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Optimization of Energy Conservation in Air Conditioned System Smart Class Room of a School building: Approach to Human comfort and Energy Management

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Abstract

High energy consumption is one of the major problems in the world scenario today and this issue is seriously focused on educational buildings. In this study, an educational building, smart class room of a school in Tamil Nadu, India is considered for the analysis of energy consumption, by employing an optimization technique. Among the various kinds of class rooms in school building, smart class room is identified as the most energy consuming room and for this room, optimization of air conditioning system is performed though Taguchi's grey relational method. Location of Air conditioning system, exhaust location, air conditioning system tonnage capacity and set point temperature are identified as control parameters, and thermal comfort index through predicted percentage dissatisfaction (PPD) and energy consumption are considered as output responses. Finally, ANOVA calculation is made and the most influencing control parameter, set point temperature of air conditioning unit is identified.

Keywords – Energy Audit, Grey Relational Analysis, Optimization methods, Smart Class room, Taguchi's DoE.

I. INTRODUCTION

The use of energy in buildings has increased in recent years due to the growing demand in energy usage for heating and cooling in buildings. Without energy, buildings could not be operated or inhabited and hence the importance of energy efficiency is observed. Electric energy consumption in buildings is becoming an important issue for individual as well as for public organizations. Among all the sectors, buildings have the greatest quota, which is about 40% of all the energy consumption in the country [1]. In that, schools provide the opportunity to promote building energy efficiency for tomorrow's citizen in the most effective way [2]. Katafygiotou and Serghides [3] studied the energy conservation in a school at Cyprus at three different locations such as inland, costal and mountain, and observed that schools with insulated building, horizontal roof and internal corridors consumes comparatively less electrical energy. Study shows that energy efficiency is very important in school buildings as it is associated with comfort and air quality conditions in their interior, and energy costs of these buildings are associated with their main operational costs [4]. Due to the high occupation density of classrooms (close to 1.8 m^2/pupil), excessive human internal gains during working hours, increased ventilation requirements and high visual environment standards exist in order to ensure an internal environment that can provide proper health and mental conditions. There is an increasing awareness throughout the globe for promotion of sustainable solutions in school buildings involving energy efficient technologies and measures [5]. Sait studied the electric energy consumption for an educational building located in Rabigh city, 150 km North of Jeddah city, Saudi Arabia [6], by recording temperature and relative humidity for several places inside the building. Based on the analysis of auditing exercise, some recommendations were suggested to reduce the electric energy consumptions which can reach up to 35.3%. The A/C units' efficiency can also be increased by 31%.

Wang et al. [7] proposed retrofit schemes for HVAC system and after the retrofit of building envelop, comprehensive consideration of energy efficiency and economic benefits are observed and, overall energy efficiency is increased by 71.20%. Chowdhury et al. [8] analyzed the energy performance of institutional buildings in subtropical climate to assess the energy consumption pattern through the analysis of the historical energy consumption data by the buildings in an academic institution located in the subtropical region of Australia to analyze the effects of climatic variation on energy utilization. Thewes et al. [9] analysed the energy consumption of 68 school buildings in Luxembourg and suggested that reducing the heating demand through better airtightness and high wall insulation consume less electrical energy. Lara et al. [10] identified that 30 % of the Italian schools have very low energy efficiency due to aging or poor quality of construction. Desideri and Proietti [11] performed energy audit on thermal and electrical for school buildings of a province in central of Italy. Energy analysis of the school buildings showed that electric energy consumption was between 15% and 25% due to non-A/C sources, while thermal consumption contributed up to 80% of the total annual energy consumption. A building gains heat energy as well as losing it, and both processes usually occur at the same time. In locations with a temperature climate, the overall gains are less than the overall losses, but the heat gains may still provide useful energy savings [12]. The factors affecting heat gains are indicated in Fig. 1.

The temperature inside a building should be kept at a constant comfort level, with appropriate variations between areas of the building and the times of their use. To keep inside temperatures constant, the heat flowing out of the building needs to be balanced by the same amount of heat energy input into the building.

From this review the importance and need of energy audit in school buildings is observed. Hence an initial attempt is made to conserve electrical energy for a smart class of school building. Generally smart class rooms are attached with Air conditioning system for providing good thermal comfort. However, most of the time either proper tonnage capacity of Air conditioning system is not installed or the air conditioning system is not running for good thermal comfort. Due to this reason, smart class rooms consume more electrical energy and hence, present study is focussed to identify the air conditioning system's best tonnage capacity, set point temperature and location of air conditioning unit through an hybrid optimization approach, Taguchi's grey relational analysis.

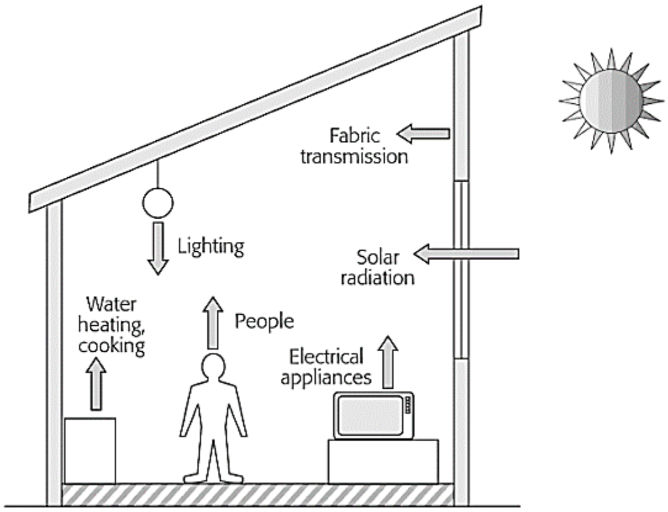

Figure 1 Typical heat gains in a building [12]

II. SMART CLASS ROOM SETUP IN SCHOOL BUILDING

In school building, a smart class room of size 7m x 5m x 3m (Length x breadth x height) with air conditioning system is considered for analysis and optimization. This class room size is taken from the one of the school that meets the standard size for 30 numbers of students, in Trichy, Tamil Nadu, India. In this study, the objective of the optimization is to minimize energy consumption for an acceptable thermal comfort. The factors that are considered for the optimization are location of air conditioning unit and exhaust for indoor from ground level, air conditioning system tonnage capacity and air conditioning system set point temperature. The first two factors are generalized with class room height as Hin* and Hout* and hence, this optimization study can fit to any height of the class room. The energy consumption for one hour and the students thermal comfort index- predicted percentage dissatisfaction (PPD) is determined, as per experimental design. The energy consumption for one hour is measured experimentally from the existing class room for one hour during the period of 1 pm to 2 pm in the month of the May by energy meter. The PPD index is determined from the Predicted Mean Vote (PMV) which is the function of metabolic rate, indoor temperature, indoor air velocity and thermal resistance of clothing. In this study, the metabolic rate and thermal resistance of clothing are considered as 70 w/m2 and 0.16m2 K/W. The indoor temperature and air velocity for the nine experimental cases are numerically simulated and predicted.

