PREDICTING NATURAL VENTILATION AIR VELOCITY USING DETERMINISTIC AND NON-DETERMINISTIC METHODOLOGIES

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ABSTRACT

An extensive experimental program on single sided natural ventilation was carried out within the frame of PASCOOL EC research project. Within the frame of these activities, four single sided natural ventilation experiments were carried out in a test cell, a full scale outdoor facility. Experimental data were used as input for numerical simulations that were carried out using air flow calculation tools based on network modeling as well as computational fluid dynamics (CFD). Finally, fuzzy logic techniques were used to predict the air velocity profile in the middle of the opening. This paper presents the simulation results using the above approaches as well as a comparison with measurements.

INTRODUCTION

Natural ventilation has proved to be an energy saving way to reduce indoor cooling load, achieve thermal comfort and also maintain a healthy indoor environment, in the case where the outdoor air conditions allow for its use. The physical processes involved in both cases are very complex and the interpretation of their role in ventilation effectiveness is a difficult task. When the building communicates with the outdoor environment through only one or more openings located at the same exterior wall, ventilation is single sided.

In order to study the physical phenomena related to single sided natural ventilation and their impact on the air velocity field at the opening level, four experiments were performed in a Test Cell, which is a full scale facility, during October 1993 in Athens, Greece. The tracer gas decay technique was used in order to measure the bulk air flow rate. Although tracer gas techniques provide an estimate of the bulk air flow rate in the investigated room(s), they do not give any information on the air flow/velocity field. This information is very important when treating problems of comfort or indoor air pollutant transport. Air velocity measurements were taken at various heights in the middle of the opening, to provide some insight of the air velocity field at the level of the opening. However, in the case of single sided natural ventilation, the uncontrollable nature of the wind, produces constantly changing air flow patterns through an exterior opening. Therefore, a lot of simultaneous multiple velocity measurements of high accuracy are required in order to predict the air flow rate successfully. This requirement implies that such an experiment is difficult and very expensive to perform.

Three modeling approaches were used in order to predict the air velocity profile in the middle of the opening: a) Bernoulli theory, b) CFD and c) fuzzy logic techniques. In the following sections, a brief description of the experimental procedure is given and the results from three modeling approaches are compared with measurements.

EXPERIMENTS

The PASSYS Test Cell is a fully equipped, two room, outdoor facility for thermal and solar monitoring [1]. Ventilation experiments were carried out in the "service room", while the door connecting it to the "test room" was kept closed and sealed. The service room has a floor area of 8.6 m^2 with a length of 2.4 m and a height of 3.29 m. It has an exterior door opening of 2.02 m^2 with a width equal to 1.01 m.

During the experiments indoor air temperature was measured by PT100 sensors (accuracy: ±0.1 ^{o}C). A mast holding four PT100 sensors was used to monitor the vertical stratification. Their heights from the floor were: 0.42m, 1.76m, 2.37 m and 3.20m. Temperature stratification at the opening was monitored by an array of five T-fast sensors (accuracy ±0.1 ^{o}C). The T-fast sensor is a 12.5E-6 m platinum wire, wired around an open Plexiglas base. The heights of these sensors from the floor were: 0.36m, 0.65m, 1.05m, 1.35m and 1.69m.

Measurements of wind speed and direction were provided by a hot wire anemometer and a vane (accuracy: ±5 deg) at a height of 1.5 m, 1m away from the Service room entrance door. At the same distance and at a height of 2 m, a T-fast sensor was

Experiment	Mean Ambient Temperature	Mean Indoor Temperature	Mean Wind Speed, (ms^{-1}), at 10 m	Mean Measured Flow Rate (m^3h^{-1})
Exp. 1	24.1 ± 0.1	23.4 ± 0.1	3.3 ± 0.07	198 ± 27
Exp. 2	24.7 ± 0.1	24.3 ± 0.1	2.5 ± 0.05	202 ± 39
Exp. 3	25.7 ± 0.1	26.2 ± 0.1	3.8 ± 0.08	245 ± 65
Exp. 4	25.6 ± 0.1	26.6 ± 0.1	3.6 ± 0.072	322 ± 62

Table 1 : Characteristics of the Test Cell Experiments.

