set their own user set points for each control, such as temperature, illumination, and air quality. For temperature, it takes minimum user set points and maximum user set points as input from each user in order to calculate actual Tmin and

Tmax. Then, Tmin is calculated by choosing maximum parameter among the user set points and Tmax is calculated by choosing minimum parameter among the user set points .

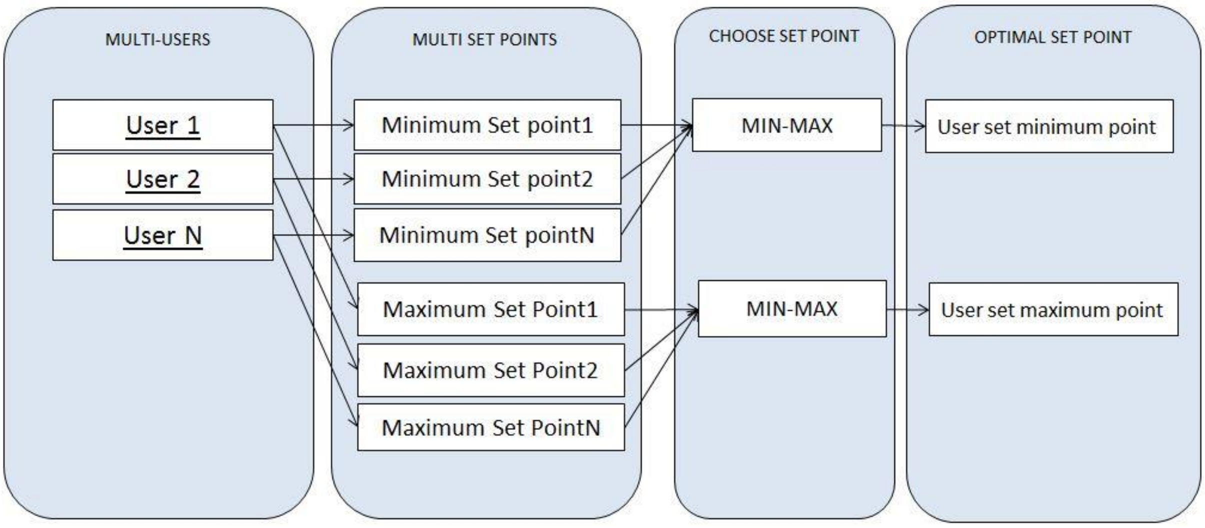

Figure 4.9 Min-max based setting for multi-users

Figure 4.9 illustrates user set point setting based minimum and maximum parameters. Minimum and maximum user set points of each user are input to the user set point setting. Then user set minimum point is calculated by rank based selection which choose minimum parameter among all minimum set points from each user. Similarly, user set maximum point is calculated by rank based selection which choose maximum parameter among all maximum set points from each user.

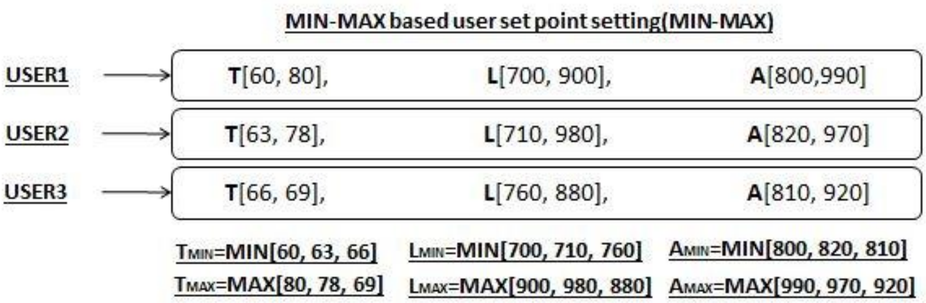

Figure 4.10 Calculation of Min-max based setting for multi-users (Example)

Figure 4.10 illustrates the calculation of Min-max based setting for multi users. We suppose that we have three users and each user set their own user set points for each control, such as temperature, illumination, and air quality. For temperature, it takes minimum user set points and maximum user set points as input from each user in order to calculate actual Tmin and

Tmax. Then, Tmin is calculated by choosing minimum parameter among the user set points and Tmax is calculated by choosing maximum parameter among the user set points .

4.5. Simulation result of optimization scheme based on dynamic user set point setting for multi-users

In order to evaluate performance of our proposed Rule based optimization scheme, we have developed and simulator in Visual Studio 2013 using c#. User preference set parameters range was Tset = [66, 78] (Kelvin), Lset = [720, 880] (lux), and Aset = [700, 880] (ppm). Brief detail of system configuration is given in Table 4.1.

The environmental configuration remains the same for all the experiments. The uniform configuration helps in the comparison of results with existing techniques. We developed the simulator by using .Net programming environment with the configuration shown in Table 4.1.

Table 4.1 Simulation Environment

Module	Hardware	Software	Remark
Virtual sensing data for temperature, illumination, and air-quality	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7
Optimization of user set parameters (temperature, illumination, and air-quality)	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7
Dynamic user set point settings for multi-users	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7
Prediction of indoor environment parameters for temperature, illumination, and air-quality	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7

In this section, we show dynamic user set points setting for multi-users in a smart home. Multi-users in smart home are able to set their comfortable set points through this setting by themselves.

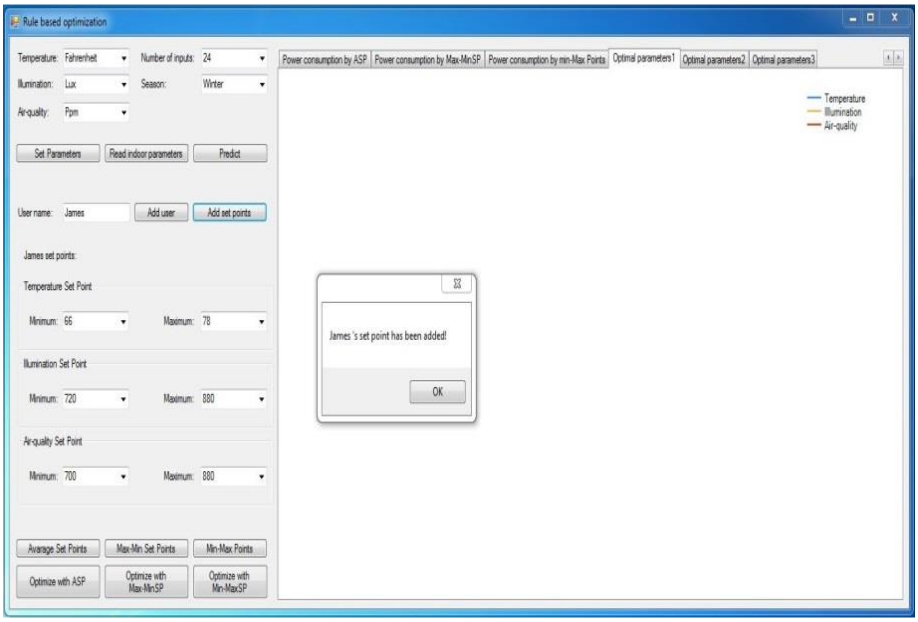

Figure 4.11 Add user to Multi-user set point setting

Figure 4.11 and 4.12 shows adding users to the system. We added two users who are James and John. Similarly, we can add more users. Then each user can set their comfortable set points. For user1 who is named James, user set points are T_{set} = [66, 78] (F), L_{set} = [720, 880] (lux) and A_{set} = [700, 880] (ppm). For user2 who is named John, user set points are T_{set} = [68, 77] (F), L_{set} = [730, 870] (lux) and A_{set} = [710, 880] (ppm).

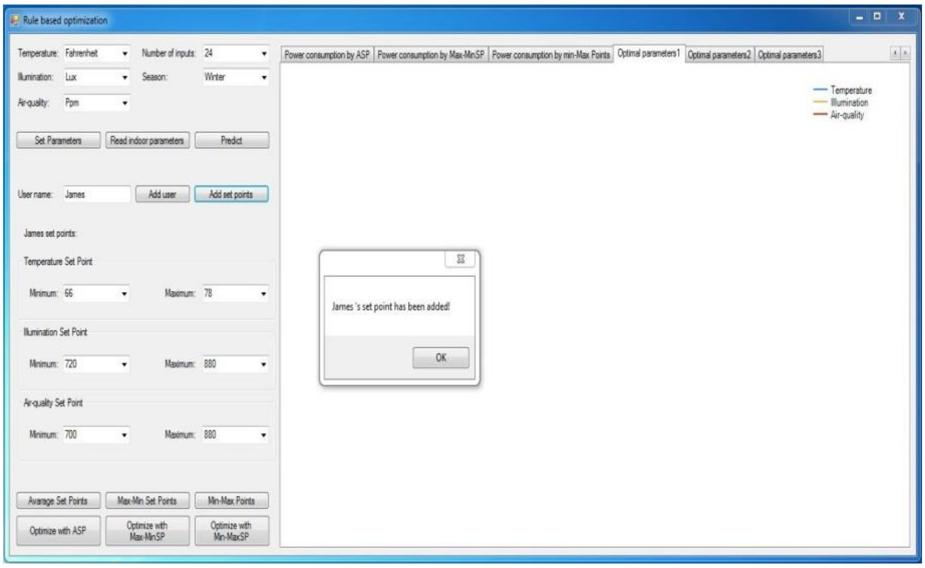

Figure 4.12 Add user to Multi-user set point setting

Figure 4.13, 4.14, and 4.15 shows multi user setting which based on average, max-min, and min-max calculations. We can calculate user set points from multi-user by those three different ways. When the multi-users set points are T_{set} = [66, 78] (F), L_{set} = [720, 880] (lux) and A_{set} = [700, 880] (ppm) and T_{set} = [68, 77] (F), L_{set} = [730, 870] (lux) and A_{set} = [710, 880] (ppm).

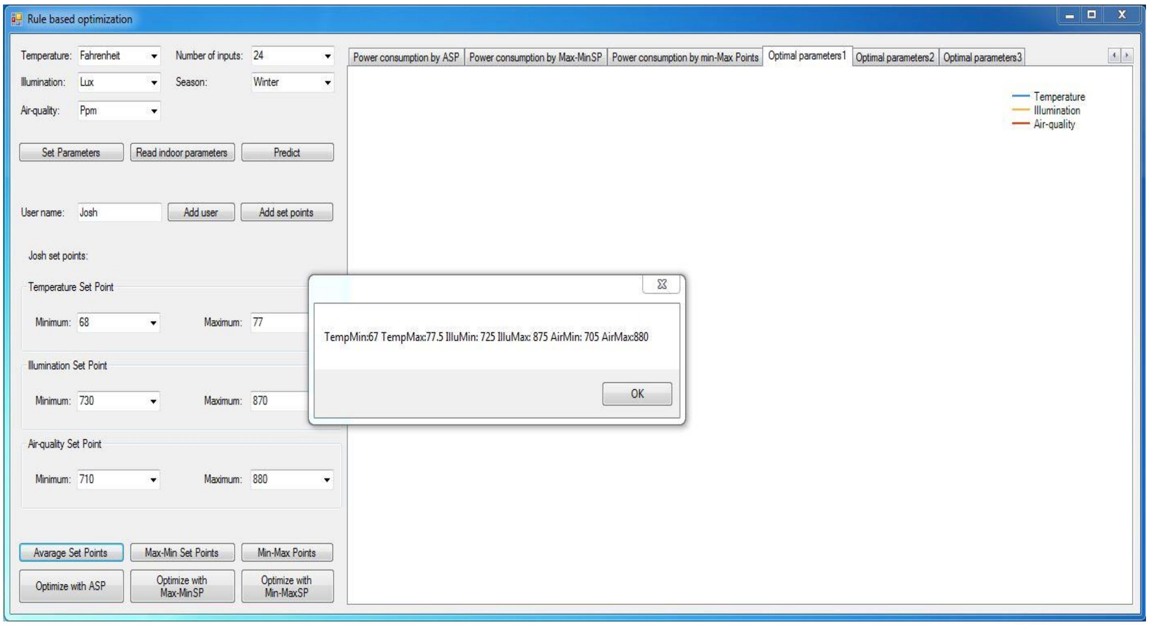

Figure 4.13 Multi-user setting by avarage based calculation

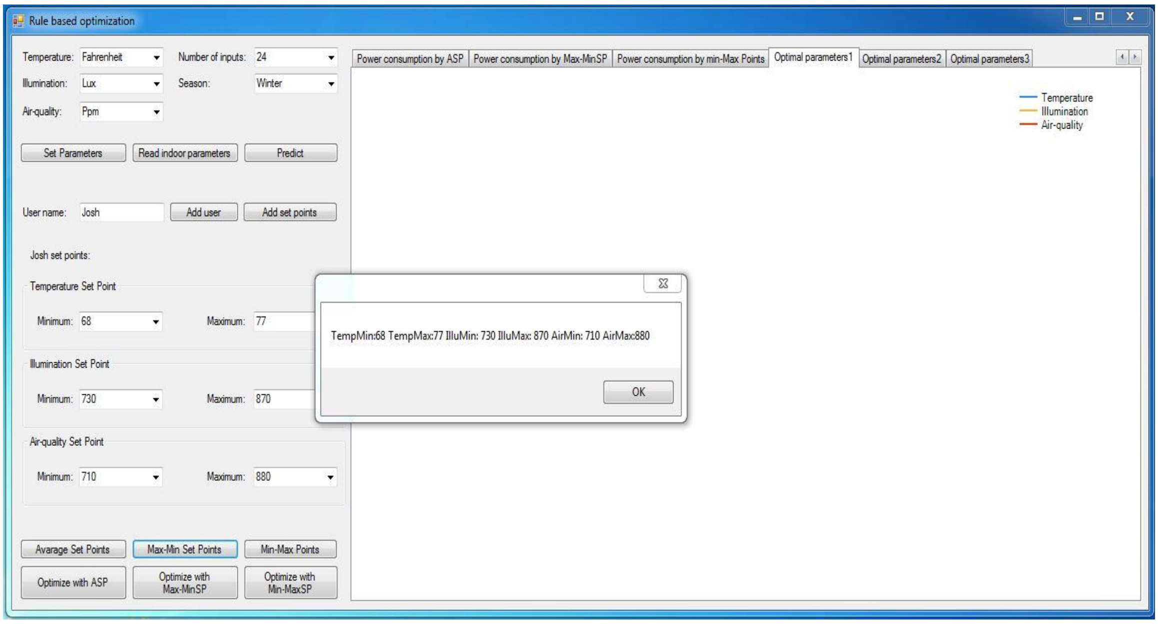

Figure 4.14 Multi-user setting by max-min based calculation

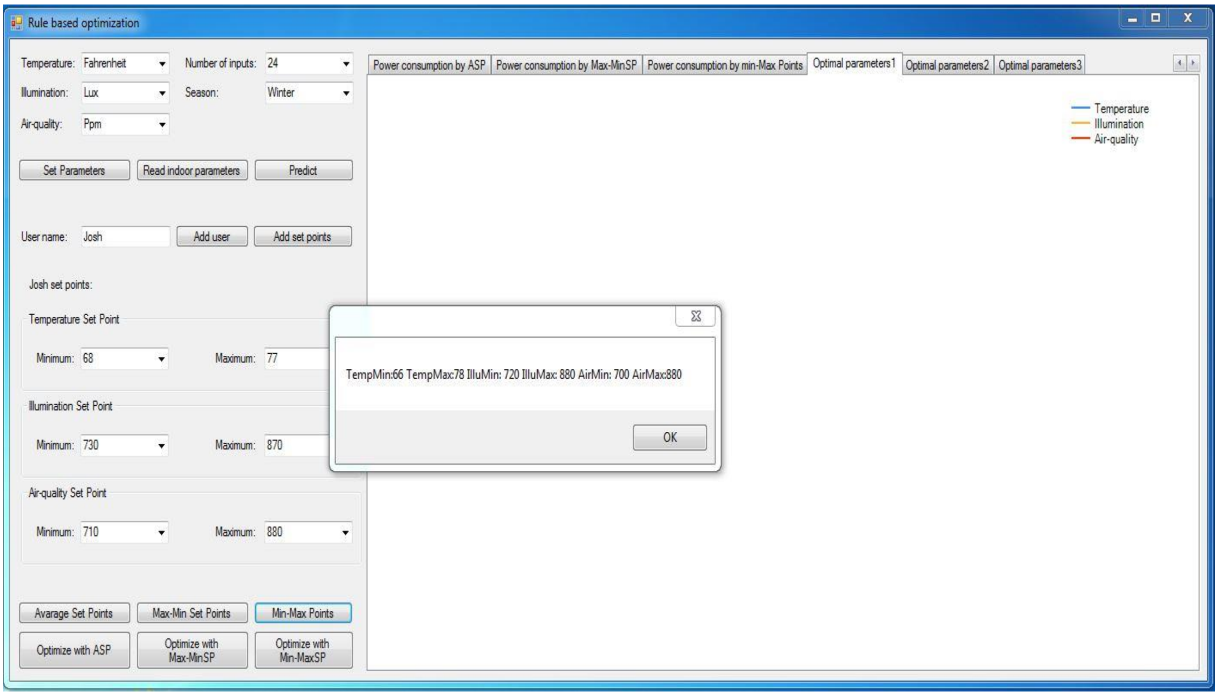

Figure 4.15 Multi-user setting by min-max based calculation

Then the average set point will be T_{set} = [67, 77.5] (F), L_{set} = [725, 875] (lux) and A_{set} = [705, 880] (ppm). Similarly, max-min set points will be T_{set} = [68, 77] (F), L_{set} = [730, 870] (lux) and A_{set} = [710, 880] (ppm) and min-max set points will be T_{set} = [66, 78] (F), L_{set} = [720, 880] (lux) and A_{set} = [700, 880] (ppm).