III. METHODOLOGY

In recent years, Computational Fluid Dynamics (CFD) technique has been widely used in aerospace, vehicle aerodynamics, food processing industries, HVAC, building airflow and indoor environment.

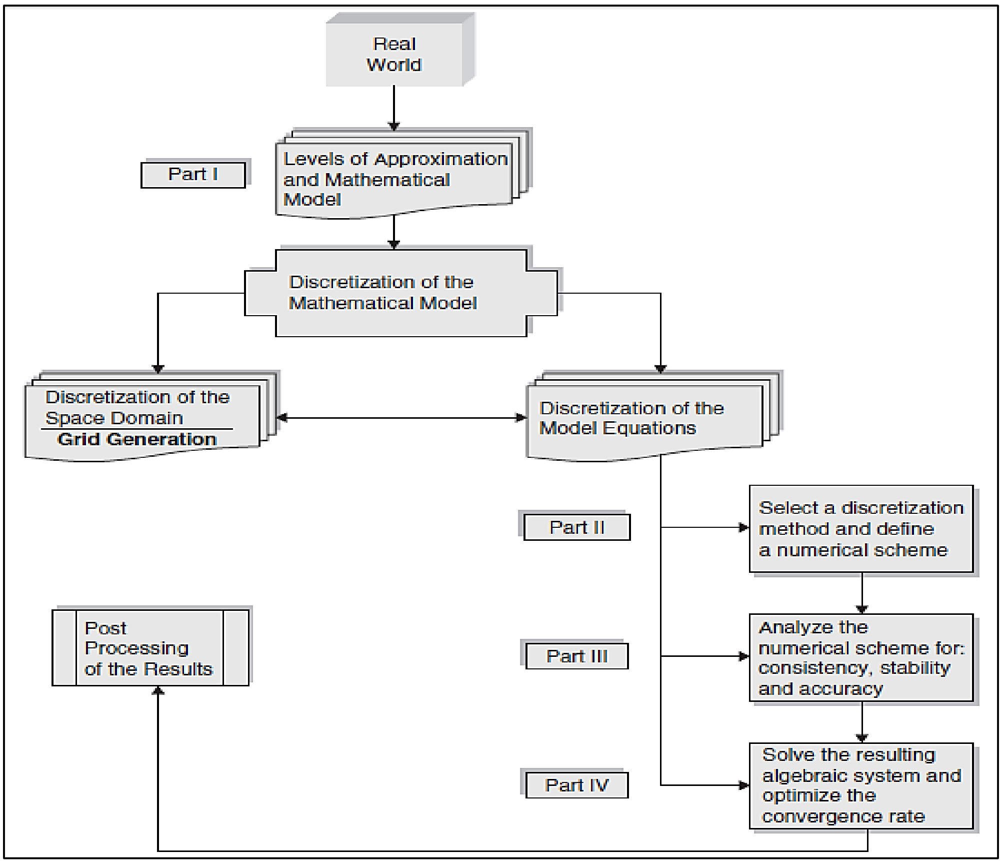

Figure 2 Flow chart representation of steps followed in CFD simulation [15]

Computational fluid dynamics technique numerically solves a set of partial differential equations for the conservation of mass, momentum, energy, chemical species concentration and turbulence quantities [13]. The solution provides the detailed field distributions of velocity, temperature, pressure and turbulence parameters for the modelled fluid domain. Its application become more and more popular in all engineering and non-engineering stream due to its increase in computational power and the improvements in turbulence modelling [14]. Many commercial software based on CFD code have been developed like Fluent, CFX, Tascflow, Phoenics, Flovent and etc.

Study of ventilation in buildings by analytical and experimental method is an approximate and expensive testing methodology respectively. Also these methods yield either bulk value for flow variable values at specific locations [16]. However, CFD technique is the cheapest method and also it predicts the flow variables value for the whole fluid domain [17]. The basic steps involved in the CFD simulation is discussed from the respective flow chart as shown in Fig. 2. The geometry for the smart class room is modelled as 3 dimensional in the Gambit software and is shown in Fig. 3.

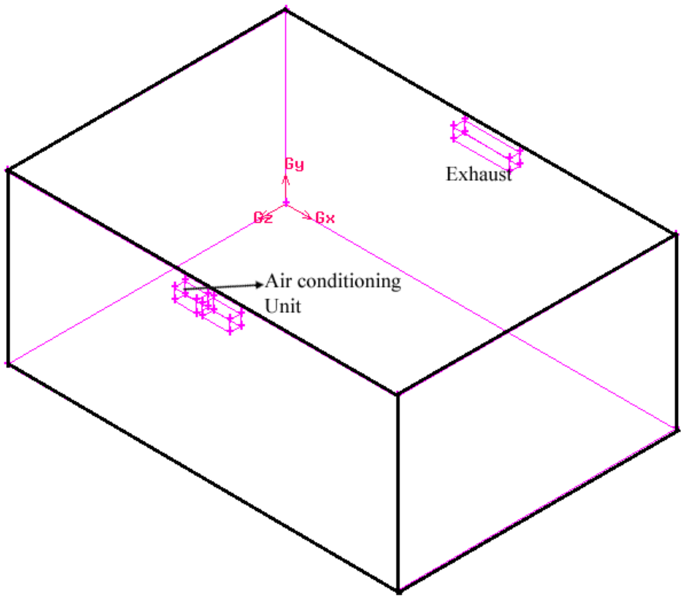

Figure 3 Schematic model of Smart class room

The created model is meshed with tetrahedral hybrid T-grid type with the size of 0.2 and the mesh size is checked for grid independence. The created model is exported to the FLUENT software for solving the flow. The boundary conditions specified are as follows: Solar radiation data for the month of May at the location 10° 48' N latitude and 78° 41' E longitude are specified at the roof top. This solar radiation value is converted into T_{solar} through the Eq. (1).

$$T_{solar} = T_a + \frac{\alpha q}{h_o} \tag{1}$$

where T_a is the ambient temperature, α, absorvity, q, solar radiation and h_o convective heat transfer coefficient at the outer surface.

The supply air temperature and velocity of the air conditioned unit is specified according to the experimental runs. The heat generation from the human beings are assumed and specified as 100 W/m^2. K-ε turbulence model is employed to define the turbulence nature of flow. The Turbulent intensity and length scale are defined as 4.4% and 0.1m respectively. The room domain is analysed under steady state with double precision segregated solver up to the convergence level of 10^{-6}. The above numerical simulation is validated with the experimental predictions made by various researchers [18]. In this validation, the same roof model is modelled in GAMBIT software and the same boundary conditions are applied. The FEA predicted temperature at the bottom of the roof surface are compared with the experimental predictions and is shown in Fig. 4.

