AMBIENT 2025

The Fifteenth International Conference on Ambient Computing, Applications, Services and Technologies

ISBN: 978-1-68558-291-3

September 28th - October 2nd, 2025

Lisbon, Portugal

AMBIENT 2025 Editors

Lorena Parra Boronat, Universidad Politécnica de Madrid, Spain

AMBIENT 2025

Forward

The Fifteenth International Conference on Ambient Computing, Applications, Services and Technologies (AMBIENT 2025), held between September 28th, 2025, and October 2nd, 2025, in Lisbon, Portugal, continued a series of international events devoted to a global view on ambient computing, services, applications, technologies and their integration.

On the way to a full digital society, ambient, sentient and ubiquitous paradigms lead the torch. There is a need for behavioral changes for users to understand, accept, handle, and feel helped within the surrounding digital environments. Ambient comes as a digital storm bringing new facets of computing, services and applications. Smart phones and sentient offices, wearable devices, domotics, and ambient interfaces are only a few of such personalized aspects. The advent of social and mobile networks along with context-driven tracking and localization paved the way for ambient assisted living, intelligent homes, social games, and telemedicine.

We take here the opportunity to warmly thank all the members of the AMBIENT 2025 technical program committee, as well as all the reviewers. The creation of such a high-quality conference program would not have been possible without their involvement. We also kindly thank all the authors who dedicated much of their time and effort to contribute to AMBIENT 2025. We truly believe that, thanks to all these efforts, the final conference program consisted of top-quality contributions. We also thank the members of the AMBIENT 2025 organizing committee for their help in handling the logistics of this event.

We hope that AMBIENT 2025 was a successful international forum for the exchange of ideas and results between academia and industry for the promotion of progress in the field of ambient computing, applications, services and technologies.

AMBIENT 2025 Chairs

AMBIENT 2025 Steering Committee
Lorena Parra Boronat, Universidad Politécnica de Madrid, Spain
Kenji Suzuki, Tokyo Institute of Technology, Japan
Yuh-Jong Hu, National Chengchi University, Taiwan
Valerie Camps, Paul Sabatier University - IRIT, Toulouse, France

AMBIENT 2025 Publicity Chairs
Laura Garcia, Universidad Politécnica de Cartagena, Spain
Lorena Parra Boronat, Universidad Politécnica de Madrid, Spain

AMBIENT 2025
Committee

AMBIENT 2025 Steering Committee

Lorena Parra Boronat, Universidad Politécnica de Madrid, Spain
Kenji Suzuki, Tokyo Institute of Technology, Japan
Yuh-Jong Hu, National Chengchi University, Taiwan
Valerie Camps, Paul Sabatier University - IRIT, Toulouse, France

AMBIENT 2025 Publicity Chairs

Laura Garcia, Universidad Politécnica de Cartagena, Spain
Lorena Parra Boronat, Universidad Politécnica de Madrid, Spain

AMBIENT 2025 Technical Program Committee

Anas Abouelkalam, Cadi Ayyad University - ENSA Marrakesh, Morocco
Ali Al-Badi, Gulf College, Oman
El Arbi Abdellaoui Alaoui, Ecole Normale Supérieure – Meknes | Moulay Ismail University, Morocco
Aaroud Abdessadek, Chouaib Doukkali University, Morocco
Ana Alves, CISUC - Centre for Informatics and Systems of the University of Coimbra, Portugal
Francisco Arcas Túnez, Universidad Católica de Murcia (UCAM), Spain
Hassan Badir, Abdelmalek Essaâdi University, Morocco
Ayoub Bahnasse, ENSAM Casablanca - University Hassan II of Casablanca, Morocco
Hind Bangui, Masaryk University, Czech Republic
Rachid Beghdad, Bejaia University, Algeria
Samir Brahim Belhaouari, Hamad Bin Khalifa University, Qatar
Siham Benhadou, National School of Electricity and Mechanics, Casablanca (ENSEM-Casablanca), Morocco
David Bouck-Standen, Kingsbridge Research Center, UK
Andrés Bueno-Crespo, Universidad Católica de Murcia, Spain
Valerie Camps, IRIT | Universite Paul Sabatier, France
Juan-Carlos Cano, Universitat Politécnica de Valencia, Spain
Dimitris Charitos, National and Kapodistrian University of Athens, Greece
Richard Chbeir, Université de Pau et des Pays de l'Adour (UPPA) | IUT de Bayonne, France
Albert M. K. Cheng, University of Houston, USA
Stéphanie Combettes, IRIT | University of Toulouse III, France
Rémy Courdier, University of Réunion Island, France
Mohammad Javad Darvishi, University of Montreal, Canada
Ruediger Dillmann, Karlsruhe Institute of Technology (*KIT*), Germany
William Germain Dimbisoa, University of Fianarantsoa, Madagascar
Paul-Eric Dossou, ICAM, France
Karim El Bouchti, Mohammed V University in Rabat, Morocco
Nour-Eddin El Faouzi, Gustave Eiffel University, France
Mohamed El Khaili, Université Hassan II de Casablanca, Morocco