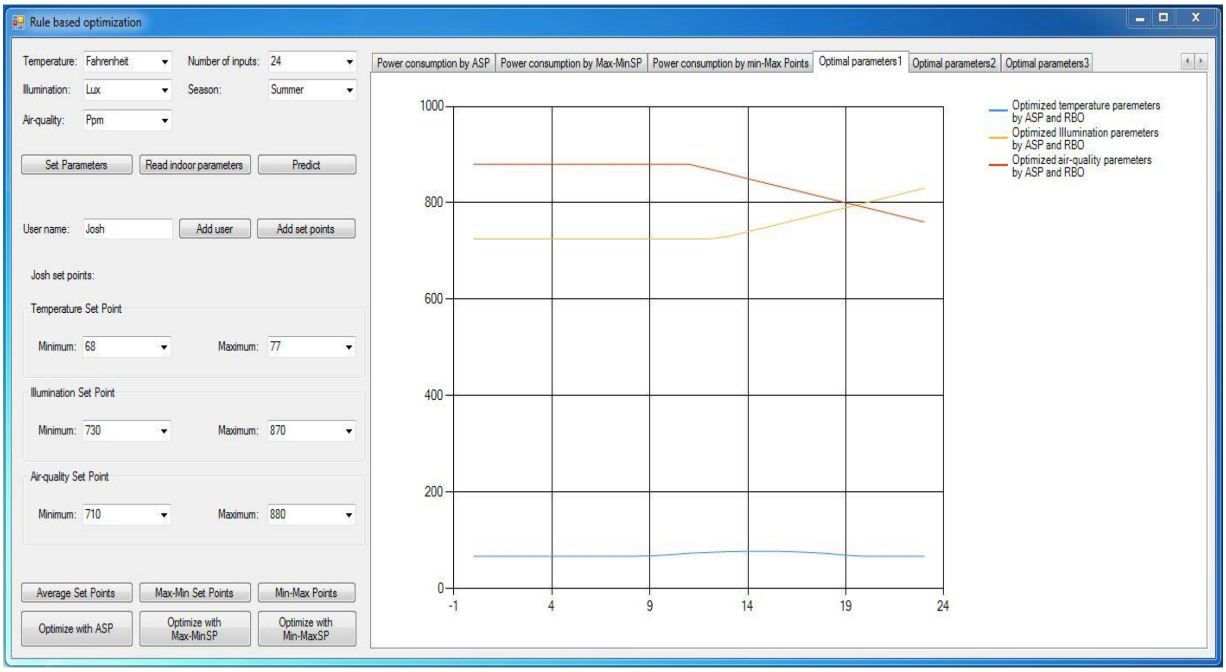

Figure 4.16 Optimization with average user set points by RBO

Figure 4.16 shows the optimal parameters for each of the temperature, illumination, and air-quality of average user set point setting and RBO. In case of temperature figure 4.16, the optimal temperature changes between 67° to 77.5° Fahrenheit. The multi-users feel comfortable if the temperature level is between [67, 77.5]. Therefore, using Rule based optimization, we can achieve optimal temperature in that certain comfortable set point range, which is calculated by average set points setting for multi-users in a smart home. In case of optimal illumination figure 4.16, the illumination parameter changes between 725° to 875° Lux as compare to indoor environment illumination parameters. Then the user set points are optimized to [725, 875]. So we can achieve optimal illumination parameter using rule based optimization. In case of optimal air-quality figure 4.16, the air quality parameter changes between 705 to 880 ppm as compare to predicted indoor air-quality parameters. Then the user set points are optimized to [705, 880]. So we can achieve optimal air-quality parameter using rule based optimization.

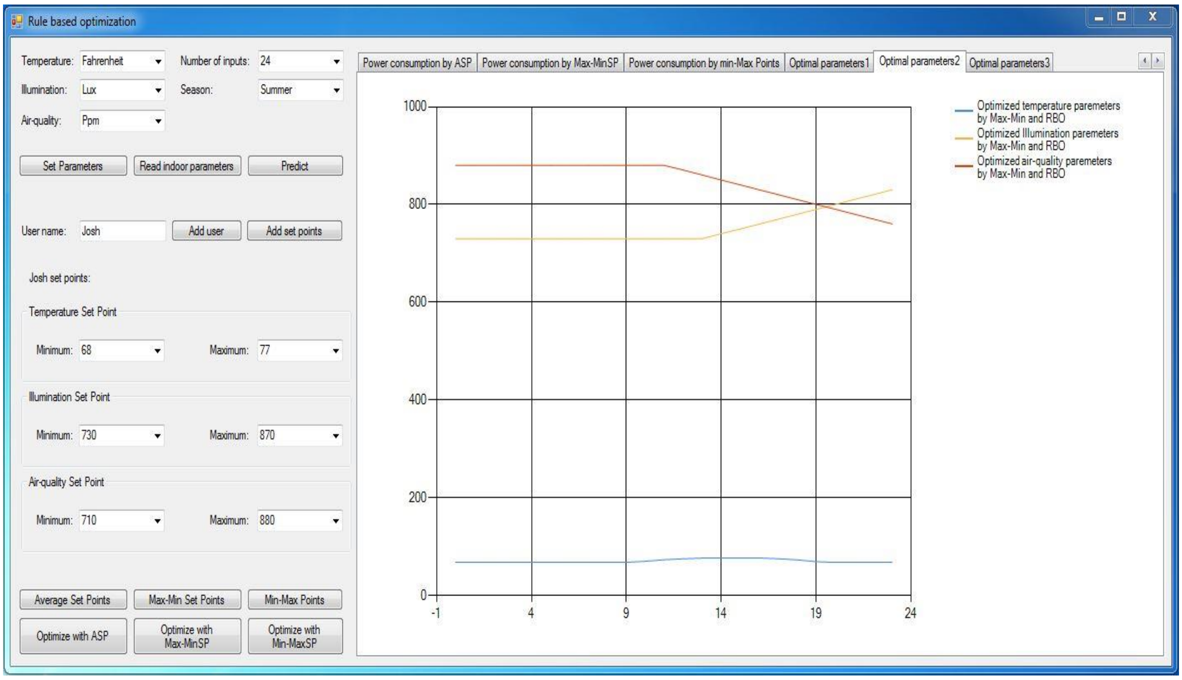

Figure 4.17 Optimization with Max-min user set points by RBO

Figure 4.17 shows the optimal parameters for each of the temperature, illumination, and air-quality by Max-min user set point setting. In case of temperature figure 4.17, the optimal temperature changes between 68° to 77° Fahrenheit. The multi-users feel comfortable if the temperature level is between [68, 77]. Therefore, using rule based optimization, we can achieve optimal temperature in that certain comfortable set point range, which is calculated by average set points setting for multi-users in a smart home. In case of optimal illumination figure 4.17, the illumination parameter changes between 730^{o} to 870^{o} Lux as compare to indoor environment illumination parameters. Then the user set points are optimized to [730, 870]. So we can achieve optimal illumination parameter using rule based optimization. In case of optimal air-quality figure 4.17, the air quality parameter changes between 710 to 880 ppm as compare to indoor environment air-quality parameters. Then the user set points are optimized to [710, 880]. So we can achieve optimal air-quality parameter using rule based optimization.

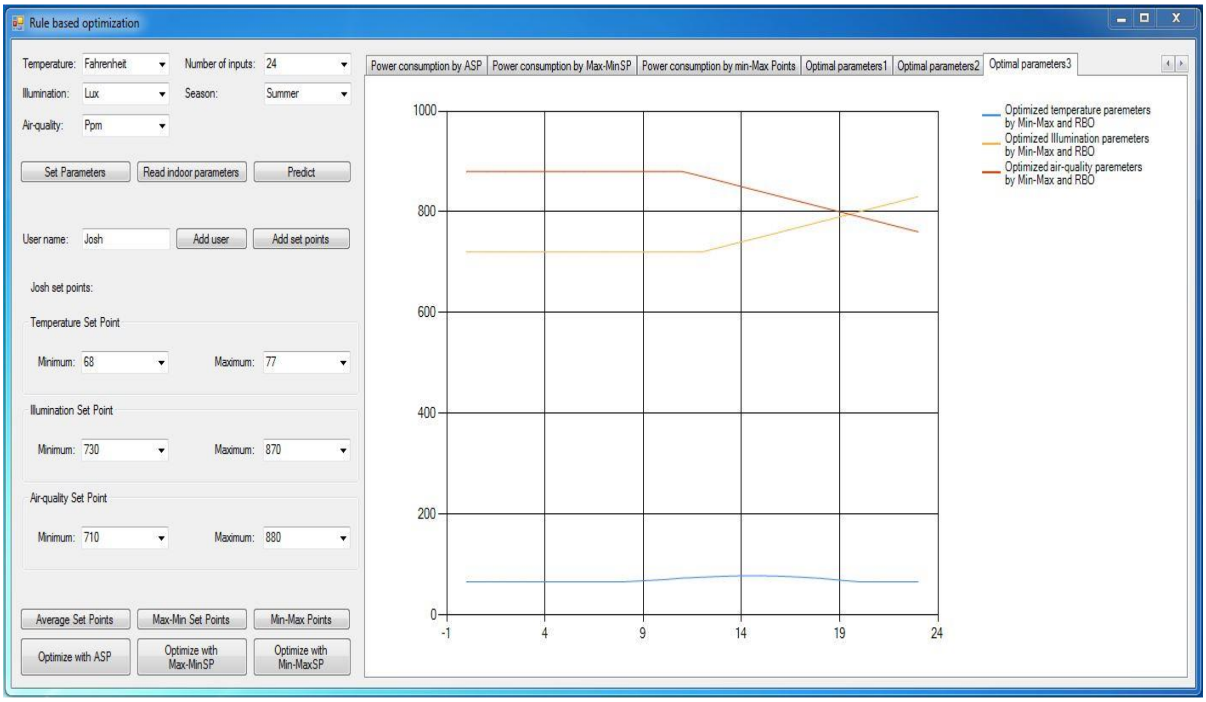

Figure 4.18 Optimization with Min-max user set points by RBO

Figure 4.18 shows the optimal parameters for each of the temperature, illumination, and air-quality by Min-max user set point setting. In case of temperature figure 4.18, the optimal temperature changes between 66o to 78o Fahrenheit. The multi-users feel comfortable if the temperature level is between [66, 78]. Therefore, using rule based optimization, we can achieve optimal temperature in that certain comfortable set point range, which is calculated by average set points setting for multi-users in a smart home. In case of optimal illumination figure 4.18, the illumination parameter changes between 720o to 880o Lux as compared to indoor environment illumination parameters. Then the user set points are optimized to [700, 880]. So we can achieve optimal illumination parameter using rule based optimization. In case of optimal air-quality figure 4.18, the air quality parameters changes between 700 to 880 ppm as compare to indoor environment air-quality parameters. Then the user set points are optimized to [700, 880]. So we can achieve optimal air-quality parameter using rule based optimization.

In this section, simulation of power consumption by average user set points setting and RBO is described below one by one.