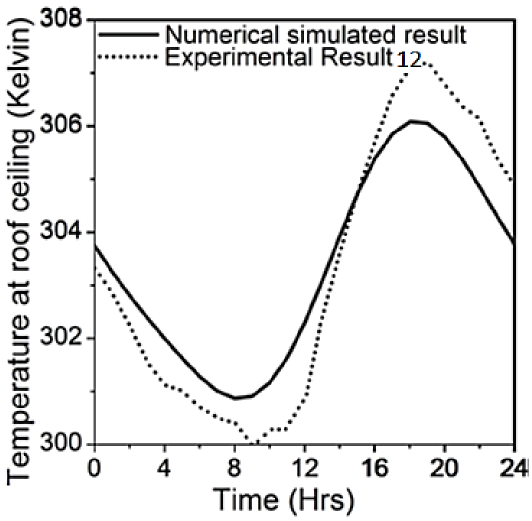

Figure 4 Validation of CFD simulated temperature with Experimental value [19]

III.I Taguchi's Design of Experiment

Taguchi's Design of Experiments (DoE) is a statistical technique that is used to study many factors simultaneously and most economically [20]. By studying the effects of individual factors on the results, the best factor combination can be determined. When applied to a design, the technique helps to seek out the best design among the many alternatives [21]. Taguchi's technique is a powerful tool in quality optimization. Taguchi's technique makes use of a special design of Orthogonal Array [22] to examine the quality characteristics through a minimal number of experiments [23]. The experimental results based on the Orthogonal Array (OA) are then transformed into S/N ratios to evaluate the performance characteristics.

In order to analyze the energy consumed in a smart class room, a suitable orthogonal array is formulated to conduct experiments for varying combinations of different parameters considering human comfort. The parameters considered in this work is: capacity of AC unit used, its positon, output set temperature and ventilation position. Table 1 shows the different parameters chosen and their level values for numerical simulation study.

Table 1 Chosen Parameters and its Level values for Simulation

Parameter / Level	Level I	Level 2	Level 3
Height of AC unit (m)	2	1.5	1.2
Height of Exhaust (m)	2	1.5	1.2
AC Capacity (Ton)	1	1.5	2
AC Temperature (°C)	15	20	25

The minimum number of experiments to be conducted for the parametric optimization is calculated as, [(L-1) x P] + 1 = [(3-1) x 3] + 1= 7 ≈ $\mathbf{L_9}$. The various combinations of AC capacity, its set output temperature, its position in the wall and the position of exhaust with respect to the ground condition, designed using Taguchi’s DoE is presented in Table 2.

Table 2 Experimental L_9 Orthogonal Array for AC performance

Trial No	Height of AC unit (m)	Height of Exhaust (m)	AC Capacity (Ton)	AC Temperature (°C)
1	2	2	1	15
2	2	1.5	1.5	20
3	2	1.2	2	25
4	1.5	2	1.5	25
5	1.5	1.5	2	15
6	1.5	1.2	1	20
7	1.2	2	2	20
8	1.2	1.5	1	25
9	1.2	1.2	1.5	15

For analysis, there are three categories of performance characteristics, (i.e.) Smaller-the-better, Larger-the-better and Nominal-the-better, to determine the Signal-to-Noise (S/N) ratio in Taguchi’s technique [24]. The impact of noise factors on performance is measured by means of S/N ratio. If the S/N ratio is larger, the product will be more robust against noise. For Smaller-the-better category, the quality characteristics are usually an undesired output and for Larger-the-better category, the quality characteristics are usually a desired output and for Nominal-the-best category, the quality characteristics are usually a nominal output.

Smaller-the-better (Minimize):

$$S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{2}$$

where $\overline{y}_i$ represents the experimentally observed value of i^{th} experiment and n is the no. of replications of each experiment. Smaller-the-better objective is to reduce the value of the quality characteristics to the smallest possible value zero, which is the ideal or target value e.g. energy consumption.

III.II Grey Relational Analysis

Grey Relational Analysis (GRA) is used to determine the optimum condition of various input parameters to obtain the best quality characteristics [25]. Grey Relational analysis is broadly applied in evaluating or judging the performance of a complex project with meagre information. However, the data to be used in Grey analysis must be pre-processed into quantitative indices for normalizing raw data for another analysis [26]. Pre-processing raw data is a process of converting an original sequence into a decimal sequence between 0.00 and 1.00 for comparison. If the expected data sequence is of the form "Smaller-the-better", then the original sequence can be normalized as,

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{3}$$

where $x^o_i(k)$ is the original sequence, $x^*_i(k)$ the sequence after the data pre-processing, max $x^o_i(k)$ the largest value of $x^o_i(k)$, and min $x^o_i(k)$ imply the smallest value of $x^o_i(k)$. Following data pre-processing, a grey relational coefficient is calculated to express the relationship between the ideal and actual normalized experimental results [27]. Thus, the grey relational coefficient can be expressed as,

$$\zeta_i(k) = \frac{\Delta_{\min} + \zeta.\Delta_{\max}}{\Delta_{0i}(k) + \zeta.\Delta_{\max}} \tag{4}$$

where Δ_{oi} (k) is the deviation sequence of the reference sequence, which is given by,

$$\Delta_{0i}(k) = \left\| x_0^*(k) - x_i^*(k) \right\| \tag{5}$$

$$\begin{aligned} \Delta_{\max} &= \max_{\forall j \varepsilon i} \max_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\|, \\ \Delta_{\min} &= \min_{\forall j \varepsilon i} \min_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\| \end{aligned} \tag{6}$$

ζ is distinguishing or identification coefficient: $\zeta\varepsilon$ [0, 1]. ζ = 0.5 is generally used. After obtaining grey relational coefficient, normally the average of the grey relational coefficient is taken as the grey relational grade. The grey relational grade is defined as,

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} {}_i\zeta_i(k) \tag{7}$$

IV. RESULTS AND DISCUSSIONS

To Numerical simulation method using Fluent software is employed for all the nine experimental runs in L_9 orthogonal array [28] and the average temperature and velocity are predicted at the heights of 1.2, 1.5 and 2 m from the floor. Later the predicted mean vote value for the nine cases are determined from the Fanger's equation [29] and the Predicted Percentage Dissatisfaction (PPD) is calculated [30]. The predicted PPD and energy consumption for the nine experimental cases are given in Table 3.

