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# Robust Stochastic Control Model for Energy and Comfort Management of Buildings

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**Abstract:** The world's population, approximately 90% spend most of their time inside the buildings, which results in 40 – 45% of the total energy consumption. The annual demand of building energy is increasing in the range of 1.5 - 1.9% due to growing world's population. To reduce energy consumption and wastage, effective energy management within the buildings is very essential. Therefore, the concept of smart and energy efficient buildings has become a future trend. It becomes challenging to design and develop the control system for such buildings that require energy efficiency with optimum comfort level for dwellers. In this connection, various studies have been conducted to meet the challenges in this area. However, very limited studies are reported in the literature, especially on the relationship model between energy consumption and comfort parameters within the building. Therefore, in this work, a robust stochastic control model (RSCM) has been developed between the relationship of energy consumption and comfort parameters. The developed model will be helpful for the further minimization of building energy consumption with maximum comfort level in designing building control system.

**Key words:** Buildings, Energy consumption, Energy management, Energy efficiency, Robust model.

## INTRODUCTION

The rapid depletion of fossil resources and climatic threats all around the world, since two decades have diverted the attention of the researchers and scientists to work more on energy efficiency and sustainability. In order to tackle this situation with limited time and resources, demand side management (DSM) addresses the issue. DSM also relies on smart automated buildings for their energy efficiency and sustainability for future trend. The benefits of these buildings include high power efficiency, increased comfort and environmentally friendly.

The building industry is an emerging energy user, as approximately 90% (Benjamin *et al*. 2011) of the population spend most of their time in buildings, thus consuming about 40 – 45 % of the overall energy (Torcellini *et al*., 2006; Doukas and Patlizianas, 2007). The annual rising rate of 1.5 - 1.9 % is recorded for energy consumption in this sector alone, along with 1% peak demand increase of system network (Torcellini *et al*., 2006; Peng *et al*., 2008; Lertlakkhanakul and Choi, 2008). Therefore, significant potential exists to reduce building energy demand at reduced costs with high returns.

The function of the intelligent building management system is to monitor, control and optimize building services, such as heating and cooling, visualization, air quality, humidity and other equipments. It is obvious that, the improvement of the indoor environment comfort demands, increased energy consumption. This signifies an issue of smart efficient buildings to balance the occupant's comfort requirements and power consumption. In order to achieve high level comfort and power efficiency, an effective control system should be developed. The occupants living quality and health are vital, realizing the control strategy for the systems of thermal, visual and air quality comforts. Thus managing the power availability and ensuring the comfortable environment with optimal exploitation of outdoor environment control are in conflict with each other. The factors influencing the two conflicting objectives are the user preferences, sensor position and accuracy and variable outdoor climate conditions.

In a building system, numerous methods for comfort control have been proposed. Predictive control model with weather predictions coupled with the energy saving potential of HVAC system developed in (Kusiak *et al*. 2010; Siroky *et al*. 2011; Yang and Wang, 2013). (Zhun *et al*. 2010) Developed visual comfort control with a fuzzy logic controller. (Zhu *et al*. 2010) Linked day light with artificial lighting system for visualization comfort. (ASHRAE, 2009) examined a robust control for air flow rate and (Baker *et al*. 1993) develop fuzzy reasoning control machine for air quality control. (Dounis *et al*. 2011; Alexandridis *et al*. 2007) reported fuzzy control model with human decision making and combine the comfort factors. This model provides the approach for dynamic model relationship for power consumption and comfort factors. The main objective of this study is to drive the model relationship for the precision and dynamic control scheme capable of satisfying both energy demand and indoor comfort. As the standard interval stochastic model relation to energy consumption does not report in the previous studies. The developed robust model is useful in designing the building control

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characteristics with learning and weighted decision making and devise the position for the sensor measurement mechanism.

