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Moisture content monitoring in industrial-scale composting systems using low-cost sensor-based machine learning techniques

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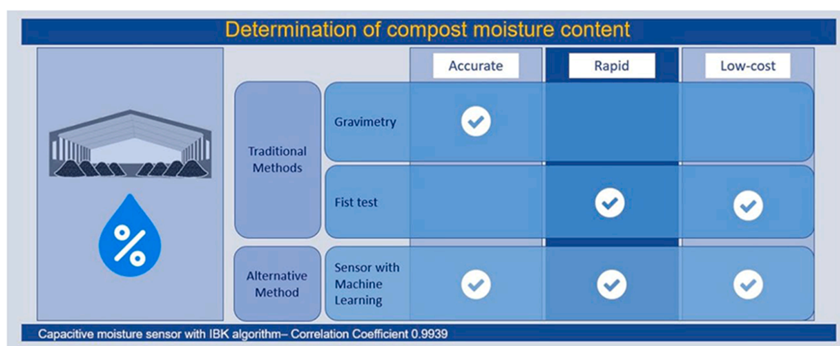
HIGHLIGHTS

- Low-cost real-time monitoring for industrial composting is a challenge.
- Moisture measurement in composting through a capacitive sensor was validated.
- Machine learning enables self-adjustment for different composts.
- Portable sensors eliminate the need to send samples to laboratories.
- The IBK algorithm allows sensor self-adjustment.

GRAPHICAL ABSTRACT



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ABSTRACT

Moisture is a key aspect for proper composting, allowing greater efficiency and lower environmental impact. Low-cost real-time moisture determination methods are still a challenge in industrial composting processes. The aim of this study was to design a model of hardware and software that would allow self-adjustment of a low-cost capacitive moisture sensor. Samples of organic composts with distinct waste composition and from different composting stages were used. Machine learning techniques were applied for self-adjustment of the sensor. To validate the model, results obtained in a laboratory by the gravimetric method were used. The proposed model proved to be efficient and reliable in measuring moisture in compost, reaching a correlation coefficient of 0.9939 between the moisture content verified by gravimetric analysis and the prediction obtained by the Sensor Node.

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1. Introduction

Food production from animals and plants consumes a large amount of non-renewable matter and energy, generating considerable volume of waste that may be harmful for the environment, if not properly treated. A sustainable alternative for treatment and reuse of organic waste from livestock and agricultural production is composting. Composting is a controlled process of microbial decomposition, oxidation, and oxygenation of a heterogeneous mass of organic matter in a solid and moist state (Wei et al., 2022). The resulting humus from composting is widely used as a soil conditioner and organic fertilizer, reintroducing a stable organic waste into the production process (Torrijos et al., 2021).

When conducted on industrial scale, composting presents some operational challenges, such as controlling moisture, aeration, and nutrient values within technically recommended limits (Onwosi et al., 2017; Thomas et al., 2020). When those operational parameters are met, the material in composting enters the thermophilic stage, essential for waste sanitization and subsequent humification (Bao et al., 2021). Thus, temperature is the most commonly monitored parameter during composting plants. Although nearly 90% of the European composting plants monitor temperature frequently, half of them do that manually (López et al., 2014). As water is essential for microbial life, the moisture content should also be monitored during composting (Guo et al., 2012), with special attention to the high content of organic matter and the porosity presented by that material (Carbó et al., 2021). Traditionally, the moisture content during composting may be monitored through gravimetry and by the Hand-squeeze test (fist test). The fist test can be done quickly, but it is heavily dependent on the experience of the employee involved, presenting low reliability (van der Wurff et al., 2016). On the other hand, gravimetry provides a slow response since the collected samples must be dried at 105 °C for 24 h in a laboratory (Martins et al., 2022), which is impractical in the field. Therefore, both such methods are currently applied in less than half of the European composting plants.

