DOI: 10.1590/1809-4430-Eng.Agric.v37n5p887-899/2017

engenharia agrícola
Journal of the Brazilian Association of Agricultural Engineering
ISSN: 1809-4430 (on-line)

EVATUATION SYSTEM OF EXHAUST FANS USED ON VENTILATION SYSTEM IN COMMERCIAL BROILER HOUSE

Doi:http://dx.doi.org/10.1590/1809-4430-Eng.Agric.v37n5p887-899/2017

WAGNER SILVA[1*], DANIELLA MOURA[2], THAYLA CARVALHO-CURI[2], ROGÉRIO SEBER[2], JULIANA MASSARI[2]

[1*]Corresponding author. Universidade Estadual de Campinas/ Campinas - SP, Brasil. E-mail: wagts2006@yahoo.com.br

ABSTRACT: This study aim to develop a system, called FANS-N, for evaluation the exhaust fans in the ventilation system of broiler facilities. The system is divided into: 1) Mechanical Structure - consisting of two stepper motors for positioning a anemometer sensor in the vertical and horizontal coordinates; 2) Electronic Interface - control of the anemometer positioning and record data of wind speed; 3) Control Programming Module – accountable for the cursor movement, measurement and record the wind speed data with the anemometer at predetermined points; and 4) Analysis Programming Module - responsible for the interpretation of wind speed values at each point. The software uses artificial neural networks (Multi-Layer Perceptron) for images analyses of data base. The output of neural network give to the user the following recommendations: "possible changing", "maintenance", "standard limit", and "within standard". The system was able to evaluate the exhaust fans, identify the failures and proposing solutions to farmers of a preventive diagnosis.

KEYWORDS: broiler, neural network, ventilation systems, air flow.

INTRODUCTION

The quantification of the ventilation rate is crucial for the control and maintenance of the environment in broilers production. Adequate management of ventilation rates helps to maintain optimal growing conditions inside the facility for the well-being and poultry production (Calvet et al., 2013).

However, determining the actual ventilation rate in a poultry facility is a difficult and complex task due to the effects of weather, unhealthy environment, maintenance lack of exhaust fans, dynamic and irregular effects of the winds, different positioning of the exhaust fans, variable number of exhaust fans, differentiated openings for air intake, existing cracks and the different typologies of the aviaries, although this one uses artificial ventilation system (Zhu et al., 2012; Zhao et al., 2013).

In this sense, several methodologies, standards and procedures were developed to determine the performance of exhaust fans and to measure airflow in laboratories (ASHRAE Standards, 1992, Wheeler & Bottcher, 1995; AMCA, 1999; ASHRAE, 2001).

Afterwards, the methodology to evaluate the airflow of exhaust fans installed in broiler house *in situs* was developed by Simmons & Hanningan (2000) and later used by Gates et al. (2004). The developed system, called FANS (*Fan Assessment Numeration System*), allows accurate mapping of air velocity at the exhaust outlet. The system has proved to be adequate for evaluating the performance of the exhaust fans in environments protected from animals and plants (Morello et al., 2010; Zhi et al., 2015) including being adopted by the USDA (*United States Department of Agriculture*) as the standard methodology for assessing gas emission from poultry and pig farms in the United States of America.

Another technique to evaluate the ventilation system, zootechnical performance, and decision support are the Artificial Neural Networks (ANN). ANN are artificial intelligence tools that present a mathematical model inspired by the neural structure of intelligent organisms and that acquire knowledge through experience, adapts and learns to perform a certain task, or behavior, from a set

[2] Universidade Estadual de Campinas/ Campinas - SP, Brasil.

Received in: 5-23-2016
Accepted in: 5-3-2017

of given examples. Many studies have been carried out in the area of precision Zootechny using ANN to evaluate economic loss, evaluation and prediction of productivity, diet, ventilation system, among others (Faridi et al., 2012, 2014; Sefati et al., 2014; Curi et al., 2014).

The use of artificial neural network is adequate in the analysis of figure patterns, since this technique is able to classify, organize and give answers related to the results to be obtained. The efficiency on finding patterns in figures and comparing them with a pre-established database is already very common in many situations, such as in the identification of people by their fingerprints or the iris (Al-Allaf et al., 2013; Godara & Gupta, 2013).

In this context, a system called FANS-N was developed for *in situ* evaluation of the performance of the exhaust fans in broiler house. This system, composed of automatic measurement of air velocity, neural networks for database interpretation and analysis, has the following recommendations: "possible switching", "maintenance", "standard limit", and "within standard".

MATERIAL AND METHODS

The system developed in the present study is divided into:

Mechanical structure

The assembly of the prototype was based on the recommendations proposed by Gates et al. (2004) for air velocity measurement at the exhaust outlet and improvements were included in the model that will be presented throughout the text (Fig. 1).

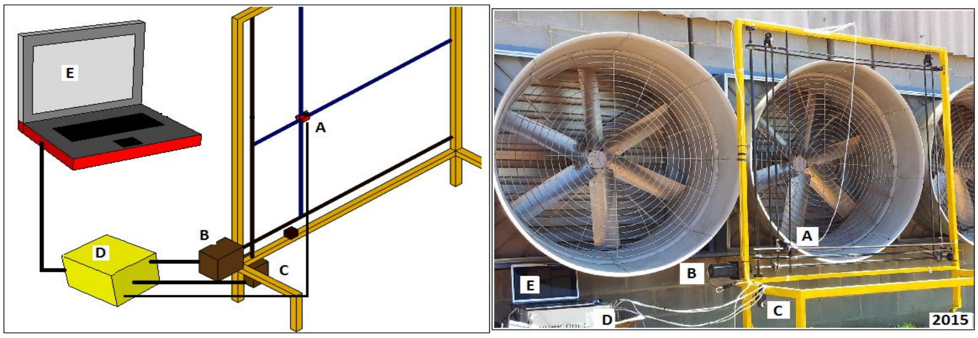


FIGURE 1. Parts of the developed equipment: anemometer (a), motors for horizontal (b) and vertical (c) displacement, engine controller interface (drives) and analog / digital converter (d) and computer and software for engine movement, data logging and data analysis by neural networks (e).