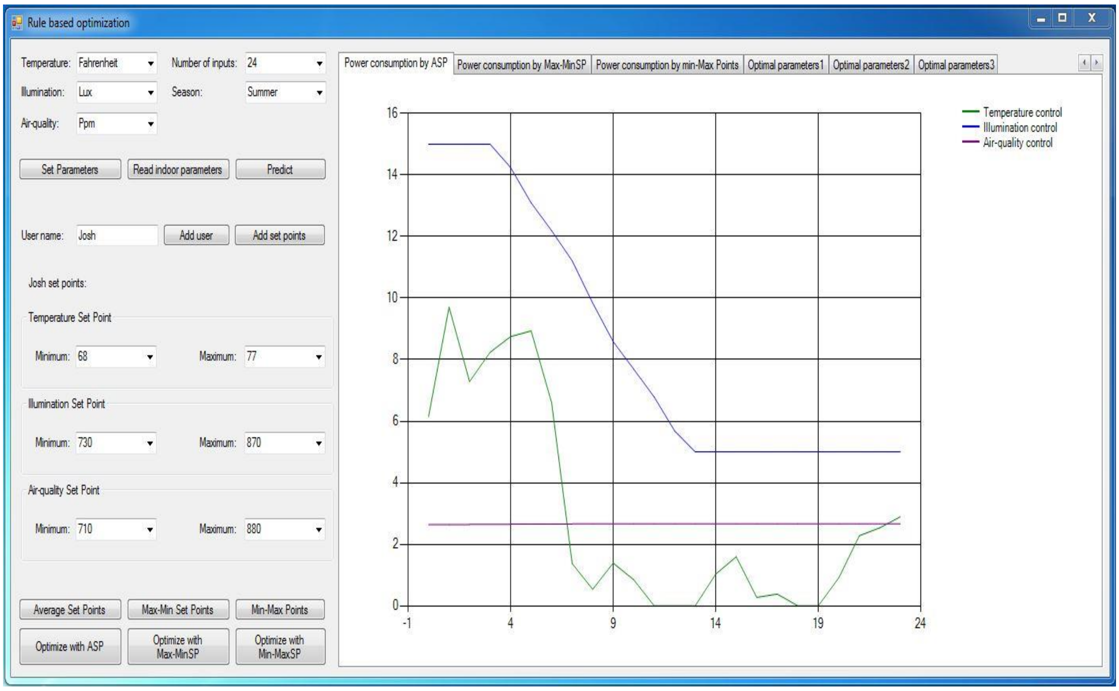

Figure 4.19 Power consumption of average user set points and RBO

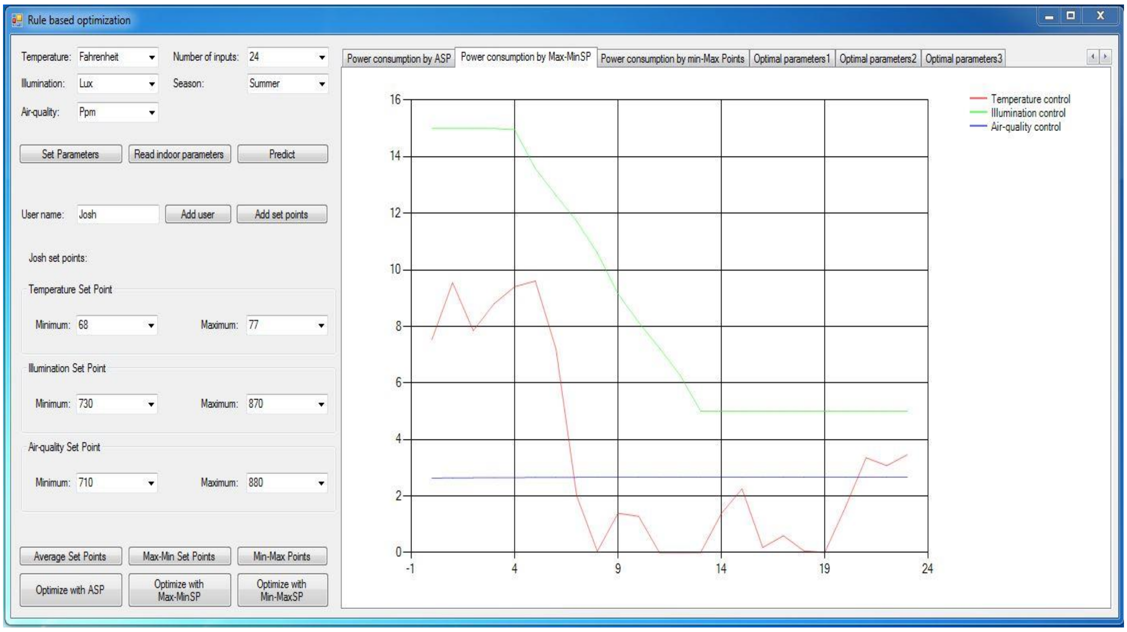

Figure 4.20 Power consumption of Max-min set points and RBO

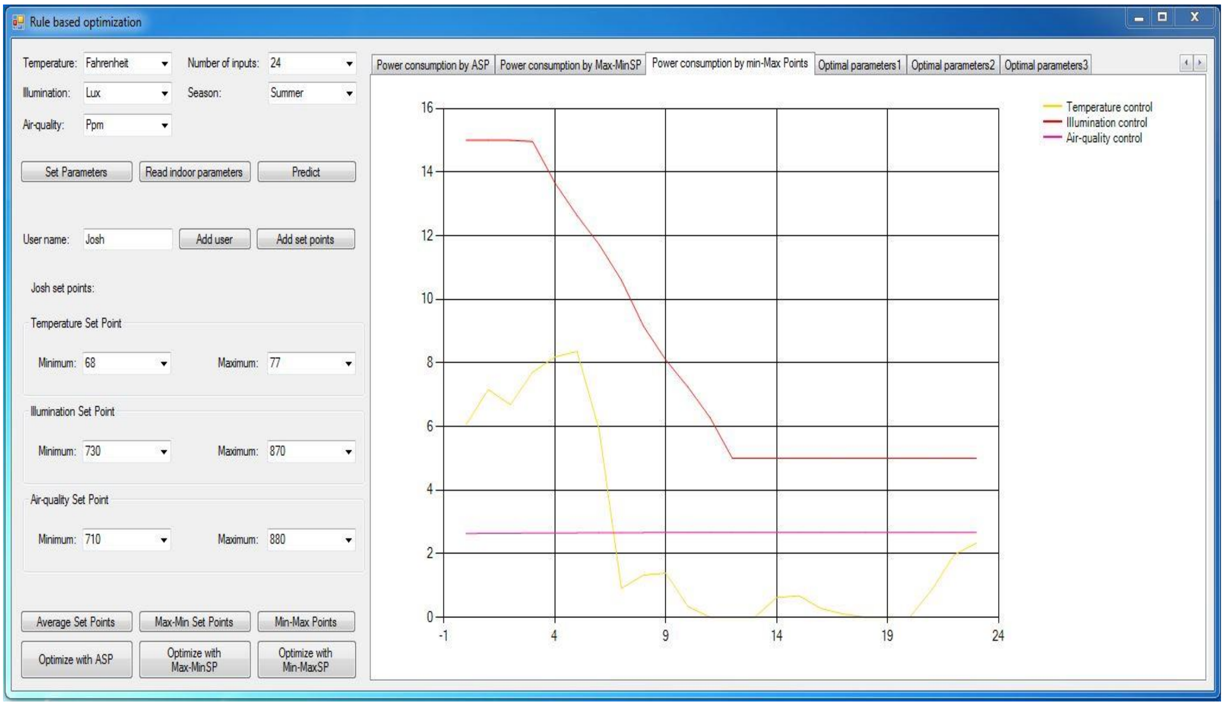

Figure 4.21 Power consumption of Min-max user set points and RBO

The figures 4.19, 4.20, 4.21 show power consumption of temperature, illumination, and air quality separately. Actual user set points are calculated by dynamic user set point settings which are average, max-min, and min-max based user set points settings for multi-users. Power consumption is calculated by these three methods and rule based optimization. The power consumptions are described results section with detailed.

4.6. Comparison result of power consumption by dynamic user set point settings and RBO

In this section, we will show that comparisons of power consumption results using dynamic user set point setting for multi users in smart home and RBO. User set point is calculated by three different methods. Then, using the user set point, we get optimal parameters by RBO.

So the figure 4.22 shows a power consumption comparison for temperature control. It compared average based set point setting, max-min based set point setting, and min-max set point setting. X-axis shows the time in hours while Y-axis shows the temperature power consumption in KWT. The average based power consumption starts from 6.18kwt at 1o'clock and it reaches to 9.59kwt at 6o'clock. Then it decreases to 3.04kwt at 9o'clock.

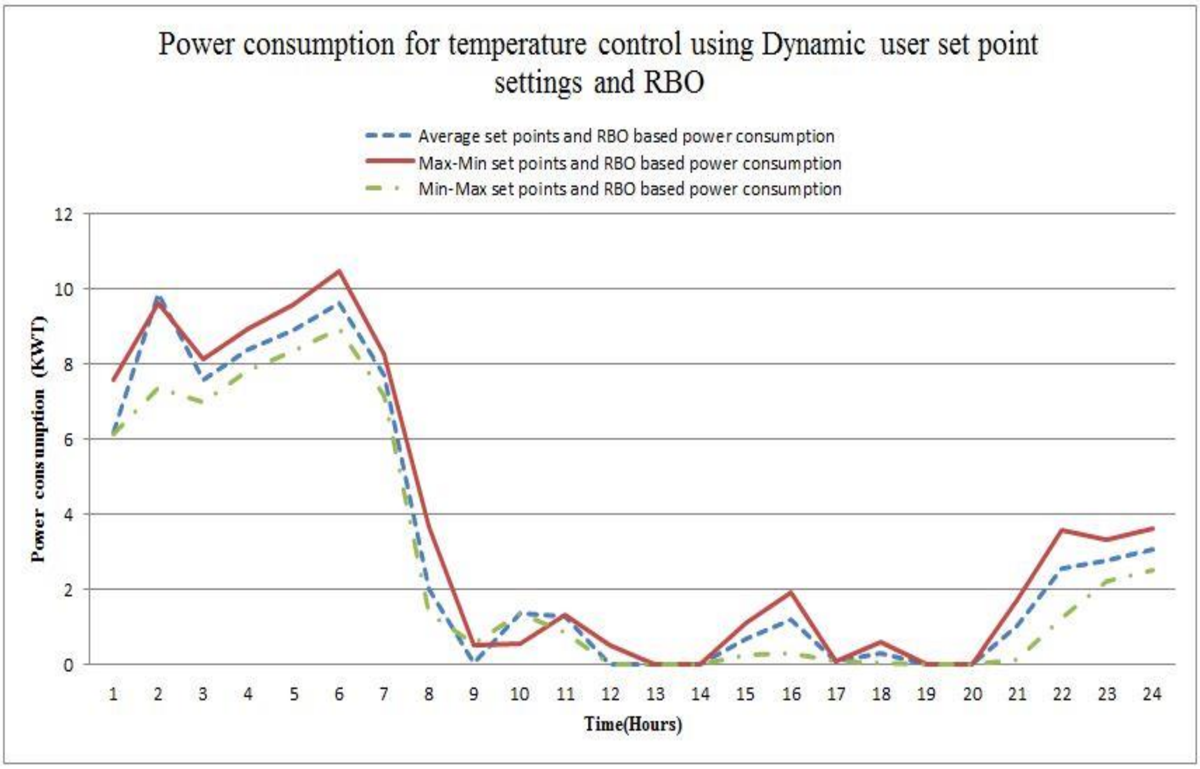

Figure 4.22 Power consumption comparison for temperature control using dynamic user set point settings and RBO

Similarly, max-min based power consumption starts from 7.55kwt at 1o'clock and it reaches to 10.46kwt at 6o'clock. Then it decreases to 3.63kwt at 12o'clock. Then min-max based power consumption starts from 6.13kwt at 1o'clock and it reaches to 8.92kwt at 6o'clock. Then it decreases to 0.04kwt at 18o'clock. From that result, we can say that power consumption based on min-max set point setting consume less power than average and max-min based user set points setting.

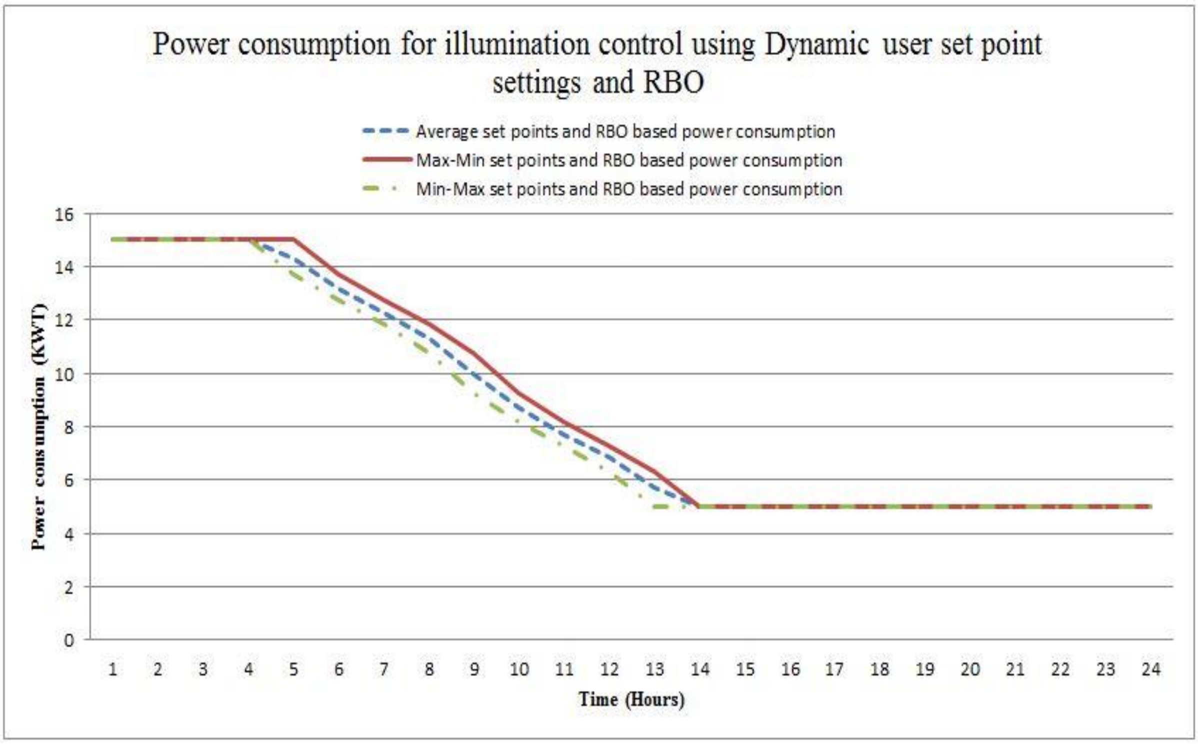

Figure 4.23 Power consumption comparison for illumination control using dynamic user set point settings and RBO

The figure 4.23 shows a power consumption comparison for illumination control. It compared average based set point setting, max-min based set point setting, and min-max set point setting. X-axis shows the time in hours while the Y-axis shows the illumination power consumption in Lux. Average based power consumption starts from 14.99kwt at 1o'clock and it decreases to 5kwt at 15o'clock. Similarly, max-min based power consumption starts from 14.99kwt at 1o'clock and it decrease to 5kwt at 15o'clock. Then min-max based power consumption starts from 14.99kwt and it decreases to 5kwt at 13o'clock. From the total result, we can say that power consumption of min-max user set point setting consume less power compare than average and max-min user set point setting.

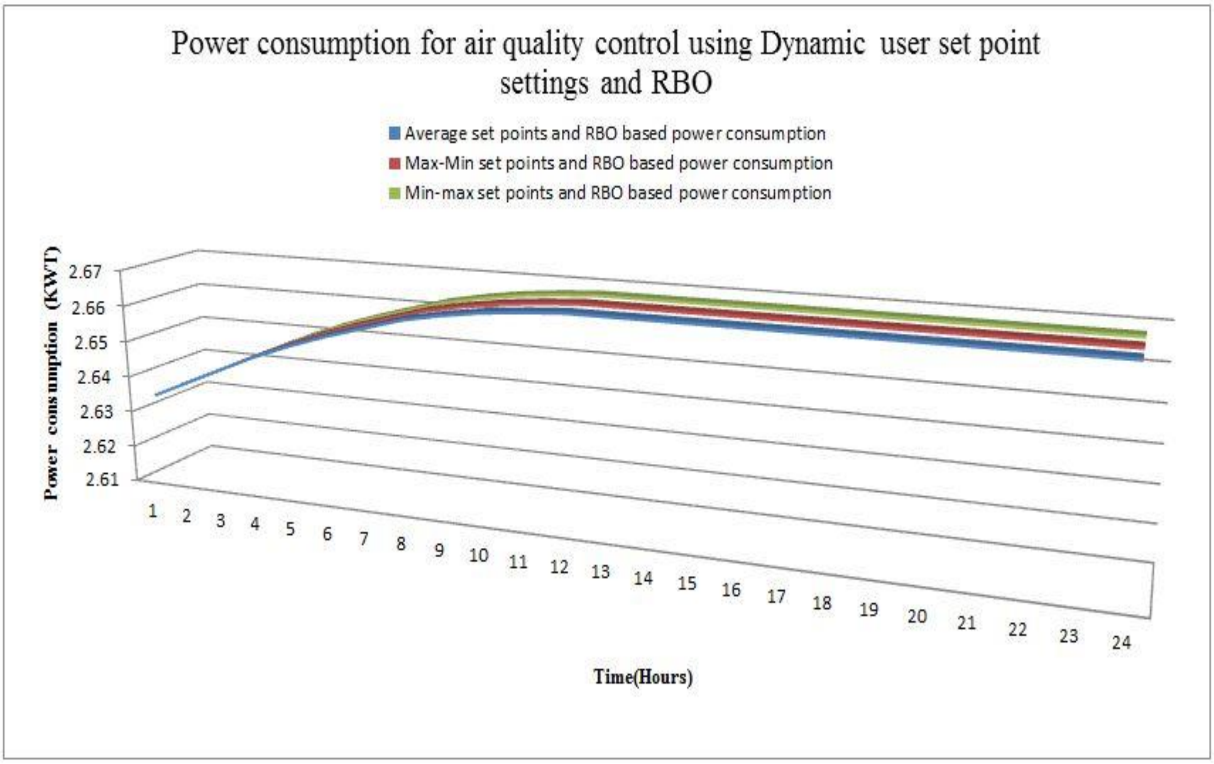

Figure 4.24 Power consumption comparison for temperature control using dynamic user set point settings and RBO

The figure 4.24 shows a power consumption comparison for air quality control. It compared average based set point setting, max-min based set point setting, and min-max set point setting. X-axis shows the time in hours while the Y-axis shows the air quality power consumption in ppm. For air quality control, we get almost similar results in our certain simulation case. Average based power consumption starts from 2.63kwt at 1o'clock and it increases to 2.66kwt at 9o'clock. Similarly, max-min based power consumption starts from 2.62kwt at 1o'clock and it increases to 2.66kwt at 9o'clock. Then min-max based power consumption starts from 2.63kwt and it increases to 2.66kwt at 10o'clock. From the total result, we can say that power consumptions of these three methods are almost same.

Table 4.2 shows a comparison of total power consumption by three user set point setting methods and RBO. For temperature control, ABS and RBO based power consumption consumed total 74.60748kwt power. Then Max-Min and RBO based power consumption consumed 85.00414kwt power. Similarly, Min-Max and RBO based power consumption consumed 63.60321kwt power. Then we can see that power consumption difference between ABS and RBO, Max-Min and RBO, and Min-

Max and RBO based power consumption. As a result, we can see that Min-Max and RBO based power consumption is consuming less power compare than Max-min and RBO and ABS and RBO based power consumptions for temperature control.

