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A System for the Monitoring and Predicting of Data in Precision Agriculture in a Rose Greenhouse Based on Wireless Sensor Networks

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Abstract

In order to provide the best growing conditions for roses in a greenhouse, a Wireless Sensor Network has been designed and implemented that allows for agricultural environment data collection such as temperature, humidity and light. Each sensor node can transmit monitoring data to the cloud. Data mining techniques were used with the purpose of identifying behavioral patterns given the environment conditions captured by the sensor network. The operationalization of this research was taken as a case study within the rose greenhouses available to Universidad de las Fuerzas Armadas – ESPE, Ecuador.

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1. Introduction

Technological development has influenced the dynamics of necessities of people by providing technological

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solutions aimed at improving the productivity of crops¹. However, in many countries, like Ecuador, access to technology resources is a restriction to small and medium producers, given high costs of the technologies or unawareness of the use of market solutions². This restricts the competitiveness of those farmers when it comes to the quality of production. It is therefore required to provide new, low-cost alternatives that allow for the collection and processing of data in order to obtain information with added value that can improve agricultural productivity.

Problems related to climate change, water scarcity and environmental inattention, demand automated methodologies and tools that allow adequate decision making with the goal of reducing negative impact caused by those factors in agricultural production. Information systems melded with information management techniques are gaining popularity in the global setting³. Studies have indicated that adequate control over environmental conditions such as temperature, relative humidity, ventilation, among others; prevent the rise of plagues and in case of infection, help adequate treatment⁴. In order to control environmental conditions, crops are farmed in greenhouses equipped with the adequate infrastructure that includes: heaters, ventilators, watering systems, among others, which are operated manually or automatically, achieving care and preventive actions that improve both quality and production⁵.

Greenhouses in Ecuador, where this work took place, are installed in sites that lack reliable Internet access, which complicates the tasks of monitoring and crop control⁶. Information management is manual and there is no crop-specific empirical data, affecting decision making. Therefore, it is needed to strengthen the use of information and communication technologies as Wireless Sensor Networks (WSN), together with the use of data management techniques, to provide predictive solutions that support adequate decision making and opportune management of crop production. WSNs, used in the Internet of Things projects as information collection agents, allow capturing great data flows that support determining behaviors and predicting environmental variables that influence the growing of crops⁷.

A WSN is a network formed by a series of small low-cost, low-energy, easily-deployable sensors⁸. Providing scalability, flexibility and cost reduction, it is a viable solution for precision agriculture applications^{9, 10}. In this context, precision agriculture refers to data detection, collection, and transfer to a control station for decision making, in order to improve the performance of crops and assure sustainable growing. WSN technologies are used in agriculture to provide remote monitoring of parameters such as temperature, relative humidity, luminosity, among others, in order to create a simple and effective interaction environment to monitor the growing of crops^{11, 12}.

There are several technological solutions in order to motorize climatic conditions in the yard or greenhouse, however, most of those implementations provide individual monitoring and represents a strong investment, many of husbandmen cannot effort this amount of money to put on this solution in their greenhouse. Therefore, it is imperative to provide a solution which can be implemented by small agriculturalists.

This work's goal was the development of an environmental conditions monitoring system applied to high precision agriculture, within a controlled environment. For this, a WSN was developed within a greenhouse of roses. The sensor network allows environmental conditions data collection, visualization in a web or mobile application and subsequently, using data mining techniques, obtaining a prediction model with good accuracy.

Nomenclature

WSN	Wireless Sensor Networks
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What remains of this article is structured as follows: Section 2 presents the state of the art. Section 3 describes the developed system, its architecture, design and tests. Section 4 describes the web/mobile application, its architecture and features. Section 5 describes the prediction model, the tests, results and discussion. Finally, in Section 6 some conclusions are derived and future work is advanced.

2. State of the Art

In this section, we compile some works with similar experimentation alignments to that of ours; we highlight their progress and differences when compared with this work's goal.