The anemometer used was the thermistor. Its calibration principle is based on the technique known as "*hot-wire*" (Jorgensen, 2002; Valença, 2003). In this technique, the heating of a resistance is caused by the passage of electric current; the resistive element is maintained at a constant temperature. Then, when measuring the electric voltage in the resistor, the values are obtained proportional to the natural logarithm of the air velocity (Equation 1), observed in Valença, 2003.

$$U(T, v) = (0.00608 \times T) \times \ln v + 1.64 \quad (1)$$

U = anemometer voltage, [V];

v = air velocity, [m s^{-1}],

T = ambient temperature, [°C].

Electronic Interface and Control Programming Module

The sensor displacement system was made by means of belts positioned vertically and horizontally, being these moved by step motors of the type NEMA 34 (model KTC-5034-349). The *driver* controls the motors of the equipment which provides the necessary electrical voltage and the correct energizing cycle of the motors spirals. The interface board between the equipment and the computer consists of a circuit based on the microcontroller PIC18F4550 (Microchip®) with serial communication via USB with analogical digital conversion (A / D) capability and digital outputs for the control of the motor drives.

Analysis Programming Module

The development of the entire FANS-N system was performed in the Delphi® 6 programming language with two internal components: the first was the serial control called *ComPort* used to communicate the software with the project equipment via USB and the second component was the neural networks Multi-Layer Perceptron, for analysis by artificial neural network with Perceptron modeling.

The FANS-N system, as a whole, performs multiple functions, among them: Function 1 - movement of the motors for the positioning of the sensor; Function 2 - capture and storage of values measured by the anemometer and, Function 3 - use of algorithms and neural networks to interpret the results by searching for image patterns, relating to previous standards and efficiency data provided by the manufacturers of the studied equipment.

Neural networks

The neural network model, *Multi-Layer Perceptron* (MLP), was built in the WEKA® program (*Waikato Environment for Knowledge Analysis*) version 3.6.9 (2013) through the *backpropagation* algorithm. The *Cross-validation* test was used for the model construction and validation. The cross-validation technique uses the method of partitioning the data set into mutually exclusive subsets, then some of these subsets are used to estimate the model parameters (training data) and the rest of the subsets (Validation data) is used in the model validation.

MLP modeling provides sufficient information for decision-making in exhaust systems in broiler house (Curi et al., 2014). The use of neural network in MLP modeling is therefore satisfactory for image recognition and treatment (Lima et al., 2010).

In this study 500 images were collected and were used in the neural network modeling, with an average of 20 images for each related static pressure value. The training and testing of the neural network were performed subsequently.

The network parameters used were: ten epochs, zero neurons of hidden layer, ninety of learning rate and thirty of inertia rate, seven input levels (corresponding to each static pressure value) for each expected result (within the standard, standards limit, maintenance and possible changing). The neural network evaluation was performed by the accuracy of the model, that is, mean error less than 1% (0.00012) (Leal et al., 2015).

The inputs of the neural network were: air velocity, exhaust ventilation airflow, electric current, and static pressure.

The statistical method of analysis of variance (ANOVA) and the Tukey test were used to verify if the inputs to the neural network developed in the FANS-N program had significant importance and thus to validate the use of the chosen neural network.

With the result of the obtained flow and the graphical analysis performed by the neural network, the program provides as output, results of generated static pressure and energy efficiency (relation between the flow and the consumption of the exhaust fan). As the last return four types of *status* classification are made regarding the exhaust: “good”, “need for maintenance”, “need for technical adjustment” or “change exhaust “.

The validation of the equipment was performed in *Blue House* sheds with negative pressure ventilation of tunnel type with the following characteristics:

Installation typology: broiler house with negative pressure artificial ventilation system with air inlet on the opposite side to the exhaust.

Location: municipality of Elias Fausto-SP**.**

Isolation: Roof made of asbestos cement tiles with slope of 14°, polyethylene curtain lining in blue color, polyethylene curtain side walls in the blue color on the inner face and silver on the outer face.

Building materials: Masonry structure in pillars and beams, wooden structure to support the roof, concrete floor, wall with 0.30 m of masonry height and anti-bird screen.

Dimensions: 17.00 x 90.00 x 2.45m (width x length x height).

Ventilation system: composed by exhaust fans Big Dutchman® model**.**

The study of the exhaust fans in broiler house consisted in the identification of those from 1 to 10 to start counting from left to right (Fig. 2). The air velocity was measured in certain exhaust fans, subsequently (Table 1) as a function of the number of exhaust fans and also of the static pressure produced by them. The methodology used was adapted from the method proposed by Morello et al. (2010).

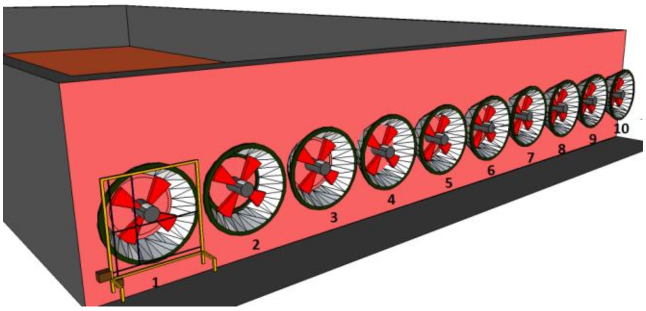


FIGURE 2. FANS-N System positioned to collect the wind speed data of exhaust fans.

TABLE 1. Groups of operated exhaust fans with their respective static pressures.

Exhaust fans in simultaneous operation	Fixed static pressures (Pa)
Group 1: 1, 3, 5	16
Group 2: 1, 3, 5, 6, 8, 10	25
Group 3: All connected	40

RESULTS AND DISCUSSION

Validation of the FANS-N program

From the air velocities mean values measured in the observations set of the exhaust fans, (Fig. 3 and Table 2), it is possible to observe that there are differences between the regions of the exhaust surface in relation to the air velocity as a function of the static pressure. Therefore, it is considered that the variations change due to the increase of the static pressure and the regions of the surface maintain their differences in relation to the means of their velocities (Fig. 3). There is convergence of the curves when the static pressure increases, helping in the confirmation of the feasibility of using the regions velocities mean with inputs to the neural network created in FANS-N.