Table 4.2 Total power consumption by dynamic user set point settings and RBO for temperature control

	Temperature	Illumination	Air quality	TOTAL
Average based power consumption	74.60748	205.059	63.86507	343.5316
Max-Min based power consumption	85.00414	210.0556	63.86507	358.9249
Max-Min based power consumption	63.60321	200.0592	63.86507	**327.5275**

For illumination control, ABS and RBO based power consumption consumed total 205.059kwt power. Then Max-Min and RBO based power consumption consumed 210.0556kwt power. Similarly, Min-Max and RBO based power consumption consumed 200.0592kwt power. Then we can see that power consumption difference between ABS and RBO, Max-Min and RBO, and Min-Max and RBO based power consumption. As a result, we can see that Min-Max and RBO based power consumption is consuming less power compare than Max-min and RBO and ABS and RBO based power consumptions for illumination control. For air quality control, ABS and RBO based power consumption consumed total 63.86507kwt power. Then Max-Min and RBO based power consumption consumed 63.86507kwt power. Similarly, Min-Max and RBO based power consumption consumed 63.86507kwt power. Then we can see that power consumptions between ABS and RBO, Max-Min and RBO, and Min-Max and RBO methods are similar to each other in our certain case. Finally, we have total consumed power from each three methods and RBO. Then total power consumption of ABS and RBO was 343.5316kwt and total power consumption of Max-Min and RBO was 358.9249kwt. Also, power consumption of Min-Max and RBO was 327.5275kwt. Therefore, we can say that Min-max user set point setting and RBO based power consumption consumed less power compared as the average based user set point setting with RBO and max-min based user set point setting with RBO. In addition, we can see that Min-Max based user set point setting gives better results among the three methods.

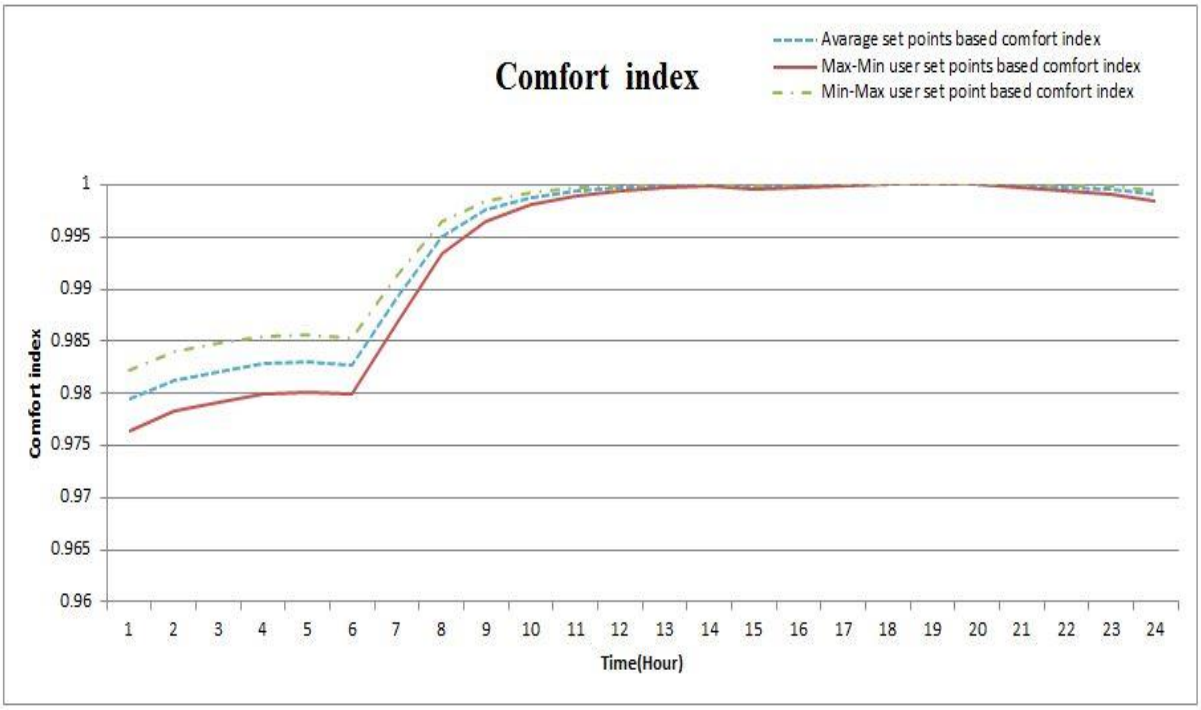

Figure 4.25 Comparison of comfort index of dynamic user set point settings and RBO for multi-users

The figure 4.25 shows the comfort index of dynamic user set point settings, which based on an average, max-min, and min-max user set point setting. X-axis shows the time in hours while the Y-axis shows the comfort indexes from 0 to 1. User set points based on Max-min starts from 0.967 and it reaches to 1 comfort index at 18o'clock. Then user set point based on min-max starts from 0.98 and it reaches to 1 comfort index at 13o'clock. The user set point based on average starts from 0.979 and it reaches to 1 at 14o'clock. As a result, we can see that user set point based on min-max setting comfort index is higher than average and max-min based user set points.

5. Optimization scheme based on prediction of indoor environment parameters

5.1. Conceptual design optimization scheme based on prediction of indoor environment parameters

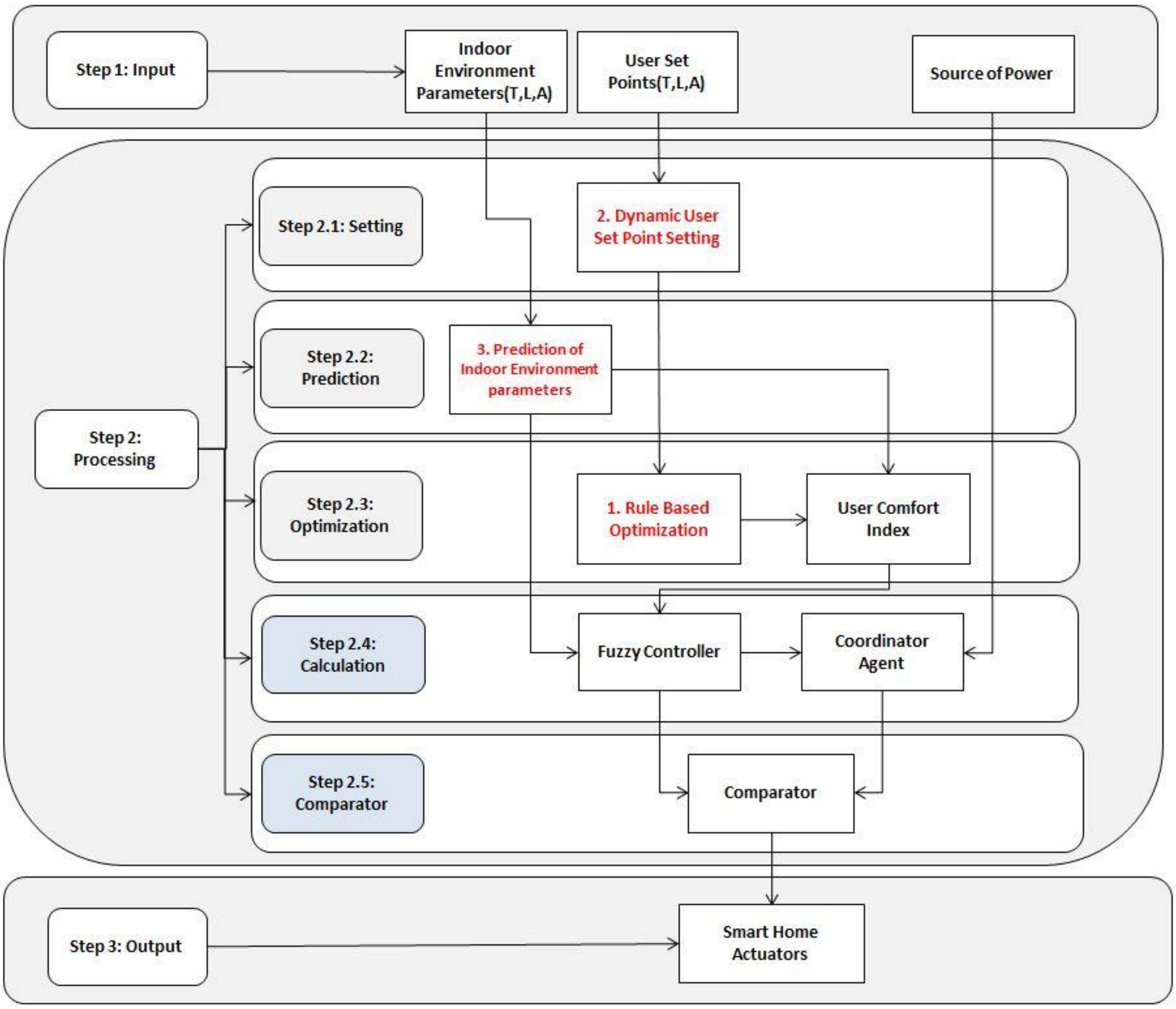

Figure 5.1 Conceptual design of optimization scheme based on prediction of indoor environment parameters

Figure 5.1 shows the conceptual design of an optimization scheme based on prediction of indoor environment parameters. Conceptual design includes three basic steps which are input, processing, and output. In step1, we have indoor environment parameters (temperature, illumination, and air-quality), user set points (temperature, illumination, and air-quality), and source of power. In step2, it includes five sub steps which are setting, prediction, optimization, calculation, and comparison. In step2.1, it includes dynamic user set point setting. In step 2.2, it includes prediction of indoor parameters. In step 2.3, it includes rule based optimization and user comfort index. In step2.4, it includes fuzzy controller and coordinator agent. In step 2.5, it includes comparator. Then, in step3, it includes smart home actuators.

5.2. Block diagram of optimization scheme based on prediction of indoor environment parameters

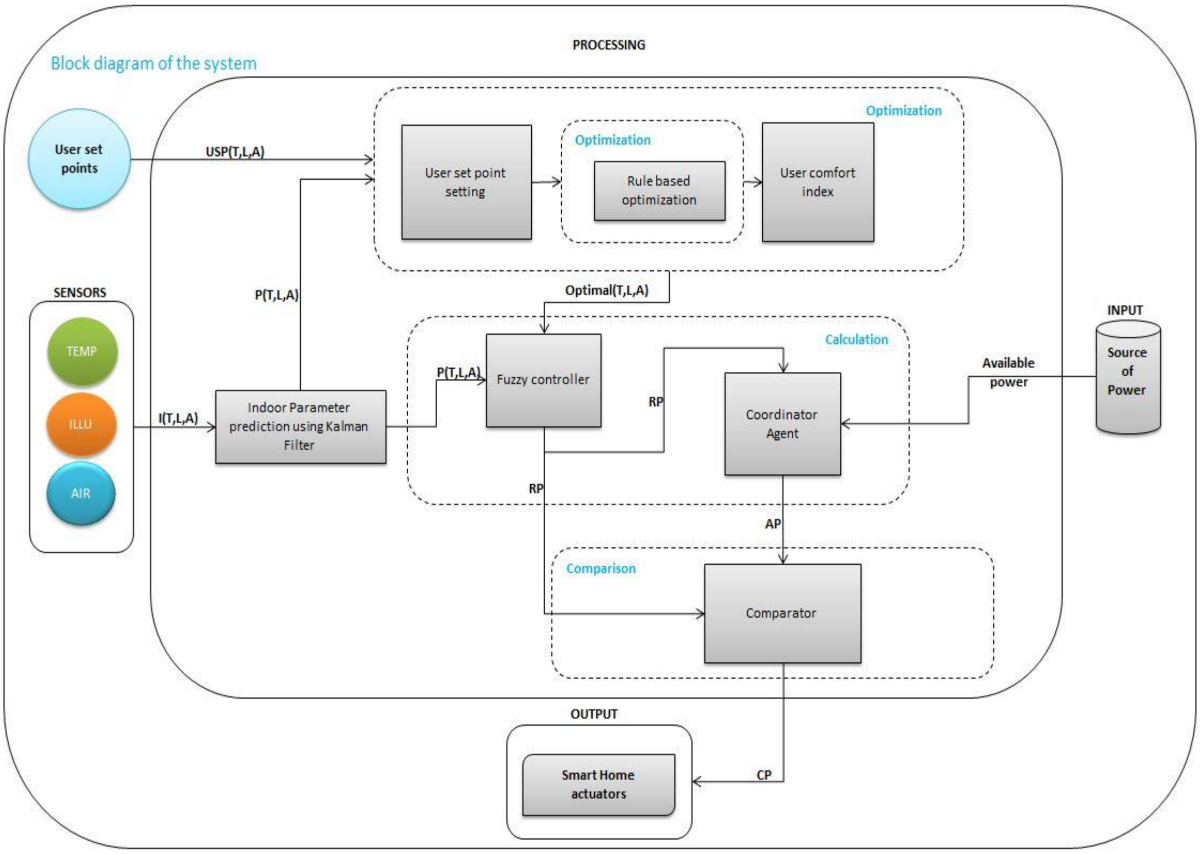

Figure 5.2 Block diagram of an optimization scheme based on prediction of indoor environment parameters

Figure 5.2 shows a block diagram of an optimization scheme based on prediction of indoor environment parameters. User set points of multi user are input to the dynamic user set point setting.

Then indoor environment parameters (temperature, illumination, and air quality) from the sensors are input to the indoor parameter prediction using a Kalman filter to predict indoor environment parameters. Then predicted indoor environment parameters and multi user set points from dynamic user set point setting are input to the RBO optimizer for optimization. Then the optimized parameters are input to user comfort index to calculate the user comfort index. Then optimized parameters from RBO and predicted indoor environment parameters are input to the fuzzy controller to calculate required power for temperature, illumination, and air quality. Then the coordinator agent adjusted the power, according to the required power from the fuzzy controllers and available power from the source of power. Then comparator takes required power from fuzzy controller and adjusted power from coordinator agent. Then consumed power from the comparator is input to smart home actuators which are devices utilized the power inside the smart home.

5.3. Design of indoor environment parameters prediction using Kalman filter

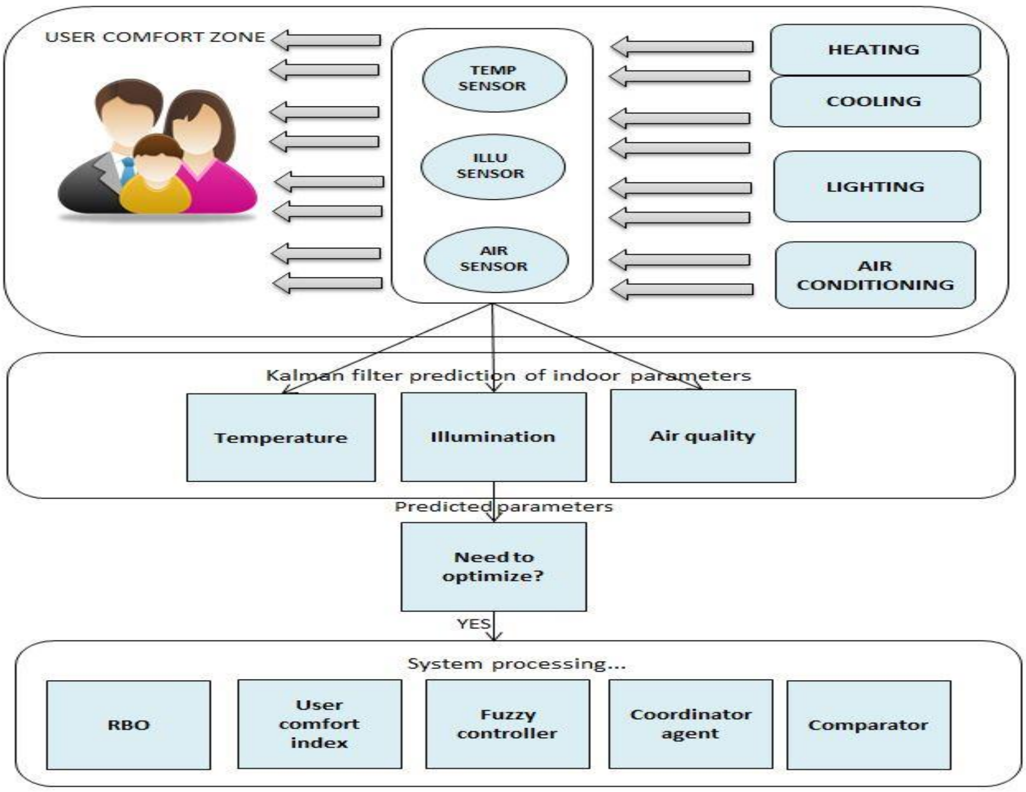

Figure 5.3 Design of indoor environment parameters prediction using Kalman filter

The figure 5.3 shows the design of indoor environment prediction using Kalman filter. The temperature, illumination, and air quality from the sensor are input to the Kalman filter prediction of indoor parameters. Then after getting predicted parameters, we check that whether predicted parameters still need to optimize or don't need to optimize. If it is needed to optimize, predicted indoor parameters are given to system processing part.