Moisture monitoring during composting may be conducted through sensors, which are widely used to measure soil humidity and provide fast and accurate responses. Nonetheless, the use of sensors may be limited by their acquisition cost. Capacitive sensors would be a low-cost alternative for moisture monitoring, since they cost at least 200 times less than NIRS (Near Infrared Spectroscopy) (Suehara et al., 1999) and nearly 20 times less than FDR (Frequency Domain Reflectometry) (Martí et al., 2013). Capacitive sensors are adopted to determine the irrigation time in agricultural crops (Adla et al., 2020), monitoring the water content of the soil based on the electric field variation (Domínguez-Niño et al., 2020). However, capacitive sensors need calibration for each type of material (Kizito et al., 2008), especially for moisture monitoring in windrow composting. Compared to soil composting, in which chemical and physical characteristics are uniform over time, in windrow composting, carbon, nitrogen, porosity and moisture content present wide variability in life cycle.

The ability of a sensor to self-adjust to different scenarios is a key feature to maintain its metrological state (Rivera et al., 2007). Self-adjustment of capacitive sensors to distinct residues at different stages of composting could be accomplished by adopting artificial intelligence techniques, through the acquisition of structural descriptions from examples, predicting future instances based on data from past instances. Such techniques would allow precise waste stabilization, minimizing the production of greenhouse gases and the wastage of matter and energy, and favoring residue recycling, (Dhar, 2020).

Linear regression is a primary modeling process that seeks to summarize and systematize data, widely used for sensor calibration to indicate a behavioral trend (Gardner et al., 1998; Suehara et al, 1999; Bogena et al., 2017). The linearization of the sensor output signal and the calibration process are the main items involved in defining the capabilities of an intelligent sensor. However, if the data are nonlinear, these models will provide incorrect interpolations or extrapolations. Hence, the use of more complex models may be beneficial.

Machine learning emerges from information automation processes, which is a method of data analysis that automates the construction of analytical models (Garouani et al., 2022). Machine learning can be defined as the field of study that gives computers the ability to learn without being explicitly programmed (Mahesh, 2020), through algorithms that can learn from their mistakes (Padala et al, 2019). An algorithm widely used for machine learning is the multilayer perceptron (MLP) (Martí et al., 2013; Al-ghobari et al., 2016; Rivera et al., 2007). The MLP operates by building a model from sample inputs to make data-driven predictions or decisions, rather than following inflexible and static programmed instructions. Thus, MLP learns rules directly from the data, without the need for a prior analytical model. There are computational tools that allow automating the search for algorithms for construction of analytical models. One of the open-access tools adopted by researchers in different fields is WEKA (Waikato Environment for Knowledge Analysis) (Slater et al., 2017). WEKA provides a uniform interface to many learning algorithms, along with methods for pre- and post-processing and for evaluating the outcome of learning schemes with different datasets (Witten et al., 2016). The principle of machine learning is its ability to generalize beyond the available data, predicting new scenarios. Thus, there is an opportunity to develop a model that links the value from the sensor to a moisture content value using supervised learning, targeting the value obtained in laboratory and optimizing resources and time assertively.

The aim of this study was to design a model of hardware and software that would allow the self-adjustment of a low-cost capacitive sensor to measure moisture content in a composting process at different periods and with different materials through machine learning techniques.

2. Material and methods

2.1. Hardware

A hardware with low-cost sensors and an embedded software was developed. Thereafter, the moisture content from samples previously collected in an industrial composting plant was determined by gravimetry and recorded through the sensors. Machine learning techniques were applied to the collected data to validate the model. After the learning process, unknown samples were presented to the sensor and the obtained values were compared to the values determined through gravimetry and through the fist test.

The hardware consisted of a Sensor Node (Fig. 1), composed of a coplanar capacitive sensor (US$ 4.00) to measure moisture (±0.3%), and a probe thermocouple sensor (US$ 15.00) to measure temperature (±0.25 °C). Both sensors were attached to a rigid rod connected to the case, with a lithium battery and an LCD display to read the values from the compost. Two capacitive sensors to read temperature (±0.5) and relative humidity (±2) (US$ 10.00) were added to the case. The Sensor Node had as basic premises to be portable, low-cost, to take readings from at least three different sensors, to present data on an LCD display, to record on an SD card, and to transmit via Wi-Fi. The microcontroller used in the Sensor Node was the ESP8266-07, which presents small dimensions, low energy consumption, low cost (US$ 5.50), enough input/output ports for the intended sensor and peripherals, and connectivity for data transmission via Wi-Fi.

