Journal of King Saud University – Engineering Sciences (2016) xxx, xxx–xxx

King Saud University

Journal of King Saud University – Engineering Sciences

www.ksu.edu.sa
www.sciencedirect.com

ORIGINAL ARTICLE

Intelligent multi-objective optimization for building energy and comfort management

Pervez Hameed Shaikh [a,b,*], Nursyarizal Bin Mohd Nor [b], Perumal Nallagownden [b], Irraivan Elamvazuthi [b]

[a] *Department of Electrical Engineering, Mehran University of Engineering and Technology, Jamshoro 76062, Pakistan*
[b] *Department of Electrical & Electronic Engineering, Universiti Teknologi PETRONAS, Malaysia*

Received 30 January 2015; accepted 6 March 2016

KEYWORDS

Energy;
Buildings;
Comfort;
Management;
Optimization;
Trade-off

Abstract The rapid economic and population growth in developing countries, effective and efficient energy usage has turned out to be crucial due to the rising concern of depleting fossil fuels, of which, one-third of primary energy is consumed in buildings and expected to rise by 53% up to 2030. This roaring sector posing a challenge, due to 90% of people spend most of their time in buildings, requires enhanced well-being of indoor environment and living standards. Therefore, building operations require more energy because most of the energy is consumed to make the indoor environment comfortable. Consequently, there is the need of improved energy efficiency to decrease energy consumption in buildings. In relation to this, the primary challenge of building control systems is the energy consumption and comfort level are generally conflicting to each other. Therefore, an important problem of sustainable smart buildings is to effectively manage the energy consumption and comfort and attain the trade-off between the two. Thus, smart buildings are becoming a trend of future construction that facilitates intelligent control in buildings for the fulfillment of occupant's comfort level. In this study, an intelligent multi-objective system has been developed with evolutionary multi-objective genetic algorithm (MOGA) optimization method. The corresponding case study simulation results for the effective management of users' comfort and energy efficiency have been carried out. The case study results show the management of energy supply for each comfort parameter and maintain high comfort index achieving balance between the energy consumption and comfort level.

* Corresponding author at: Department of Electrical Engineering, Mehran University of Engineering and Technology, Jamshoro 76062, Pakistan.
E-mail address: engr.pervezhameed@gmail.com (P.H. Shaikh).
Peer review under responsibility of King Saud University.

ELSEVIER Production and hosting by Elsevier

1. Introduction

The prompt rise in world's energy consumption has been observed for last two decades and is estimated to rise by 53% until 2030 (International Energy Agency, 2007). The second largest energy-consuming sector after transport is buildings (which includes residential and commercial sectors) hold

http://dx.doi.org/10.1016/j.jksues.2016.03.001
1018-3639

Please cite this article in press as: Shaikh, P.H. et al., Intelligent multi-objective optimization for building energy and comfort management. Journal of King Saud University – Engineering Sciences (2016), http://dx.doi.org/10.1016/j.jksues.2016.03.001

approximately, one-third of the global energy, thus touching 40% of buildings' primary energy consumption in developing countries (Costa et al., 2013). The factors contributing this energy level mainly involve population growth, increased building amenities, and improved comfort index along with the time spent inside the buildings, show an upward trend for rise in building energy demand in near future.

The building operations need improved energy efficiency to decrease energy consumption. Conversely, the attainment of quality indoor environment requires more energy. Hence, an important problem of sustainable smart buildings is to achieve the trade-off between the requirement of power and the occupant's comfort. The main factors in the tropical areas, which define quality lives of occupants in the indoor environment are temperature, humidity, illumination and air quality. Therefore, an intelligent control of the thermal, humidification, illumination and air quality, comfort factors, is important for energy efficiency and occupants' quality of living.

Generally, temperature defines thermal comfort in indoor building environment, whereas other factors are supposed to be subjective for simplification of the control system. Auxiliary cooling and heating system is employed to maintain the temperature inside the building environment. Relative humidity is a rising concern inside the buildings of tropical climate areas, due to very hot and humid environment. Thus, relative humidity factor indicates humidity comfort inside the buildings. Auxiliary dehumidifiers and humidifiers are employed to maintain the relative humidity in indoor building environment. Illumination level describes the visual comfort and artificial lighting systems are used with actuators for illumination controls. CO_2 concentration is used as an index to measure the air quality comfort and ventilation system is employed for attaining low CO_2 concentrations (Hussin et al., 2014). The prime objective of the control of building energy management system (BEMS) was to maintain high comfort index and reduce total energy consumption.

Various conventional on/off and proportional integral derivative (PID) control schemes have widely been applied in buildings (Mathews et al., 2000). These have shown unsatisfactory performance at instants when, system peak demand occurs, prompt overshoot of set point and enormous time-delays with nonlinearity been observed (Li et al., 2006). Several artificial intelligent techniques have been anticipated including fuzzy logic systems (FLCs) (Kukolj et al., 2001; Kolokotsa, 2003), neural networks (Curtis et al., 1996), neuro-fuzzy systems (Chen et al., 2006) which have been intensive on specific types of buildings. The pervasive monitoring of human attitude has been addressed in Liu et al. (2010). Multi-agent control scheme has been proposed to manage energy consumption and comfort employing particle swarm optimization (PSO) (Yang and Wang, 2013). It also uses graphical user interface (GUI) for occupants in order to manage building operations (Wang et al., 2010). The model predictive optimization with linear programming method has been employed in Dagdougui et al. (2012) using LINDO system tool. Moreover, the detail review on control systems and the optimizations in buildings have been presented in Shaikh et al. (2014a).