Table 3 L_9 Orthogonal array with experimental runs and results

Trial No	PPD %	Energy consumption (kW-h)
1	31.500	1.028
2	38.700	1.394
3	67.000	1.852
4	70.000	1.205
5	6.900	2.100
6	57.500	0.957
7	34.200	1.913
8	84.900	0.896
9	9.300	1.565

The velocity vector plots and temperature plots shown in Figure 5 to Figure 13 for a plane parallel to the floor at the mid height of the room is shown for the cases analysed in the Table 2. Cases 5 and 9 shows the indoor temperature value comparatively as low and this is mainly due to the AC set point temperature at 15°C. This is not reflected in the case 1 since the AC tonnage capacity is low. The location of AC unit and exhaust unit from the ground level also plays the major role in the distribution of air. If the both units are the same height, then the conditioned air from the AC system directly vents out through the exhaust without taking the heat from the indoor space. On the other hand, if the AC unit is at higher level in comparison with exhaust then the air from the air-conditioned unit not effectively absorbs the heat from the floor level.

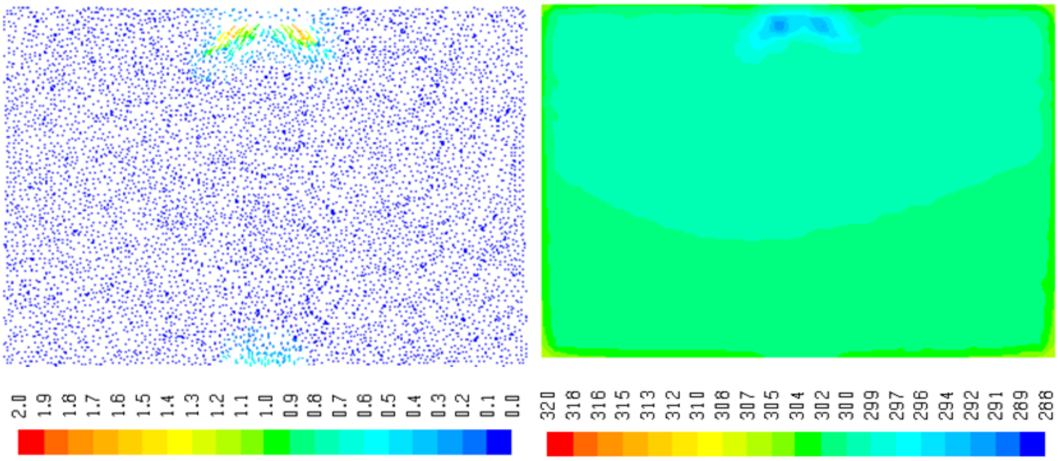

Figure 5 Velocity and Temperature distribution for Trial no. 1

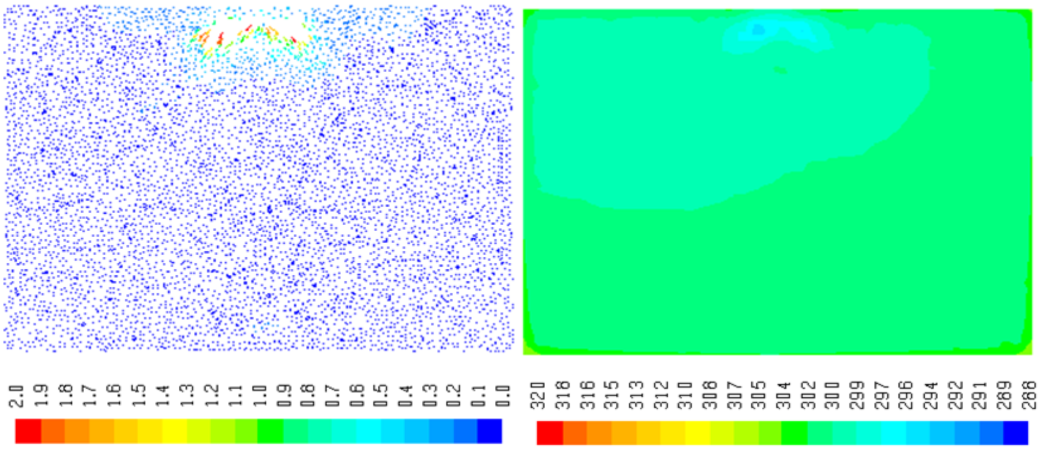

Figure 6 Velocity and Temperature distribution for Trial no. 2

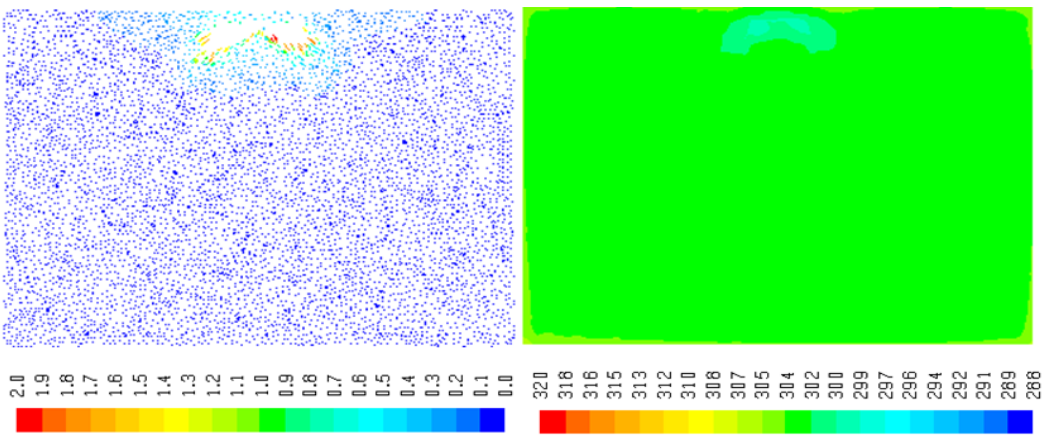

Figure 7 Velocity and Temperature distribution for Trial no. 3

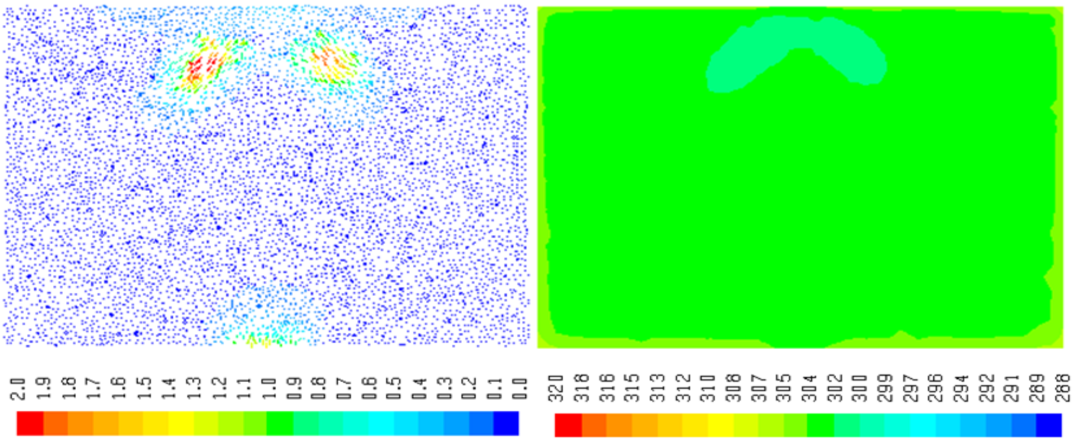

Figure 8 Velocity and Temperature distribution for Trial no. 4

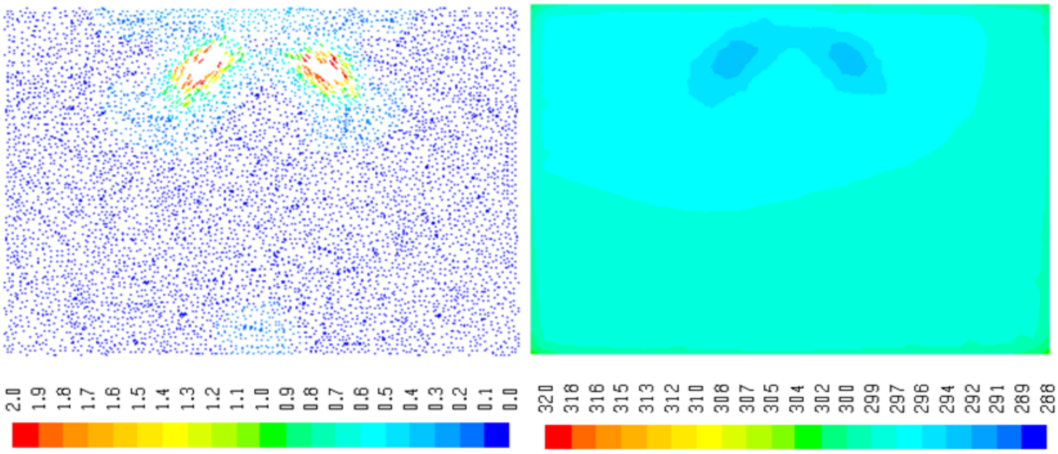

Figure 9 Velocity and Temperature distribution for Trial no. 5

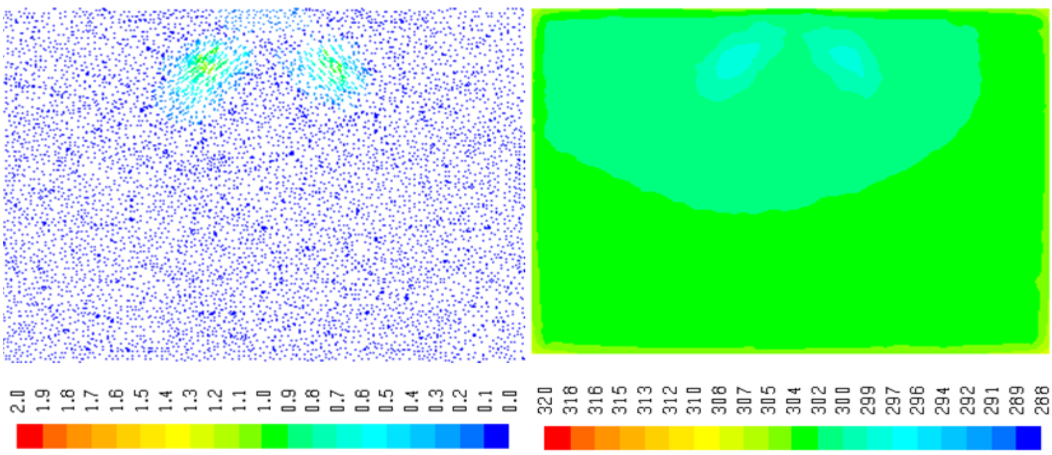

Figure 10 Velocity and Temperature distribution for Trial no. 6

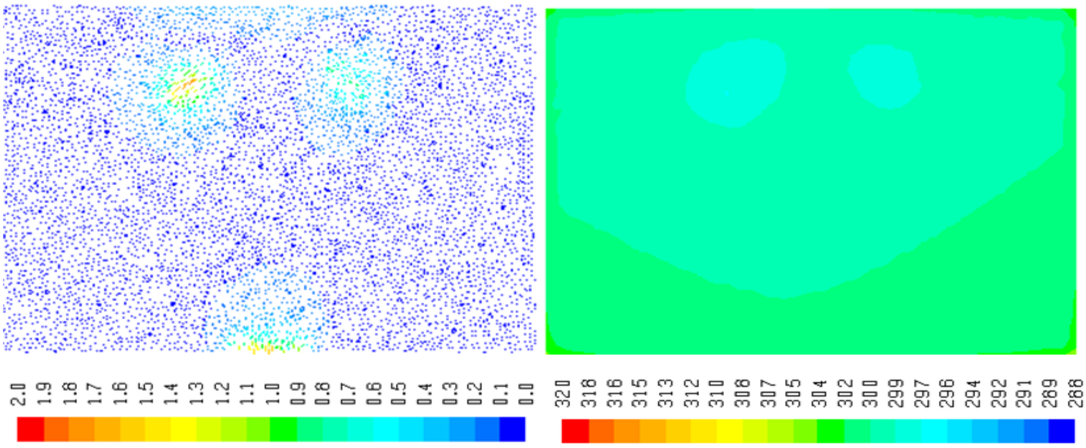

Figure 11 Velocity and Temperature distribution for Trial no. 7

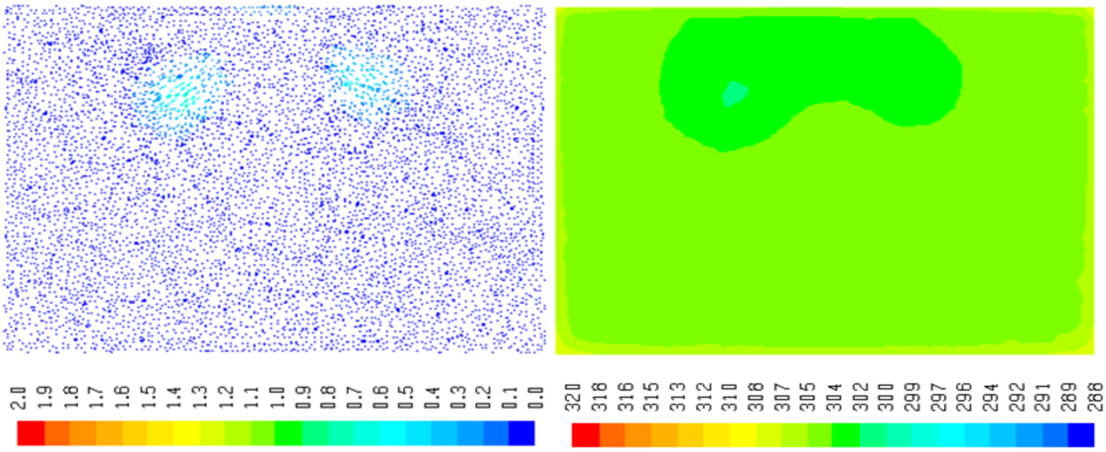

Figure 12 Velocity and Temperature distribution for Trial no. 8

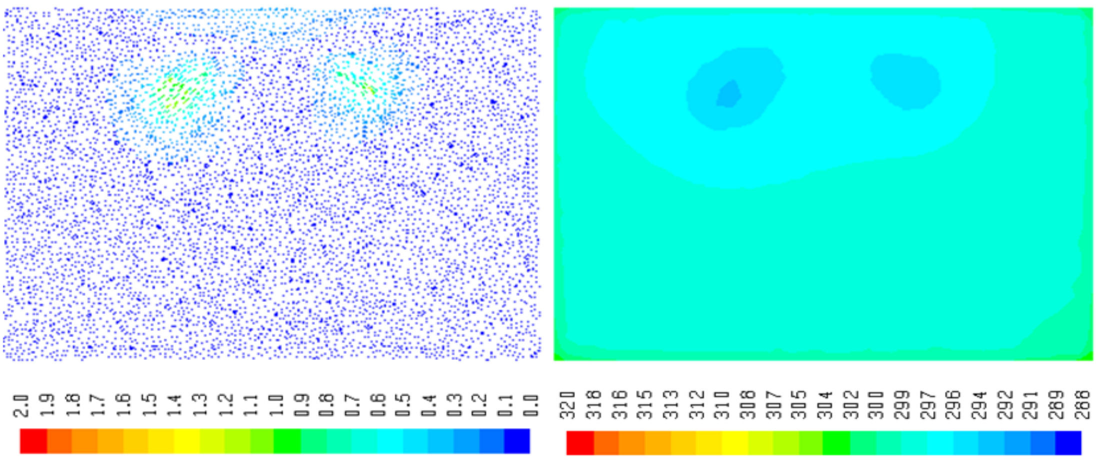