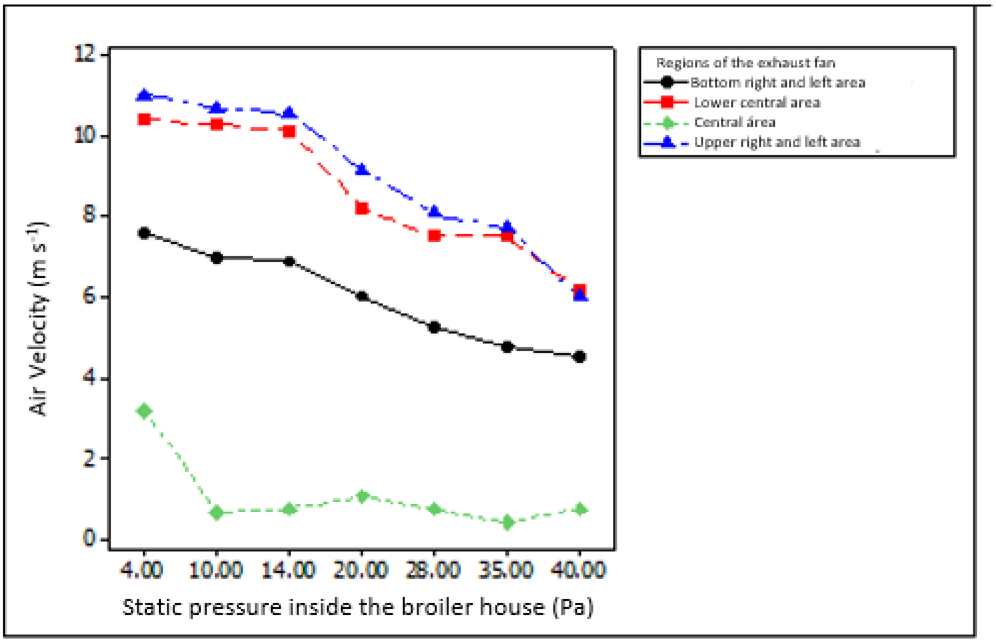


FIGURE 3. The relationship between the wind speed values (m s^{-1}) and the static pressure (Pa) in the four exhaust fans studied (1, 3, 5 and 6).

TABLE 2. Statistical results to select the regions of entry of the neural network.

Region	Points	Mean	Standard deviation
Higher Edges	324	9.04	1.44
Central Low er	324	8.62	2.13
Lower Edges	324	6.01	1.88
Central	324	1.11	2.41

Considering the total set of data concerning the exhaust fan surface, the differences between the regions stand out, as observed in the mean values of Table 2.

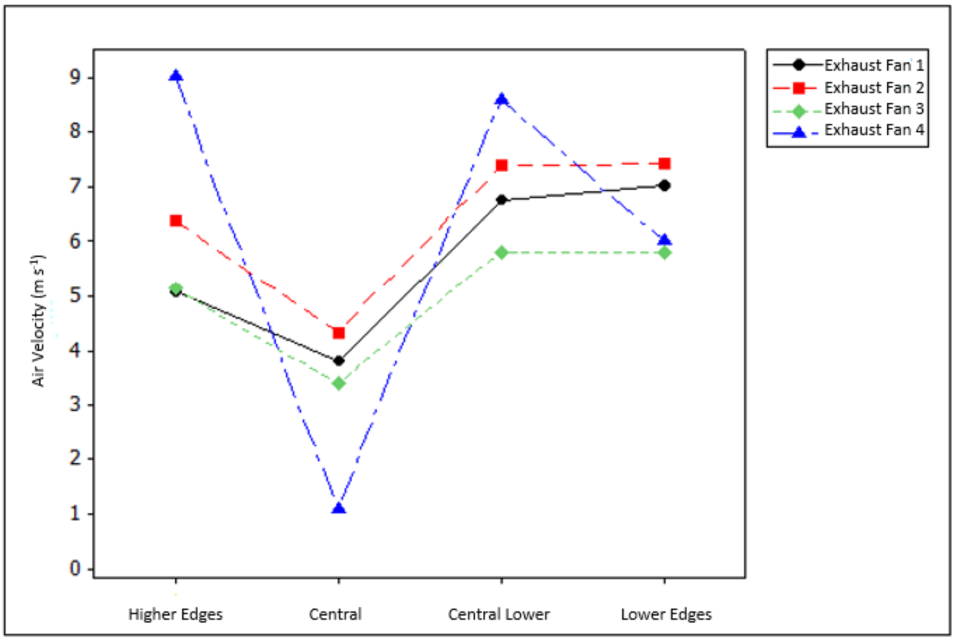


FIGURE 4. Variation of air velocities in different regions on the surface of each exhaust fan studied.