***Methodology:***

The extensive literature study leads towards the comfort identification factors (that are thermal, visual and air quality) in building envelopes and was found from the ASHARE, 2009 standard range of the comfort set point. The fuzzy controller exploits the exterior environmental parameters and user defined set points as inputs. The fuzzy controller exploits the exterior environmental parameters and user defined set points as inputs. The fuzzy model and rule base of (Wang, *et al*, 2010, Shaikh, P.H. *et al*, 2013) are developed and applied for our function development. The input to the fuzzy control system is the stochastic standard interval taken from the environmental protection agency (EPA) primary range (Mark, 1996). Curve fitting is done to drive out the appropriate standardized model relationship using MATLAB®. The models are generalized as it works with the error between outdoor sensor data and the set points of individual environmental factors. Since, the power given by the central controller agent is sufficient, the indoor environmental parameters will be maintained at comfortable values; otherwise, the comfort level is negotiated. The three control variables of temperature, $CO_2$ concentration and illumination are provided through sensors as inputs to compute the desired power.

***Comfort Criteria:***

***A. Thermal Comfort:***

Temperature level in the building envelope is used to indicate the thermal comfort poses high impact on living quality. The maintenance of temperature in the specified range for occupants pleasure and efficiency, the auxiliary heating and cooling system is applied. It is normally considered as occupants body sensation, generally known as indexed Predictive Mean Vote (PMV) based on heating, ventilation and air conditioning (HVAC) systems. It is proportionate to temperature, mean radiant temperature, air velocity , humidity and clothing factors as determined in (Lah *et al*. 2005; Sri Andari, 2011). The PMV standard index swings in the range of -3 to +3, while it varies between -0.5 and +0.5 and satisfy a large population of around 90 % of the dwellers exposed to a certain environment. It is specified with envelope temperature and is a vital feature in the computing PMV index. Generally, single actuator system is associated with both the heating and cooling systems.

***B. Visual Comfort:***

Electric lighting is reported to consume 20-30 % of energy in building envelopes (Lah *et al*. 2005; Sri Andari, 2011; Virote and Neves-Silva, 2012). Lighting offers an important component of smart grid provides an attractive potential as controllable loads to offer dynamic load management services. The radiance level in the building environment is provided to indicate the visual comfort, measured in lux (Zhu *et al*. 2010). The electrical lighting system is used to control illumination to achieve the visual comfort (Zhu *et al*. 2010). Other parameters that are glare, wall colors etc. are subjective and challenging to measure. Lighting systems provide distributed load shedding flexibility, resulting power reduction with illumination requirements with associated lights through outdoor solar illumination or other illumination compensation system.

***C. Air Quality:***

The indoor concentration of pollutants is subjective, predominantly for space indicated with the $CO_2$ concentration (Dounis and Caraiscos, 2009; Frontczak and Wargocki, 2011; Peschiera *et al*., 2010). The availability of $CO_2$ at certain level, causes to be lazy and drowsy, get headaces or function activity at low levels. This signifies the existence of the dwellers and metabolic activities, ventilation levels and several pollution sources in the building envelope (Zhu *et al*. 2010). The air quality index is indicated with $CO_2$ concentration on the building envelope, measured in parts per million (ppm). It is generally recommended for $CO_2$ to have a total of less than 600 ppm difference above outdoor level.

***Building Model and Control Design:***

The proposed BECMS system aims at controlling thermal, visual and air-quality comfort parameters. These parameters poses significant impact on the user's quality of living (Sri Andari *et al*. 2011). The uncertain targeted comfort is treated with overall system optimization through the use of fuzzy control technique. Therefore, real world implication and user activities rise numerous sources of suspicions, from unknown dynamic environment in buildings (Rattan and Brehm, 2011; Jang and Healy, 2010). In realizing intelligent building control model, the distributed fuzzy control design is depicted in Fig. 1. This satisfies adaptable comfort demands in achieving building automation dealing with consumer comfort and power requirement.

