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# Integration of low-cost technologies for real-time monitoring of pigs in pre-fattening stage

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**Abstract.** Measurement of environmental, behavioural, and physiological variables is essential for decision making in intensive animal production systems. Data collection and analysis, in real time, employing low-cost tools are fundamental to increase competitiveness and animal wellness. In this context, the goal of this research was to develop a low-cost measurement system for monitoring bioclimatic and behavioural parameters in the production of pigs in the pre-fattening stage. Internet of things technologies was employed in order to increase control over the production and as a tool for decision-making in real time. Sensor Networks were developed using low-cost sensors open-source platforms and code. The system was validated in a pig farm located in Antioquia-Colombia with two groups of 10 pigs in the pre-fattening stage. Parallel tests with three sequential repetitions were carried out. The system was validated through continuous environmental data collection and periodic physiological measurements. The developed system includes temperature, relative humidity, global radiation, wind speed, pressure, and lighting sensors. A high microclimatic variability was found inside the facilities, presenting thermal discomfort conditions in some hours of the day, which impacted the development and behaviour of the animals. The adaptation of low-cost technologies for real-time monitoring of pigs is viable and facilitate decision-making in real time improving the productive efficiency, supplying important information at a productive and scientific level.

**Key words:** bioclimatic, comfort, ethology, pig farming, sensors, precision livestock farming.

## INTRODUCTION

The 4.0 technology emerged in Germany in 2011 as a result of the fourth industrial revolution. This technology is based on the automation of processes and the incorporation of the Internet of Things to objects and systems in order to connect devices, collect information through the Internet and create interconnected intelligent devices in the digital world. This technology has spread around the world and it has made possible to improve the productive efficiency of different industries. The application of this technology to the livestock sector is known as Precision Livestock Farming (PLF), an idea that was presented in the 90s in the United States of America (Morrone et al., 2022). The PLF focuses on the incorporation of different technologies in intensive systems to have real-time monitoring and more precise control over the physiological and environmental parameters in livestock production, in order to provide an early solution to possible problems that may arise in the production system (Buller et al., 2020).

It is estimated that by the year 2050 the world population will increase to more than 9 billion people, an aspect that requires intensifying food production in the world, in order to meet the needs of the population. The use of this type of technology is associated, among other things, with an increase in productive efficiency, therefore, the implementation of these technologies in PLF it is crucial (Benjamin & Yik, 2019b; Zhang et al., 2021).

Additionally, to facilitate the analysis of productive parameters in real time, PLF also provides tools for the monitoring and evaluation of environmental variables and animal welfare (Morrone et al., 2022). In this context, pig production is impacted by environmental factors determining the heat exchange of the animal with its surroundings. Because these animals are homeothermic, to regulate their temperature under unfavourable conditions, pigs employ energy that could be used in physiological processes associated with weight gain.

Bioclimatic management is very important at PLF. Many bioclimatic indices have been developed to represent the effect of different variables on the comfort of production facilities and animals. The THI is one of the most widespread, due to its easy calculation and the variables involved. This index represents the combined effect of air temperature and humidity on animal comfort in livestock production facilities. It is an empirical calculation that depends on the air temperature, relative humidity, genetics and physiology of the animal, among others. For this reason, different authors propose indices to monitor animal heat stress in intensive production facilities. In this work, the equation proposed by Cao, et al. (2021) will be used, this being one of the most up-to-date equations, obtained for conditions like those of our experiment.

$$THI = 0.8T + \left(\frac{RH(T - 14.4)}{100}\right) + 46.4 \tag{1}$$

In general, Colombian swine production is carried out in open or semi-open facilities without controlled climatic conditions, where climate regulation is carried out through natural ventilation through the windows of the facilities. In these spaces, it is possible that stress conditions associated with high temperatures are generated affecting the welfare and production of the animals (Machado et al., 2016). There are predetermined temperature and relative humidity conditions that can increase the production efficiency enhancing the genetic conditions of animals (Kuhl et al., 2023; Sales et al., 2008).The integration of technologies for the measurement of environmental variables in real time in this type of facilities plays a very important role in preventing the appearance of stressful situations and in decision-making (Buller et al., 2020).