Interpolation surfaces

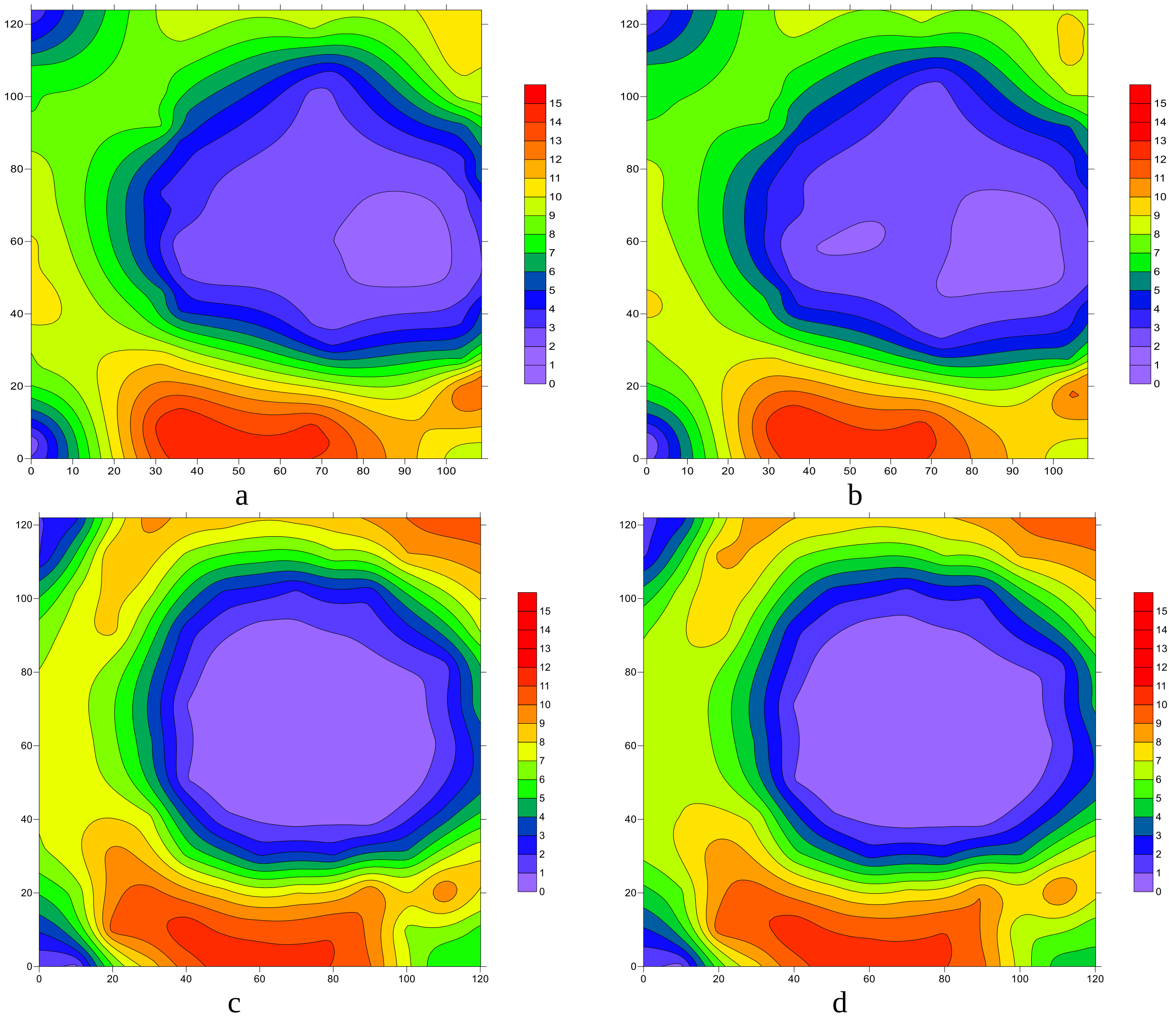
The interpolation surface is a mathematical tool that enables the study of air velocities on the surface of the exhaust fans, and its interpretation is able to identify the operating system of them. The generation of the interpolation surfaces in this study was performed by Surfer® software version 10. The studied exhaust fans presented large central regions of low velocity, less than 3m s^{-1} and peripheral regions with higher velocities, above 8 m s^{-1}, similar to the results by Morello et al. (2010), and Wheeler et al. (2006). On Fig. 4, 5 and 6 it is possible to observe the precise details of the ventilation surfaces on the exhaust fans, such figures show the air flow produced by them. Details obtained by the interpolation figures indicate the influence of external factors on the exhaust fans as well as on the performance of them. Broiler house exhaust fans suffer greatly from heavy use and their engines undergo extreme wear and tear conditions, mainly due to the humidity and dust in which they are subjected.

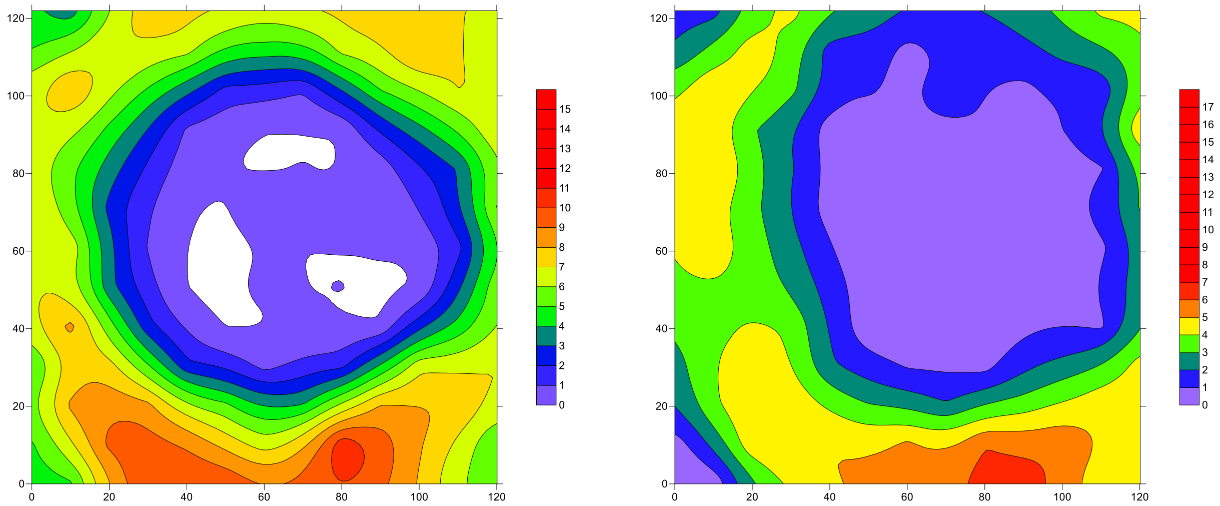
Through the analysis of the interpolation surfaces it is possible to find the relation of this with the static pressure inside the broiler house, or to relate the height of the curtains with the flow produced by the exhaust fans.

Interpolation surfaces and static pressure variation by the exhaust fans control

Results of static pressure variation in exhaust fan 1

With a negative pressure of at 4 Pa there is a low interference in the operating system of the exhaust fans, so that Fig. 5 (a) and (b) show the region of higher air velocity in the lower central part (greater than 14 m s^{-1}), and low-speed in the central region (below 3 m s^{-1}).





e f

FIGURE 5. Interpolation of the wind speed values of exhaust fan 1 on coordinates x and y to: (a) SP of 4 Pa, (b) SP of 16 Pa, (c) SP of 20 Pa, (d) SP of 25 Pa, (e) SP of 30 Pa, and (f) SP of 40 Pa.