Nonetheless, multi-objective optimization techniques have been proposed (Nguyen et al., 2014) to instantaneously deal with multi-modal problems generally in conflict with each other. The evolutionary algorithms turned to be the most popular and widely used optimization method for resolving multi-objective problems. Genetic algorithm (GA) being the meta-heuristic, population based technique can instantaneously explore and utilize various solution space regions. GA being very suitable for Pareto optimality set in complex spaces. Various multi-objective genetic algorithm techniques exist for assigned fitness, maintaining diversity and preserving elite solutions. Multi-islanded genetic algorithm (MIGA) and simple genetic algorithm (GA) have been used for energy conservation and comfort management developed in Safdar and Dohyeun (2013), and this employs MIGA at the input fuzzy parameters optimization for environmental difference. Wang et al. (2011), proposed multi-agent controller structure to manage energy consumption and occupants' comfort. It employed particle swarm optimization (PSO) at the central agent to observe the trade-off solutions for informed decision-making. However, yet multi-objective genetic algorithm needs to be employed for several strategies. To accomplish, the distributed control of several comfort demands, the main task of the intended building control systems is to figure out the feasible distribution of energy for the higher comfort level possible. Besides optimization the studies consider individual comfort parameters such as mostly thermal and visual, while air quality is considered in combination of the two others. However, the thermal loading is increased in tropical climatic regions where heavy rainfall, in this context relative humidity parameter within the buildings is significant for various health issues. Therefore, the system should be capable to accommodate the varying user preferences. Therefore, the intended building control systems may take both maximizing the comfort level (thermal, relative humidity, visual, air quality) and minimizing the energy consumption as objective. This should also provide multiple optimized trade-off solutions to users for their specific choices. This is considered as multi-faceted problem, in which the objective functions to be optimized generally are in conflict with each other.

This study is the advancement of our previous works as in Shaikh et al. (2014b) and Shaikh et al. (2016). The major contribution of this study is an added comfort parameter of relative humidity. Therefore, in this study, a multi-agent coordinator system has been developed for energy consumption and environmental comfort management. The system aids in developing the energy consumption of the actuator system. In addition to this, an evolutionary multi-objective genetic algorithm (MOGA) has been employed for attaining trade-off between energy consumption and comfort. The significant contributions of this manuscript are the addition of humidity comfort parameter along with its model function. This parameter of humidity comfort has been integrated with other three parameters of thermal, visual and air quality comfort. Implementation of multi-objective genetic algorithm has not been employed in this kind of study and the modification of the comfort function as an additional parameter has been integrated. The remainder of the paper is organized as follows: Section 2 describes the overall system model and framework, and Section 3, in detail the algorithm for multi-objective optimization problem. Simulation results and analysis are given in Section 4, whereas Section 5 presents the conclusion and future works.

2. System framework and modeling

The multi-agent coordinator system comprises of the master coordinator agent and peripheral coordinator agents for each comfort parameter. The master agent coordinator is capable of coordinating all peripheral coordinating agents. It allows the occupant's preferences and coordinates with the optimization algorithm in order to maximize the user set value as quick as possible. The evolutionary optimization method uses the network knowledge and permits consumer to state the required comfort range to tune and update the best set points in each step. Its function is to optimize and update the set point values of master and peripheral coordinator agent, thus, adding intelligence to the system. The main aim was that, when the peripheral coordinator agent cannot reach the required target, the master coordinator agent will offer more power for attaining the desired set value as soon as possible. The entire optimization system framework has been shown in Fig. 1.

The users can set their different comfort range based on their preferences, which is represented as, [C_{min}, C_{max}], where, "C" denotes the required comfort parameter. In this study, the parameters selected are thermal, relative humidity, visual and air quality comfort. The users are allowed to set their specific requirement of the comfort value. This signifies the optimizer to achieve the targeted comfort in contrast to its best capabilities ensuring all the indoor and outdoor information satisfying their needs.

The management of building energy and comfort is through distributing the entire system into various subordinate systems. Primarily four comfort parameters have been considered, include thermal, visual, air quality and humidity. These comfort indexes have been corresponding to temperature for thermal comfort, artificial illumination for visual comfort, CO_2 concentrations in air for air quality comfort and relative humidity for humidity comfort respectively. Moreover, the actuator systems that drive the comfortable environment constitutes of auxiliary heating and cooling system for thermal comfort, electrical lighting system for visual comfort, automated window and fan operations to maintain CO_2 concentrations for air quality comfort and dehumidifier/humidifier systems for humidity comfort.

The fuzzy controllers are utilized to compute the power demand by each environmental parameter to maintain a high comfort level with the control of corresponding actuators. The implication of the fuzzy controllers helps to overcome the nonlinear problems in the control process. The inputs to the fuzzy inference system (FIS) of each parameter are random data set processed within the standard ASHARE (ASHARE Standard, 1992) comfortable range. The range has been provided with the set of intervals as proposed in the base quality