Sensor Type	Height (m)	EXP1		EXP2		EXP3		EXP4	
		V(m/s)	SD	V(m/s)	SD	V(m/s)	SD	V(m/s)	SD
D1	1.87	0.47	0.09	0.54	0.12	0.62	0.14	0.57	0.14
HW1	1.73	0.35	0.05	0.39	0.09	0.44	0.10	0.39	0.09
HW2	1.43	0.44	0.12	0.42	0.12	0.48	0.10	0.43	0.10
HW3	0.93	0.65	0.27	0.43	0.08	0.54	0.13	0.50	0.12
HW4	0.63	0.61	0.27	0.39	0.07	0.47	0.12	0.45	0.11
HW5	0.33	0.64	0.27	0.42	0.11	0.51	0.14	0.49	0.10
D2	0.16	0.68	0.23	0.46	0.10	0.63	0.12	0.60	0.13

Table 2: Average air velocity measurements at the cell entrance

placed to measure ambient temperature. Data on the wind at a 10 m height were also available. These measurements included 1min data, while the ones at 1.5 m were 1sec data. Data in front of the door were chosen for this analysis as more appropriate for studying the physical processes at the door level.

The air exchange rates were derived using the single tracer gas decay technique. N_20 was used as tracer gas. Injection and sampling points were carefully chosen and distributed at various heights inside the studied rooms in order to supply the tracer gas homogeneously and also to monitor its spatial variation with time. The sampling period was set at 30 sec. Tracer gas concentration was measured by an infra-red gas analyser.

Comparison between indoor and outdoor average air temperature measurements shows that the average air temperature was higher indoors than outdoors. During the four experiments, this difference ranged between 0.5-3^oC. No significant temperature stratification was observed. Table 1 summarizes the mean characteristics of the Test Cell experiments.

The air velocity at various heights in the middle of the opening was measured by an array of five triple hot wire anemometers (lower threshold: 0.2 m/s, accuracy: ±0.02m/s) developed in the Laboratory of Meteorology of the University of Athens [2] and two commercial sensors manufactured by DANTEC (accuracy: ±0.4%). The heights of the hot wires from the floor were 0.33 m, 0.63 m, 0.93 m, 1.43m and 1.73m. The heights of the commercial sensors from the floor were 0.16 m and 1.87 m. Measurements were taken every second. Table 2 summarizes the mean air velocity values measured by each sensor.

SIMULATIONS

a) NETWORK MODELS

Network models predict the air velocity at different heights at the opening level using the Bernoulli theory. According to the theory, the air velocity at a height z is:

$$V_B(z) = C_d \sqrt{2\Delta P/\rho} \text{ , m/s} \quad (1)$$

where

$$\Delta P = P_{oi} - P_{dyn} + (\rho_a - \rho_i)gz \text{ , Pa} \quad (2)$$

where P_{oi} and P_{dyn} are the reference and dynamic wind pressures (Pa), ρ_a, ρ_i are the outdoor and indoor air density (kg/m^3), while ρ is the air density in the direction of the flow.

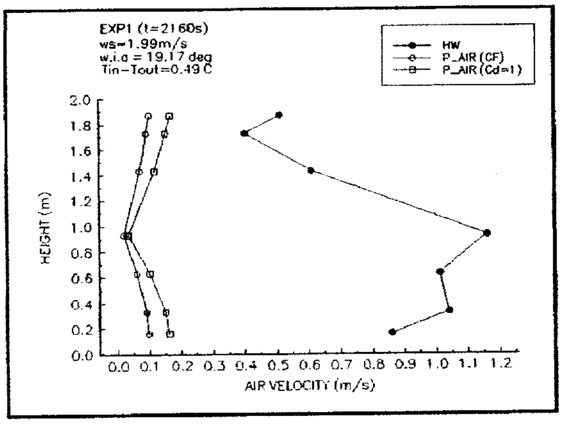


Fig.1: Predicted air velocity at the opening level using the Bernoulli theory. Comparison with measurements.