According to other studies (Kostadinovic et al., 2021; Lloret et al., 2021), the humidity sensors need to be frequently calibrated for each substrate mixture under evaluation, which is performed manually. For the development of the Sensor Node, the original analog reading was maintained, without calibration, under the premise that the machine learning algorithm would correlate the moisture reading in the windrow, obtained by the gravimetry, with the value shown in the sensor.

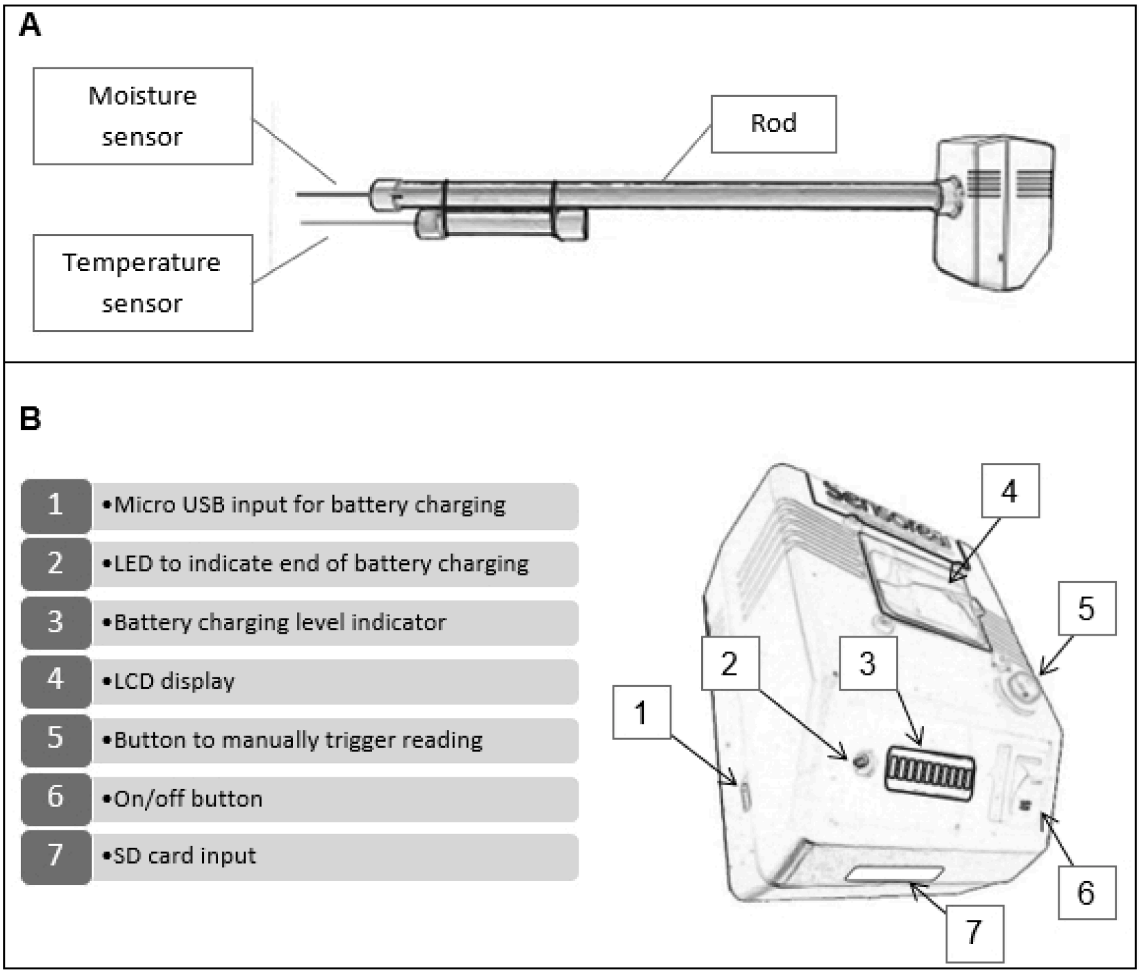

Fig. 1. Sensor Node overview (A) and component details (B).