Figure 13 Velocity and Temperature distribution for Trial no. 9

By proving the AC unit system lower than the exhaust system carries the heat at the floor level and makes good comfort for the occupants and later the warm air rises, vents through the exhaust. This phenomenon is clearly observed from the velocity and temperature contour plots. Among the analyzed cases, case number 3 and 4 shows elevated temperature at the same plane and this due to the fact that the AC unit supply air temperature is at 25°C. Also, the case 3, 5 and 7 shows high indoor velocity at some local regions and this is due to tonnage capacity of AC unit system. Even though, the AC tonnage capacity enhances the good reach to the supply air, the indoor thermal comfort is not highly influenced by the tonnage capacity and this clearly evident from the ANOVA result. Also, the reach of supply air to the entire indoor space is not enough even for high tonnage capacity of AC unit system. Additional systems may be used to enhance indoor air circulation to provide better indoor thermal comfort to the occupants. In this study, both the output responses, PPD and energy consumption to be minimized. A hybrid optimization approach: Taguchi-Grey relational analysis is applied to obtain the optimum conditions [31].

Table 4 Determination of S/N ratio and Normalizing sequence

Trial No.	S/N ratio		Normalizing Sequence	
	PPD	Energy Consumed	PPD	Energy Consumed
1	-29.966	-0.240	0.605	0.161
2	-31.754	-2.885	0.687	0.519
3	-36.521	-5.353	0.906	0.852
4	-36.902	-1.620	0.923	0.348
5	-16.777	-6.444	0.000	1.000
6	-35.193	0.382	0.845	0.077
7	-30.681	-5.634	0.638	0.891
8	-38.578	0.954	1.000	0.000
9	-19.370	-3.890	0.119	0.655

For this initially S/N ratio has to be determined and hence "Smaller-the-better" given in (2) is selected for calculating S/N ratio. Followed by this, normalizing sequence of grey relational analysis is calculated as per (3) as both the PPD and energy consumption should be minimum. Table 4 shows the normalized data for the output responses, PPD and energy