Within the pork production sector these technological tools have been implemented for the measurement of productive parameters (Terrasson et al., 2017). The estimation of live weight, behaviour, movement patterns and posture are some of the measurements that can be performed (Benjamin & Yik, 2019a). Sensors, software and artificial vision have been employed in the measurement of biophysical, behavioural and physiological parameters in intensive animal production systems (Berckmans, 2017; Aceto et al., 2019; Morrone et al., 2022). Image analysis and detection of body dimensions can estimate the weight of pigs in real time (Li et al., 2014). Infrared devices have been employed in the measurement of physiological and pathological processes in animals (Lu et al., 2018). Low-cost sensors have been used in the monitoring of the environmental space variability in different pig production facilities (Osorio et al., 2021). Additionally, mathematical models that predict productive parameters in pig production systems have been developed (Montoro et al., 2020).

In general, small and medium-sized Colombian pork producers do not have facilities with monitoring and control systems, the piggeries are usually natural ventilated and some climatic variables are measured manually. It is required adapted and low-cost systems that allow them to make informed decisions on climatic and productive management. This study seeks to implement a low-cost sensor network for real-time monitoring of bioclimatic, physiological and behavioural conditions of pre-fattening pigs, in order to support business decision-making in real time, through the incorporation of technology 4.0.

## MATERIALS AND METHODS

### Sensor network

The cost of the monitoring equipment employed in LPF can difficult its implementation in medium and small pig production farms (Sumiahadi et al., n.d.). Therefore, a low-cost open-source IoT tool for monitoring livestock production was developed. The sensor network was composed by two modules: internal environmental monitoring (Figs 1, B; C and D) and external monitoring (Fig. 1, A). For the measurement of internal environment, an ESP32 microprocessor was employed, this module was equipped to measure air temperature, relative humidity, pressure, light intensity and wind velocity. For the external module an ESP8266 microprocessor was used, this module was equipped to measure air temperature, relative humidity, atmospheric pressure, global radiation, wind speed and direction. The characteristics of the installed sensors are detailed in Table 1. All the sensors were installed outside the cases (Fig. 1, C).

**Table 1.** Low-cost sensor characteristics

| Variable | Reference | Range | Resolution |
|---|---|---|---|
| Temperature | SHT31(Sensirion) | -40 to 90 °C | 0.015 °C |
| Relative Humidity | SHT31(Sensirion) | 0–100% | 0.01% |
| Pressure | BMP280(Bosh) | 300–1,100 hPa | 0.16 hPa |
| Light | MAX44009(Maxim) | 0.045–188,000 Lux | Variable |

Internal modules were located in the middle of each pen at 1.5 m over the slat floor (Fig. 1, B). Outside module was installed over a ceiling at 3.5 m over de floor as can be detailed in Fig. 1, A).

The ESPNow communication protocol were employed to communicated the internal and external modules, sending the information wireless to the Raspberry Pi module, using the MQTT protocol through the open-source message broker Eclipse Mosquitto.

The measurements of all devices were stored in a micro-SD memory. All data and video can be online access employing Bluetooth protocol as can be seen in Fig. 1, D.


**Figure 1.** A) External module and experimental piggery (red circle); B) Internal module location. C) Internal module detail; D) Internal module interior.

**Swine tests**

The customized network was tested in the monitoring a production of pigs in pre-fattening stage. Environmental and physiological conditions of the pigs were measured allowing the study of the thermal comfort inside the facility employing the THI index (Cao et al., 2021).

The tests were carried out at the Universidad Nacional San Pablo agrarian station, located in the department of Antioquia-Colombia (6°07'56"N 75°27'17"W 2.154 m.o.s.l). The place has an average temperature of 16.2 °C, mean RH of 82% and rainfall average of 2,645 mm. Two groups of pigs in pre-fattening stage were used, each group was composed of 10 pigs, as can be seen in Fig. 2.