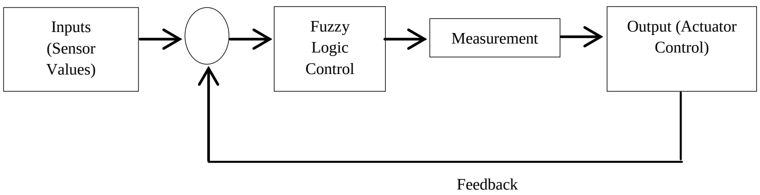



**Fig. 1:** Structural Design for Building Envelope Automation.

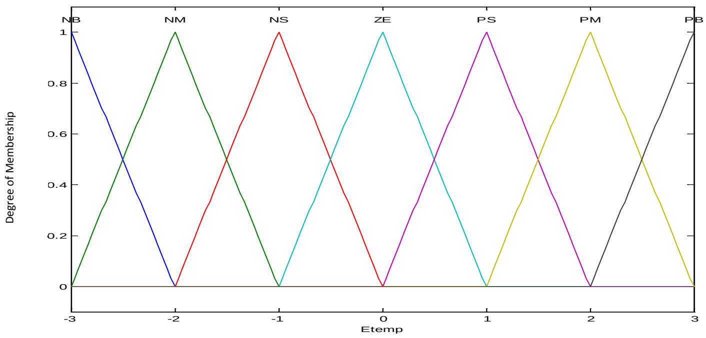
The fuzzy control action is hooked with the gains of the input and output as well as with fuzzified practice, information base, and the defuzzified process. The input to fuzzification block transforms incoming discrete values to fuzzy values. This lets into the fuzzy inference engine and connects knowledge incorporation with the set of rules using fuzzy approximate reasoning. The goal is to compute the discrete output from the resulting fuzzy set with de-fuzzification block.

### A. *Thermal Control Model:*

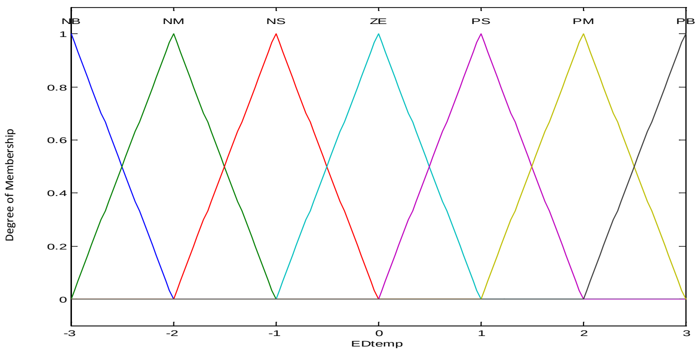
The fuzzy linguistic membership functions for input and outputs as in Fig. 2. namely; negative large 'NL', negative average 'NA', negative small 'NS', neutral 'NE', positive small 'PS', positive average 'PA', positive large 'PL' represents fuzzy sets. Mamdani implication inference with the constraints of the proportional derivative (PD) controller (Dixit *et al*. 2010; Masoso and Grobler, 2010; Emmerich and Persily, 2001) knowledge base is employed as shown in Table 1. The common centroid de-fuzzification is employed to carry out the power required at the end.