consumed. After the normalizing procedure of data analysis, the deviation sequence of the responses is determined, followed by determining the a grey relational coefficient for individual responses and then a common grey relational grade has to be calculated in order to convert the single objective optimization into multi-objective optimization by considering the average values of individual grey coefficients of outputs as shown in Table 5.

Table 5 Grey relational coefficient and grade

Trial No.	Deviation Sequence		Grey Relational Coefficient		Grey Relational Grade
	PPD	Energy Consumed	PPD	Energy Consumed	
1	0.395	0.839	0.559	0.374	0.466
2	0.313	0.481	0.615	0.510	0.562
3	0.094	0.148	0.841	0.772	0.807
4	0.077	0.652	0.867	0.434	0.650
5	1.000	0.000	0.333	1.000	0.667
6	0.155	0.923	0.763	0.351	0.557
7	0.362	0.109	0.580	0.820	0.700
8	0.000	1.000	1.000	0.333	0.667
9	0.881	0.345	0.362	0.592	0.477

To determine the response table of grey relational grade, shown in Table 6, average values of each parameter level is considered and from that the optimum conditions are identified with larger grey grade. The best/optimal parameter levels are identified from the response table as AC height of 1.5 m, exhaust ventilation position at 1.5 m, AC capacity as 2 Tons and AC set temperature as 25°C. Response plot of grey relational grade is drawn based on response table which is shown in Figure 14.

Table 6 Response table for Grey relational grade

Factors	Level 1	Level 2	Level 3	Max - Min	Rank
AC Height	0.612	0.625	0.615	0.013	4
Exhaust Height	0.606	0.632	0.614	0.026	3
AC Capacity	0.563	0.563	0.724	0.161	2
AC Temperature	0.537	0.607	0.708	0.171	1

For determining the most influential parameters, ANOVA method is employed. Results of ANOVA method is given in Table 7. With zero degrees of freedom of error, the ANOVA table shown does not provide enough data. This happens when four input parameters with three level values are considered and an L_9 OA is chosen for analysis. Hence ANOVA pooling is to be performed.