5.4. Simulation result of optimization scheme based on prediction of indoor environment parameters

In order to evaluate performance of our proposed Rule based optimization scheme, we have developed and simulator in Visual Studio 2013 using c#. User preference set parameters range was Tset = [66, 78] (Kelvin), Lset = [720, 880] (lux), and Aset = [700, 880] (ppm). Brief detail of system configuration is given in Table 5.1.

The environmental configuration remains the same for all the experiments. The uniform configuration helps in the comparison of results with existing techniques. We developed the simulator by using .Net programming environment with the configuration shown in Table 5.1.

Table 5.1 Simulation Environment

Module	Hardware	Software	Remark
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Dynamic user set point settings for multi-users	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7
Prediction of indoor environment parameters for temperature, illumination, and air-quality	Intel(R) Xeon(R) CPU W3503 @2.4GHz 2.39GHz 4GB RAM	Microsoft Visual Studio	C# Windows 7

In this section we are showing indoor environment parameters for temperature, illumination and air-quality. The indoor parameters show here for 24 hours of the day. Each one point represents one hour of the day. In case of temperature the unit is Fahrenheit, for illumination the unit of measurement is lux and for air-quality, the measurement unit is ppm. Figures 5.4, 5.5, 5.6, 5.7 relatively show the indoor parameters for temperature, illumination and air-quality. We have two sorts of temperature data. One is the indoor sensor data in winter time. Another one is the indoor sensor data in summer time.

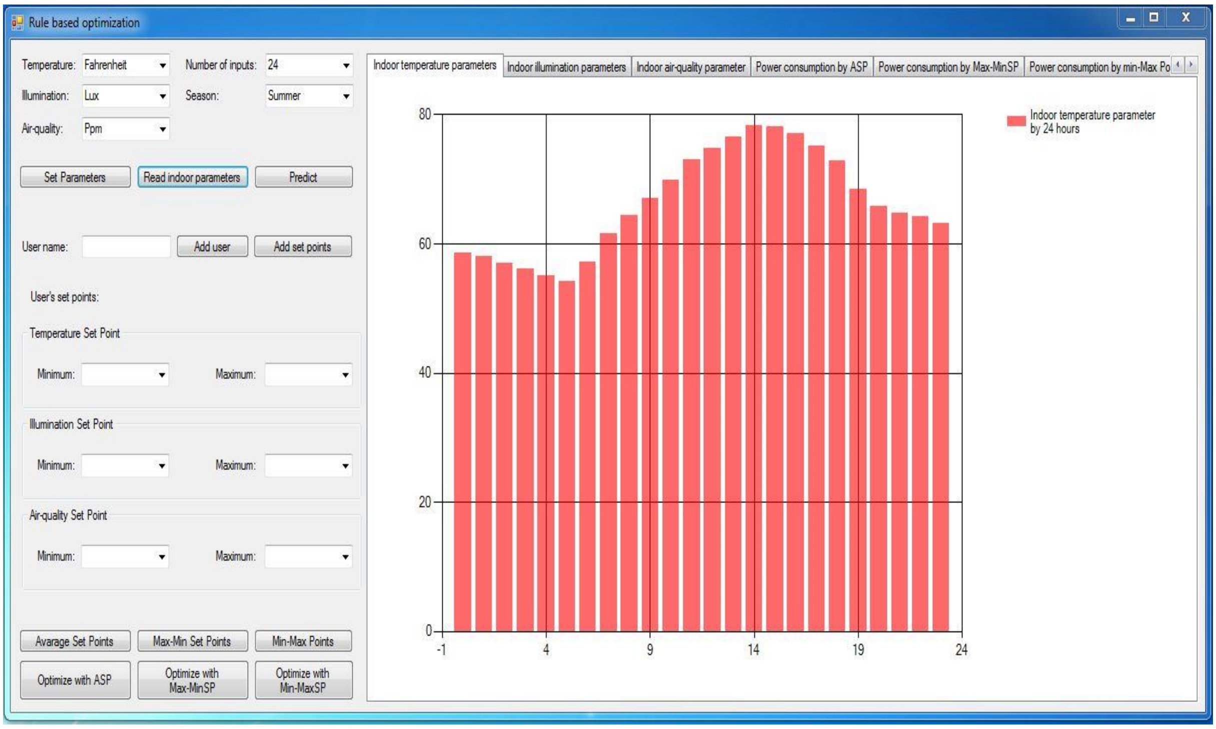

Figure 5.4 Indoor parameters in summer for temperature

Figure 5.4 illustrates indoor parameters summer for temperature. The indoor data come from the sensor. We used actual indoor temperature data from actual sensor. We can see that temperature starts from 58.64 degree Fahrenheit at 1o'clock of the day. Then it increases and reaches at 78.26 degree Fahrenheit at 15o'clock of the day.

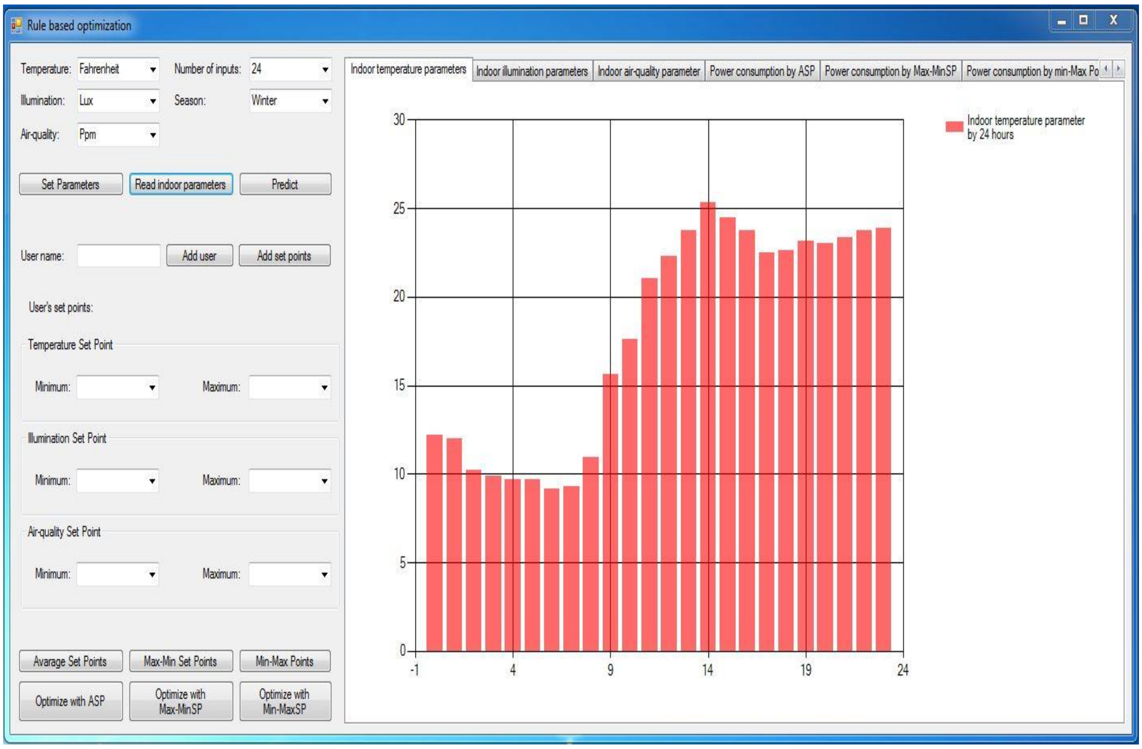

Figure 5.5 Indoor parameters in winter for temperature

Figure 5.5 illustrates indoor parameters winter for temperature. The indoor data come from the sensor. We used actual indoor temperature data from actual sensor. We can see that temperature in winter is less than the summer temperature. It starts from 12.2 degree Fahrenheit at 1o'clock of the day. Then it increases and reaches at 24.44 degree Fahrenheit at 16o'clock of the day.

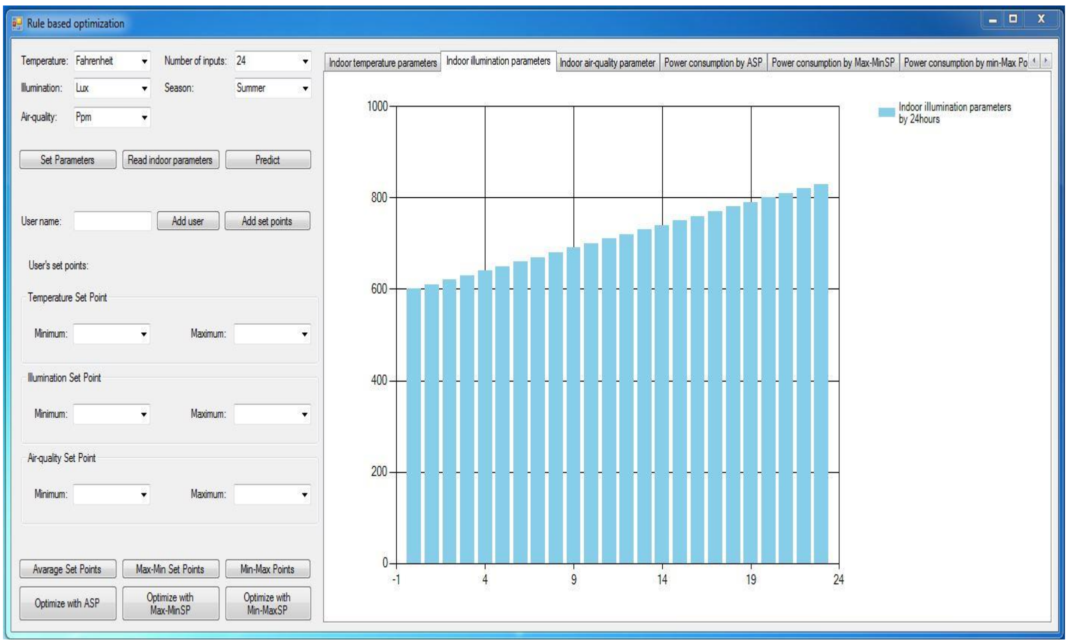

Figure 5.6 Indoor parameters for illumination

The change in illumination starts from 600 lux at 1o'clock and reaches 830 lux at 23 o'clock. Similarly, change in air quality starts from 990 ppm at 1o'clock and it decreases to 760 ppm at 23o'clock.

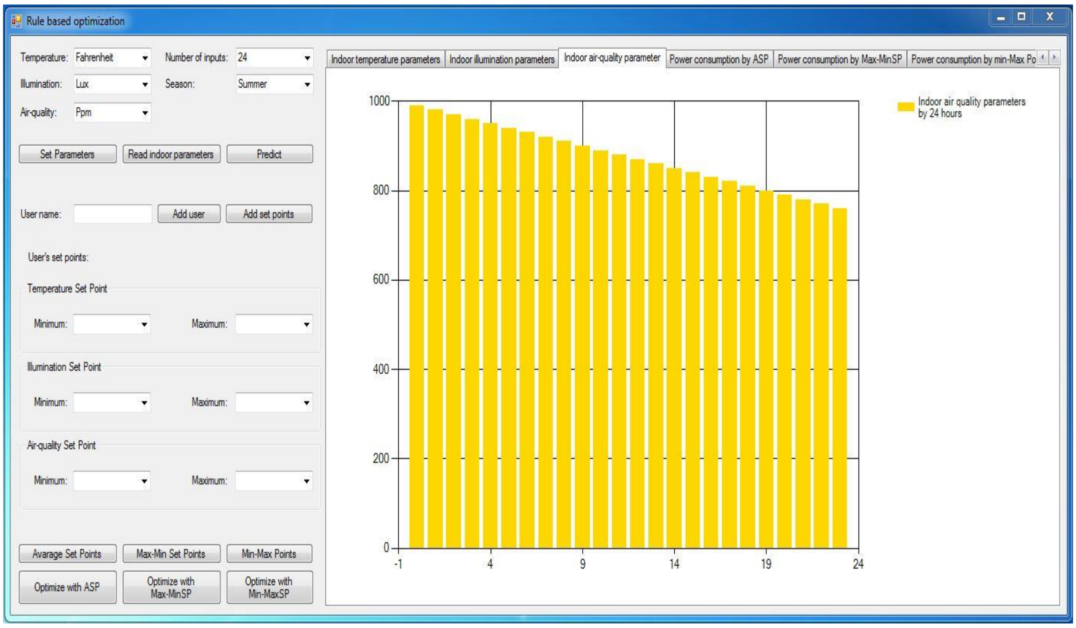

Figure 5.7 Indoor parameters for air-quality

Here, we show that predicted indoor environment parameters. Kalman filter prediction is used to predict indoor parameters.