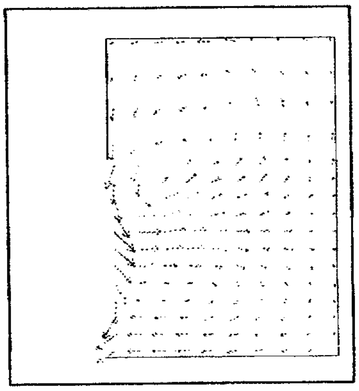
Data (1 sec) from all experiments were included in a dataset resulting in a total of 2734 different measurements for each sensor. The wind speed in front of the cell, as well as the indoor-outdoor air temperatures were used as input values for simulations using PASSPORT-AIR [3] and the air velocity at the sensors' heights was calculated.

Figure 1 gives a comparison between measured and predicted values. Predicted and measured values were not found to be in good agreement. The observed difference is attributed to the fact that network modeling considers homogenous airflow along the door. In fact, in the case of single sided ventilation, the effect of turbulence is practically ignored. In reality, however, the air velocity field at the opening must be strongly affected by this factor, which is introduced by the constantly changing nature of the wind. Thus, despite its accuracy in predicting the air exchange rates, the Bernoulli theory does not provide much information on the flow field at the opening.

b) COMPUTATIONAL FLUID DYNAMICS (CFD)

CFD modeling is based on the solution of the Navier-Stokes system of equations for mass, momentum and energy conservation. This modeling type provides a detailed set of output on the air flow patterns and velocity fields. A very comprehensive set of input data is required, the accuracy of which determines the accuracy of the obtained results. The domain size and grid discretization also plays an important role towards achieving convergence. A computational fluid dynamics model, PHOENICS [4] was used in order to simulate single sided natural ventilation when the wind impinges normally on the opening (incidence angle ≅0 degrees).

The domain size that was chosen for the simulation was 20m x 32.4m (height x width). The adopted grid discretization had 36 x 35 points and was finer in the viscinity of the opening and inside the cell. The upper and lower boundaries of the solution domain were defined as adiabatic walls while the right and left edges were defined as inlet and outlet respectively. The inlet was located at 10m in front of the cell entrance while the outlet was located at 20m behind the cell. These distances were found to ensure the formation of a logarithmic profile of the wind in the windward area as well as a total recovery of the flow after the formation of the wake in the leeward area. The temperature at the inlet was set equal to 24 °C. The wind speed at the inlet was taken uniform with height. As the wind speed components were not available at 10m away from the opening, various scenarios were tried by using different boundary conditions at the inlet. Figure 2 shows the results obtained using two scenarios of wind speed at the inlet. In the first scenario the horizontal and vertical component were taken equal to 6 m/s and 0.001 m/s respectively. In the second scenario the horizontal component was taken equal to 4 m/s.



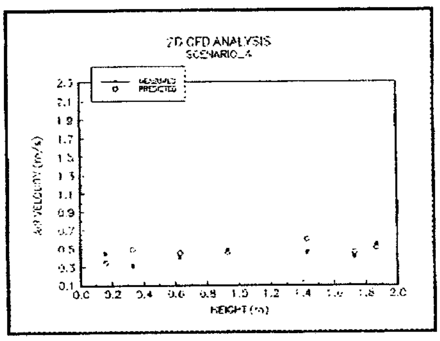
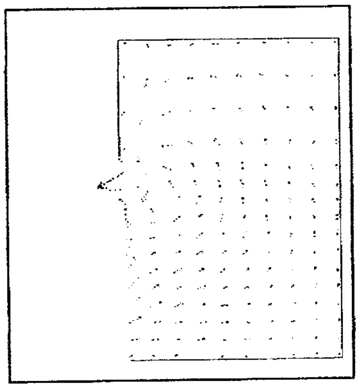