2.2. Software

The Arduino IDE development platform (Arduino, 2019) was selected as the programming language for the Sensor Node, because it is open source and presents maintainability and performance. That platform is a free integrated development environment developed in Java. The software was designed in the language C++.

2.3. Features

The main functional and non-functional requirements listed in the Sensor Node operation are presented below:

a) option to turn on and off by an electromechanical switch;
b) indication of moisture and temperature shown on the LCD display;
c) recording of date, moisture and temperature on the SD card;
d) connection via Wi-Fi network;
e) low consumption mode, to preserve the battery, when not in read operation and/or data transmission;
f) configuration option to take automatic readings every 10 min, displaying, recording and sending the data;
g) battery with autonomy of approximately 120 h in operation; and.
h) battery charging level bar.

2.4. Sample collection

The Sensor Node self-adjustment mechanism was based on a machine learning algorithm. As a first procedure, data was collected from three different composts (Fig. 2).

The collected data were used in different stages of the process of learning, testing and evaluating results. Samples of the composts A, B and C were collected at seven different periods of the industrial-scale windrows, comprising changes in temperature, moisture, porosity and chemical characteristics during distinct stages of the composting process: mesophilic stage, at day 1; thermophilic stage, at days 20, 40, 60 and 80; and maturation, at days 100 and 120.

2.5. Laboratory analysis

The samples collected from the industrial plant (1.25 L each) were divided into five replicates and placed in 250 mL beakers. In each replicate, three readings were taken per beaker to extract the average. At each change of beaker, the sensors were cleaned with a brush until no traces of the previously read sample were observed.

Each replicate had its temperature measured with a mercury thermometer (±0.5∘C) to validate the thermocouple measurements. For the moisture content, reference values were determined by gravimetry. From each replicate, 30 g were placed in Petri dishes, in duplicate, do be dried in an oven at 105 °C for 24 h. After drying, the samples were cooled in a desiccator at room temperature. Mass determinations were made on an analytical balance (±0.0001) (Martins et al., 2022).

2.6. Linear regression

A linear regression model was developed using the moisture values of the compost obtained both from the analog reading of the capacitive

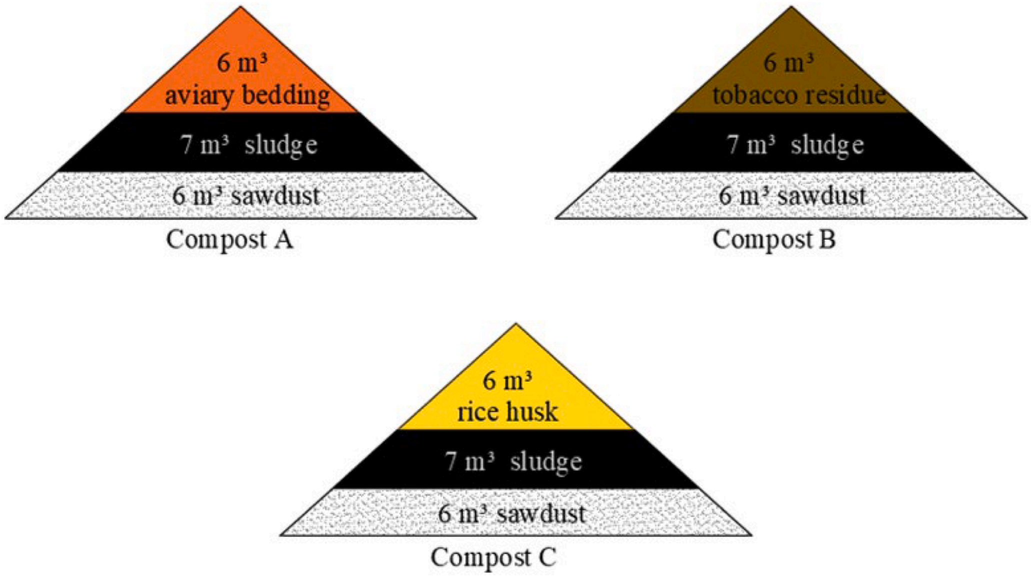

Fig. 2. Composition of organic composts with different agro-industrial wastes used in the learning phase of the Sensor Node.

sensor and by gravimetry. The following parameters were also used: (a) composting period in days; (b) air temperature; (c) humidity; (d) compost temperature, and (e) compost moisture.