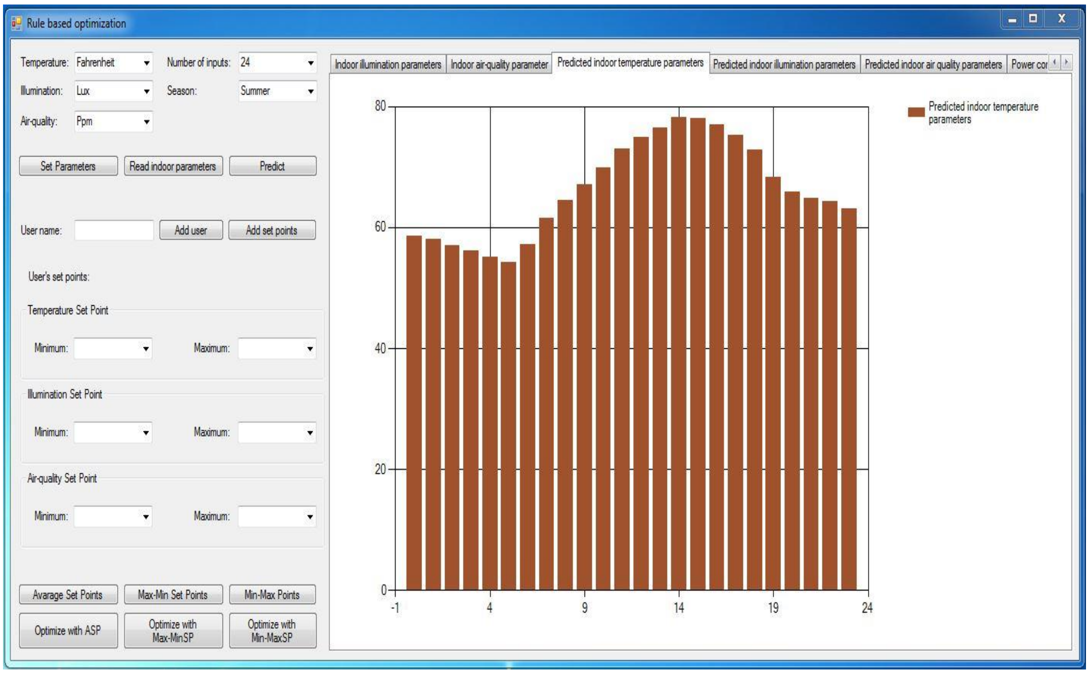

Figure 5.8 Predicted Indoor parameters of summer temperature

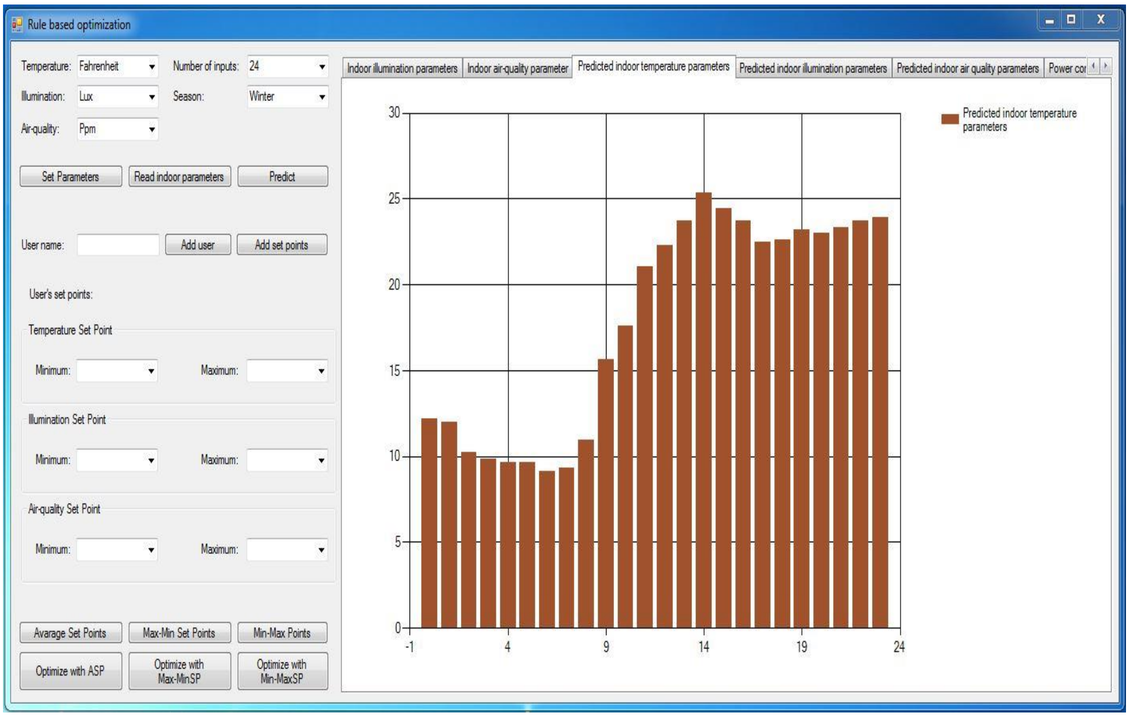

Figure 5.9 Predicted Indoor parameters of winter temperature

Figure 5.8 and 5.9 shows that predicted indoor temperature parameters in summer and winter. Predicted temperature in the summer starts 59.0089 degree Fahrenheit and it reaches to 78.87 degree Fahrenheit at 15o'clock. Similarly predicted temperature in winter time starts 12.85 degree Fahrenheit and reaches to 26.24 degree Fahrenheit at 16o'clock of the day.

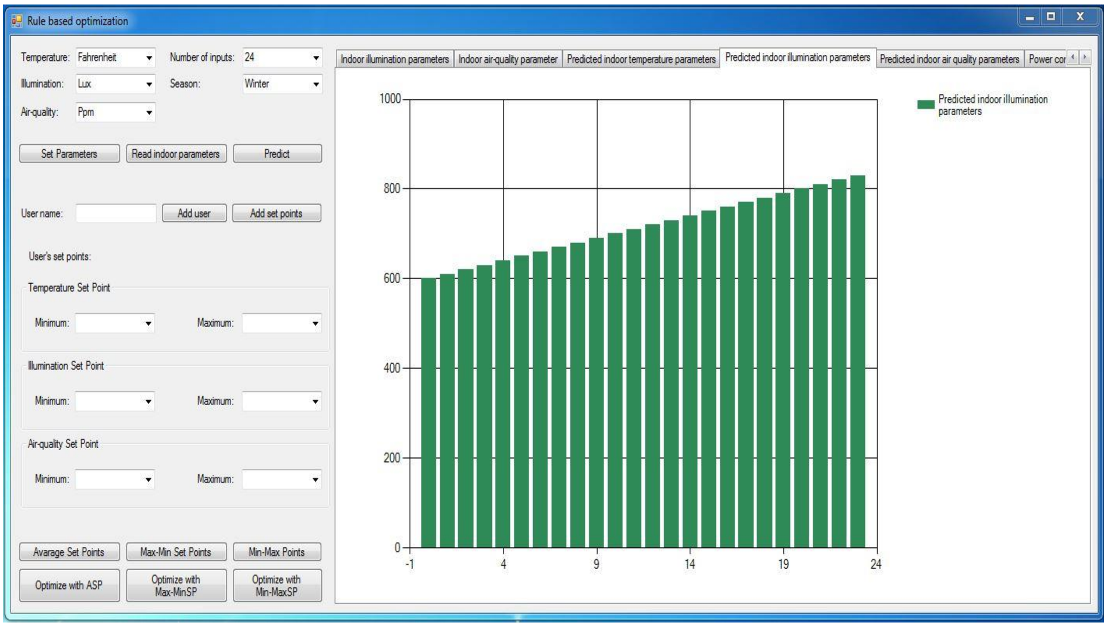

Figure 5.10 Predicted Indoor parameters of illumination

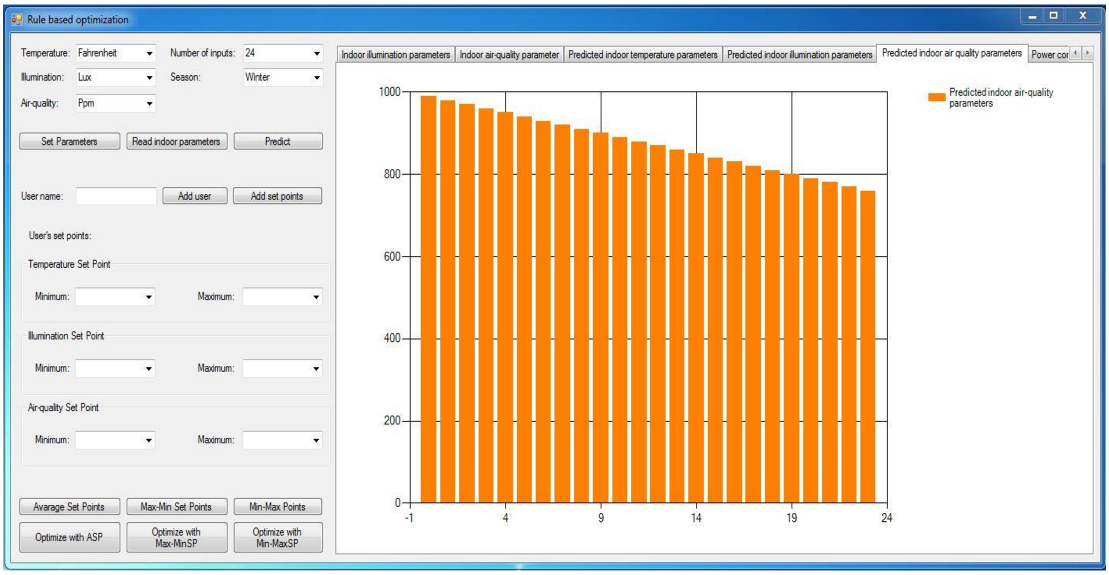

Figure 5.11 Predicted Indoor parameters of air quality

Figure 5.10 and 5.11 shows predicted indoor parameters of illumination and air quality. The change in predicted illumination starts from 600.65 lux at 1o'clock and reaches 830.64 lux at 23 o'clock. Similarly, change in air quality starts from 990.65 ppm at 1o'clock and it decreases to 760.65 ppm at 23o'clock.

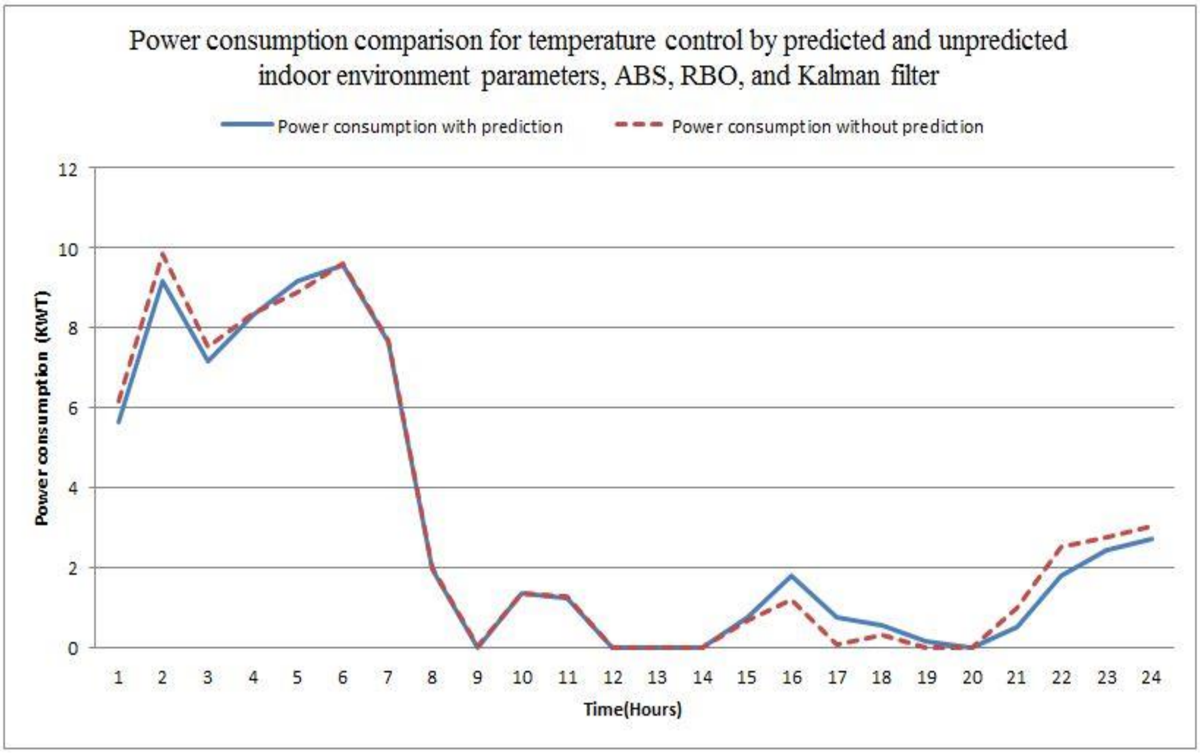

Figure 5.12 Power consumption comparison of temperature of predicted and unpredicted indoor environment parameters, ABS, RBO, and Kalman filter

Figure 5.12 shows a power consumption comparison for temperature control of predicted and unpredicted indoor environment parameters, ABS, RBO, and Kalman filter. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. Power consumption with prediction starts from 5.64kwt at 1o'clock. At the same time, power consumption without prediction starts from 6.18kwt. As a result, total power consumption with prediction consumed slightly less than power consumption without prediction for temperature control.

Figure 5.13 shows a power consumption comparison for illumination of predicted and unpredicted indoor environment parameters, ABS, RBO, and Kalman filter. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. Power consumption with prediction starts from 14.99878kwt at 1o'clock. At the same time, power consumption without prediction starts from 14.99898kwt. As a result, total power consumption with prediction consumed slightly less than power consumption without prediction for illumination control.

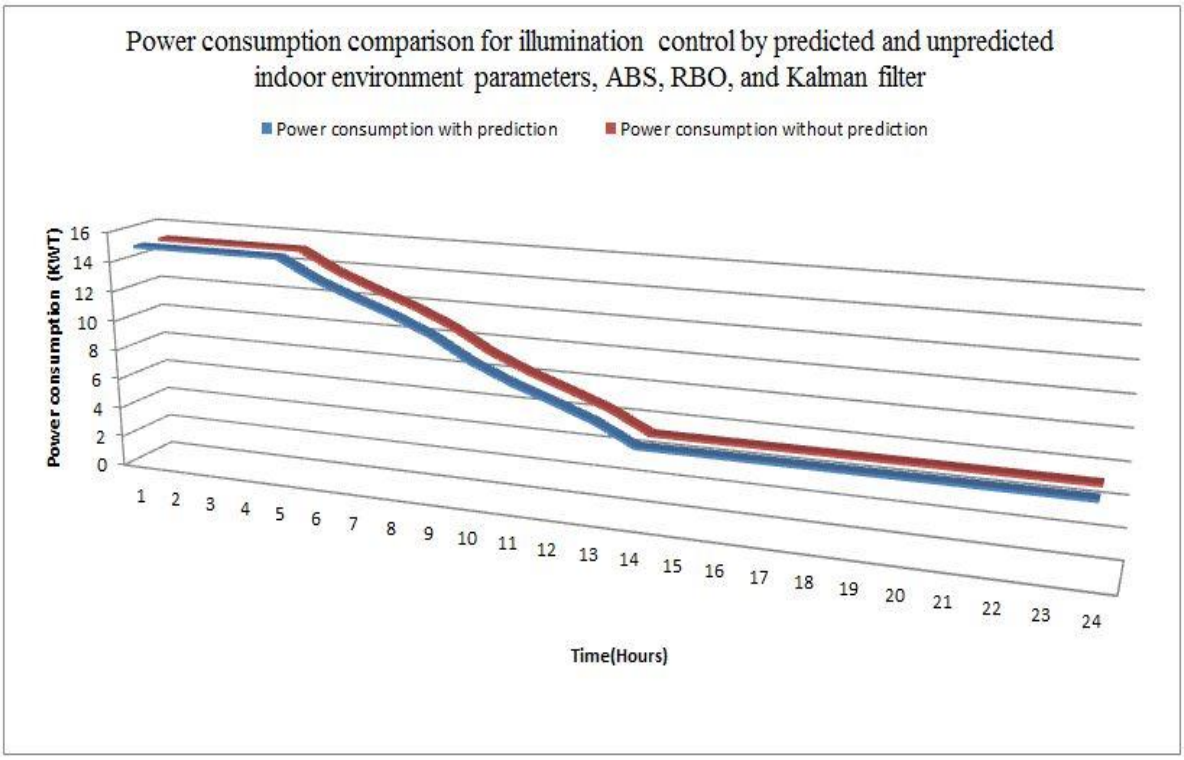

Figure 5.13 Power consumption comparison for illumination of predicted and unpredicted indoor environment parameters, ABS, RBO, and Kalman filter

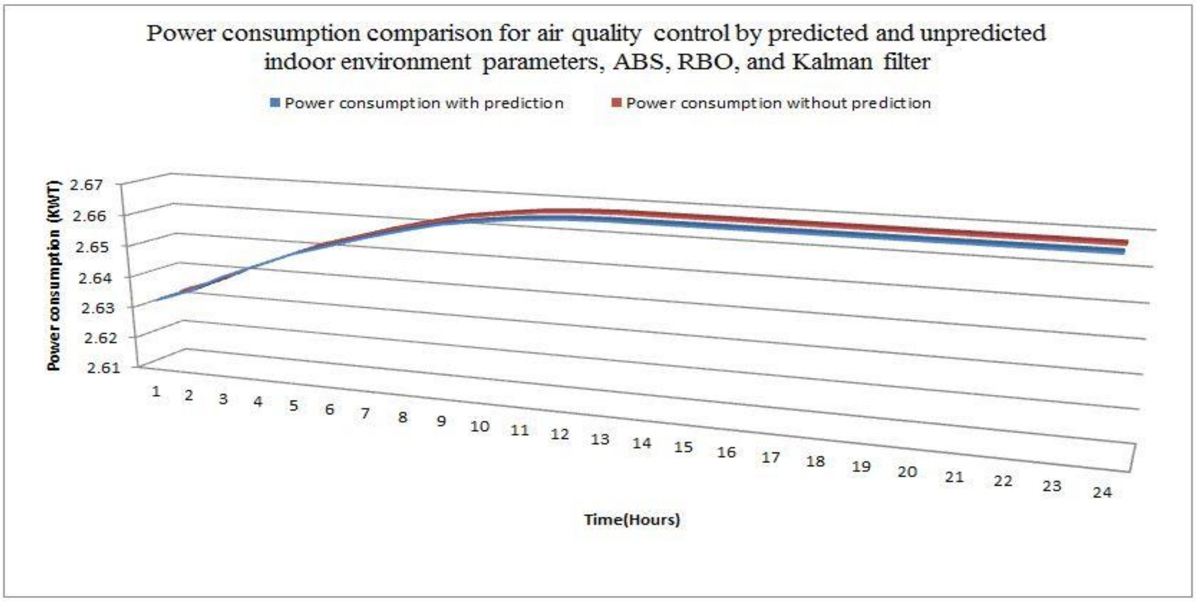

Figure 5.14 Power consumption comparison of air quality of predicted and unpredicted indoor environment parameters, ABS, RBO, and Kalman filter

Figure 5.14 shows a power consumption comparison for air quality of predicted and unpredicted indoor environment parameters, ABS, RBO, and Kalman filter. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. Power consumption with prediction starts from 2.6321kwt at 1o'clock. At the same time, power consumption without prediction starts from 2.6324kwt. As a result, total power consumption with prediction consumed slightly less than power consumption without prediction for air quality control.