Fig. 5 (c) and (d) show a large central region of low air velocity (less than 1 m s^{-1}) in relation to Fig. 5 (a) and (b) as consequence of the decrease in air velocity, as a whole result on the increase in static pressure. However, it is still observed in the same figure the central part with a considerable air velocity (greater than 10 m s^{-1}). On Fig.5 (e) and (f) there are white stretches with zero velocity and large fall on air velocities when compared with the previous figures. The white area represents absence of air velocity. The lower central region, where the highest air velocities are observed, has velocity values between 5 and 7 m s^{-1}, considerably lower than the values obtained in the previous figures. In general, it is observed that in all the figures except for the central inferior region, the other regions do not have many regions with air velocities superior to 8m s^{-1}.

Results of static pressure variation in exhaust fan 3

In Fig. 6 (a) and (b) air velocities are practically zero in the centers and large amplitude in the periphery. The lower region in which the higher air velocities appear (shown in the previous figures for the exhaust fan 1) is less evident for this exhaust at 16 Pa. It is also observed that at 16 Pa there are several points in distinct regions with peaks of air velocities around 14 m s^{-1}, and it can be considered that there is more turbulence in the flow regime in this exhaust fan. Fig. 6 (b) and (c) maintain the central region feature at zero velocity, but the generalized air velocity drop can be observed in relation to the previous one (Fig.6 a) few points where the air velocity exceeds 11 m s^{-1}. There are few differences between Fig.6 (c) and (d) for the static pressures of 20 or 25 Pa. In Fig.6 (e) and (f) there is decrease of the zero velocity region, but the region with velocity between 0 and 1 m s^{-1} increases considerably. There are few regions with air velocities greater than 6 m s^{-1} in either Fig. 6 (e) or (f) which is very similar to each other. The high static pressure influences the drop in air velocities, again observed in these figures.

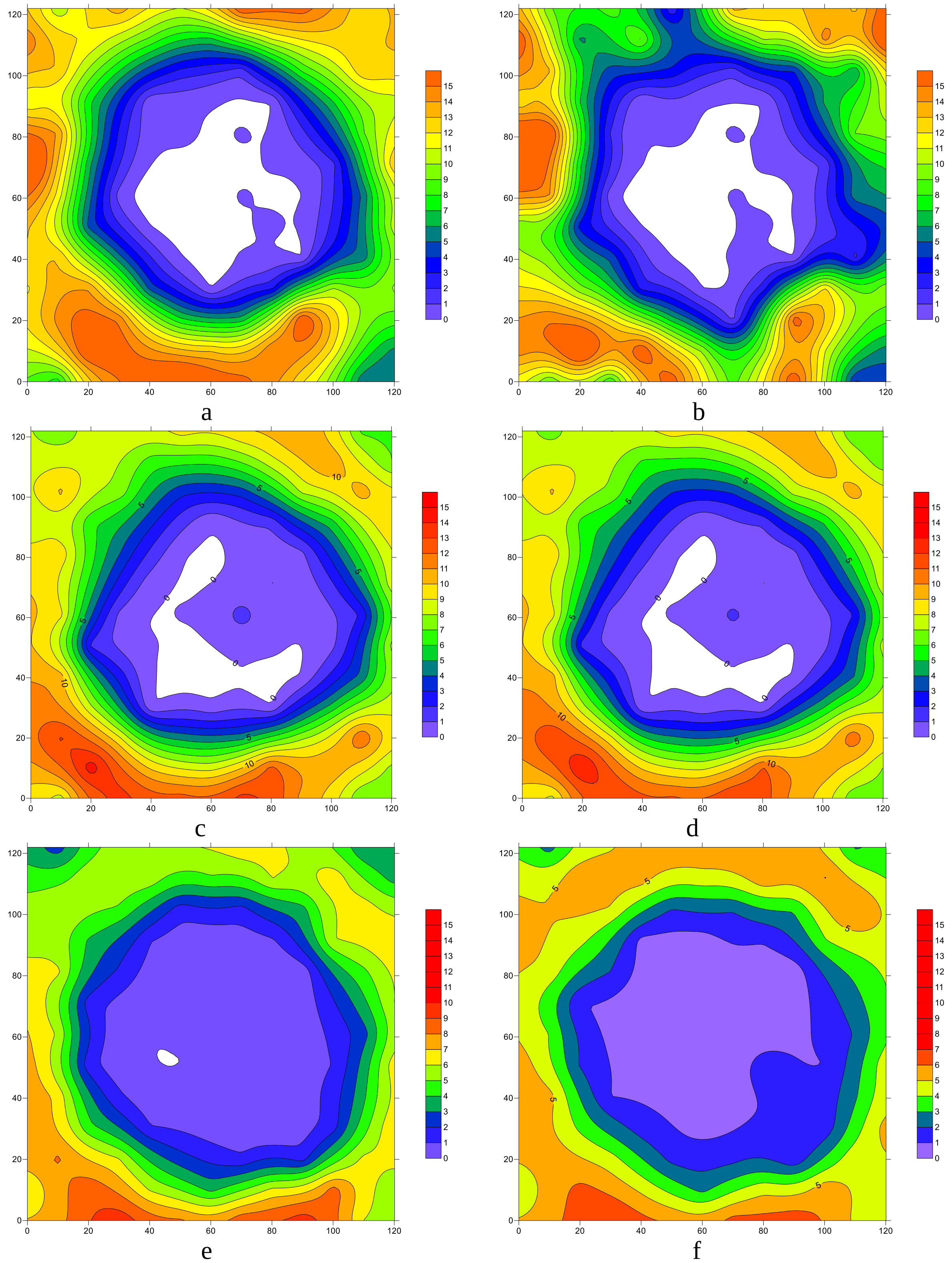


FIGURE 6. Interpolation of the wind speed values of the exhaust fan 3 on coordinates x and y to: (a) SP of 4 Pa, (b) SP of 16 Pa, (c) SP of 20 Pa, (d) SP of 25 Pa, (e) SP of 30 Pa, (f) SP of 40 Pa.

Results of static pressure variation in exhaust fan 5

As in the previous analyzed figures, Fig. 7 (a) and (b) have the central regions with low velocity. Many "nodes" appear, corresponding to spikes of velocities scattered in both figures, mainly in Fig. 7 (b).