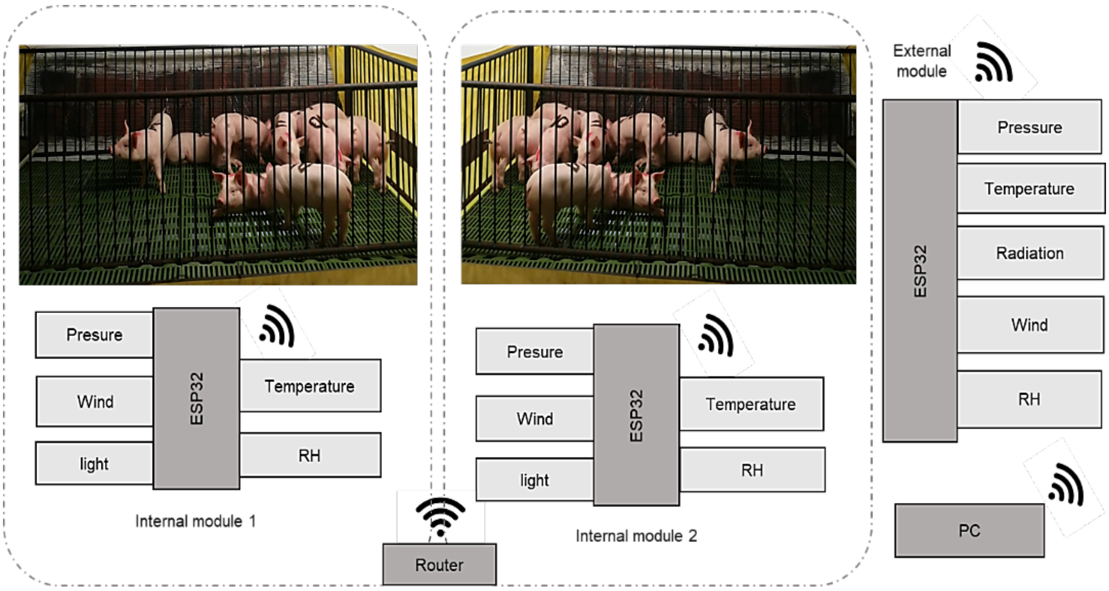


**Figure 2.** Test assembly description.

All piglets in the same band (within a range of three days of birth) were weighed at weaning, with 26 days of birth. Ten males and ten females weighing between 8–10 kg of live weight at weaning were selected for the trials. The sex and weight at the beginning of the experiment were homogeneous, separating males from females on each pen. Three repetitions were made, with a total of 60 animals. Each test started seven days after weaning, with duration of 42 days, with separation between test of 30 days.

The piggery where the trials were carried out contained two pens elevated 0.5 m above the ground. Two identical 2×2 m pens, with a 1m distance between them were used. The facilities did not have controlled climatic conditions. The entry and exit of air were controlled manually by opening the window shades, which remained closed along the night (5:00PM to 7:00AM).

At weaning the piglets were taken to the pre-fattening module. Ten animals were placed in each of the of the elevated pens with the aim of isolate them from the cold floor. Each pen had steel bars on the sides and was open at the top. The floor was of plastic slats for aeration and waste management. In addition, each pen had four drinkers and two linear feeders with 16 stalls each.

The facilities have double curtains in the ventilation to isolate the animals from the cold when was needed. Additionally, IR heating lamps were also used to adapt the piglets when they were transferred to the pre-fattening module.

The animals had a diet with commercial concentrate during all trials, with water and food ad libitum.

All the tests and production conditions of the animals were approved by the Ethics and Bioethics committee of the National University of Colombia-Medellín. The trials were carried out respecting the principles of animal welfare, guaranteeing the health, comfort and nutrition of the animals and following the guidelines of the ARRIVE (https://arriveguidelines. org) with the supervision of a zootechnician.