Table 5.2 Total power consumption by predicted and unpredicted indoor environment parameters, ABS, RBO, and Kalman filter

	Temperature	**Illumination**	**Air quality**	**Total**
Power consumption with prediction	73.09353	210.0001	**63.8465**	**346.9401**
Power consumption without prediction	74.60748	210.0556	63.8472	348.5103

Table 5.2 shows a comparison of total power consumption for each control. For temperature control, power consumption with prediction consumed total 73.09353kwt power. Similarly, power consumption without prediction consumed 74.60748kwt power. As a result, we can see the much difference between power consumption with prediction and power consumption without prediction. Then we can see that power consumption with prediction consumes less power compared as power consumption without prediction. For illumination control, power consumption with prediction consumed total 210.0001kwt power. Similarly, power consumption without prediction consumed 210.0556kwt power. As a result, we can see the slightly difference between power consumption with prediction and power consumption without prediction. For air quality control, power consumption with prediction consumed total 63.8465kwt power. Similarly, power consumption without prediction consumed 63.8472kwt power. As a result, we can see the little difference between power consumption with prediction and power consumption without prediction. Then we can see that power consumption with prediction consumes almost same, but less power compared as power consumption without prediction. As an overall result, the total power consumption with prediction consumed 346.9401kwt. Then the total power consumption without prediction consumed 348.5103kwt. We can consume less power using Kalman filter prediction of indoor environment parameters.

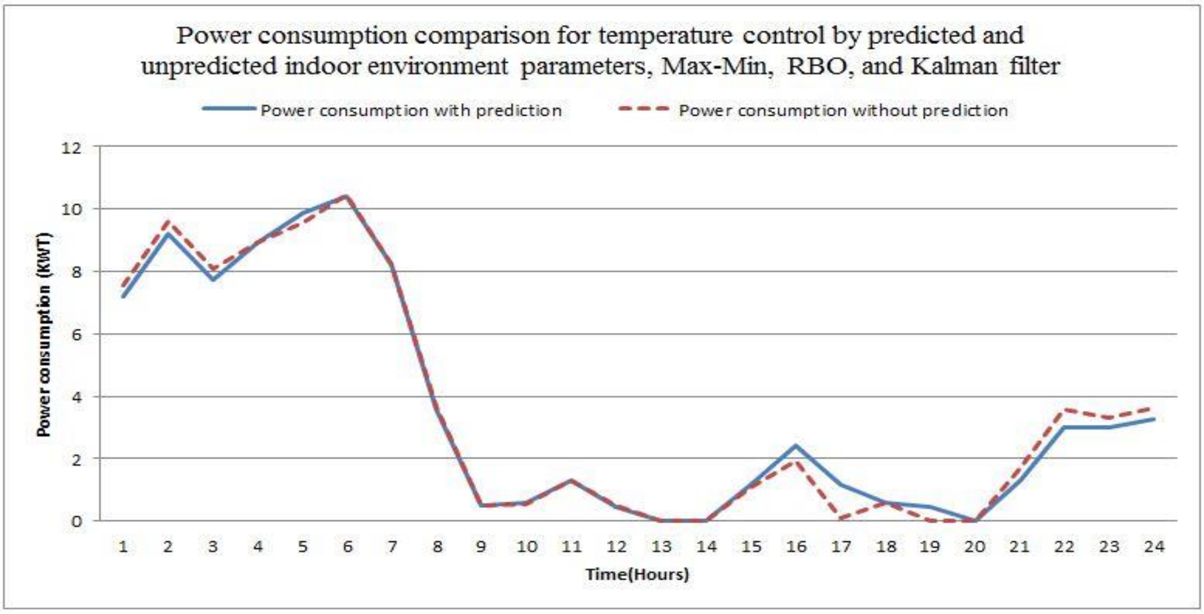

Figure 5.15 Power consumption comparison of temperature of predicted and unpredicted indoor environment parameters, Max-Min, RBO, and Kalman filter

Figure 5.15 shows a power consumption comparison for temperature control of predicted and unpredicted indoor environment parameters, Max-Min, RBO, and Kalman filter. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. Power consumption with prediction starts from 7.17kwt at 1o'clock. At the same time, power consumption without prediction starts from 7.55kwt. As a result, total power consumption with prediction consumed slightly less than power consumption without prediction for temperature control.

Figure 5.16 shows a power consumption comparison for illumination of predicted and unpredicted indoor environment parameters, Max-Min, RBO, and Kalman filter. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. Power consumption with prediction starts from 14.99984kwt at 1o'clock. At the same time, power consumption without prediction starts from 14.99965kwt. As a result, total power consumption with prediction consumed slightly less than power consumption without prediction for illumination control.

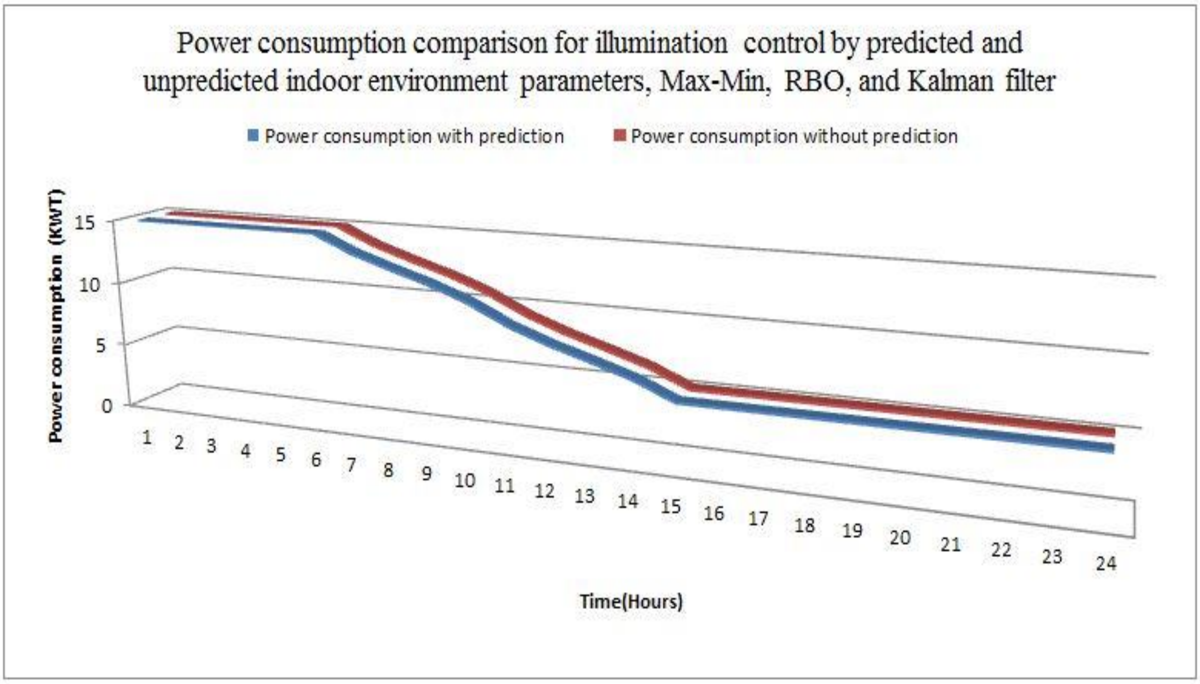

Figure 5.16 Power consumption comparison for illumination of predicted and unpredicted indoor environment parameters, Max-Min, RBO, and Kalman filter

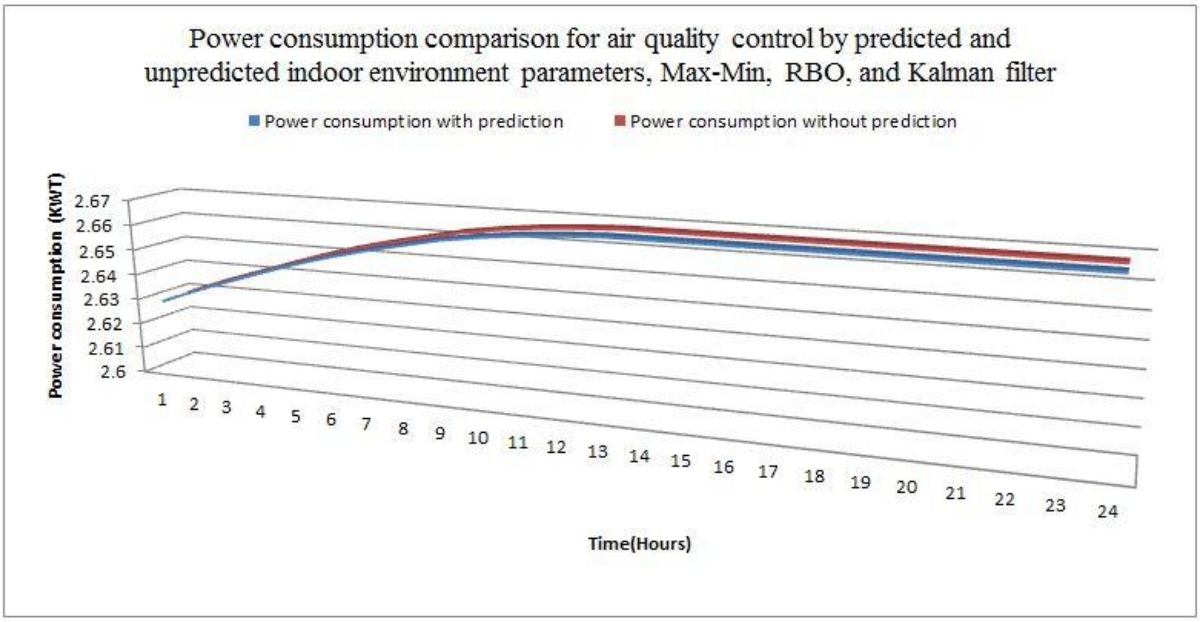

Figure 5.17 Power consumption comparison of air quality of predicted and unpredicted indoor environment parameters, Max-Min, RBO, and Kalman filter

Figure 5.17 shows a power consumption comparison for air quality of predicted and unpredicted indoor environment parameters, Max-Min, RBO, and Kalman filter. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. Power consumption with prediction starts from 2.6288kwt at 1o'clock. At the same time, power consumption without prediction starts from 2.6292kwt. As a result, total power consumption with prediction consumed slightly less than power consumption without prediction for air quality control.

Table 5.3 Total power consumption by predicted and unpredicted indoor environment parameters, Max-Min, RBO, and Kalman filter

	Temperature	**Illumination**	**Air quality**	**Total**
Power consumption with prediction	84.39	219	**63.8262**	**368.21**
Power consumption without prediction	85	220	63.8271	368.88

Table 5.3 shows a comparison of total power consumption for each control. For temperature control, power consumption with prediction consumed total 73.09353kwt power. Similarly, power consumption without prediction consumed 74.60748kwt power. As a result, we can see the much difference between power consumption with prediction and power consumption without prediction. Then we can see that power consumption with prediction consumes less power compared as power consumption without prediction. For illumination control, power consumption with prediction consumed total 210.0001kwt power. Similarly, power consumption without prediction consumed 210.0556kwt power. As a result, we can see the slightly difference between power consumption with prediction and power consumption without prediction. For air quality control, power consumption with prediction consumed total 63.8465kwt power. Similarly, power consumption without prediction consumed 63.8472kwt power. As a result, we can see the little difference between power consumption with prediction and power consumption without prediction. Then we can see that power consumption with prediction consumes almost same, but less power compared as power consumption without prediction. As an overall result, the total power consumption with prediction consumed 368.21kwt. Then the total power consumption without prediction consumed 368.88kwt. From the result, we can say that Kalman filter prediction of indoor environment parameters can make power consumption decrease.

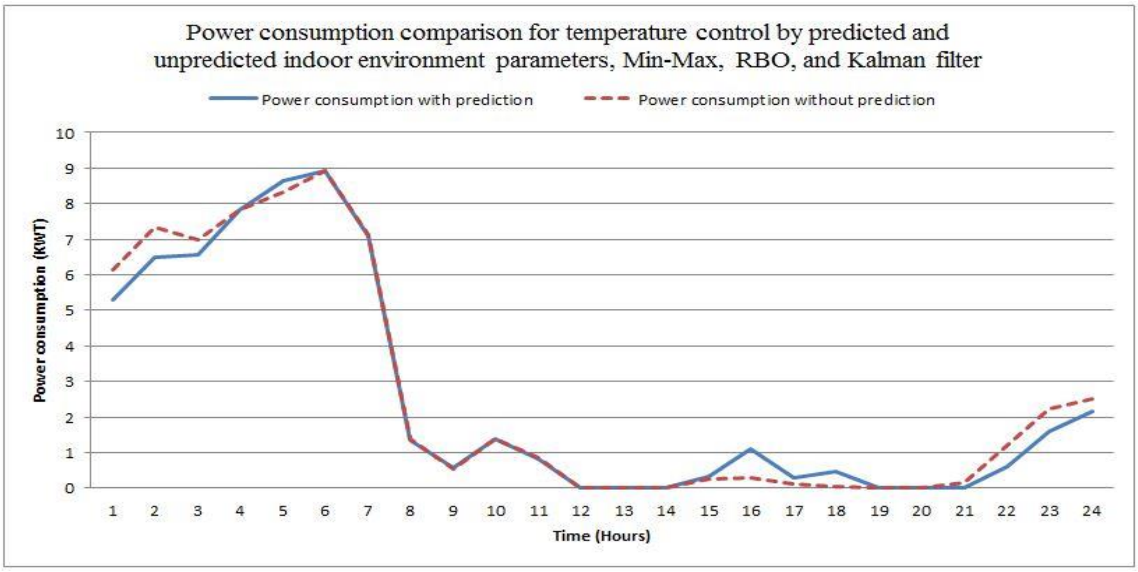

Figure 5.18 Power consumption comparison of temperature of predicted and unpredicted indoor environment parameters, Min-Max, RBO, and Kalman filter

Figure 5.18 shows a power consumption comparison for temperature control of predicted and unpredicted indoor environment parameters, Min-Max, RBO, and Kalman filter. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. Power consumption with prediction starts from 5.27kwt at 1o'clock. At the same time, power consumption without prediction starts from 6.13kwt. As a result, total power consumption with prediction consumed slightly less than power consumption without prediction for temperature control.

Figure 5.19 shows a power consumption comparison for illumination of predicted and unpredicted indoor environment parameters, Min-Max, RBO, and Kalman filter. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. Power consumption with prediction starts from 14.99936kwt at 1o'clock. At the same time, power consumption without prediction starts from 14.99938kwt. As a result, total power consumption with prediction consumed slightly less than power consumption without prediction for illumination control.