Fig.2a: Prediction of the air velocity at the opening level using CFD and comparison with measurements. Scenario 1 (wind speed at inlet : 6m/s (horizontal) and 0.001m/s (vertical)



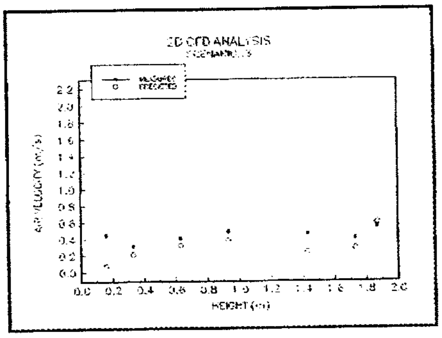


Fig.2b: Prediction of the air velocity at the opening level using CFD and comparison with measurements. Scenario 2 (wind speed at inlet : 4m/s (horizontal) and 0.001m/s (vertical)

As shown, the derived air flow patterns are very different, though both scenarios give air velocity values that are close to the measured ones. Thus, the uncertainty of the boundary conditions at the inlet results in an uncertain flow pattern which implies that no unique solution can be derived. However, it is difficult to know in advance the exact values of the wind speed and its variation with height at any distance from the opening where this may be required according to the chosen simulation domain.

c) CORRELATION METHODOLOGIES

Using 1sec data an attempt was made to check how correlation techniques can be used in order to predict the vertical profile of the air velocity at the cell entrance. The statistical analysis involved an investigation and possible correlation of the air velocity measurements of each sensor with the physical parameters that mostly affect natural ventilation, namely, the wind speed and the temperature difference. Air velocity data from the five hot wire anemometers and the two commercial sensors as well as wind speed and indoor-outdoor temperature data were used for this analysis.

The original dataset containing data from all the experiments (a total of 2734 values from each sensor) was split into two: the even numbered lines were included in the original training dataset, while the odd numbered lines were included in the original checking dataset. Using the data of wind direction and considering the symmetry of the problem, the wind incidence angle, WIA, was derived (WIA=ABS(wind direction-180)). Each of the original training and checking datasets was split into four datasets corresponding to four different ranges of wind incidence angle: $0 \leq WIA \leq 30°$, $30 < WIA \leq 60°$, $60 < WIA \leq 90°$ and $90 < WIA \leq 180°$.

A surface fitting was carried out for the original training dataset using x: temperature difference, y: wind speed and w: air velocity. The equations derived from the fitting were applied to the original checking dataset. Poor agreement was observed between predicted and measured air velocity values for each sensor. In order to improve the methodology, an attempt was made to follow the same procedure using discrete training data. This was achieved by dividing the ranges of wind speed, temperature difference and air velocity into shorter intervals and replacing each value with the mean value of the range it belonged to. Surface fitting was carried out using wind speed, temperature difference and air velocity data from the discretized training dataset. The equations derived from the above described procedure were applied to the discretized checking dataset. The predicted air velocity values for every sensor were plotted versus the measured ones and it was found that the agreement between predicted and measured values was not satisfactory.

d) FUZZY LOGIC SYSTEMS

Fuzzy Logic Systems, have already been successfully applied to control and operate efficiently naturally ventilated buildings [5-6]. As fuzzy logic systems are considered as universal approximators, these systems are capable of uniformly approximate any non linear continuous unknown function, and thus can be used as non-linear dynamic system identifiers.

Air flow through large external openings, in single sided ventilation configurations, can be well approximated by non linear functions of specific meteorological and geometrical inputs. Therefore, it could be expected that such a function could be well approximated by a fuzzy system, when the necessary inputs and outputs are available.