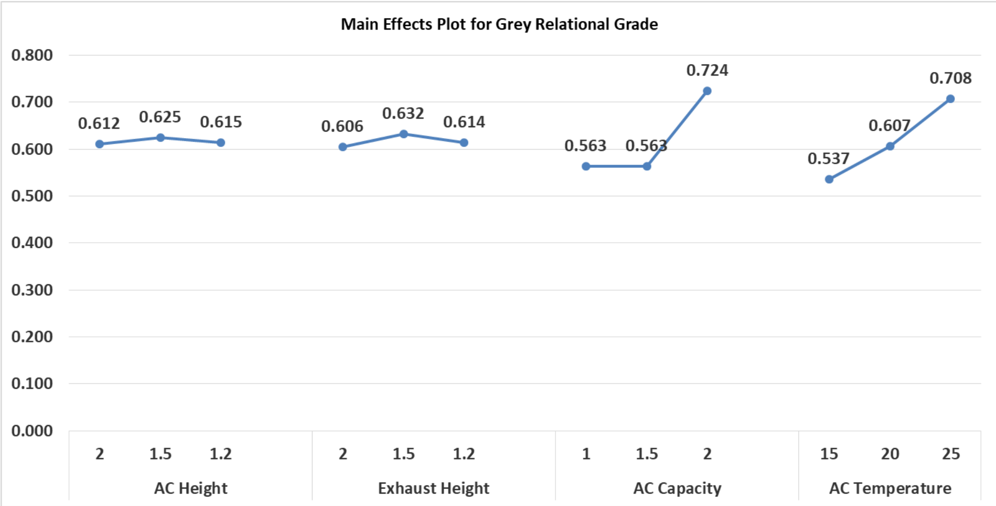

Figure 14 Main effects plot for Grey relational grade

Table 7 ANOVA table of Grey relational grade before Pooling

Factors	DoF	SS	MS	F Value	P Value	% Contribution
AC Height	2	0.0003	0.0001	*		
Exhaust Height	2	0.0011	0.0005	*		
AC Capacity	2	0.0520	0.0260	*		
AC Temperature	2	0.0446	0.0223	*		
Error	0	*	*			
Total	8	0.0979	0.0122			

Pooling is the process of ignoring a factor once it is deemed insignificant, which is done by combining the influence of the factor with that of the error term. Pooling is a common practice of revising and re-estimating ANOVA results [32]. A factor is pooled when it fails the test of significance. Unfortunately, the test of significance can be done only when the error term has nonzero DOF. Pooling is started with the factor that has the least influence [33].

Table 8 ANOVA table of Grey relational grade after Pooling

Factors	DoF	SS	MS	F Value	P Value	% Contribution
Exhaust Height	2	0.0011	0.0005	3.870	0.199	1.12%
AC Capacity	2	0.0520	0.0260	183.716	0.005	53.10%
AC Temperature	2	0.0446	0.0223	157.398	0.006	45.49%
Error	2	0.0003	0.0001			0.29%
Total	8	0.0979	0.0122			100.00%

From the ANOVA table before pooling, it is identified that, height of AC position is having the least influence; hence it is pooled as shown in Table 8. From the pooled ANOVA table shown, it is evident that the capacity of the AC is the most prominent parameter that contributes towards the grey relational grade by 53.10%, followed by the capacity of the AC set temperature by 45.49% and position of the exhaust ventilation unit by 1.12%. The ‘S’ value of ANOVA is 0.0118, R^2 value is 99.72% with R^2 (adj.) value of 98.87%. Figure 15 shows the percentage contribution of input parameters over the grey relational grade.

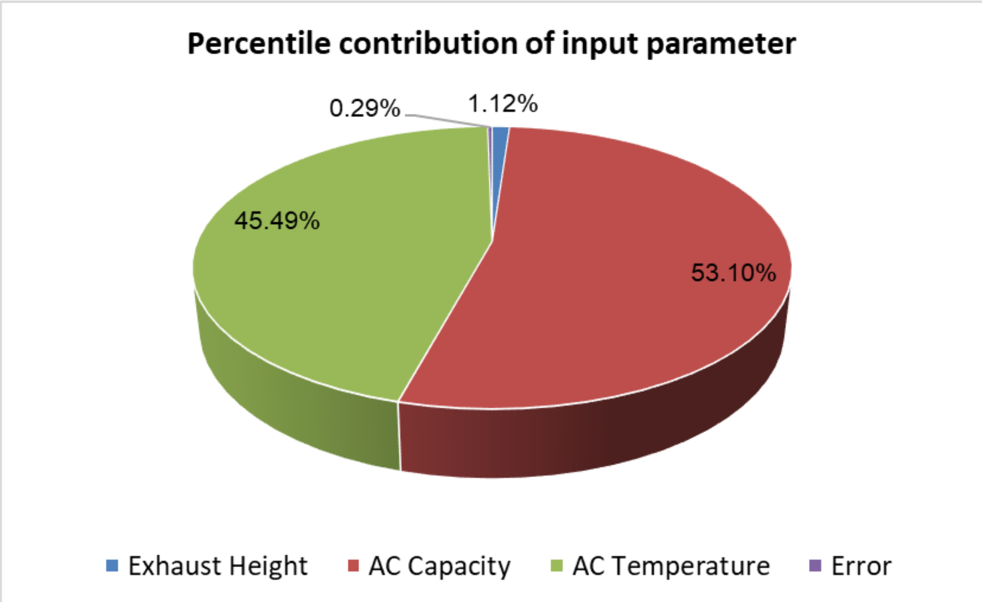

Figure 15 Percentage contribution of input parameters

IV.I Confirmation Test

From the hybrid Taguchi-grey relational method of optimization, the best levels of values for the parameters position of AC unit, position of exhaust ventilation, AC capacity and AC set point temperature are identified as 1.5m, 1.5m, 2 Tons and 25°C respectively. For this parametric values the indoor thermal comfort index PPD is numerically predicted as 33.7 % and energy consumption as 1.23 kWh, which is 24.62% and 14.34% lower than the average values of experimental PPD values. From this study it is clearly observed that the positioning of AC system at the height of 1.5m offers a good air circulation for entire class room and for an exhaust ventilation position of 1.5m effectively ventilates indoor air.

V. CONCLUSION

In this study, analysis and optimization on energy consumption and indoor comfort are made for a smart class of a school building. Taguchi’s grey relational technique is employed for the multiple objective optimization of energy consumption and indoor thermal comfort. The control factors are identified as location of Air conditioning system, location of exhaust, tonnage capacity of air conditioning unit and set point temperature. Based on the optimization study, the best parameters for this multiple objective are identified, and energy savings in comparison with existing smart class is predicted as 1.23 kWh over a period of one hour. Finally, ANOVA identifies the most influencing parameter as air conditioning system's set point temperature. The results predicted from this study is confined to this room, however this methodology can be adopted for any kind of air-conditioned rooms.

REFERENCES

[1] F. Bagheri, V. Mokarizadeh, and M. Jabbar, Developing energy performance label for office buildings in Iran, *Energy and Buildings*, *61*, 2013, 116-124.