Automatic measurements of environmental variables were saved along the experiments. Manual air temperature and relative humidity were also taken at the high of the animals in the middle of the piggery, as usually is made in this production system. A Fluke 971 sensor with a resolution of 0.1 °C for temperature and 0.1% for relative humidity was used. Additionally, animal temperature was also taken employing a thermographic camera (Flir i3). Variable measurements allowed the analysis of the relationship between the environmental variables and the comparison between the THI computed using automatic and manual data.

## RESULTS AND DISCUSSION

A large amount of data associated to the manual and automatic monitoring of bioclimatic variables was obtained. 239,660 data for each variable per test was saved, with a sample time of 10 s. The temperature is one of the most important variables to be consider in animal production systems. Temperature data shows high temporal and space variability between test and along them. When temporal variation of temperature along tests were analysed, it was found differences between the means and variances of the manual and automated data, also differences in the dynamic behaviour of the variable. Comparison of the temporal variability of the temperature in the same test and different pens (males and female) also showed different means and variances, but with similar dynamic behaviour. Fig. 3 shows the comparison of the temperature behaviour along the first test in the male pen.

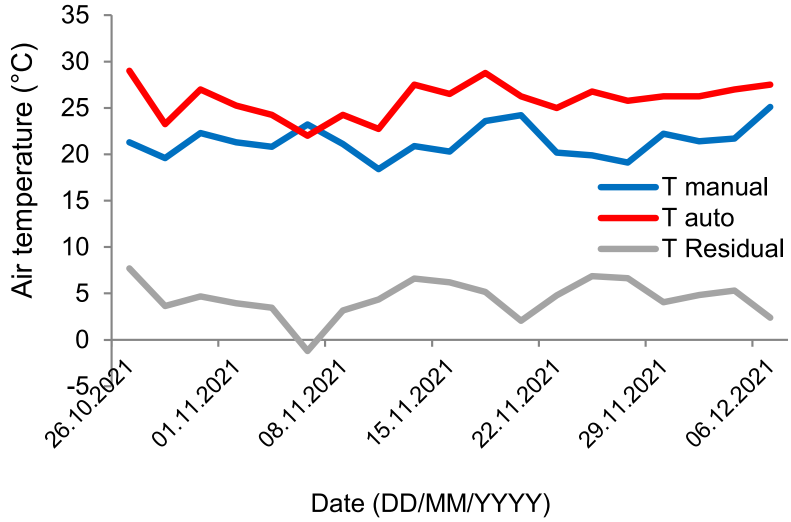


**Figure 3.** Comparison of the air temperature measurement employing manual and automatic sensor.

As can be seen in Fig. 3 manual and automatic temperatures are different, being the automatic temperature higher than the manual one, with means of 25.9 °C and 21.4 °C respectively, as can be seen in Table 2. The difference can be associated to the location of the sensor, due to the automatic sensor is near to the animals than the manual one, the radiation of the pigs' body heat increases the measurement, considering that both measurement systems (manual and automatic) were exposed to the air of the pig pen and were calibrated together with the same stimuli. In addition, the dynamic behaviour of the manual and automatic variables differs, as in November the 5$^{th}$, when the manual temperature increases and the automatic one, decreases. Residuals (T automatic-T manual difference) are not constant, with a summatory different to zero. The standard deviation of the temperatures is higher than the accuracy and resolution of the sensor and the Person correlation between the two variables are 0.13, showing that no biased error is made in the measurement and the relation between the variable is no linear or other variables must be considered in the model.