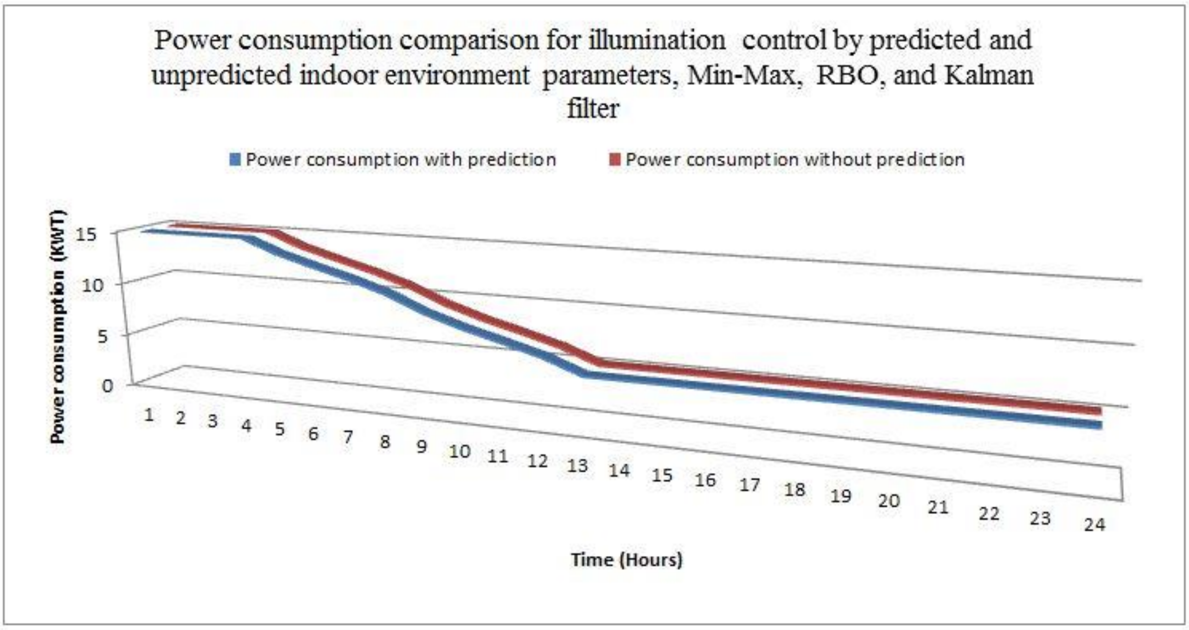

Figure 5.19 Power consumption comparison for illumination of predicted and unpredicted indoor environment parameters, Min-Max, RBO, and Kalman filter

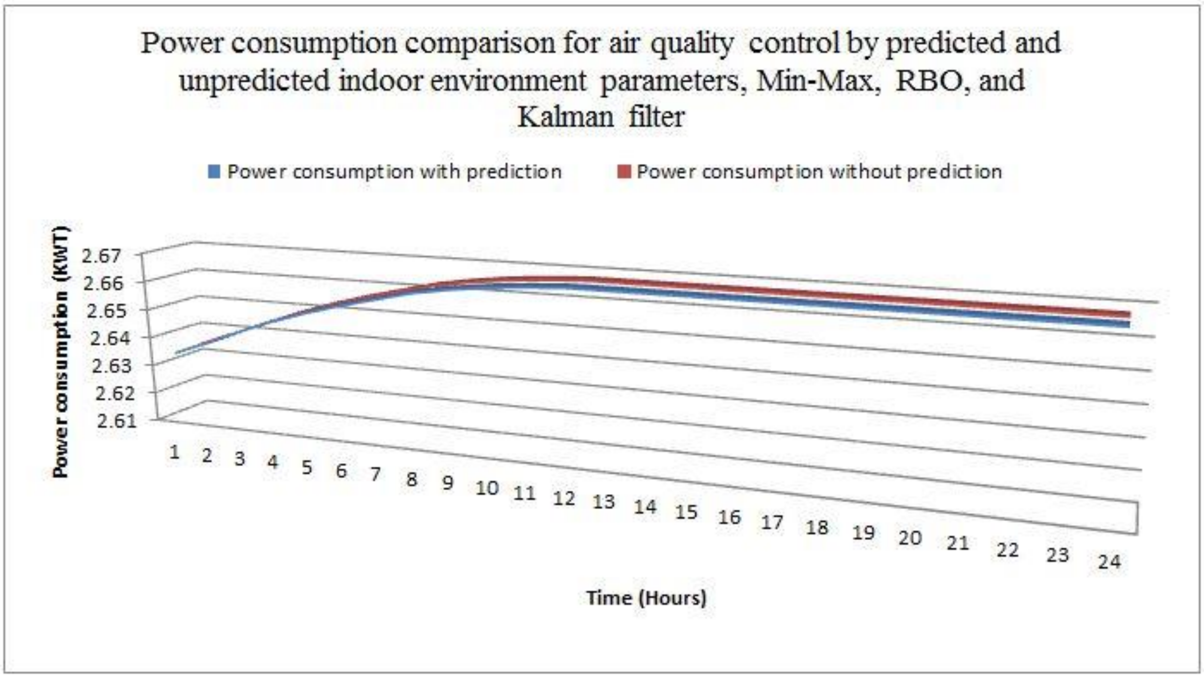

Figure 5.20 Power consumption comparison of air quality of predicted and unpredicted indoor environment parameters, Min-Max, RBO, and Kalman filter

Figure 5.20 shows a power consumption comparison for air quality of predicted and unpredicted indoor environment parameters, Min-Max, RBO, and Kalman filter. X-axis shows time in hours and the Y-axis shows the power consumption in kilowatts. Power consumption with prediction starts from 2.6341kwt at 1o'clock. At the same time, power consumption without prediction starts from 2.6344kwt. As a result, total power consumption with prediction consumed slightly less than power consumption without prediction for air quality control.

Table 5.4 Total power consumption by predicted and unpredicted indoor environment parameters, Min-Max, RBO, and Kalman filter

	Temperature	**Illumination**	**Air quality**	**Total**
Power consumption with prediction	61.51	200.008	63.864	325.38
Power consumption without prediction	63.6	200.059	63.865	327.52

Table 5.4 shows a comparison of total power consumption for each control. For temperature control, power consumption with prediction consumed total 61.51kwt power. Similarly, power consumption without prediction consumed 63.6kwt power. As a result, we can see the much difference between power consumption with prediction and power consumption without prediction. Then we can see that power consumption with prediction consumes less power compared as power consumption without prediction. For illumination control, power consumption with prediction consumed total 200.008kwt power. Similarly, power consumption without prediction consumed 200.059kwt power. As a result, we can see the slightly difference between power consumption with prediction and power consumption without prediction. For air quality control, power consumption with prediction consumed total 63.864kwt power. Similarly, power consumption without prediction consumed 63.865kwt power. As a result, we can see the little difference between power consumption with prediction and power consumption without prediction. Then we can see that power consumption with prediction consumes almost same, but less power compared as power consumption without prediction. As an overall result, the total power consumption with prediction consumed 325.38kwt. Then the total power consumption without prediction consumed 327.52kwt. From the result, we can say that Kalman filter prediction of indoor environment parameters can make power consumption decrease.

6. Conclusion

In this thesis work, we proposed improved energy and comfort index optimization scheme based on rule in smart home. Our proposed system has three major contributions. Firstly, rule based optimization which consumed less power as compared to genetic algorithm and incremental genetic algorithm. Secondly, optimization algorithm based on dynamic user set point setting for multi-users, which uses three methods such as average based user set point setting, max-min based user set point setting, and min-max based user set point. As a result of the power consumption comparison of these three methods, we can say that min-max based user set point setting consumes less power compared to the other two methods. Thirdly, the proposed idea is that optimization based on prediction of indoor environment parameters using Kalman filter. The proposed work consumed less power compared to unpredicted indoor environmental parameters. To conclude, our system improved user comfort index and decreasing consumed power by temperature, illumination, and air quality control in a smart home. As a result, RBO reduced power consumption by 24.32% as compared to GA, 10.26% as compared to IGA, and 25.72% as compared to ACO. Then to satisfy multi users' comfort of smart home, we proposed dynamic user set points setting by three methods. Among the three methods, max-min based user set point setting consumed highest power. Then average based user set point setting reduced power by 4.28% as compared to max-min based user set point setting and min-max based user set point setting reduced power by 8.74% as compared to max-min based user set point setting. We compared predicted indoor environment parameters and unpredicted indoor parameters. For illumination and air quality control, we got results with almost similar. Then prediction of indoor parameters, for temperature control ABS, and RBO based system reduced power consumption by 2% as compared to unpredicted indoor parameters, ABS, and RBO based system. Prediction of indoor parameters, for temperature control Max-min, and RBO based system reduced power consumption by 0.71% as compared to unpredicted indoor parameters, Max-min, and RBO based system. Similarly, prediction of indoor parameters, for temperature control Min-max, and RBO based system reduced power consumption by 3.28% as compared to unpredicted indoor parameters, Min-max, and RBO based system.

References

1. Ali, S., & Kim, D. H. (2013). Optimized power control and comfort management in building environment. *FTRA-AIM Advanced IT, Engineering and Management Conference*, pp. 145-146, 2013.

2. Ali, S., & Kim, D. H. (2013). Effective and comfortable power control model using Kalman filter for building energy management. *Journal of Wireless Personal Communication*, 73 (4), pp. 1439-1453.

3. Ali, S., & Kim, D. H. (2015). Optimized power control methodology using genetic algorithm. *Journal of Wireless Personal Communication*, http://dx.doi.org/10.1007/s11277-015-2405-3.

4. Wang, Z., Yang, R., & Wang, L. (2010). Multi-agent control system with intelligent optimization for smart and energy-efficient buildings. *In proceedings of the 36th annual conference of the IEEE Industrial Electronics Society*, pp. 1144-1149, November 2010.

5. Dounis, A. I., & Caraiscos, C. (2009). Advanced control systems engineering for energy and comfort management in a building environment—a review. *Renewable and Sustainable Energy Reviews*, 13(6–7), 1246–1261.

6. Wang, Z., Yang, R., & Wang, L. (2010). Multi-agent intelligent controller design for smart and sustainable buildings. *In Proceedings of 4th annual IEEE international systems conference*, pp. 277–282.

7. Emmerich, S. J., & Persily, A. K. (2001). *State-of-the-art review of CO2 demand controlled ventilation technology and application*. National Institute of Standards and Technology, Technology Administration, US. Department of Commerce, March 2001.

8. Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. Proc IEEE Int. Joint Conf. on Neural Networks, vol.4, pp.1942-1948.

9. Holland, J. H. (1975). Adaptation in natural and artificial systems", Ann Arbor, MI, The University of Michigan Press, 1975.

10. Huang, W., & Lam, HN. (1997). Using genetic algorithms to optimize controller parameters for HVAC systems. Energy and Buildings, 26, pp. 277–282.

11. Obara, S., & Kudo, K. (2003). Multiple-purpose operational planning of fuel cell and heat pump compound system using genetic algorithm. Transaction of the Society of Heating, Air-Conditioning and Sanitary Engineers of Japan, 91, pp. 65–75.

12. Wright, J. I., & Loosemore, H. A., & Farmani, R. (2002). Optimization of building thermal design and control by multi-criterion genetic algorithm. Energy and Buildings 34, pp. 959–72.

13. Hongwei, Li., Nalimi, R., & Haldi, P. A. (2006). Thermal-economic optimization of a distributed multi-generation energy system. A case study of Beijing: Applied Thermal Engineering, 26, pp. 709–19.

14. Montazeri-Gh, M., Poursamad, A., & Ghalichi, B. (2006). Application of genetic algorithm for optimization of control strategy in parallel hybrid electric vehicles, Journal of the Franklin Institute, 343, 420-435.

15. Azadeh, A., & Tarverdian, S. (2007). Integration of genetic algorithm, computer simulation and design of experiments for forecasting electrical energy consumption. Energy Policy, 35(10), 5229–5241.

16. Yu, T. (2010). Modeling occupancy behavior for the energy efficiency and occupants comfort management in intelligent buildings. *Ninth International Conference on Machine Learning and Applications*, pp. 726-731.

17. Ming-hai, L., & Qing-chang, R. (2010). Optimization for the chilled water system of HVAC systems in an intelligent building. In *Proceedings of international conference on computational and information sciences (ICCIS)*, pp. 889–891, December 2010.

18. Azadeh, A., Ghaderi, S. F., Tarverdian, S., & Saberi, M. (2007). Integration of artificial neural networks and genetic algorithm to predict electrical energy consumption. *Applied Mathematics and Computation*, 186 (2), pp. 1731-1741.

19. Mossolly, M., Ghali, K., & Ghaddar, N. (2009). Optimal control strategy for a multi-zone air conditioning system using a genetic algorithm. *Energy*, 34 (1), pp. 58-66.

20. Sorrentino, M., Arsie, I., Di-Martino R. & Rizzo, G. (2010). On the Use of Genetic Algorithm to Optimize the On-board Energy Management of a Hybrid Solar Vehicle, IFP International Conference – Advances in Hybrid Powertrains, January–February, 2010.

21. Kayo, G., & Ooka, R. (2009). Application multi-objective genetic algorithm for optimal design method of distributed energy system. In Proceedings of eleventh international IBPSA conference, pp. 167–172.

22. Levermore, G. J. (1992). Building Energy Management Systems: An Application to Heating, Natural Ventilation, Lighting and Occupant Satisfaction. 2nd ed., London, E & FN SPON.

23. Dounis, A. I., Bruant, M., Santamouris, M. J., Guarrancino, G, & Michel, P. (1996) Comparison of conventional and fuzzy control of indoor air quality in buildings. Journal of Intelligent & Fuzzy Systems, 4(2), 131–40.

24. Bernard, C., Guerrier, B., & Rasset-Louerant, M. M. (1982). Optimal building energy management. Part II: Control. ASME *Journal of Solar Energy Engineering*, 114, 13–22.

25. Curtis, P. S., Shavit, G., & Kreider, K. (1996). Neural networks applied to buildings—a tutorial and case studies in prediction and adaptive control. *ASHRAE Transactions*, 102(1), 732–737.

26. Kolokotsa, D. (2003). Comparison of the performance of fuzzy controllers for the management of the indoor environment. Building and Environment, 38, 1439–50.

27. Kolokotsa, D., Tsiavos, D., Stavrakakis, G., Kalaitzakis, K., & Antonidakis, E. (2001). Advanced fuzzy logic controllers design and evaluation for buildings' occupants thermal–visual comfort and indoor air quality satisfaction. Energy and Buildings, 33(6), 531–43.

28. Calvino, F., Gennusca, M. L., Rizzo, G., & Scaccianoce, G. (2004). The control of indoor thermal comfort conditions: introducing a fuzzy adaptive controller. Energy and Buildings, 36, 97–102.

29. Morel, N., Bauer, M., El-Khoury, Krauss, J. N. (2000). a predictive and adaptive heating control system using artificial neural networks. International Journal of Solar Energy, 21, 161–201.

30. Wang, S., & Jin, X. (2000). Model-based optimal control of VAV air-conditioning system using genetic algorithms. Building and Environment, 35, 471–87.

31. Dalamagkidis, K., Kolokotsa, D., Kalaitzakis, K., & Stavrakakis, G. S. (2007). Reinforcement learning for energy conservation and comfort in buildings. Building and Environment, 42(7), 2686–98.

32. Anderson, C. W., Hittle, D., Kretchmar, M., & Young, P. (2004). Robust reinforcement learning for heating, ventilation and air conditioning control of buildings. In: Si J, Barto AG, Powell WB, Wunsch DII, editors. Handbook of learning and approximate dynamic programming. IEEE Press/Willey Interscience, pp. 517–34.

33. Kolokotsa, D., Stavrakakis, G. S., Kalaitzakis, K., & Agoris, D. (2002). Genetic algorithms optimized fuzzy controller for the indoor environmental management in buildings implemented using PLC and local operating networks", *Engineering Application of Artificial Intelligence*, 15(5), pp. 417–428.

34. Kusiak, A., Li, M., & Zhang, Z. (2010). A data-driven approach for steam load prediction in buildings. *Applied Energy*, 87 (3), pp. 925–933.

35. Siroky, J., Oldewurtel, F., Cigler, J., & Privara, S. (2011). Experimental analysis of model predictive control for an energy efficient building heating system. *Applied Energy*, 88 (9), pp. 3079–3087.