Fig.7 (c) and (d) are similar to those above analyzed. Fig.7 (c) shows large central region with regions of zero velocities and lower central region with velocities between 8 and 10 m s^{-1}. Fig 7 (d) has its air velocities on the surface smaller than on Fig. 7 (c), and the verification will be evidenced in the flow analysis of the two situations presented here.

Fig.7 (e) and (f) show as in the previous figures, the large central regions and with low air velocities becoming zero in white stretch of the figures. Both have few regions with velocities greater than 6 m s^{-1}. The analysis of flow and air velocity will support the analysis of these figures.

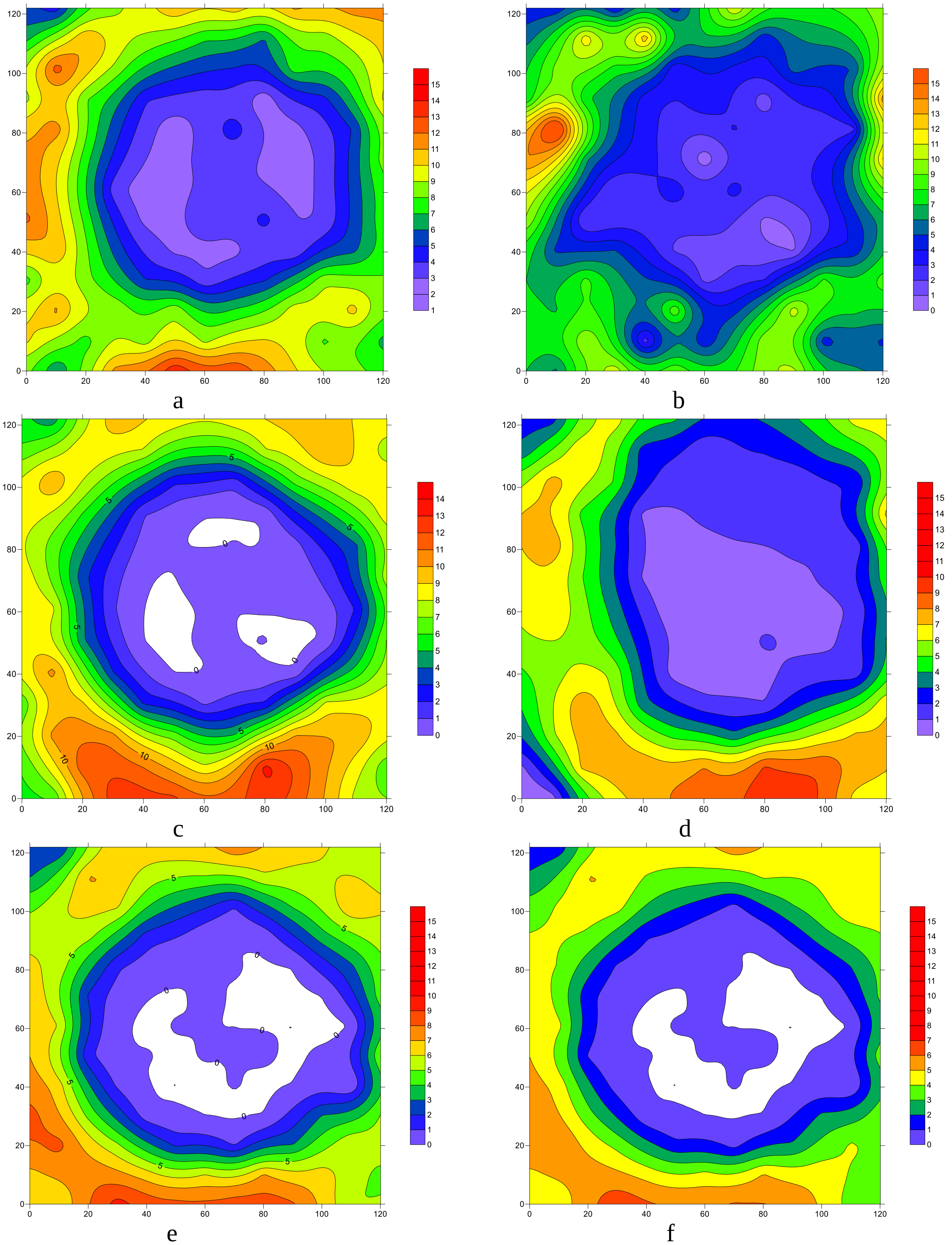


FIGURE 7. Interpolation of the wind speed values of the exhaust fan 5 on coordinates x and y to: (a) SP of 4 Pa, (b) SP of 16 Pa, (c) SP of 20 Pa, (d) SP of 25 Pa, (e) SP of 30 Pa, (f) SP of 40 Pa.

Statistical analysis

Table 3 presents the flow results obtained by exhausts 1, 3 and 5 following the methodology of data collection adapted from Morello et al. (2010), where the activation and shutdown of the exhaust fans occurred to control static pressure and data collection. For statistical analysis, the Tukey test was performed at 5% of significance.

TABLE 3. Results for air flow obtained by statistical analysis.

Exhaust fans	SP¹ (Pa)	Q² ($m^3 s^{-1}$)	V³ medium ($m s^{-1}$)	V⁴min ($m s^{-1}$)	V⁵max ($m s^{-1}$)	CV²	Standard error
			Exhaust fans 1, 3 and 5 on				
1	4	10.11	6.77	1.54	14.97	0.51	0.03
1	16	8.86	5.91	1.57	12.97	0.50	0.03
3	4	10.82	7.20	0.67	18.30	0.64	0.05
3	16	9.46	6.31	0.60	17.51	0.57	0.05
5	4	10.18	6.79	2.48	13.69	0.40	0.02
5	16	8.38	5.59	0.60	12.28	0.49	0.02
			Exhaust fans 1, 3, 5, 6, 8 and 10 on				
1	20	7.51	5.01	0.00	11.53	0.68	0.03
1	25	6.88	4.59	0.00	10.57	0.56	0.03
3	20	8.35	5.57	0.29	14.42	0.71	0.04
3	25	7.51	5.01	0.26	12.98	0.27	0.03
5	20	7.81	5.21	0.24	13.23	0.57	0.03
5	25	6.24	4,16	0.19	10.58	0.39	0.03
			All exhaust fans on				
1	30	5.52	3.68	0.11	9.90	0.68	0.02
1	40	3.58	2.39	0.07	6.40	0.77	0.01
3	30	5.28	3.52	0.00	9.65	0.75	0.02
3	40	4.53	3.02	0.26	6.98	0.62	0.01
5	30	4.95	3.30	0.20	9.32	0.65	0.02
5	40	3.52	2.35	0.14	6.65	0.62	0.01