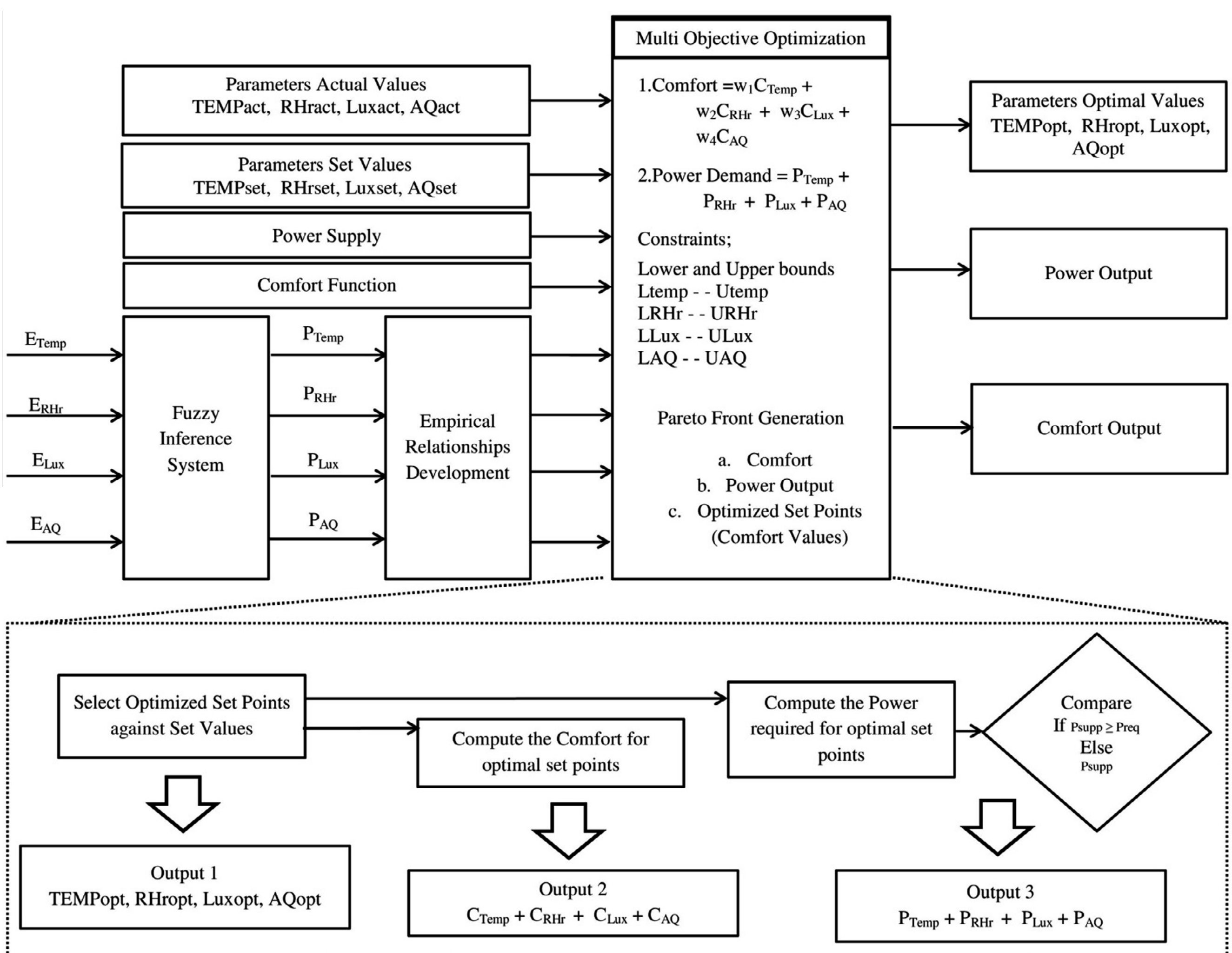

Figure 1 Optimization system framework.

assurances plan (Mark, 1996) for sensor measurement accuracy. These set of inputs has been supplied to the FIS system of each comfort parameter, which gives an output in terms of power demand. Since all the parameters have been processed in form of error values it transforms into a unit-less system with common output power demand. Therefore, the inputs and outputs of the FIS system have been treated with the statistical curve to fit empirical model development. The empirical models for each comfort parameter are capable of closely intimating the behavior of the developed FIS system. The FIS system characteristic membership functions and rule bases have been discussed in detail in our previous work (Shaikh et al. (2013a,b)). Moreover, the FIS provides empirical model functions as shown in Eqs. ((6)–(9)) having been observed through the fuzzy inference system. The developed functions for the power requirement of multi-agent coordinator of each comfort parameter are determined as follows. The four control variables of temperature, relative humidity, CO_2 concentration and illumination are provided through sensors as inputs to compute the desired power.

Meanwhile, all the power demand empirical models have been added together that constitute of four variables (that are four comfort parameters). On the other hand, comfort model function has been utilized from the literature (Wang et al., 2011) and has been modified with an additional relative humidity comfort factor constituted in the range of [0, 1]. This is due to the subjectivity of the comfort index; therefore, consider 0 being the lowest comfort level and 1 being the highest. As comfort for each individual varies, so, it is measured in terms of dwellers' percentage satisfaction; defined in terms of discomfort, utilizing the error between the measured sensor values and the user set points.

The two objective functions power demand and overall comfort constitute of four similar variables to be dealt with the multi-objective optimization techniques. Since the optimization has to be simplified in form of either minimization or maximization, indeed power demand needs to be minimized whereas, overall comfort has to be maximized. Here as the overall comfort is subjective represented in percentage therefore the function has been transformed to minimize the overall discomfort, simply by subtracting the overall comfort from the highest possible comfort level. Therefore, for the objective functions of overall comfort and energy consumption of the targeted comfort parameters are set as the vectors of four decision variables.

The demanded power in the building, allows the actuator system of each comfort parameter to cause variation in the indoor environmental parameter of the building. The key goal of the entire automation process is to achieve the required comfort index in the building. The level sensor sub-systems will give feedback to the environmental variation for calculating the input error to the fuzzy system. This feeds back the power demand to the master coordinator agent determining further adjustment of power demand. In relation to this, when the difference between set point and sensor value decreases, the power demand by the actuator system decreases and ultimately, the comfort value increases. Consequently, the selection of comfort set points has impact on both the energy consumption and the comfort level.

These coordinator agents acquire adjusted set points from the master agent controller and real time indoor environmental parameter. It provides the actual power demand for the actuator system to maintain the required comfort level. However, fuzzy rule base and membership function help to compute the required power during indefinite circumstances. In this proposed system, it is primarily supposed that the building indoor environment is very sensitive to the outdoor environmental variations. Therefore, the building indoor environment is closely following the change of outdoor environmental conditions, if no optimal system is applied. In that case, the ambient environmental parameters can serve as the input signals for the building control system. Besides, building optimization system it also considers the inhabitant's preferences for the attaining the user centered design.

$$\text{Comfort} = 1 - \text{Discomfort}_N \tag{1}$$

Broadly, when dealing with each comfort parameter into a single function the weighting factor needs to be added and can be written mathematically as follows:

$$\text{Overall comfort} = \sum_{i=1}^{n} w_i \cdot \text{comfort} \tag{2}$$

where w_i is the weighting coefficient and for comfort$_i$ is the each factor. Furthermore, in Eq. (2) expressively for each comfort parameter of thermal, relative humidity, visual and air quality comfort it can be written in the form as follows:

$$\begin{aligned} \text{Comfort} = {} & w_1\left[1-\left(\frac{\varepsilon_{\text{Thermal}}}{\text{Temp}_{\text{set}}}\right)^2\right] + w_2\left[1-\left(\frac{\varepsilon_{\text{RHr}}}{\text{RHr}_{\text{set}}}\right)^2\right] \\ & + w_3\left[1-\left(\frac{\varepsilon_{\text{Lux}}}{\text{Lux}_{\text{set}}}\right)^2\right] + w_4\left[1-\left(\frac{\varepsilon_{CO_2}}{\text{AQ}_{\text{set}}}\right)^2\right] \end{aligned} \tag{3}$$

The prime control goal is to maximize comfort under variable operating conditions. w_1, w_2, w_3 and w_4 are the user defined weighting coefficients of importance provided for each comfort parameter. These weighting coefficients are in the range of [0, 1] and generally expressed as $w_1 + w_2 + w_3 + w_4 = 1$. On the other hand, Temp_{set}, RHr_{set} Lux_{set} and AQ_{set} are the set points of temperature, relative humidity, illumination and indoor air quality respectively. The user preferences and adaptive rules, which reflect the human behavior pattern to determine four set points. $\xi_{\text{Thermal}}, \xi_{\text{Humidity}}, \xi_{\text{Lux}}$, and ξ_{CO_2} are the differences between the measured sensor values and set point values of the each comfort demand factors. The weighting coefficients and set points of environmental parameters are defined by the user's based on the occupant's preferences. On the other hand, the measured values of the environmental parameters are obtained from the peripheral agents for computing the differences.