**Table 1:** Fuzzy Rule Base for Temperature Control

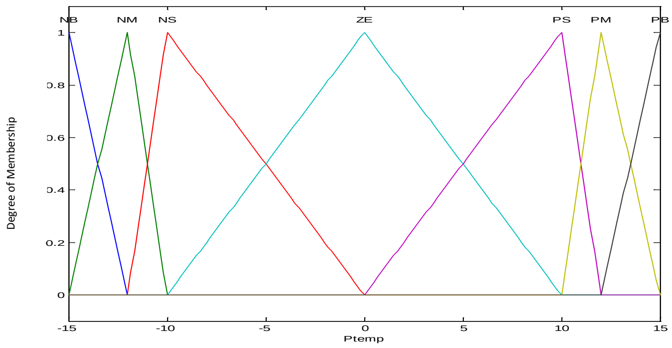
| Power Required | | $E_{Temp}$ | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | NL | NA | NS | NE | PS | PA | PL |
| $ED_{Temp}$ | NL | NL | NS | PS | PL | PL | PL | PA |
| | NA | NL | NA | NE | PA | PA | PL | PA |
| | NS | NL | NA | NS | PS | PA | PL | PA |
| | NE | NL | NA | NS | NE | PS | PA | PA |
| | PS | NL | NL | NA | NS | PS | PA | PA |
| | PA | NL | NL | NA | NA | NE | PA | PA |
| | PL | NL | NL | NL | NL | NS | PS | PA |




(a)




(b)




(c)

**Fig. 2:** Membership function for inputs (a & b) and output (c) of temperature control

The mathematical model as in equation 1 between the power demand and the sensor measurement value as depicted in and in Fig. 3. The statistical validity of the piecewise linear fuzzy robust model is expressed in Table 2, shows 95 % confidence level fit, in regard to the normalized mean (-1.4) and standard deviation (2.02). The bisquare robust method is employed with equation 2, which assigns the weight to minimize SSE. The weight is given to each data point, depends on how far the point is from the fitted line.

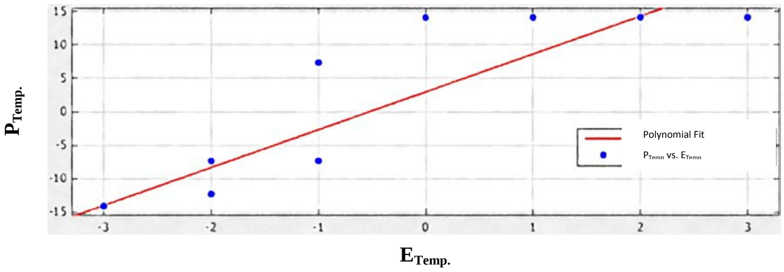



**Fig. 3:** Curve fitting plot for the temperature and power demand

$$P_{Temp} = 5.655 * E_{Temp} + 2.961 \quad (1)$$

Where, $P_{Temp}$ is power required for the temperature control actuator and $E_{Temp}$ is the temperature error between the sensor and set point value. The developed linear model in equation (1) depicts the behavioural relationship between the power consumption and interior thermal change. Further, for every 5.655 unit change in $E_{Temp}$ , the corresponding 1 unit variation is observed in $P_{Temp}$. While the constant 2.961 is expected ratio of power being consumed at time t=0. This is perhaps the minimum rated power required for the HVAC system to operate in its least operating condition.

$$\frac{1}{n}\sum_{i=0}^{n-1} w_i (f(x_i) - y_i)^2 \quad (2)$$

**Table 2:** Statistical characteristics for robust model relationship of temperature control

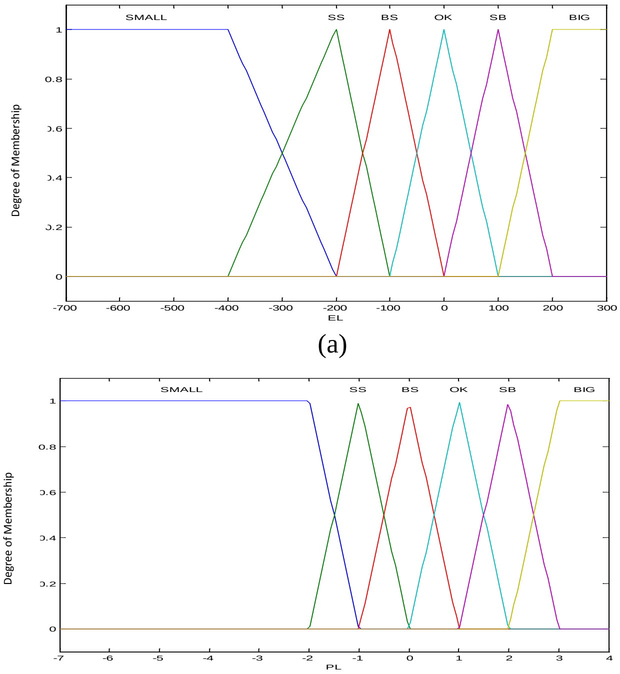
| | |
|---|---|
| Where $E_{Temp}$ is normalized | |
| Mean | -1.4 |
| Standard Deviation | 2.028 |
| Goodness of Fit | |
| Sum of Squares due to Error (SSE) | 69.37 |
| R-square ($R^2$) | 0.9691 |
| Adjusted R-square ($R^2$) | 0.9667 |
| Root Mean Squared Error (RMSE) | 2.31 |