¹SP = static pressure; ²Q = exhaust flow rate; V³Mean = air velocity means; V⁴min = minimum air speed; V⁵maximum = maximum air velocity; CV = coefficient of variation

Table 3 shows that the values of air velocities obtained by the system are directly related to the values of static pressure of the broiler house, and the increase of the mean value of the air velocity is accompanied by the direct ratio of the flow rate and the inverse of the static pressure. The calculation of flow in this study (Equation 2) presented similar values to those obtained by the study done by Gates et al. (2004) and Morello et al. (2010).

$$Q = A.Varm \tag{2}$$

Q = flow rate, [$m^3 s^{-1}$];

A = Exhaust fan area, [m^2],

Varm = $\frac{\int v(n)dn}{n}$, mean air velocity [$m s^{-1}$].

Ventilation is one of the environmental parameters and may contribute to the elevation of zootechnical indexes and well-being. The study of ventilation allows better understanding on the distribution of climatic variables inside the installations (Liang et al., 2014; Purswell et al., 2013; Mostafa et al., 2012; Guerra-Galdo et al., 2015).

Results using neural network

Difference between exhaust fans and operating adequacy

It can be observed in Fig.8, obtained by FANS-N the flow drop as a function of the static pressure increase for each studied exhaust fan. As well as Morello et al. (2010), the curves obtained for the exhaust fans are linear relationships that can certainly characterize the exhaust fan and its operating conditions, since the curve establishes an exhaust fan behavior equation compared to the static pressure changes.

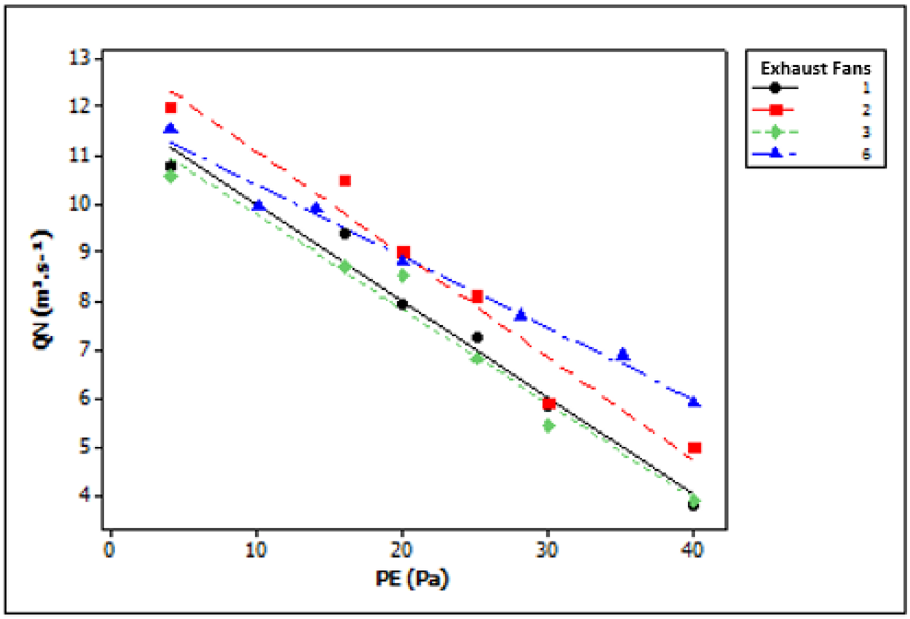


FIGURE 8. Comparison of the air flow of exhaust fans by the static pressure using FANS-N program.

Table 4 shows that the obtained equations by both Minitab program as for FANS-N program it is verified a lot of similarity between the linear and angular coefficients of the calculated lines.

TABLE 4. Linearized Line ratio of the air flow (Q, $m^3 s^{-1}$) as a function of static pressure SP (SP, Pa).

Exhaust fan	Equation (Minitab)	R^2	Equation (FANS-N)	R^2
1	[1]Q_{e1} = 11.3 – 0.187 PE	0.98	Q_{e1} = 12.0 – 0.200 PE	0.96
3	Q_{e3} = 12.0 – 0.191 PE	0.97	Q_{e3} = 13.2 – 0.212 PE	0.98
5	Q_{e5} = 11.2 – 0.195 PE	0.97	Q_{e5} = 11.7 – 0.195 PE	0.95
6	Q_{e6} = 11.3 – 0.143 PE	0.98	Q_{e6} = 11.9 – 0.147 PE	0.96

[1]Qei = Exhaust fan flow rate i.

Table 4 shows the similarity between the linear and angular coefficients of the calculated lines, which indicates that both models are suitable for reference as the basis for the decision making / classification of the exhaust fan.

The generated interpolation figures followed as reference for analysis of all exhaust fans studied in their various static pressures and associated flow. For purposes of comparison and classification of the interpolation figures it became necessary to establish a standard figure. To do so, the exhaust fan 6 was chosen among the studied exhaust fans to originate the standard, since it is new and factory calibrated. The FANS-N system divided the interpolation figures into areas of greater importance to be considered as inputs to the developed artificial neural network. With the data of the sectors on generated figures for the exhaust fan 6 was established the results table of inputs for the neural network of the FANS-N system.

As a probabilistic responses to the performed tests, the obtained output of the neural network by the FANS-N system resulted in the values showed on Table 5.

TABLE 5. Probabilistic responses of FANS-N for the operational performance of the exhaust fans.