[2] T.G. Theodosiou, and K.T. Ordoumpozanis, Energy, comfort and indoor air quality in nursery and elementary school buildings in the cold climatic zone of Greece, *Energy and Buildings*, *40(12)*, 2008, 2207-2214.

[3] M.C. Katafygiotou, and D.K. Serghides, Analysis of structural elements and energy consumption of school building stock in Cyprus: Energy simulations and upgrade scenarios of a typical school, *Energy and Buildings, 72*, 2014, 8-16.

[4] A. Dimoudi, and P. Kostarela, Energy monitoring and conservation potential in school buildings in the C′ climatic zone of Greece, *Renewable energy, 34(1)*, 2009, 289-296.

[5] EC-DG TREN. The guide to sustainable energy solutions for schools. ENERGIE Publication – European Commission. Produced by Energie-Cites. Besancon, France; 2002.

[6] H.H. Sait, Auditing and analysis of energy consumption of an educational building in hot and humid area, *Energy Conversion and Management*, *66*, 2013, 143-152.

[7] Z. Wang, Y. Ding, G. Geng, and N. Zhu, Analysis of energy efficiency retrofit schemes for heating, ventilating and air-conditioning systems in existing office buildings based on the modified bin method, *Energy Conversion and Management*, *77*, 2014, 233-242.

[8] A.A. Chowdhury, M.G. Rasul, and M.M.K. Khan, Analysis of Energy Performance of Institutional Buildings in Subtropical Climate, *Energy Procedia*, *110*, 2017, 604-610.

[9] A. Thewes, S. Maas, F. Scholzen, D. Waldmann, and A. Zürbes, Field study on the energy consumption of school buildings in Luxembourg, *Energy and Buildings, 68*, 2014, 460-470.

[10] R.A. Lara, G. Pernigotto, F. Cappelletti, P. Romagnoni, and A. Gasparella,

Energy audit of schools by means of cluster analysis, *Energy and Buildings, 95*, 2015, 160-171.

[11] U. Desideri, S. Proietti, Analysis of energy consumption in the high schools of a province in central Italy, *Energy and Buildings, 34(10),* 2002, 1003-1016.

[12] R. McMullan, Environmental Science in Building, seventh edition, Palgrave Macmillan, New York, 2012.

[13] Y. Zhu, Applying computer-based simulation to energy auditing: A case study, *Energy and Buildings, 38(5),* 2006, 421-428.

[14] K.H Kim, and J.S. Haberl, Development of a home energy audit methodology for determining energy and cost efficient measures using an easy-to-use simulation: Test results from single-family houses in Texas, USA, *Building Simulation, 9(6)*, 2016, 617-628.

[15] C. Hirsch, Numerical Computation of Internal and External Flows: The Fundamentals of Computational Fluid Dynamics, second edition, Elsevier, UK, 2007.

[16] P. Taylor, R.J. Fuller, and M.B. Luther, Energy use and thermal comfort in a rammed earth office building, Energy and Buildings, 40(5), 2008, 793-800.

[17] S. Bertagnolio, P. Andre, and V. Lemort, Simulation of a building and its HVAC system with an equation solver: Application to audit, *Building Simulation, 3(2),* 2010, 139-152.

[18] A. Pasupathy, and R. Velraj, Effect of double layer phase change material in building roof for year round thermal management, *Energy and Buildings, 40(3), 2008*, 193-203.

[19] H.S.L. Hens, Applied Building Physics: Ambient Conditions, Building Performance and Material Properties, second edition, Ernst & Sohn, USA, 2012.

[20] V. Selvakumar, S. Muruganandam, T. Tamizharasan, and N. Senthilkumar, Machinability evaluation of Al–4%Cu–7.5%SiC metal matrix composite by Taguchi–Grey relational analysis and NSGA-II, *Sadhana, 41(10),* 2016, 1219-1234.

[21] R.K. Roy, Design of experiments using the Taguchi approach: 16 steps to product and process improvement, Wiley-Inderscience Publication, New York, 2001.

[22] N. Senthilkumar, T. Tamizharasan, and V. Anandakrishnan, Experimental Investigation and Performance Analysis of Cemented Carbide Inserts of different geometries using Taguchi based Grey Relational Analysis, *Measurement, 58*, 2014, 520-536.

[23] P.J. Ross, Taguchi Techniques for Quality Engineering, Tata McGraw Hill publishing company Ltd., New Delhi, 2005.

[24] N. Senthilkumar, T. Ganapathy and T. Tamizharasan, Optimization of Machining and Geometrical parameters in Turning process using Taguchi Method, *Australian Journal of Mechanical Engineering, 12(2)*, 2014, 233-246.

[25] D. Prakash, and P. Ravikumar, Multi-Objective Optimization of Residential Building Roof Layer Thickness for Minimization of Heat Entering the Room Using FEM and Grey Relational Analysis, *Journal of The Institution of Engineers (India): Series A, 95(1)*, 2014, 39-47.

[26] N. Senthilkumar, B. Deepanraj, K. Vasantharaj, and V. Sivasubramanian, Optimization and performance analysis of process parameters during anaerobic digestion of food waste using hybrid GRA-PCA technique, *Journal of Renewable Sustainable Energy 8*, 063107 (2016); doi: 10.1063/1.4972884

[27] A.H. Suhail, N. Ismail, S.V. Wong, and N.A. Abdul Jalil, Surface Roughness Identification Using the Grey Relational Analysis with Multiple Performance Characteristics in Turning Operations, *Arabian Journal for Science and Engineering, 37(4)*, 2012, 1111-1117.

[28] T. Tamizharasan, and N. Senthilkumar, Numerical Simulation of effects of Machining parameters and Tool Geometry using DEFORM-3D: Optimization and Experimental Validation, *World Journal of Modelling and Simulation, 10(1)*, 2014, 49-59.

[29] P.O. Fanger, Thermal comfort: Analysis and applications in environmental engineering, Danish Technical Press, Denmark, 1970.

[30] H.B. Awbi, Ventilation of Buildings, second edition, Spon press, London, UK, 2003

[31] N. Senthilkumar, J. Sudha, and V. Muthukumar, A grey-fuzzy approach for optimizing machining parameters and the approach angle in turning AISI 1045 steel, *Advances in Production Engineering & Management, 10(4)*, 2015, 195-208.

[32] G. Gamst, L.S. Meyers, and A.J. Guarino, Analysis of Variance Designs - A Conceptual and Computational Approach with SPSS and SAS, Cambridge University Press, Cambridge, London, 2008.

[33] M. Last, G. Luta, A. Orso, A. Porter, and S. Young, Pooled ANOVA, *Computational Statistics & Data Analysis, 52(12)*, 2008, 5215-5228.