*B. Visual Control Model:*

The fuzzy based model (Emmerich and Persily, 2001; Ipakchi and Albuyeh, 2010) is developed with membership function as ‘small’, small ‘SS’, big small ‘BS’, ‘OK’, small big ‘SB’, ‘Big’as shown in Fig. 4. The proportional control rule base is applied to the model to get the discrete output.

**Table 3:** Fuzzy rule base for illumination control

| Lighting | | | | | | |
|---|---|---|---|---|---|---|
| | Small | SS | BS | OK | SB | Big |
| $P_{required}$ | OFF | S | REG | SB | BB | ON |




(a)

(b)

**Fig. 4:** Membership function for input (a) and output (b) of illumination control

The robust model relationship in equation 3 is drived with discrete output of the behavioral relation between the power demand and illumination as shown in Fig. 5. The sum of sine model is best fitted as described in the statistics Table 4, shows 95 % confidence level fit, in regard to the normalized mean (-200) and standard deviation (310.2).

$$P_L = 4.428 * Sin(0.9603 * E_L - 0.4234) \tag{3}$$

Where, $P_L$ is power required for the lighting control actuator and $E_L$ is the lux error between the sensor and set point value. The developed sum of sine model in equation (3) depicts the behavioural relationship between the power consumption and interior illumination level. The model function represents the smooth and continuous sinusoidal behavior. The value 4.428 represents the magnitude required for the power consumption. While 0.9603 is the unit horizontal cycle difference in $E_L$ frequency, along with sine function will result in corresponding variation of the power consumption. The constant 0.4234 represents the vertical phase shift in the sine curve.

