Sindh Univ. Res. Jour. (Sci. Ser.) Vol. 48 (1) 57-60 (2016)

SINDH UNIVERSITY RESEARCH JOURNAL (SCIENCE SERIES)

Non-linear Empirical Model for Energy and Thermal Comfort in Buildings

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Received 13th July 2015 and Revised 22nd November 2015

Abstract: Energy consumption in building sector is approximately 40% and is continuously increasing. This is due to the increased living comforts required by the inhabitants within the buildings. Thermal, visual, air quality and humidity are the main comfort parameters within the indoor environment. However, the indoor thermal comfort is core parameter for the inhabitants' consideration and consumes approximately 30-50% of total building energy consumption. Meanwhile thermal comfort is also challenging for the scientists, researchers and engineers to meet the energy demands of these systems in buildings. In context to that an effort has been made in this paper to develop a non-linear empirical model for energy consumption and thermal comfort. Since, both the objectives are in contradiction and cannot form any direct relationship. However, in linguistic terms these objectives can be described which is so far challenging to drive the behavioral relationship model. Considering this, black box approach of fuzzy inference system map-ping model has been developed. The fuzzy inference mapping system has employed various rule base and membership functions mappings to drive out the most appropriate empirical model function. The developed model function is significant and can be further employed in the optimization of energy and thermal comfort within the buildings.

Keywords: Building, Comfort, Thermal, Energy, Fuzzy Inference System.

1. INTRODUCTION

The energy demands all around the world is continuously transforming due to the rise in population, economic progressions, technological advancements, quality life styles, climate change and regulation spaces (Lee and Braun, 2010). These challenges are altering the balance in energy landscape in terms of its demand and supply. The energy consumption in building sector is approximately 40% (Shaikh, *et al.,* 2014) and is continuously increasing. Therefore, maintaining inhabitants' working efficiency and satisfaction, indoor building thermal comfort possesses high impact (Marinakis, *et al.,* 2013). Approximately 30-50% of total energy consumed in buildings spend on maintaining the indoor thermal comfort (Kusiak and Xu, 2012). Due to the subjectivity of thermal comfort, it is difficult to state environmental and personal comfort index. This is why the comfort index for thermal commonly defined in terms of Predictive Mean Vote (PMV) and has been majorly established on heating, ventilation and air conditioning (HVAC) schemes (Duburcq and Guillerminet, 1997). PMV is normally devised as occupants' body sensation and consciousness comfort index for thermal. The PMV index prevails within the range of -3 to +3 with seven human sensational points from cold to hot. This has a variation occurrence in between the range of -0.5 and +0.5, and thus satisfies around 90% of the building dwellers (Dounis *et al.,* 1993). The thermal comfort index has already been a prime feature in PMV index computation and the building's temperature has generally been specified with PMV (Dounis *et al.,* 2009). The mean temperature radiance, speed of air, outfit elements and humidity are in direct proportion to the temperature (Wang and Xu, 2004, Mark, 1996). Both heating and cooling techniques are associated with a one-unit actuator system (Kastner, *et al.,* 2010). The fuzzy inference system consists of two set strategies, one is comfort optimization and the second is energy consumption minimization (Ben-Nakhi. and Mahmoud, 2002).

2. MODELING METHODOLOGY

The nonlinear empirical model for energy and thermal comfort comprises of fuzzy inference system which has been utilizing various rule base and membership functions. When the input of difference between previous and present thermal values along with change in error has been fed to fuzzy system an output power demand has been observed. These input and output have been treated with empirical model derivation.

(a) Fuzzy Inference System

The error is the difference between set point and the sensor value and the fuzzy plot for the error and the power demanded for the actuator (Shaikh, *et. al.* 2016). This describes the direct relation; as there is an increase in thermal error, power demand will be increased either for heating or for cooling actuators. However, the relation of error difference between two consecutive sensor readings and the required power for which controller behaves in an inverse relation.

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The seven linguistic variables for MFs are negative large (NL), negative average (NA), negative small (NS), neutral (NE), positive small (PS), positive average (PA) and positive large (PL). The required power has been computed with the change is previous and present temperature values along with the change in error that is previous and present value of error. This is due to the measurement accuracy for actuators power demand. The rule base have been shown in **(Table 1).**

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	PL
	NA	NL	NA	NE	PA	PA	PL	PL
	NS	NL	NA	NS	PS	PA	PL	PL
	NE	NL	NA	NS	NE	PS	PA	PL
	PS	NL	NL	NA	NS	PS	PA	PL
	PA	NL	NL	NA	NA	NE	PA	PL
	PL	NL	NL	NL	NL	NS	PS	PL

The input fuzzy sets for error and error difference employed polynomial pi based membership function (MF) mapping as shown in **Equation (1).** Mamdani implication method has been employed with approximate rule base reasoning, along with equal preference provided to each rule. Typical rule is if E_{Temp}= NS and EDTemp = NE, Then Power Required P_{Temp}= PS.That is when error is negative small and error difference is neutral, then auxiliary cooling system should be turned on with positive small power consumption. However commonly used centroid de-fuzzified method is considered for transforming fuzzy crisp output. This output power will be compared to the master controller to adjust according to the power available for maintaining the indoor temperature negotiated to operate actuator in order to maintain thermal comfort. The input and output membership functions are depicted in **(Fig.1).**

$$f(x;a,b,c,d)=\begin{cases} 0, & x\le a \\ 2\left(\dfrac{x-a}{b-a}\right)^2, & a\le x\le \dfrac{a+b}{2} \\ 1-2\left(\dfrac{x-b}{b-a}\right)^2 & \dfrac{a+b}{2}\le x\le b \\ 1-2\left(\dfrac{x-c}{d-c}\right)^2 & c\le x\le \dfrac{c+d}{2} \\ 2\left(\dfrac{x-d}{d-c}\right)^2, & \dfrac{c+d}{2}\le x\le d \\ 0, & x\ge d \end{cases} \quad (1)$$

The pi-shaped membership function is generally evaluated at the points, which are determined through vector x. whereas, the parameters a and d locate the feet of the curve while, b and c parameters locate the shoulders of the curve.