The power requirement function will be computed at the local control level, but as the demand rises by the individual agents, the power demand function will supply accordingly as described in the following pattern;

$$P_{\text{Temp}}(t) + P_{\text{RHr}}(t) + P_{\text{Lux}}(t) + P_{\text{AQ}}(t) = P_{\text{in}}(t) \tag{4}$$

$$P_{\text{in}}(t) \leqslant P_{\max}(t) \tag{5}$$

The P_{in} is the actual power supplied from the utility electric grid and $P_{\max}$ is the maximum power that can be supplied by the electric grid.

The peripheral controller agents were developed to control thermal, humidity, visual and air quality comfort factors. The fuzzy controllers were utilized to calculate the power demand by each environmental parameter for maintaining high comfort level with the control of corresponding actuators. The generalized functions were developed for the power required by each subsystem. This power function has been compared to the power determined by the supervisory agent to adjust the real amount of power used. The actuator systems then drive the auxiliary heating/cooling system, electrical lighting system and air-quality system for all environmental parameters.

The temperature index is utilized to evaluate the thermal comfort in the building environment; thus, a linear best fit stochastic empirical model is derived with 98% confidence fit interval.

$$P_{\text{Temp}} = 5.655 * T_{\text{Temp}} + 2.961 \tag{6}$$

where P_{Temp} is power required for the temperature control actuator and T_{Temp} is the temperature control difference input value.

The per unit relative humidity is used to evaluate humidity comfort in the building environment; thus, a Gaussian model best fit stochastic model is derived with 98% confidence fit interval.

$$P_{\text{RHr}} = 13.23 * e^{\left(-\frac{\text{RHr}-0.9594}{0.6572}\right)^2} \tag{7}$$

P_{RHr} is power required for the temperature control actuator and RH_{r} is the relative humidity control difference input value.

The lux metric is used to evaluate the illumination level of the building environment; thus, the sum of sine model is best fitted and shows 99% confidence level fit.

$$P_{\text{Lux}} = 4.428 * \text{Sin}(0.9603 * I_{\text{Lux}} - 0.4234) \tag{8}$$

P_L is power required for the lighting control actuator and I_L is the lux control difference input value. On the other hand, the CO_2 concentration is used to evaluate the air quality index measured in ppm in building indoor environment; thus, the Gaussian model is best fitted and shows 99% confidence level fit.

$$P_{\text{AQ}} = 9.444 * e^{\left(-\frac{W_{\text{AQ}}-1163}{389}\right)^2} \tag{9}$$

P_{AQ} is power required for the air quality control actuator and W_{AQ} is the CO_2 concentration control difference input value.

3. Multi-objective optimization (MO) algorithm

Multi-objective optimization tries to improve vector-valued cost function components generally in conflict with each other (Nguyen et al., 2014). The aim of multiple objective optimizations was to find the solution set diversity, decisive with trading off among various objective functions. Multi-objective optimization has been applied in various fields of electrical engineering problems and yet at initial stages developing interests of researchers, where optimal decisions required for the presence of trade-offs between two or more contradictory objective functions. Moreover, the Pareto optimal solution set points will be generated in contrast to single solution as in single objective optimization. The solution is known as non-dominated, non-inferior Pareto efficient, mean if no objective function can be improved without degrading the other objective function. Therefore, MO usually looks for "trade-offs", rather than single solutions when dealing with multi-objective optimization problems. The MO problem requiring the optimization of "n" objectives may be formulated as follows: General MO problem can be mathematically represented in Eqs. (10)–(12);

$$\text{MOP} \quad \min_{x \in C} F(x) = \begin{bmatrix} f_1(x) \\ f_1(x) \\ . \\ . \\ . \\ f_n(x) \end{bmatrix} \quad n \geqslant 2 \tag{10}$$

Subject to,

$$C = \{x : h(x) = 0,\ g(x) \leqslant 0,\ a \leqslant x \leqslant b\} \tag{11}$$

$$\text{where, } x = [x_1, x_2, x_3, \ldots, x_p]^T = \Omega \text{ (Parameter Space)} \tag{12}$$

A point $x^* \in C$ is Pareto Optimal (or non-dominated) for multi-objective optimization problem (MOP) if and only if there is no $x \in C$ such that $f_i(x) \leqslant f_i(x^*)$ for all $i \in 1, 2, 3, \ldots, n$ with at least one strict inequality.

"$F(x)$" is the objective vector, the C represent the constraints and "x" is a P-dimensional vector representing the decision variables within a parameter space "Ω". The space spanned by the objective vectors is called the objective space. The subspace of the objective vectors, which fulfills, the constraints, has been called the feasible space.

A genetic algorithm (GA) is a population based stochastic approach and is suitable for multi-objective problems. GA is capable to stochastically search various regions, instantaneously in a solution space and discover trade-off solutions for different problems with discontinuous, non-convex and multi-modal solution space. The GA is capable of intuitiveness, easy in implementation, and solves nonlinear problems and mixed integer optimizations. It simply works with objective functions rather than the requisite of derivative and other auxiliary information. It parallel searches in population and implements probabilistic rules, which proceed toward optimum solutions using genetic operators and converge to high quality solutions within the few generations with minimized computational costs (Horn et al., 1994). In order to generate fresh non-dominated solutions in unmapped Pareto front measures, the GA crossover operator uses creditable solutions with regard to various objectives. Adding to this, MOGA does not necessitate scale, order or weigh objectives, thus being the most popular heuristic approach for multi-objective design and problems (Horn et al., 1994). Fig. 2 below shows the pseudo code that depicts the working of MOGA.