However, when the predictable parameter is not the air flow rate but the profile of the air velocity on the surface of the opening, the overall

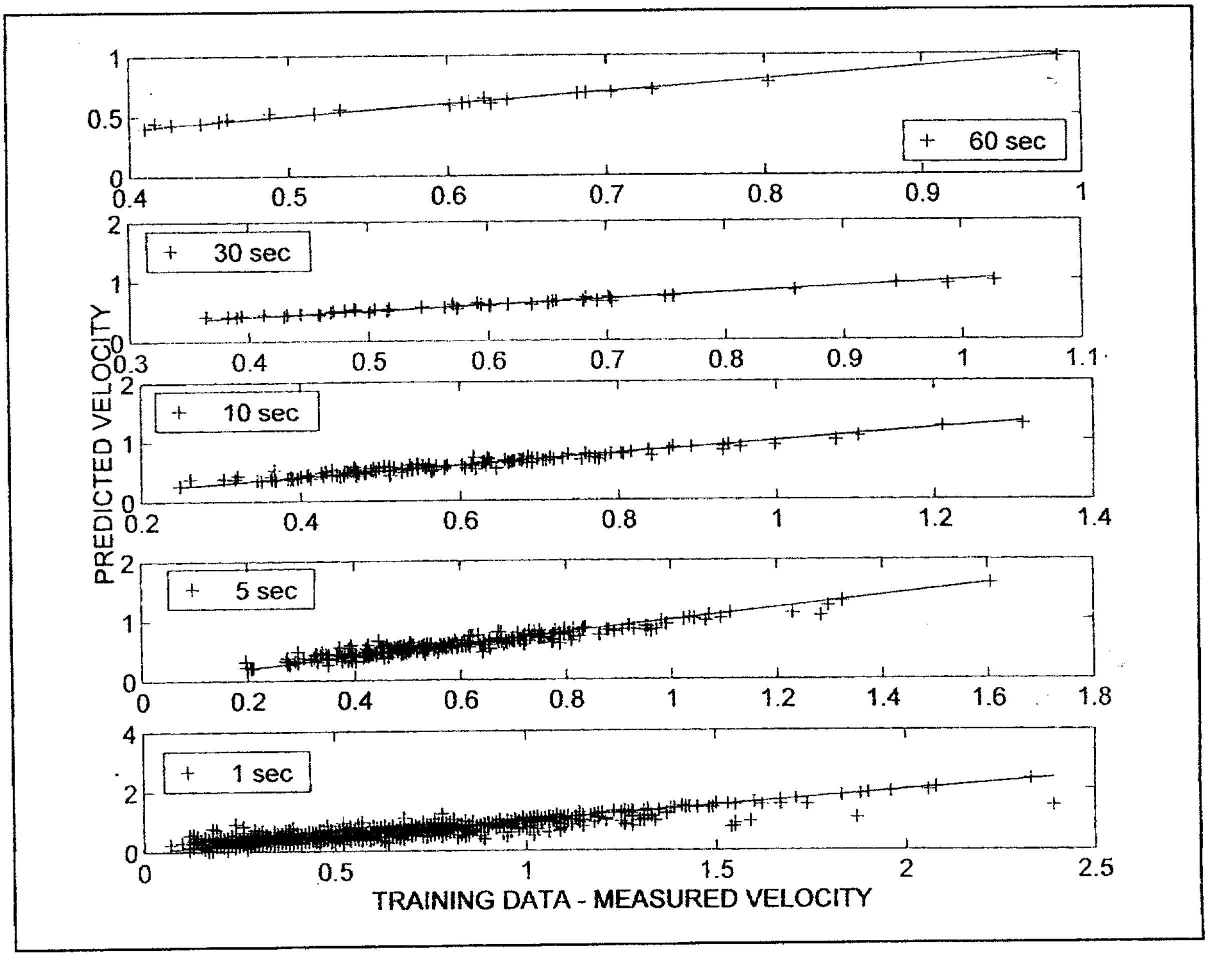


Fig.3: Training dataset: Predicted and Measured air velocity

characteristics of the problem are completely different. The temporal variation of the profile of the air velocity on a large external opening is a random variable. The sample function of the air speed at a specific point (x,y) on the surface of the large opening represents a continuous non deterministic random process as future values of this function cannot be predicted from observed past values. The use of fuzzy techniques to describe such a process presents an important interest. What is interesting is to investigate in which cases appropriate fuzzy rules can be developed based on the existing inputs, which are also random variables, and also if such a fuzzy estimator has the ability for proper response to input patterns not presented during the training process (generalisation).

To reply to the above questions, a fuzzy estimator predicting the air speed at a specific point (x,y), on the surface of a large external opening has been developed. Three types of inputs have been considered : a) The wind velocity as measured in front of the Test cell, b) The wind direction measured also in front of the test cell, c) The mean temperature difference between indoor and outdoor of the test cell.

Data measured at 1 sec time intervals have been used, and the corresponding air velocity on the surface of the opening for time intervals of one second, has been predicted. It should be noted that prediction of the air velocity at the opening surface for periods of one second has not any practical interest. However, one second data can be used to calculate mean values for larger time intervals, like 10 seconds, one minute or higher. The procedure to use one second input data instead of mean values for larger time intervals offers the advantage that a higher number of input data are used for training, while these inputs describe better the "physics" of phenomenon than the mean values of larger the time intervals. In the following paragraphs, the discussion will focus on the data set composed by the values of the air velocity measured by one sensor at the highest measuring point of the door. A similar methodology can be applied to all other