2.7. Machine learning

Six data inputs were used for the machine learning process:

I – Number of days since the start of the composting window assembly (recorded manually);
II – Temperature of the sample obtained by a thermocouple sensor;
III – Moisture of the sample obtained by a capacitive sensor;
IV – Air temperature obtained by a capacitive sensor;
V – Humidity obtained by a capacitive sensor; and.
VI – Moisture of the sample obtained by gravimetry (oven).

Among the different algorithms and possible parameters to be used (Kotthoff et al., 2019), the Weka software (Waikato, 2019) was adopted for this study. The main criterion was the possibility of automating the different routines associated with machine learning. The data were separated into two arff (Attribute-relation Format) type files. The test data were randomly chosen by the software, covering 20% of the total data, while 80% was used in training, totaling 21 and 84 records, respectively. To validate the model generated by Weka, the results obtained by linear regression were compared with the data obtained by MLP.

The comparison between the results for the capacitive sensor approximation and the compost moisture obtained in the laboratory by gravimetry was performed by correlation analysis, as recommended by Suehara et al. (1999).

2.8. Validation of the proposed model with samples unknown to the sensor Node

A software written in Java was implemented using the Eclipse-IDE development environment with Weka-API (Application Programming Interface), which is an application programming interface that allowed integration between Java and Weka. These two languages were chosen because they are integrated, and both free. To validate the model, samples different from those used in the initial training were presented to the Sensor Node, coming from different windrows (D, E and F). They constituted only of sawdust and biosolids (12:7; v:v), but in different stages of composting. The reference value for the moisture content of these composts, obtained by gravimetry, was not shown to the sensor node. When samples D, E and F were collected from the composting plant, the operator, with extensive experience in the management of the windrows, empirically estimated the moisture content for each sample using the established fist test (van der Wurff et al., 2016).

3. Results and discussion

3.1. Estimates of moisture content in composts by machine learning

As a result of the machine learning phase, Auto-Weka presented weka.classifiers.lazy.IBk as the best classifier. This is an instance-based algorithm (IBL) derived from the k-nearest neighbor method (KNN). Corroborating this result, IBK presented the value closest to 1 for the correlation coefficient for the different tested models (Table 1). The IBK also presented the lowest values for absolute mean error, root mean square error, relative absolute error and root relative squared error. On the other hand, the linear regression model was the least close to the moisture values of the compost obtained by gravimetry.

In summary, IBK presented the use of the nearest neighbor value obtained by the Euclidean distance as a result for predicting the moisture content of the compost sample. The model generated by IBK, ob-

Table 1
Correlation coefficients and errors of the different models used to calibrate the sensor for moisture content in a compost from the values obtained by gravimetry.

Parameters	Linear regression	MLP	IBK
		Machine learning algorithms	
Correlation coefficient	0.9075	0.9807	0.9939
Mean absolute errors	4.9865	2.594	1.1105
Root mean square errors	5.5009	3.0288	1.5169
Absolute relative error (%)	44.7904	23.3007	9.9747
Root relative squared error (%)	43.5425	23.9749	12.0074

tained through the Euclidean distance (Tang and Haibo, 2015) presented the instances of greater similarity with the real values of moisture content in the compost determined by gravimetry. Knowing that there are two data associated with points Ei and Ej belonging to an m-dimensional space, denoted by Ei = (xi1, xi2, …, xim) and Ej = (xj1, xj2, …, xjm), the Euclidean distance (dist) between these two points is given by Eq. (1). Thus, the Euclidean distance between points Ei and Ej represents the length of the line segment connecting them.

$$dist(E_i, E_j) = \sqrt{\sum_{i=1}^{M} (x_{i1} - x_{j1})^2} \tag{1}$$

From the Euclidean distance obtained between the unknown value for the moisture content in a sample of the compost and the values acquired during training, the algorithm looked for the most similar instances, predicting the moisture content of the sample in question. For that, in search of the best performance from IBK, Weka indicated the following arguments as the result:

[-E, -K, 1, -X] (Algorithm arguments).