Responses	Exhaust Fan 1(%)	Exhaust Fan 3(%)	Exhaust Fan 5(%)	Exhaust Fan 6(%)
Possible changing	4	3	9	7
Maintenance	38	15	23	10
Standards limit	40	61	33	15
Within the standard	18	21	35	68

The response of the neural networks as observed on Table 5 helps in the understanding of what action should be taken so that the exhaust fans operate efficiently. To these four attributes (possible changing; maintenance; standard limit; within the standards) different values of probability are conferred, being the one that present greater probability should be the guideline of the attitude to be taken by the equipment user. As an example it is possible to observe that the exhaust fan 6 was most likely to be operating in the operating standard (limit -15% or within -68%) which corresponds to reality, since previously it was known that this was the calibrated exhaust fan.

CONCLUSIONS

The proposed FANS-N system was able to classify the exhaust fan in different operating modes, presenting the final *status* of the exhaust fan for decision making by the broiler house owner.

REFERENCES

Al-Allaf ONA, Abdalkader SA, Tamimi AA (2013) Pattern Recognition Neural Network for Improving the Performance of Iris Recognition System. Int'l Journal of Scientific & Engineering Research 4(6):661-667.

AMCA – Air Movement and Control Association (1999) Laboratory methods of testing fans for aerodynamic performance rating. ANSI/AMCA Standard 210-99. AMCA, 20p.

ASHRAE (1992) Handbook of fundamentals. ASHRAE.

ASHRAE (2001) Handbook of fundamentals. ASHRAE.

Calvet S, Gates RS, Zhang G, Estelles F, Ogink NW, Pedersen S, Berckmans D (2013) Measuring gas emissions from livestock buildings: a review on uncertainty analysis and error sources. Biosystems Engineering 116(3):221-231.

Curi TMRC, Vercellino RDA, Massari JM, Souza ZM, Moura DJ (2014) Geostatistic to evaluete the environmental control in different ventilation systems in broiler houses. Engenharia Agrícola 34(6):1062-1074.

Faridi A, Golian A, France J (2012) Evaluating the egg production of broiler breeder hens in response to dietary nutrient intake from 31 to 60 weeks of age through neural network models. Canadian Journal of Animal Science 92(4):473-481.

Gates RS, Casey KD, Xin H, Wheeler EF, Simmons JD (2004) Fan Assessment Numeration System (FANS) design and calibration specifications. Transactions of the ASAE 47(5):1709-1715.

Godara S, Gupta R (2013) Neural Networks for Iris Recognition: Comparisons between LVQ and Cascade Forward Back Propagation Neural network Models, Architectures and Algorithm. Neural Networks 3(1):7-10.

Guerra-Galdo EH, Sanz SC, Barber FE, López-Jiménez PA (2015) CFD model for ventilation assessment in poultry houses with different distribution of windows. International Journal of Energy and Environment 6(5):4-11.

Jorgensen FE (2002) How to measure turbulence with hot-wire anemometers, Dantec Dynamics Publication no.: 9040U6151. Skovlunde. Kashiha M, Pluk A, Bahr C, Vranken E, Berckmans D (2013) Development of an early warning system for a broiler house using computer vision. Biosystems engineering 116(1):36-45.

Leal AJF, Miguel EP, Baio FHR, Carvalho Neves D, Leal UAS (2015) Redes neurais artificiais na predição da produtividade de milho e definição de sítios de manejo diferenciado por meio de atributos do solo. Bragantia 74(4):436-444.

Liang Y, Tabler GT, Costello TA, Berry IL, Watkins SE, Thaxton YV (2014) Cooling broiler chickens by surface wetting: indoor thermal environment, water usage, and bird performance. Applied Engineering in Agriculture 30(2):249-258.

Lima FPdosA, Silva JC, Estevam GP, Minussi CR (2010) Reconhecimento de dígitos com uso de redes neurais artificiais. Omnia Exatas 3(2):29-39.

Morello GM, Overhults DG, Lopes IM, Earnest JR JW, Gates RS, Pescatore AJ, Jacob JP, Miller M (2010) Influence of Fan Operations on FANS (Fan Assessment Numeration System) Test Results. In: ASABE Annual 137 International Meeting, Pittsburgh, Pennsylvania. Technical paper number: 1009235. 2010.

Mostafa E, Lee IB, Song SH, Kwon KS, Seo IH, Hong SW, Han HT (2012) Computational fluid dynamics simulation of air temperature distribution inside broiler building fitted with duct ventilation system. Biosystems engineering 112(4):293-303.

Purswell JL, Branton SL, Luck BD, Davis JD (2013) Effects of air velocity on laying hen production from 24 to 27 weeks under simulated evaporatively cooled conditions. Transactions of the ASABE 56(6):1503-1508.

Sefati MY, Borgaee AM, Beheshti B, Bakhoda H (2014) Application of Artificial Neural Network (ANN) for Modelling the Economic Efficiency of Broiler Production Units. Indian Journal of Science and Technology 7(11):1820-1826.

Simmons JD, Hannigan TE (2000) Go with the flow. Resource Magazine. St Joseph, ASAE Publications, p9-10.

Valença GM (2003) Análise de Sensibilidade de Anemômetros a Temperatura Constante Baseado em Sensores Termo-resistivo. Dissertação, São Luís, Universidade Federal do Maranhão.

Wheeler EF et al. (2006) Ammonia emissions from twelve U.S.A. broiler chicken houses. Transactions of the ASABE 49(5):1495-1512.

Wheeler EF, Bottcher R (1995) Evaluating mechanical ventilation systems. G–82 Fact Sheet. The Pennsylvania State University, Agricultural and Biological Engineering Department, University Park. State College.

Zhao Y, Xin H, Shepherd TA, Hayes MD, Stinn JP (2013) Modelling ventilation rate, balance temperature and supplemental heat need in alternative vs. conventional laying-hen housing systems. Biosystems Engineering 115(3):311-323.

Zhi Z, Gates RS, Zhirong Z, Xiaohui H (2015) Evaluation of ventilation performance and energy efficiency of greenhouse fans. International Journal of Agricultural and Biological Engineering 8(1):103-110.

Zhu S, Yang N, Liu P, He J, Ye Z (2012) Measurements and calculations of ventilation rate for naturally ventilated animal buildings: A Review. In: International Livestock Environment Symposium (p. 3). . Saint Louis, American Society of Agricultural and Biological Engineers.