4. Results and discussion

In this section, a case study has been presented. The building is assumed to be in the islanded mode and has been supplied distributed renewable energy sources. Here, six 4.5-kW solar panels and equally 5-kW wind turbine generators are used (green energy ohio, 2013). The total amount of power being generated with these renewables is shown in Fig. 7 on a 24-h time domain. The storage bank constitutes batteries of 45 kWh, with minimum storage threshold of 4.5 kWh have been selected for distributed energy storage. In most of the entire day, the distributed energies are not capable to fulfill the complete power demand of the building. In this regard, the

Please cite this article in press as: Shaikh, P.H. et al., Intelligent multi-objective optimization for building energy and comfort management. Journal of King Saud University – Engineering Sciences (2016), http://dx.doi.org/10.1016/j.jksues.2016.03.001

```
Begin
   t = 0
Initialize population of chromosomes P(g);
   Evaluate the initialized population bycomputing its fitness measure
   P(g);
Whilenot termination criteriado
g:=g+1;
      Select P(g+1) from P(g);
Crossover P(g+1);
Mutate P(g+1);
      Evaluate P(g+1);
   End While
Output results to external archive
End
```

Figure 2 Pseudo code for multi-objective genetic algorithm (MOGA).

stochastic optimized, control system distributes the available power, sensibly and maximizes the overall comfort index inside the building.

In the simulation, the occupants' comfort ranges for the various control tasks are set at Temp = [67, 78] (°F), RH_r = [0.40, 0.60] (p.u), Lux = [750, 880] (lux) and AQ = [400, 880] (ppm). These comfort ranges, sever as the bound constraints in the stochastic MOGA to drive out the optimal set points tuning in each time step. The set points targeted for each comfort parameter are set at T_{set} = 71.6 °F, RHr_{set} = 0.5 p.u, L_{set} = 800 lux and AQ_{set} = 800 ppm and equal weighting coefficient for each comfort parameter has been set as one-fourth (1/4).

The MATLAB® simulation platform has been used for the building energy and comfort management. The optimization tool box has been used for the MOGA algorithm for the generation of Pareto front trade off solution set. The initial set parameters for the GA has been selected as the following: number of variables are four as the comfort parameters representing temperature, relative humidity, illumination level and CO^2 concentration. Constraints provided in the simulation were Lower bound [67 0.40 750 400] and upper bound [78 0.60 880 850] representing the respective comfort parameter. GA parameters use the following; population was selected as 500, selection function employs tournament method, crossover rate was set at 0.8, mutation rate was selected default of constraint dependent, migration was in forward direction with the fraction of 0.2 and an interval of 20 has been kept. On the other hand, the multi-objective problem settings use default distance crowding for the function of distance measure and the Pareto front population fraction was selected as 0.35. However, the simulation stopping criteria were having the default settings; comprising of generations: 200 * number of variables, time and fitness limit was set infinite, stall generations use default value of 100 and the fault tolerance was set at 1e-4. The simulation output describes problem type as bound constrained and generates 175 points on the Pareto front. The average distance measure of solutions on the Pareto front has been observed at 0.0063. The spread measure of the Pareto Front was 0.5049 and the number of generations was 125. On the other hand, the function counts were observed as 62,401 and the final message was displayed as "optimization

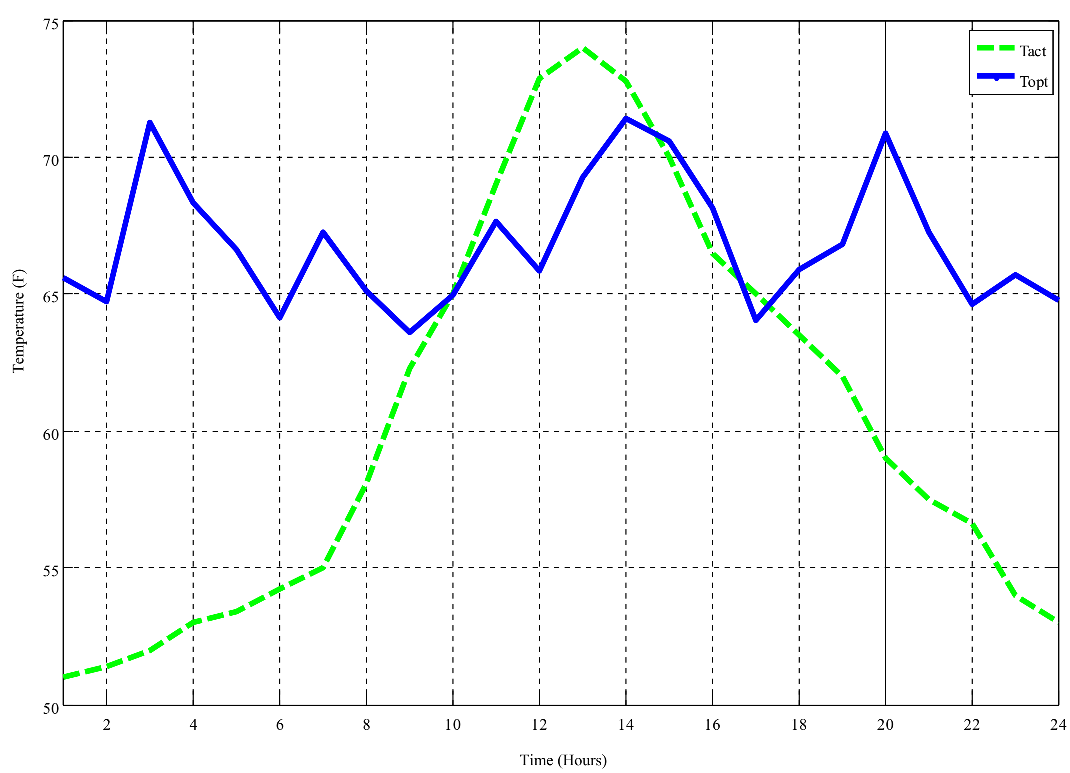

Figure 3 Temperature set points with and without MOGA.