Therefore, the Weka's result indicated that the '-E' argument did not present a corresponding value, indicating that the '-K' attribute was not used for cross validation between the data in the calculation performed by the algorithm. However, following the algorithm parameters, a value corresponding to '1′ was assigned for '-K', informing the algorithm to adopt the value of the single nearest neighbor for the prediction. Regarding the '-X' argument, it also did not assign a value, i.e., no upper bound was used by the cross-validation.

Thus, the Auto-Weka tool optimized time and assertiveness compared to the non-automated work, which would require testing individually each algorithm with its arguments by the user (Nguyen et al., 2021), until finding an algorithm that best represents the real moisture content of the compost. Still using Weka and to validate the result from IBK, two other models were implemented: MLP and linear regression.

Regarding the results obtained to model the moisture content in the compost, MLP presented a satisfactory performance. Although the value obtained for the correlation coefficient was also close to 1, it was lower than the value obtained by IBK for this parameter (Table 1). On the other hand, the values of the mean absolute error, root mean square error, relative absolute error and root relative squared error provided by MLP were greater than those achieved by IBK. As shown in Fig. 3, the linear regression model used in the calibration of the Sensor Node to determine the moisture content of the compost presented the lowest coefficient of determination (R^2). In contrast, the IBK model presented the greatest R^2, the closest to the reference value. Compared to the results of Suehara et al. (1999) and López et al. (2014), which were limited to only one type of compost, the IBK machine learning model calibrated the sensor for the composting of different types of waste, at different stages of the process, which would be relevant for the management of composting in industrial plants.

It is important to emphasize that the calibration of moisture sensors proposed by different authors (Suehara et al., 1999; Jordão et al., 2017; López et al., 2014) requires the previous determination of the moisture content of the compost by gravimetry, after taking a sample to the laboratory, which is often far from the composting plant, to be dried for no less than 24 h or until a constant weight is obtained (Guidoni et al, 2021). Thus, using a sensor calibrated through machine learning quickly generates precise data about the moisture content of the compost (Dhar, 2020), allowing efficient decision-making about the need to revolve the windrow to adjust the humidity during composting (Onwosi et al., 2017).

3.2. Validation of the proposed model with samples unknown to the sensor Node

The results of the validation of the proposed models for samples D, E and F are presented in Table 2. The IBK model presented accurate results for the moisture content of the composts of the three unknown samples, considering the differences from the results obtained by gravimetry, with standard deviation and mean error of less than one unit. This model would be feasible to be used in composting plants, as it does not require