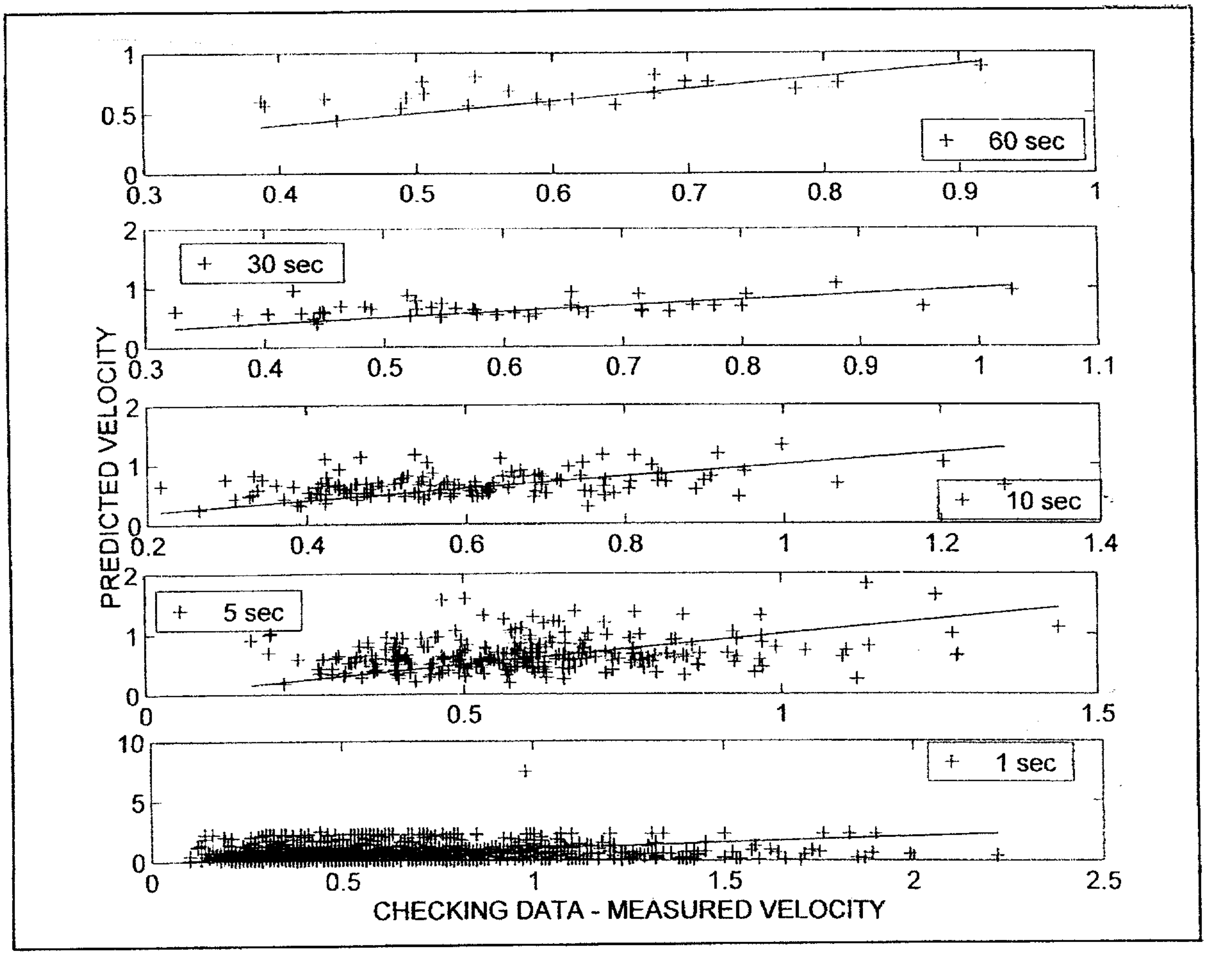


Fig.4: Checking dataset: Predicted and Measured air velocity

points at the door surface. The existing data set composed of 2734 data points has been divided in two almost equal parts. 1387 data points have been used to compose the training data set while the rest 1347 are used as a checking dataset. Clustering techniques help to distill natural grouping of data from larger set producing a concise representation of the system's behavior. The objective in clustering is to partition a given data set into homogeneous clusters where all points in the same cluster share similar attributes and they do not share similar attributes with points in other clusters [7]. Crisp classification techniques oblige each point to belong to one of the clusters at least, and their membership in the cluster to which they are assigned is unity. In fuzzy clustering techniques each data point belongs to a cluster to a degree specified by a membership grade. One of the most popular fuzzy clustering techniques, is the so called "Fuzzy C-Means" [8]. This method uses concepts in n-dimensional Euclidean space to determine the geometric closeness of data points by assigning them to various clusters or classes and then determining the distance between the clusters. When the number of the clusters in a data set is not known, subtractive clustering techniques can be used to estimate the number of clusters and the cluster centers in the set of data.

To improve classification of the input data, subtractive clustering techniques have been used. The range of influence for the wind speed, temperature difference, wind direction and air speed on the surface was set equal to 0.1,0.05, 10 and 0.05 respectively. An initial Fuzzy Inference System was generated and then back propagation techniques were used to train the system. The ANFIS - Adaptive Network based Fuzzy Inference System routine, operating in the frame of the MATLAB Fuzzy Logic Toolbox has also been used, for training.

The obtained results for both the training and checking data sets for one, five, ten, thirty and sixty seconds intervals are shown in figures 3 and 4 respectively. It is found that the present FIS predicts satisfactory the air velocity on the opening's surface for both the training and checking data while the trend of the predicted data is also satisfactory.

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CONCLUSIONS

Deterministic methodologies were used in order to predict the air velocity in the case of single sided ventilation. Comparison with experimental values has proved their inability to give accurate information on the air velocity at the opening level. This is attributed to the fact that the air velocity at the opening is strongly influenced by ever changing parameters such as the wind speed and the temperature difference across the opening. The stochastic nature of the wind was found to be better approached by non-deterministic modeling procedures, based on the principles of fuzzy logic systems.

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