Work done by Bhargava K et al.¹³ proposes a WSN design, that constructs a decision-making support system for the prediction of apple plagues, helping to identify periods that are prone to infection using registered temperature and

foliar humidity measurements. Xinjian Xiang¹⁴, designed a ZigBee WSN for drip watering. Four parameters were measured, soil moisture, temperature, light intensity and electric conductivity for decision making. Jzau-Sheng Lin et al.¹⁵ designed an agricultural environment monitoring system, based on a precision agriculture WSN using the System on Chip (SoC) platform which significantly reduces cost and physical size. Dursen and Ozden¹⁶ have developed an automated watering system and have experimented with it on cherry trees; they detected water content in specific areas and implemented an automated drip watering system, developed using Bluetooth.

Another interesting worked realized by Yoo S. et al.¹⁷ proposes a precision and intelligence agricultural system, Automated Agricultural System (A2S), to monitor and control the growth process of melon in greenhouses. Zhao Liang et al.¹⁸ propose an intelligent prediction system for the agricultural field based on wireless sensors, providing the agricultural producer with necessary information for adequate decision making. Data flows conform a knowledge base and through diffuse inference rules provide intelligent watering mechanisms. They are present as a proposal, but make no reference to application in a specific variety of crops.

In the revised readings, the focus is on design and implementation of WSNs to monitor environment variables, information is collected and is transmitted to a central repository. In some cases, this information is inferred using environmental intelligence to define actions that can be completely automated in greenhouses. In Ecuador, due to an absence of a repository of data related to environmental factors that impact in opportune crop production, it is important to provide a low-cost mechanism to be implemented in passive greenhouses with limited technology. This mechanism will allow putting forward trending actions to better productivity.

3. WSN system construction

In this sections we will show what our proposal in the implementation of a low-cost WSN is, its architecture, web network design and results obtained in this solution.

3.1. Architecture

In Fig. 1, we describe each component in our solution in a general way as follows: our proposal consists in a technological platform based on the Zigbee1 protocol used by Xbee2 cards, for the wireless transfer of a great volume of data. As shown in Fig. 1, the platform relies on electricity-fed collector nodes which obtain data related to four variables of interest which are environmental temperature, relative humidity, soil moisture and light intensity. The data obtained by the collector nodes are managed by router nodes based on Xbee cards configured in routing mode. Finally, there is a central node using Arduino and Raspberry Pi cards send data to a central Big Data repository and a monitoring and prediction client application. Information coming from the WSN is analyzed to establish techniques that allow gaining knowledge of these environmental conditions and foresee behavioral patterns within these.

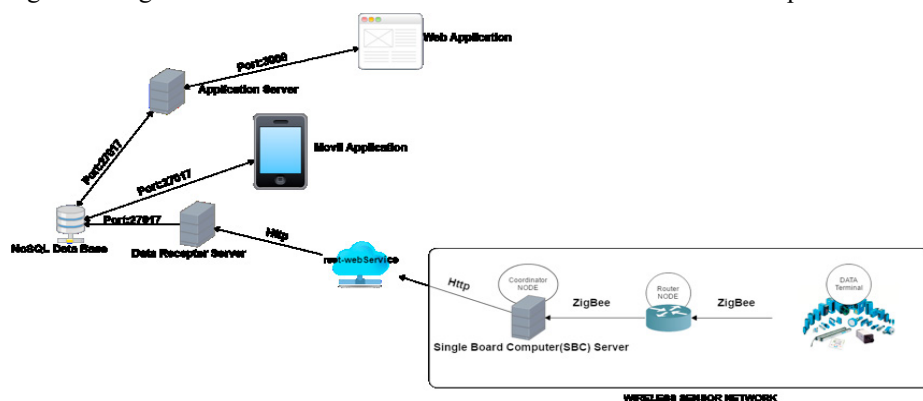


Fig. 1. System general architecture.

3.2. Node design

In the construction of the WSN, a web type network was designed based on the following three types of nodes: data nodes, router nodes and coordinator nodes. The data node, in its first version, was constructed with an Arduino Mega board and an Xbee series 2 pro device. This allows for the transmission of data using a cyphered protocol, through the coordinator node and the router node, which are the media in charge of transmission of collected information and compressing the information route.

The temperature and environmental humidity, soil moisture and luminosity variables considered for this experiment require that the prototype use sensors for these characteristics, considering the minimum and maximum factors detailed in Table 1.