**Table 2.** Descriptive statistics for the first experiment

| Variable | T animal (°C) | T manual (°C) | T auto (°C) | T Residual (°C) | RH manual (%) | RH auto (%) | RH Residual (%) | THI manual | THI auto | THI Residual |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 37.1 | 21.4 | 25.9 | 4.5 | 77.4 | 81.3 | 4.0 | 68.8 | 76.3 | 7.5 |
| Median | 36.9 | 21.3 | 26.3 | 4.7 | 79.7 | 81.1 | 3.5 | 68.6 | 76.7 | 7.6 |
| Variance* | 1.6 | 2.9 | 3.4 | 4.0 | 175.3 | 122.5 | 142.9 | 4.2 | 5.5 | 7.2 |
| SD | 1.3 | 1.7 | 1.9 | 2.0 | 13.2 | 11.1 | 12.0 | 2.0 | 2.3 | 2.7 |
| Max | 39.3 | 25.1 | 29.0 | 7.7 | 95.2 | 100 | 25.1 | 73.3 | 80.2 | 13.3 |
| Min | 34.2 | 18.4 | 22.0 | -1.2 | 38.6 | 60.8 | -13.8 | 64.6 | 71.2 | 0.1 |

*Variance units are elevated to the square.

Relative humidity has an inverse relation with air temperature. An heterogenous behaviour of this variable was found between tests, piggeries and sensors. Even though there was nonspecific trend in the temporal analysis of the variable. Sometimes, manual humidity was higher or lower than the automatic one as can be seen in Fig. 4. In general, the mean of the automatic humidity was higher than the manual one, as is showed Table 2. This behaviour can be explained by the location of the sensor, where the sensor nearest to the animals is more exposed to the water vapor of waste evaporation and animal respiration.

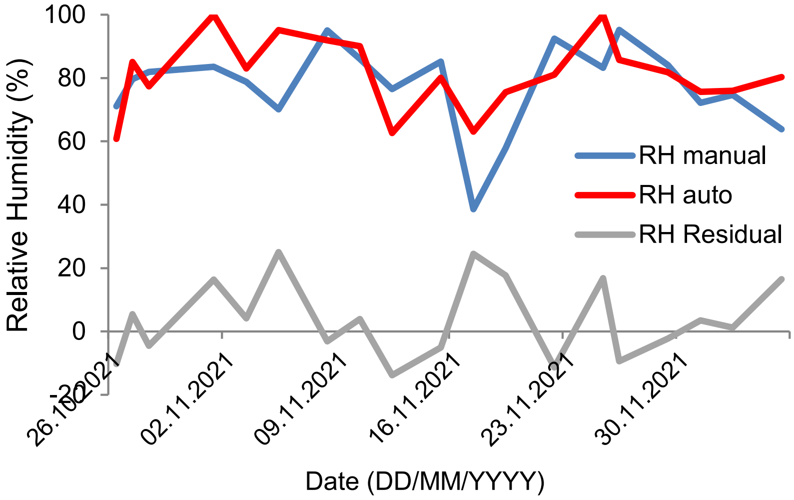


**Figure 4.** Comparison of the relative humidity measurement employing manual and automatic sensor.

The residual of the relative humidity variable has the same behaviour than in the temperature one. The standard deviation of the manual humidity was higher than the automatic one showing higher variability. But as the same in as temperature the standard deviations are higher than the sensor accuracy and resolution. Person correlation between the manual an automatic humidity was 0.28, showing a poor linear relation between them. Based in this result, it can be said that the measurement error is not biased and the relation between the variable is no linear or multivariable.

THI was computed employing Cao's equation. THI manual was calculated using manual taken temperature and humidity, while THI automatic was computed using the automatic values. As can be seen in Fig. 5 the automatic THI has higher values than the manual one with different dynamic behaviour and means of 76.3 and 68.8 respectively. The standard deviation of the THI auto, and variation range are higher than the manual one, showing more variability than the THI manual.

The threshold employed to define different rages of heat stress levels are: suitable for $THI < 74$, mild for $74 \leq THI < 78$, moderate for $78 \leq THI < 82$ and severe for $THI \geq 82$ (Cao et al., 2021). These values are depicted in Fig. 5 as horizontal lines. As can be seen in Fig. 5, all the values of THI manual are below of the suitable line, with a maximum value of 73.3, while for the THI automatic, the heat stress level goes from suitable to moderate, with a big portion of the values in mild level. Therefore, big differences can be found when automatic or manual data are used, that can lead to a poor decision for environmental management inside the facilities.