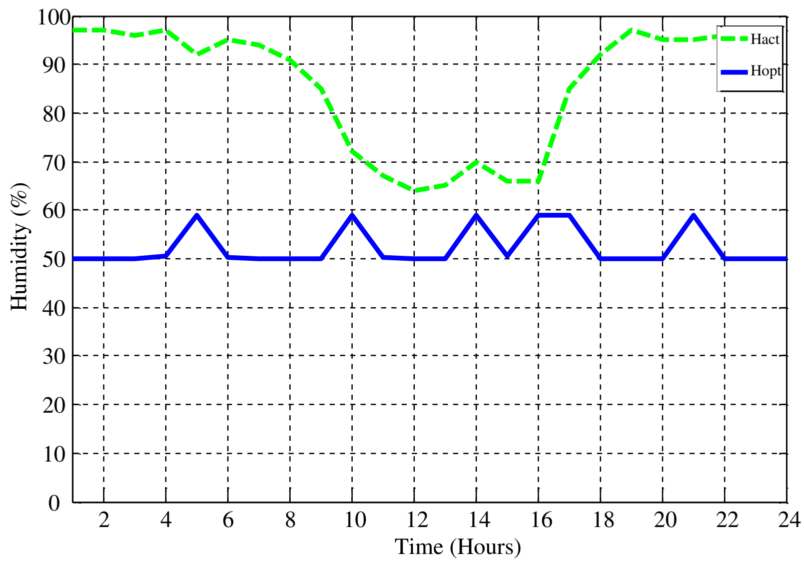

Figure 4 Relative humidity set points with and without MOGA.

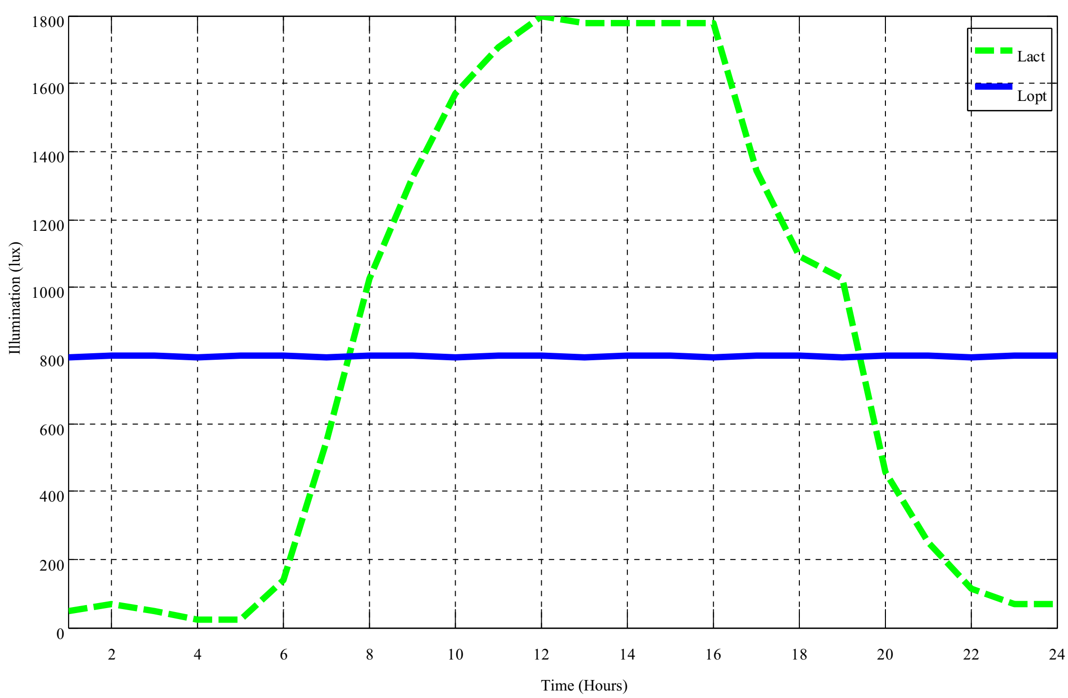

Figure 5 Illumination set points with and without MOGA.

terminated: average change in the spread of Pareto solutions less than options.TolFun."

The optimized indoor environmental set point variations over a day of 24 h are shown. On the other hand, the optimized temperature, humidity, illumination and air quality set point variations are shown in Figs. 3–6 respectively. However, the overall power consumption has been shown in Fig. 7. The overall power consumption is 654.082 kWh, whereas the total power been generated with the distributed renewable is 971.803 kWh, showing significant amount energy saving. The overall actual and optimized comfort index has been shown in Fig. 8. On an average the overall actual comfort 87.25%, whereas, the optimized comfort after MOGA has been improved to 99.73%. In spite of energy shortage from the renewable energy generation, the intelligent optimized system has distributed the energy appropriately for attaining the improved indoor comfort level. These results make evident that the system can be optimized by regulating the comfort ranges and along with this, it also proves the effectiveness of multi-agent coordinator system and MOGA optimizer.

Please cite this article in press as: Shaikh, P.H. et al., Intelligent multi-objective optimization for building energy and comfort management. Journal of King Saud University – Engineering Sciences (2016), http://dx.doi.org/10.1016/j.jksues.2016.03.001