Table 1. Manufacturer specified ranges per type of sensor.

Sensor	Measurement values(<i>t</i>)
DHT 22	Temperature: -40 a 120 °C Humidity: 0 a 100%
Photocell	Lux: 0-999
FC-28	Soil moisture: 0 a 100%

This prototype is made up of two sensors per type having an experimental coverage radius of 2.8m. For data transfers, a track formed by a header and distributed message body was collected, unified and standardized as illustrated in Fig. 2.

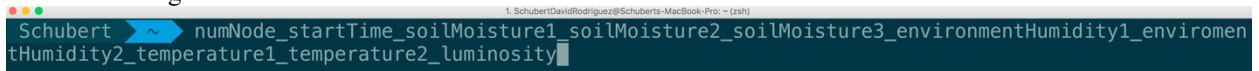


Fig. 2. Parameters plot.

The data node, in its first version, was constructed with an Arduino Mega board and an Xbee series 2 pro device. This allows for the transmission of data using a cyphered protocol, through the coordinator node and the router node, which are the media in charge of transmission and compressing collected data.

Within it, strings are received and processed. After this, the node carries out an HTTP request to the external database server (MongoDB) through a RESTful web service, which contains the needed methods to perform NOSQL database operations to consume the information. Fig. 3 shows the data node diagram.

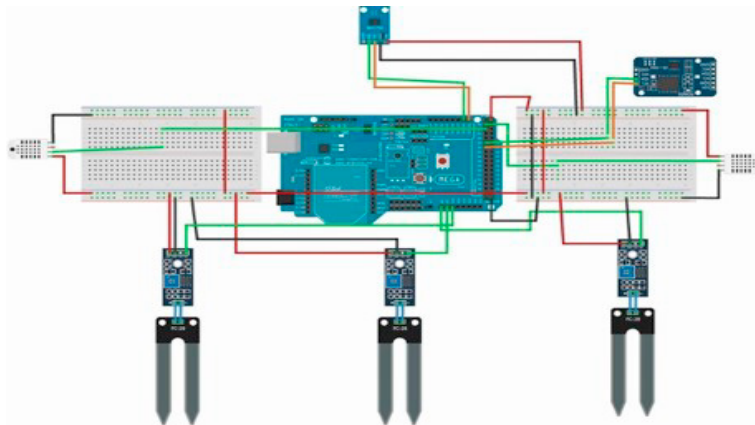


Fig. 3. Date node diagram.

3.3. Testing and experiments

During the node implementation, some functionality tests were developed that initially consisted in confirming how many sensors can form the node without the readings being compromised. On top of that, the correct functionality of each sensor was confirmed, validating readings for each sensor within the node and verifying that these were within the manufacturer specified ranges. Afterwards, the correct building of the track that is sent from the greenhouse node to the controller node and the correct conforming of the structure that is sent to the database server was verified. The controller node data was also checked for integrity after being transmitted through the HTTP protocol. Latency between information being sent and received was then confirmed. Finally, testing what happens to data if the connection is inactive and for how long this non-sent data is queued for transfer took place.

After monitoring the node functionality during ten weeks, a different node was implemented to contrast with existing data in a different section of the greenhouse.

4. Client application

The client application is built as one more component to the system. In this section, we describe its architecture and features. The prototype is an application available to any browser or mobile platform.

4.1. Architecture

The client application's physical architecture is divided into client and server like most web and mobile applications and it has a three-layer logical architecture (Fig. 4): The resource layer, which consumes the database and REST services; the Server layer, which accesses the micro services, a querying framework and a Datagram Delivery Protocol; the Client layer that manages data cache, navigation logic and application rendering.

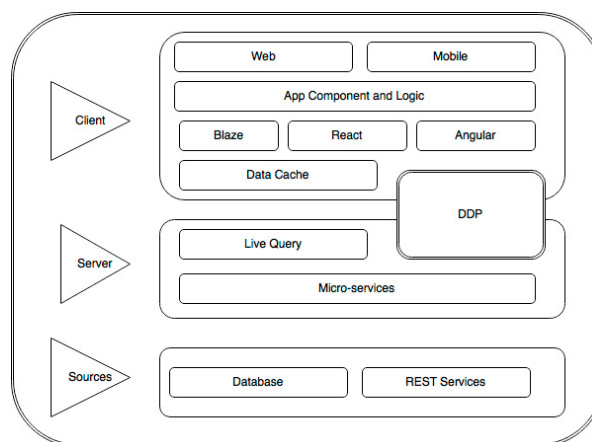


Fig. 4. Client application architecture.