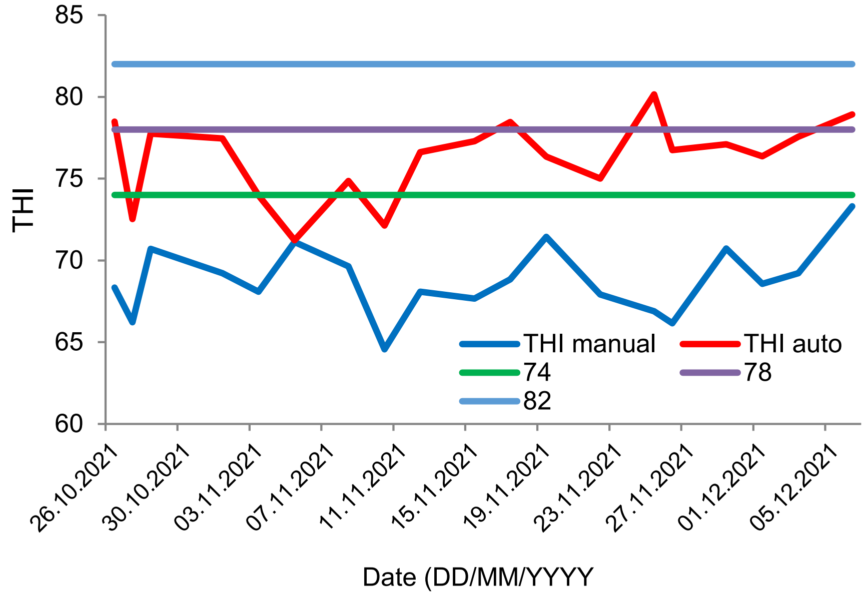


**Figure 5.** Comparison of the computed temperature and humidity index employing manual and automatic measurements.

Li et al. (2022) studied a combination of techniques for identifying an animal through video, recognizing their behaviour and analysing other variables such as outside temperature and humidity. They report that these kinds of information are the basis to generated an advance analysis of animal behaviour and wellness, being the accurate measurement of environmental variables a key for his study. In this case, the results of temperature and relative humidity in the Figs 3–4, shows that the manual data underestimate the automatic one, causing a significant difference in the computing of THI (Fig. 5). A similar behaviour was found by Neethirajan (2020) and Osorio et al. (2021b), were the authors highlight that the automatic sensors network can overestimate or underestimate the manual data.

Another important result is that the measurements of body temperature obtained using a thermographic camera were suitable, and could be an alternative to explore automated body temperature monitoring technology and have been developed in other researches employing visible and thermographic cameras (Taylor et al., 2022; Xie et al., 2023) using. If the THI data are analysed taking into account the statistics values of the animals' superficial temperature, presented in Table 2, it can be concluded that the animals were indeed subjected to thermal stress, since their average surface temperature was found to be 37.1 °C with a maximum of 39.3 °C, considering that superficial temperature measured with thermographic camera has a linear relation with rectal temperature and is usually bellow it (Zhang et al., 2019). Finally, could be consider that making climate management decisions with the manual data could cause productivity and welfare problems for the animals.

## CONCLUSIONS

The development of low-cost sensor networks for monitoring environmental and physiological variables in pig production can contribute to real-time decision-making that impacts production and animal welfare. Production facilities with manual climate management are associated with high temporal and spatial variability of air temperature and relative humidity, which in many conditions can be found outside the comfort zone of the animals. In general, Colombian medium and small pig production facilities employs a single manual measurement of temperature and humidity in the middle of the piggery to calculate the temperature and humidity index, this practice can lead to an underestimation of the index that negatively affects the management of the animals and system production. The adaptation of low-cost technologies for real-time monitoring of pigs is viable and facilitate decision-making in real time improving the productive efficiency, supplying important information at a productive and scientific level.

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