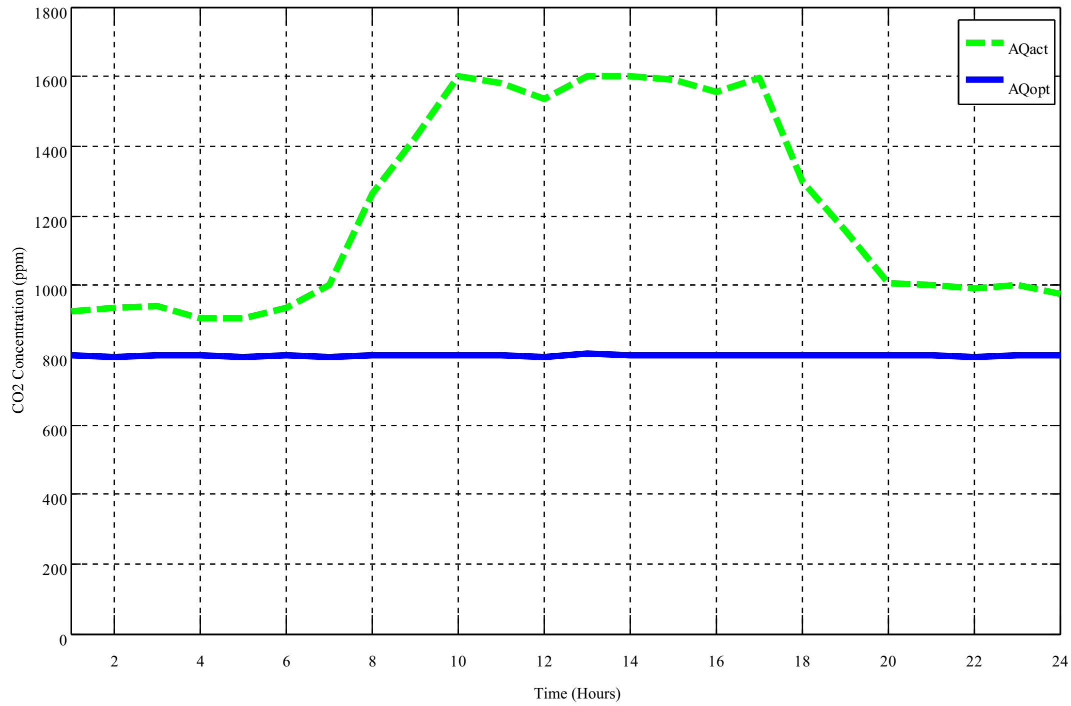

Figure 6 Air quality set points with and without MOGA.

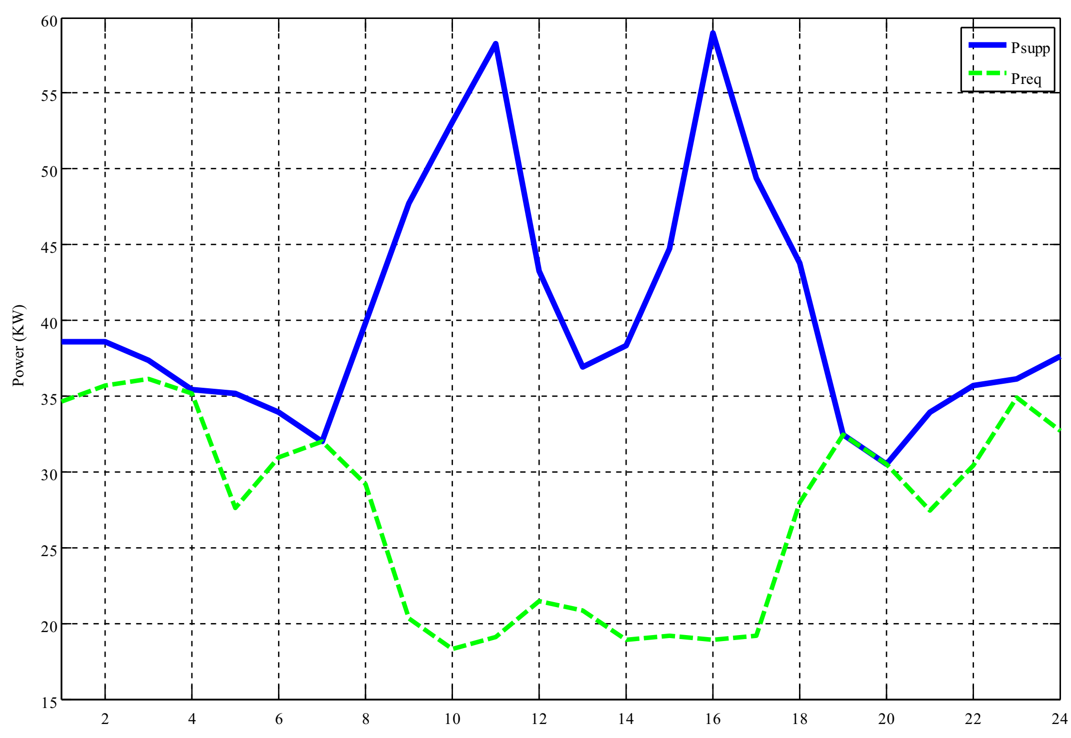

Figure 7 Overall power consumption with MOGA.

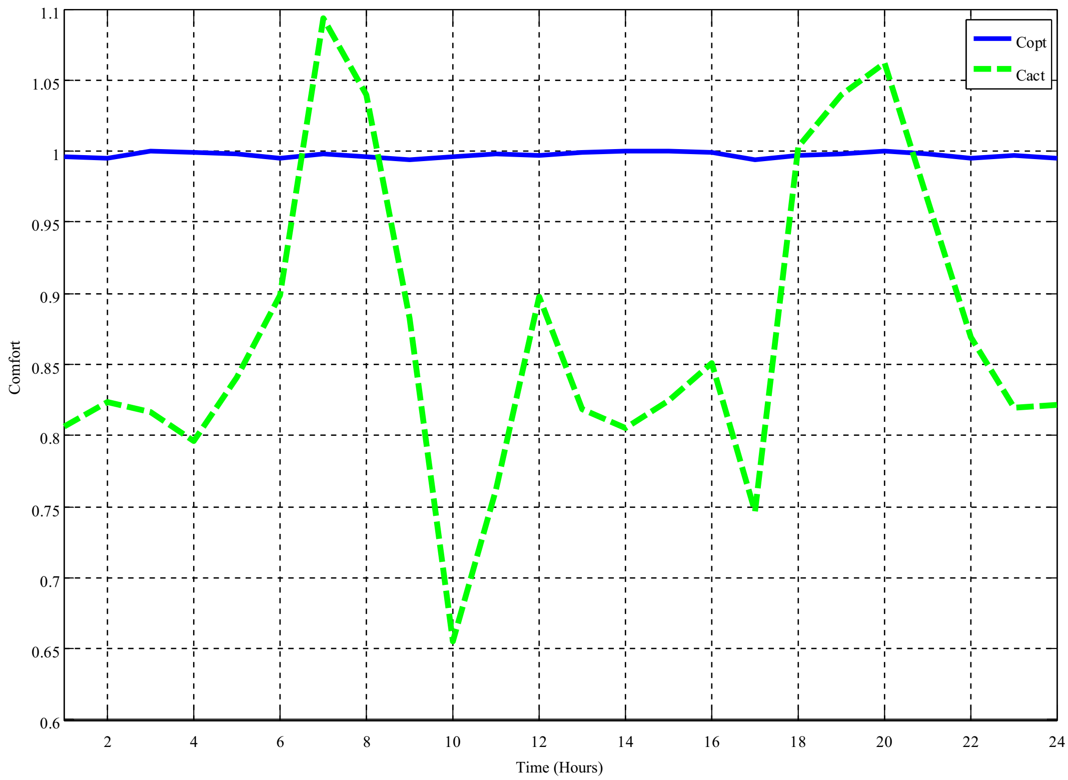

Figure 8 Overall comfort level with MOGA.