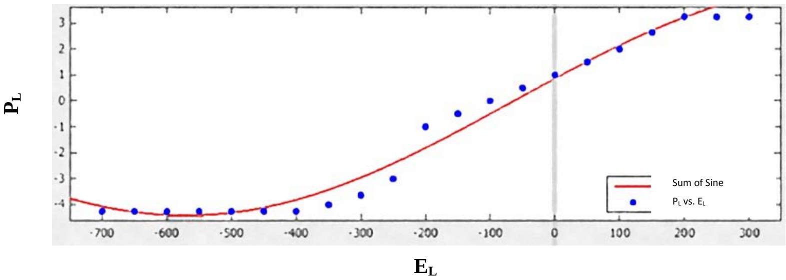



**Fig. 5:** Curve fitting plot for the illumination and power demand

**Table 4:** Statistical characteristics for robust model relationship of lighting control

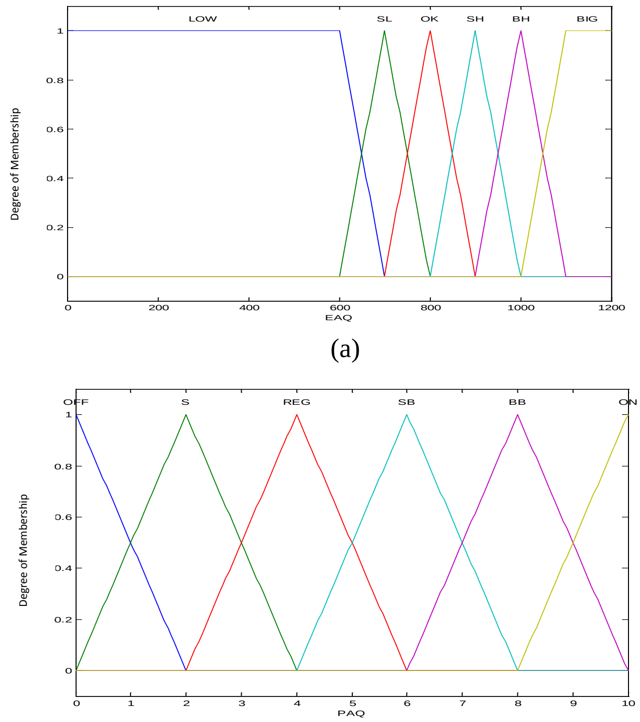
| | |
|---|---|
| Where $E_L$ is normalized | |
| Mean | -200 |
| Standard Deviation | 310.2 |
| Goodness of Fit | |
| Sum of Squares due to Error (SSE) | 11.23 |
| R-square ($R^2$) | 0.9392 |
| Adjusted R-square ($R^2$) | 0.9324 |
| Root Mean Squared Error (RMSE) | 0.7899 |

### *C. Air Quality Control Model:*

The fuzzy membership as in Fig. 6. ‘low’, small large ‘SL’, ‘OK’, small high ‘SH’, big high ‘BH’, ‘High’ and an output of required power ‘OFF’, ‘S’ (small), ‘REG’ (regular), ‘SB’ (small big), ‘BB’ (big big), ‘ON’are for input error and output power requirement Indice. The proportional controller (Rahimi and Ipakchi, 2010; Marszala and Heiselberga, 2011) knowledge base constraints are shown in Table 5. The discrete output power has been obtained with sensor inputs.

**Table 5:** Fuzzy Rule Base for Air Quality

| $CO_2$ Concentration | | | | | | |
|---|---|---|---|---|---|---|
| | LOW | SL | OK | SH | BH | High |
| $P_{required}$ | OFF | S | REG | SB | BB | ON |




(a)

(b)

**Fig. 6.** Membership function for input (a) and output (b) of air quality control

The behavorial relationship robust model as depicted in equation 4 from the fuzzy output relation with input as shown in Fig. 7. The Gaussian model is best fitted as described in the statistics Table 6, shows 95 % confidence level fit, in regard to the normalized mean (740) and standard deviation (373.3).

$$P_{AQ} = 9.444 * e^{\left(-\frac{E_{AQ}-1163}{389}\right)^2} \quad (4)$$

Where, $P_{AQ}$ is power required for the air quality control actuator and $E_{AQ}$ is the $CO_2$ concentration error between the sensor and set point value. The developed gaussian model in equation (4) depicts the behavioural relationship between the power consumption and indoor air quality. The Gaussian function is in similar manner to the bell shape which rapidly falls off towards zero. The constant 9.444 represents the maximum power consumption of the air quality actuator. While 1163 defines the center of the air quality index in the model development, and 389 represents controls the air quality index width in horizontal plane of bell shape.