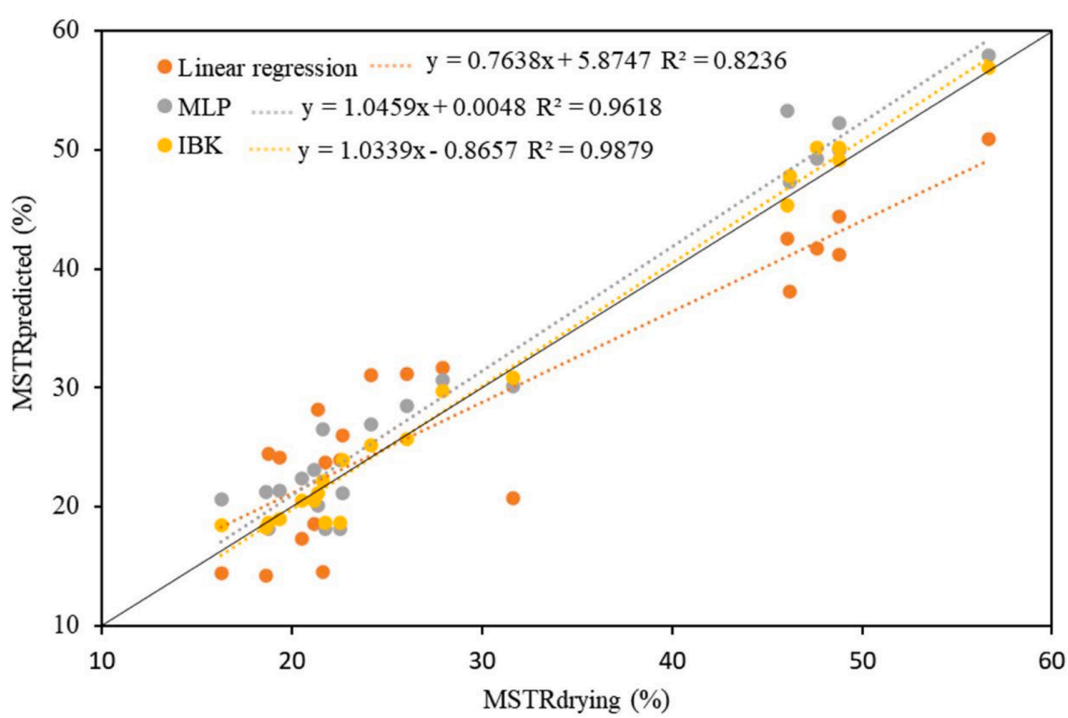

Fig. 3. Graph with the results obtained for moisture content predicted by linear regression, MLP and IBK models (MSTRpredicted), compared with the gravimetric value of the 21 test records (MSRTdrying). Solid line represents equivalent measurements.

Table 2
Validation of the proposed model with samples unknown to the Sensor Node.

Sample	Gravimetry (%)	IBK (%)	Difference IBK × Gravimetry (pp)	Fist test (%)	Difference Fist test × Gravimetry (pp)
D	31.37	28.47	−2.9	54	22.63
E	29.56	28.47	−1.09	50	20.44
F	49.68	48.15	−1.53	58	8.32
Average	36.87	35.03	−1.84	54	17.13
SD	11.13	11.36	0.94	4,00	7.71
SE	6.43	6.56	0.55	2.31	4.45

pp: Percentage points; SD: Standard deviation; SE: Standard error.

sending samples for analytical determination of the moisture content of the compost. The IBK model is as fast as the fist test, but provides values that are closer to the real moisture content of the compost.

These results are promising compared to studies that used artificial intelligence to determine the moisture content at different depths for the same soil type (Al-ghobari et al., 2016; Martí et al., 2013). In the present study, the moisture content determined by the Sensor Node for different composts were more auspicious than those obtained by Suehara et al. (1999), Jordão et al. (2017) and López et al. (2014), in which the moisture content was monitored for only one type of compost, which requires calibration each time a different waste is composted. Furthermore, the Sensor Node proposed in the present study requires lower investment than other systems (López et al., 2014).

4. Conclusions

The hardware and software developed in the present study were effective to determine the real-time moisture content in composting windrows on an industrial scale, for distinct residues and at different stages. The algorithm yielding the most precise results was IBK. The model developed in the presente study was more precise than the fist test, achieving results similar to those obtained through gavimetry.

CRediT authorship contribution statement

P.C.S. Moncks: Conceptualization, Methodology, Software, Resources, Investigation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **É.K. Corrêa:** Conceptualization, Methodology, Resources, Project administration, Visualization, Writing – original draft, Writing – review & editing. **L. L. C. Guidoni:** Formal analysis, Visualization, Investigation, Writing – original draft, Writing – review & editing. **R.B. Moncks:** Writing – original draft, Writing – review & editing. **L.B. Corrêa:** Writing – original draft, Writing – review & editing. **T. Lucia Jr:** Writing – original draft, Writing – review & editing. **R.M. Araujo:** Conceptualization, Writing – original draft, Writing – review & editing. **A.C. Yamin:** Conceptualization, Writing – original draft, Writing – review & editing. **F.S. Marques:** Conceptualization, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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