5. Conclusion

The major challenge of building automation system is to balance the conflict between the occupant's comfort and the total energy consumption. Thus, in this paper, the multi-agent control system technology has been developed for the optimized and intelligent control of the building indoor environment. Thus, it is more concerned about occupant's preferences and attaining their desired comfort. The multi-agent system has presented its capability in controlling a convoluted building system. The designed control system considers both energy efficiency in terms of power supply and consumption of entire system balanced while maintaining occupants' comfort. Moreover, the user's preferences are also taken into consideration for maintaining the required comfort level. In spite of total energy supply of renewable resources, MOGA has shown to be advantageous for maintaining high comfort level. This will make the occupants more informed prior to make their decision. Furthermore, other optimization techniques will be employed for evaluation of added intelligence in future work.

Acknowledgments

The authors are thankful to the Universiti Teknologi Petronas, Malaysia for the financial support and motivation to conduct research. They would also thank to Mehran University of Engineering and Technology, Jamshoro, Pakistan for allowing to accomplish higher studies smoothly.

References

ASHARE Standard, ANSI/ASHRAE Standard 55, 1992. Thermal Environmental Conditions for Human Occupancy. American Society of Heating, Refrigerating and Air-Conditioning Engineers. Inc., Atlanta.

Chen, K., Jiao, Y., Lee, E.S., 2006. Fuzzy adaptive networks in thermal comfort. Appl. Math. Lett. 19, 420–426.

Costa, A., Keane, M.M., Torrens, J.I., Corry, E., 2013. Building operation and energy performance: monitoring, analysis and optimization toolkit. Appl. Energy 101, 310–316.

Curtis, P.S., Shavit, G., Kreider, K., 1996. Neural networks applied to buildings – a tutorial and case studies in prediction and adaptive control. ASHRAE Trans. 1, 102.

Dagdougui, H., Minciardi, R., Ouammi, A., Robba, M., Sacile, R., 2012. Modeling and optimization of a hybrid system for the energy supply of a Green building. Energy Convers. Manage. 64, 351–363.

Green Energy Ohio, 2013. Accessed October 05 from, <www.greenenergyohio.org>.

Horn, J., Nafpliotis, N., Goldberg, D.E., 1994. A niched Pareto genetic algorithm for multiobjective optimization. In: Proceedings of the First IEEE Conference on Evolutionary Computation. IEEE World Congress on Computational Intelligence, pp. 27–29.

Hussin, M., Ismail, M.R., Ahmad, M.S., 2014. Air-conditioned university laboratories: comparing CO_2 measurement for centralized and split-unit systems. J. King Saud Univ. Eng. http://dx.doi.org/10.1016/j.jksues.2014.08.005.

International Energy Agency, 2007. International organization for standardization (IEA–ISO), international standards to develop and promote energy efficiency and renewable energy sources, special ISO focus. In: Proceedings of the World Energy Congress, pp. 5–10.

Kolokotsa, D., 2003. Comparison of the performance of fuzzy controllers for the management of the indoor environment. Build. Environ. 38, 1439–1450.

Kukolj, D.D., Kuzmanovic, S.B., Levi, E., 2001. Design of a PID-like compound fuzzy logic controller. Eng. Appl. Artif. Intell. 14, 785–803.

Li, Y., Ang, K.H., Chong, G.C.Y., 2006. PID control system analysis and design – problems, remedies, and future directions. IEEE Control Syst. Mag. 26, 32–41.

Liu, K., Nakata, K., Harty, C., 2010. Pervasive informatics: theory, practice and future directions. Intell. Build. Int. 2, 5–19.

Mark, A.C., 1996. BASE quality assurance project plan, environmental health and engineering, 60 Wells Avenue Newton, MA 02159-3210 (MS report). In: Womble, Susan (Ed.), Office of Radiation and Indoor Air United States Environmental Protection Agency, pp. 24–32, Washington, DC 20460.

Mathews, E.H., Arndt, D.C., Piani, C.B., Heerden, E., 2000. Developing cost efficient control strategies to ensure optimal energy use and sufficient indoor comfort. Appl. Energy 66, 135–159.

Nguyen, A.T., Reiter, S., Rigo, P., 2014. A review on simulation-based optimization methods applied to building performance analysis. Appl. Energy 113, 1043–1058.

Safdar, A., Dohyeun, K., 2013. Energy conservation and comfort management in building environment. Int. J. Innovative Comput. Inf. Control 9, 2229–2244.

Shaikh, P.H., Nor, N.B.M., Nallagownden, P., Elamvazuthi, I., Ibrahim, T., 2013a. Robust stochastic control model for energy and comfort management of buildings. Aust. J. Basic Appl. Sci. 7, 137–144.

Shaikh, P.H., Nor, N.B.M., Nallagownden, P., Elamvazuthi, I., 2013b. Building energy management through a distributed fuzzy inference system. Int. J. Eng. Technol. 4, 3236–3242.

Shaikh, P.H., Nor, N.B.M., Nallagownden, P., Elamvazuthi, I., Ibrahim, T., 2014a. A review on optimized control system for building energy and comfort management of smart sustainable buildings. Renewable Sustainable Energy Rev. 34, 409–429.

Shaikh, P.H., Nor, N.B.M., Nallagownden, P., Elamvazuthi, I., 2014b. Stochastic optimized intelligent controller for smart energy efficient buildings. Sustainable Cities Soc. 13, 41–45.

Shaikh, P.H., Nor, N.B.M., Nallagownden, P., Elamvazuthi, I., 2016. Intelligent multi-objective control and management for smart energy efficient buildings. Int. J. Electr. Power Energy Syst. 74, 403–409.

Wang, Z., Yang, R., Wang, L., 2010. Multi-agent control system with intelligent optimization for smart and energy efficient building. In: Proceedings: IEEE Industrial Electronics Society, Phoenix, AZ, pp. 1144–1149.

Wang, Z., Yang, R., Wang, L., 2011. Intelligent multi-agent control for integrated building and micro-grid system. In: Proceedings: IEEE PES Innovative Smart Grid Technologies Anaheim, CA, pp. 1–7.

Yang, R., Wang, L., 2013. Multi-zone building energy management using intelligent control and optimization. Sustainable Cities Soc. 6, 16–21.