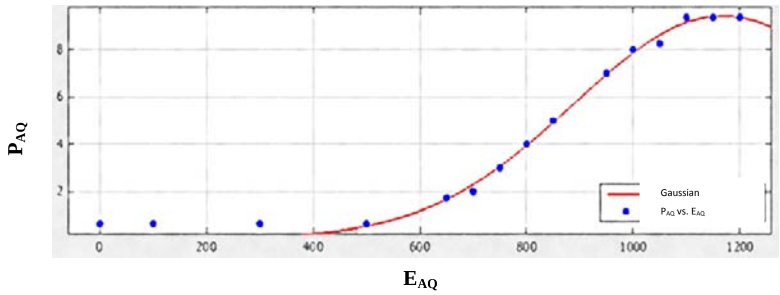



**Fig. 7:** Curve fitting plot for the air quality and power demand

**Table 6:** Statistical characteristics for robust model relationship of air quality control

| | |
|---|---|
| Where $E_{AQ}$ is normalized | |
| Mean | 740 |
| Standard Deviation | 373.3 |
| Goodness of Fit | |
| Sum of Squares due to Error (SSE) | 6.361 |
| R-square ($R^2$) | 0.9646 |
| Adjusted R-square ($R^2$) | 0.9588 |
| Root Mean Squared Error (RMSE) | 0.7281 |

***Discussion:***

The extracted fuzzy control models comprise comfort achievement and power consumption. The discrete output of fuzzy represents the dynamic behavior allows user preferences to integrate. The features of the input data from sensors presented to the model may not be authentic and is intrinsically noisy. This may result in the error of around 2 % in its upper and lower bounds. The output is the required electrical power exploited for control of each comfort parameters. The models power output is equated to the master controller to adjust the controller according to the power available. The developed model accuracy described statistically and displays over 95 % confidence level. Thus verify the models to be further implemented for system optimization. The operation of the building requires high energy efficiency to save energy consumption. The behavioral relationship model is very useful in designing the building control and devise the position for the sensor measurement mechanism.

***Conclusion:***

In this study, the RSCM comfort index model in regard to the relationship of comfort and power consumption pattern is developed. The intelligent fuzzy inference slave control model is provided for the wire or wireless sensor or by an actuator network for decision making to maintain balance. The learning and weighted decision making were considered keeping in view of consumer comfort. This will give proper awareness to consumers for taking suitable actions. The fuzzy control output has been utilized to drive the indirect behavioral relationship RSCM model for the power demand and the controlled parameter, which will be further helpful in carrying out the system optimization in the grid connected power supply and the building envelope as the future target of research.

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## REFERENCES

Alexandridis, K., A.I. Dounis, 2007. Supervisor of digital pi-like fuzzy logic controllers for indoor lighting control in buildings, in: Proceedings of the International Scientific Conference eRA— (2): 12-21.

ASHRAE Handbook, 2009. - Fundamentals (I-P Edition). American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.

Baker, N., A. Fanchiotti and K. Steamers, 2009. Daylighting in Architecture: A European Reference Book. London: James & James for the Commission of the European Communities, (1): 48-59.

Benjamin, P., E. Julien, G. Stephane and P. Monique, 2011. Hybrid PID-fuzzy scheme for managing energy resources in buildings. Applied Soft Computing, (11): 5068-5080.

Dounis, A.I., P. Tiropanis, A. Argiriou, A. Diamantis, 2011. Intelligent control system for reconciliation of the energy saving with comfort in buildings using soft computing techniques. Energy and Buildings, (43): 66-74.

Doukas, H. and K.D. Patlitzianas, 2007. Intelligent building energy management system using rule sets. Building and Environment, (10): 3562-3569.

Dounis, A.I. and C. Caraiscos, 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.

Dixit, M.K., J.L. Fernández-Solís, S. Lavy and C.H. Culp, 2010. Identification of parameters for embodied energy measurement: a literature review. Energy and Buildings, 42(8): 1238-1247.

Emmerich, S.J. and A.K. Persily, 2001. State-of-the-art review of $CO_2$ demand controlled ventilation technology and application, National Institute of Standards and Technology, Technology Administration, US. Department of Commerce., pp: 1-43.

Frontczak, M. and P. Wargocki, 2011. Literature survey on how different factors influence human comfort in indoor environments. Building and Environment, (46): 922-937.

Ipakchi, A. and F. Albuyeh, 2010. Grid of the Future. IEEE Power and Energy Magazine, (7): 52-62.