4.2. Application features

The application consumes data taken from the sensors and displays them in a format understandable to the farmer. This is done in real time with a time of under ten seconds, as long as the node is operative. The application provides an authentication method and access through a Log-in, validated through a confirmation email.

One of the main functionalities of the application is allowing the farmer to monitor the greenhouse's status in each zone where a node is found and see the measurements that each sensor is taking. The results are shown in a traffic light alert system as shown in Fig. 5.

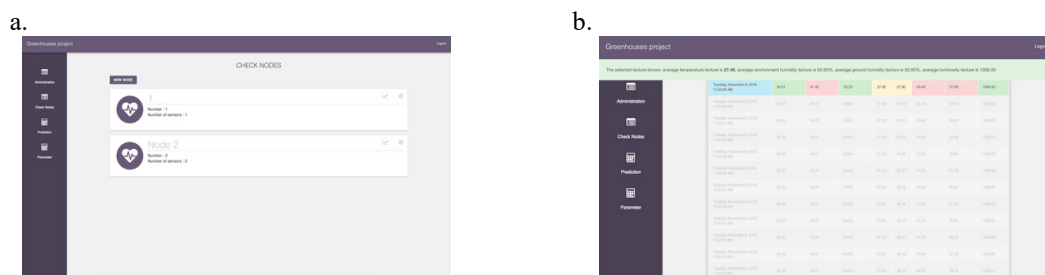


Fig. 5. (a) Node list in the greenhouse (b) Monitoring page/screen.

Another functionality, allows the farmer to parameterize optimal conditions for the different varieties of roses or crops that are being grown (Fig. 6). The parameters can define optimal and acceptable conditions for growth of the product monitored by the sensors.

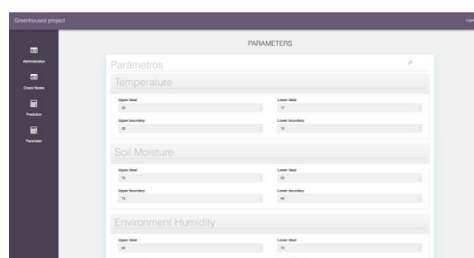


Fig. 6. Parameters page/screen.

Another of the application's features is presenting the greenhouse's status in graph form that shows sensor readings within the greenhouse and distinguish if in any zone there are better conditions than the others (Fig. 7). This functionality will also be available with data resulting from prediction models.

The application also presents forecasts of environment conditions, based on collected data, consumed from an API containing a forecast model built with WEKA. The current status of the application allows integration with this functionality which is still under development.

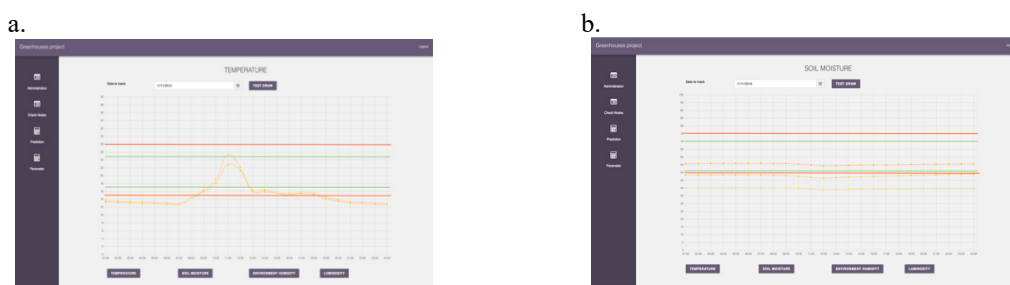


Fig. 7. (a) Graph temperature tendency (2 sensors) (b) Graph soil moisture tendency (3 sensors).