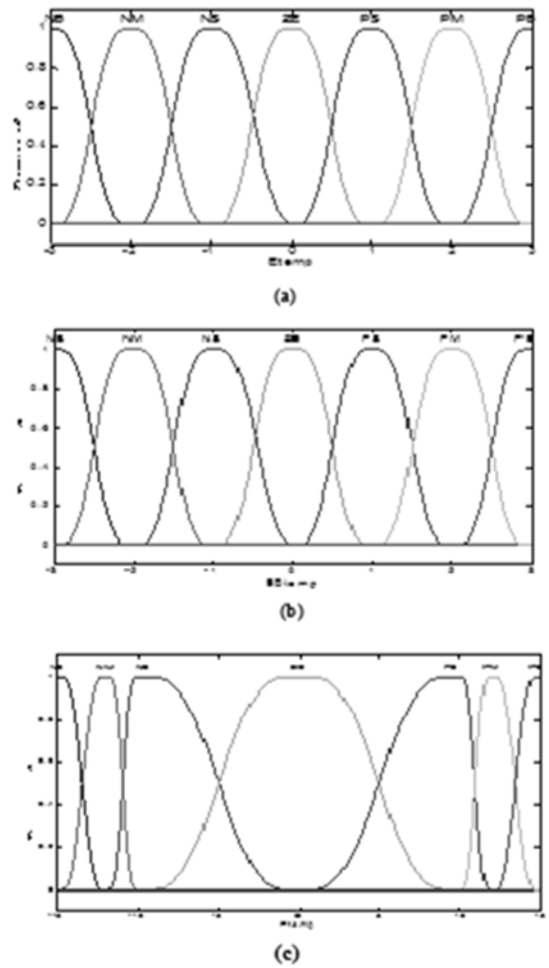

Fig.1: Membership Function for Inputs (a & b) and output (c) of Temperature

Table 2: Statistical characteristics for developed model

Where E_{Temp} is normalized	
Mean	-1.4
Standard Deviation	2.028
Goodness of Fit	
Sum of Squares due to Error (SSE)	66.43
R-square (R^2)	0.97
Adjusted R-square (R^2)	0.97
Root Mean Squared Error (RMSE)	2.26
Coefficients with 95 % Confidence Interval	
A1	(4.891,6.192)
A2	(2.124,3.467)

(b) Empirical Model Development

The raw data from the fuzzy system have possessed the nonlinear characteristic of the input vector matrix, which intends to train FIS modeling feature (MATLAB, 2013). However all the features of training data presented to the model may not be authentic and is intrinsically noisy, thus the model accuracy under such conditions will be adversely affected. The input error is the difference between set point, the sensor value and output power required data set have been trained with curve fitting in MATLAB with fit line shown in Figure 2. Employing first order polynomial shows the best fit with 95 % confidence level in regard to the normalized mean (-1.4) and standard deviation (2.02). The detailed model characteristics are shown in Table 2. Whereas the goodness of fit of the developed model as defined through R-square 97.04 % shows fitting accuracy whereas the sum of square error (SSE) and root mean square error (RMSE) is 66.43 and 2.26 respectively. It also provides validity of the piecewise linear fuzzy robust model with implications of the QR factorization algorithm. The generalized empirical polynomial is shown in Equation (2) and (3). The least weighted bisque are robust method is employed, 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.

$$\boldsymbol{P_{Temp} = A_1 . e_{Temp} + A_2} \quad (2)$$

$$\boldsymbol{P_{Temp} = 5.655 e_{Temp} + 2.961} \quad (3)$$

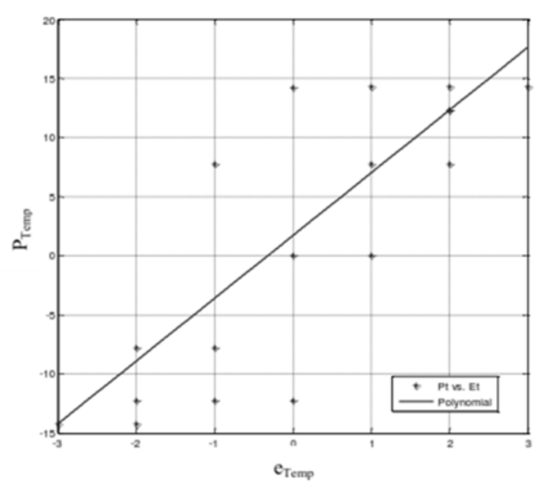

Fig. 2: Curve fitting plot for the temperature and power demand

3. DISCUCSSION

The P_{Temp} is the 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 (2) depicts the behavioral relationship between the power consumption and indoor thermal change. However, 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 actuator system to operate in its least operating condition.

4. CONCLUSION

In this paper the nonlinear empirical model for energy and thermal comfort has been developed. The model development comprises of two stages; first is the development of fuzzy inference system that deals linguistically, second the curve fit empirical model. The developed model posses robustness due to non-linearity of fuzzy inference and can be tested with other rule base and membership functions. This model will be further utilized in the future for optimization of power required and the comfort attainment in buildings.

ACKNOWLEDGEMENTS

The authors would like acknowledge Mehran University of Engineering and Technology (MUET) Jamshoro and Mehran University Center for Energy and Development (MUCED) for providing peaceful environment to conduct this research work.

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