Jang, W. and W. Healy, 2010. Wireless sensor network performance metrics for building applications. Energy and Buildings, (42): 862-868.

Kusiak, A., M. Li, Z. Zhang, 2010. A data driven approach for steam load prediction in buildings", Applied Energy, (87): 925-933.

Lertlakkhanakul, J. and J.W. Choi, 2008. Building data model and simulation platform for spatial interaction management in smart home. Automation in Construction, 17(8): 948-957.

Lah, L.M., Z. Borut, A. Krainer, 2005. Fuzzy control for the illumination and temperature comfort in a test chamber. Building and Environment, (40): 1626-1637.

Marszala, A.J., P. Heiselberga, J.S. Bourrelleb, E. Mussels, K. Vossc, I. Sartori and A. Napolitanoe, 2011. Zero Energy Building – A review of definitions and calculation methodologies. Energy and Buildings, (43): 971-979.

Mark, A.C., 1996. MS, BASE Quality Assurance Project Plan, Environmental Health and Engineering, 60 Wells Avenue Newton, MA 02159-3210 and Susan Womble, Office of Radiation and Indoor Air United States Environmental Protection Agency Washington, DC 20460, pp: 24-32.

Masoso, O. and L. Grobler, 2010. The dark side of occupants' behavior on building energy use. Energy and Buildings, (42): 173-177.

Peng, Z., S. Suryanarayanan, M. Godoy Simões, 2010. An Energy Management System for Building Structures Using a Multi-Agent Decision-Making Control Methodology. IEEE Industry Applications Society Annual Meeting (IAS).

Peschiera, G., J.E. Taylor and J.A. Siegel, 2010. Response–relapse patterns of building occupant electricity consumption following exposure to personal, contextualized and occupant peer network utilization data, Energy and Buildings, 42(8): 1329-1336.

Rattan, K.S. and T. Brehm, 2011. Fuzzy Logic Controller Output Equation Analysis, Department of Electrical Engineering, Wright State University, Dayton, Ohio, 45435(2): 1-15.

Rahimi, F. and A. Ipakchi, 2010. Demand response as a market resource under the smart grid paradigm, IEEE Transactions on Smart Grid, (1): 82-88.

Shaikh, P.H., N. Mohd. Nor, P. Nallagownden and I. Elamvazuthi, 2013. Building energy management through a distributed fuzzy inference system, International Journal of Engineering and Technology, (IJET) 5(4): 3236-3242.

Siroky, J., F. Oldewurtel, J. Cigler and S. Privara, 2011. Experimental Analysis of model predictive control for an energy efficient heating system. Applied Energy, (88): 3079-3087.

Sri Andari, H., P. Ashish, T. Ludo, W. Ying and Z. Meng, 2011. Lighting systems control for Demand Response, Philips Research, High Tech Campus 34, Eindhoven, The Netherlands IEEE PES Innovative Smart Grid Technologies, (5): 1-6.

Torcellini, P., S. Pless and M. Deru, 2006. "Zero energy buildings: A critical look at the definition," presented at the ACEEE Summer Study, Pacific Grove, CA, pp: 14-18.

Virote, J. and R. Neves-Silva, 2012. Stochastic models for building energy prediction based on occupant behavior assessment, Energy and Buildings, 53: 183-193.

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

Zhun, Y., H. Fariborz and C.M.F. Benjamin, 2010. Y. Hiroshi, A decision tree method for building energy demand modeling, Energy and Buildings, 42: 1637-1646.

Zhu, W., Y. Rui and W. Lingfeng, 2010. Multi-agent control system with intelligent optimization for smart and energy-efficient buildings, 36$^{th}$ IEEE Industrial Electronics Society IECON 2010.

Zhu, W., Y. Rui and W. Lingfeng, 2010. Multi-agent intelligent controller design for smart and sustainable buildings, 4$^{th}$ Annual IEEE Systems Conference.