5. Predictive model

The collected data is prepared with a parameterized script in order to be mined. Subsequently, it is processed through the learning tool to generate a prediction model. The temporal and numerical nature of the data looks to adjust itself to the algorithm that gives the best results and can show a prediction with the least amount of deviation to the parameters that were taken for the study.

To date, approximately 1,250,000 records of data were collected. The data has been grouped through a statistical media in 30 minute intervals forming sets for each of the variables; each data set is organized taking into account a

total of four, three or two previous hours to predict the next thirty minutes. Data sets are presented raw and normalized, the former being as they were as collected by the nodes and the latter normalized between zero and one, according to Ecuador's climate condition ranges.

5.1. Testing and experiments

To date, three prediction model-making learning algorithms have been used to perform tests: linear regression¹⁹, neuronal networks²⁰ and support vector machines (SVM)²¹.

Tests consisted in using each algorithm with different sets for each variable (raw and normalized), each of these conditions classifying the data using and not using standard deviation for each attribute. Total data was distributed 70% for model training and 30% for testing.

To search for a variable's prediction model, two scenarios can be considered, one where previous values for the other environment variables are taken into account or another where only previous values for the target variable (the one which value we want to be able to predict) are considered. Here, we report results for the temperature target variable. To evaluate the results obtained in each test, the correlation coefficient, mean absolute error and relative absolute error are considered; these three parameters are what indicate how optimal a prediction model is. For every learning algorithm were selected the best scenarios after trying the most of all possible combinations in parameters like hidden layers in neural networks and complexity in SVM. An amount of twenty test were made for each scenario.

5.2. Results

Construction of the predictive model is in development. However, the results obtained so far look quite promising. The Linear regression results show that it is a good prediction algorithm for this phenomenon. The best result set within the tested scenarios used only previous temperature data as inputs (i.e. without considering values from other environment variables) and without taking into account standard deviation. A relative absolute error of 13.18% was obtained. Although the error is high on first look, it corresponds to a mean absolute error of 0.807 °C.

The results obtained with neural networks showed a high mean absolute error of 0.998 °C approximately, which was the worst results until now. Currently, various algorithm configurations are being put forth to find better results.

Finally, the SVM algorithm also shows to be an acceptable algorithm for this phenomenon. We obtained a relative absolute error of 11.33 %, corresponding to a mean absolute error of 0.698°C. The results show that SVMs seem to provide the best prediction model. Currently, work is being done exploring different algorithm parameterizations.

6. Conclusions and future work

The technology that was developed in this project is fundamentally a support and management tool for the agricultural sector, whose results can extend to other sectors. It is hoped that the predictive system that is being developed influences directly with decision making in respect to the adequate management of the agro-ecological parameters of temperature, luminosity and relative humidity, which directly affect in the normal growth of crops. The goal consists in reaching optimal characteristics of the crops, as size, duration, sanitary status and a proportional and well-formed floral stem. The proposed system will grant the floriculture a permanent monitoring tool for the mentioned factors. It will allow farmers to take preventive or corrective actions, when needed, providing a technological platform based on free software and low-cost hardware, as well as the use of data mining techniques.

The client application constitutes a usable tool for the farmers as it does not force them to be physically present in the greenhouse to see what happens in real time. The application is in a staging state and is ready to be integrated with the prediction API once the predictive model is selected and debugged. The two constructed nodes work correctly and their signal readings do not overlap neither during information collection nor during transmission through wireless protocols. The learning algorithms are currently being tuned up in order to enhance greenhouse environmental conditions forecasting. Additionally, a comparison with other techniques will be put into effect.

In the future, a complete solution using different hardware and software components designed during this project's work may be put in place. Based on this work, one of the future focus will be the design of a solution that allows for

automatic control of data regarding phenological states through the use of high-definition cameras and image processing. Another improvement that can be suggested from the present work is improving the feed sources of the infrastructure installed in the greenhouse, giving the nodes the capacity of self-sufficiency since the currently need of an electric connection for them to function.

References

1. Castillejo Ertivi M. Agricultura de precisión mediante redes inalámbricas de sensores, MSc Thesis, Public University of Navarra; 2013.
2. NU. CEPAL, FAO, IICA. Perspectivas de la agricultura y del desarrollo rural en las Américas: una mirada hacia América Latina y el Caribe 2014. IICA, Santiago CEPAL FAO IICA 2013. CEPAL, Santiago (Chile); 2013.
3. Ojha T, Misra S, Raghuvanshi NS. Wireless sensor networks for agriculture: The state-of-the-art in practice and future challenges. *Computers and Electronics in Agriculture*; 2015. 118: 66-84.
4. Van Lenteren J, Van Woets J. Biological and integrated pest control in greenhouses. *Annual review of entomology*; 1988. 33:239-269.
5. Hernández JCL, Parra JP, Evolución de las estructuras de invernadero. *Plasticulture: Revue du CIPA Journal of CIPA*; 2006. 125:8-17.
6. Cuji CDE, Pazmiño MDX. Diseño e implementación de una red WSN (Wireless Sensor Network) basado en los protocolos Zigbee, Wifi y Zigbee Mesh, para el monitoreo de variables climáticas en el invernadero ubicado en el barrio Rumipamba del Navas, cantón Salcedo, provincia de Cotopaxi. Universidad de las Fuerzas Armadas ESPE Extensión Latacunga. Carrera de Ingeniería en Electrónica e Instrumentación; 2015.
7. Want R, Schilit BN, Jenson S. Enabling the internet of things. *Computer*; 2015. 1:28-35.
8. Kalaivani T, Allirani A, Priya P. A survey on Zigbee based wireless sensor networks in agriculture. In *IEEE Trendz Information Sciences and Computing (TISC), 3rd International Conference*; 2011, p. 85-89.
9. Martinelli FVMBM, Ioriatti L, Massa A. A WSN based solution for precision farm purposes. In: *GRSS, IEEE Int. IGARSS*; 2009, 5:469-472.
10. MacRuairi MR, Coleman G. A WSN application requirements taxonomy. In *Sensor Technologies and Applications. SENSORCOMM '08. 2nd Int. Conf*, 2008, p. 209–216.
11. Beckwith R, Teibel D, Bowen P. Report from the field: results from an agricultural wireless sensor network. In *Local Computer Networks, 29th Annual IEEE International Conference*; 2004, p. 471-478.
12. Wang N, Zhang N, Wang M. Wireless sensors in agriculture and food industry - Recent development and future perspective. *Computers and Electronics in Agriculture*; 2006. 50(1):1-14.
13. Bhargava K, Kashyap A, Gonsalves TA. Wireless sensor network based advisory system for Apple Scab prevention. In *IEEE Communications (NCC), Twentieth National Conference*; 2014, p. 1-6.
14. Xinjian X. Design of Fuzzy Drip Irrigation Control System Based on ZigBee Wireless Sensor Network. Springerlink, IFIP Advances in Information and Communication Technology; 2011.
15. Azman M, Nasirudin A, Abd I. Preliminary Design on the Development of Wireless Sensor Network for Paddy Rice Cropping Monitoring Application in Malaysia. *European Journal of Scientific Research, ISSN 1450-216X*; 2009. 37(4):649-610.
16. Dursun M, Ozden S. A wireless application of drip irrigation automation supported by soil moisture sensors. *Academic journals, Scientific Research and Essays*; 2011. 6:1573-1582.
17. Yoo S, Kim J, Kim T, Ahn S, Sung J, Kim D. A2S: Automated Agriculture System based on WSN. *Consumer Electronics, 2007, ISCE. In IEEE International Symposium*; 2007. p.1-5.
18. Zhao L, He L, Harry W, Jin X. Intelligent agricultural forecasting system based on wireless sensor. *Journal of networks*; 2013, 8(8): 1817-1824.
19. Witten I, Frank E, Hall M. *DATA MINING Practical Machine Learning Tools and Techniques*. Elsevier Inc; 2011, 3rd ed., p. 124-125.
20. Shavlik J, Mooney RJ, Towell. G. Symbolic and Neural Learning Algorithms: An Experimental Comparison. *Machine Learning*; 1991, p. 111-143.
21. Hearst MA, Dumais ST, Osuna E, Platt J, Scholkopf. Support vector machines. In *IEEE, Intelligent Systems and their Applications*; 1998, 14:18-28.