Lorena Parra Boronat, Universidad Politécnica de Madrid, Spain
Hugo Daniel Peixoto, Centro Algoritmi | University of Minho, Braga, Portugal
Jorge Peña Queralta, Turku Intelligent Embedded and Robotic Systems (TIERS) Group - University of Turku, Finland
António Pinto, ESTG - Polytechnic of Porto / INESC TEC, Portugal
Ivan Miguel Pires, Instituto de Telecomunicações | Universidade da Beira Interior, Covilhã, Portugal
Sigmundo Preissler Jr., Universidade do Contestado, Brazil
Awatif Ragmani, University Hassan II of Casablanca, Morocco
Hajarisena Razafimahatratra, University of Fianarantsoa, Madagascar
Diego Reforgiato Recupero, University of Cagliari, Italy
Fernando Reinaldo Ribeiro, Polytechnic Institute of Castelo Branco, Portugal
Valérie Renault, CREN Laboratory - Le Mans University, France
Daniele Riboni, University of Cagliari, Italy
Claudio Rossi, LINKS Foundation, Italy
David Ruete Zuñiga, Universidad Andrés Bello, Chile
Michele Ruta, Politecnico di Bari, Italy
Mohamed Saad Azizi, ENSAM | Moulay-Ismail University, Morocco
Khair Eddin Sabri, The University of Jordan, Jordan
José Iván San José Vieco, University of Castilla-La Mancha, Spain
Peter Schneider-Kamp, University of Southern Denmark, Denmark
Floriano Scioscia, Polytechnic University of Bari, Italy
Halima Semaa, Université Hassan premier, Morocco
Atriya Sen, University of New Orleans, USA
Antonio Sgorbissa, Università di Genova, Italy
Navid Shaghaghi, Santa Clara University, USA
Syed Ihtesham Hussain Shah, Institute of High-Performance Computing and Networks (ICAR) | National Research Council (CNR), Italy
Riaz Ahmed Shaikh, University of East Anglia, UK
Ahmed Shehata, University of Alberta, Canada
Sheng Shen, University of Illinois at Urbana-Champaign, USA
Fábio Silva, School of Management and Technology | Polytechnic Institute of Porto, Portugal
José Luís Silva, ITI/LARSYS & Instituto Universitário de Lisboa (ISCTE-IUL), ISTAR-IUL, Portugal
Shihao Song, NVIDIA Corporation, USA
Carine Souveyet, Université Paris 1 Panthéon-Sorbonne, France
Daniela Elisabeth Ströckl, Carinthia University of Applied Science - Institute for Applied Research on Ageing (IARA), Austria
Mu-Chun Su, National Central University, Taiwan
Kenji Suzuki, Tokyo Institute of Technology, Japan
John Symons, University of Kansas, USA
Vladimir Trajkovik, University "Ss Cyril and Methodius", Skopje, Republic of Macedonia
Markku Turunen, Tampere University, Finland
Rob van der Mei, Vrije Universiteit Amsterdam, Netherlands
Thomas Waas, Ostbayerische Technische Hochschule Regensburg (OTH Regensburg), Germany
Marcin Wozniak, Silesian University of Technology, Poland
Xiang Xiao, Google Inc., USA
Kin-Choong Yow, University of Regina, Canada
Abdellah Zaaloul, Université Ibn Zohr, Morocco
Christos Zaroliagis, University of Patras, Greece

Copyright Information

For your reference, this is the text governing the copyright release for material published by IARIA.

The copyright release is a transfer of publication rights, which allows IARIA and its partners to drive the dissemination of the published material. This allows IARIA to give articles increased visibility via distribution, inclusion in libraries, and arrangements for submission to indexes.

I, the undersigned, declare that the article is original, and that I represent the authors of this article in the copyright release matters. If this work has been done as work-for-hire, I have obtained all necessary clearances to execute a copyright release. I hereby irrevocably transfer exclusive copyright for this material to IARIA. I give IARIA permission or reproduce the work in any media format such as, but not limited to, print, digital, or electronic. I give IARIA permission to distribute the materials without restriction to any institutions or individuals. I give IARIA permission to submit the work for inclusion in article repositories as IARIA sees fit.

I, the undersigned, declare that to the best of my knowledge, the article is does not contain libelous or otherwise unlawful contents or invading the right of privacy or infringing on a proprietary right.

Following the copyright release, any circulated version of the article must bear the copyright notice and any header and footer information that IARIA applies to the published article.

IARIA grants royalty-free permission to the authors to disseminate the work, under the above provisions, for any academic, commercial, or industrial use. IARIA grants royalty-free permission to any individuals or institutions to make the article available electronically, online, or in print.

IARIA acknowledges that rights to any algorithm, process, procedure, apparatus, or articles of manufacture remain with the authors and their employers.

I, the undersigned, understand that IARIA will not be liable, in contract, tort (including, without limitation, negligence), pre-contract or other representations (other than fraudulent misrepresentations) or otherwise in connection with the publication of my work.

Exception to the above is made for work-for-hire performed while employed by the government. In that case, copyright to the material remains with the said government. The rightful owners (authors and government entity) grant unlimited and unrestricted permission to IARIA, IARIA's contractors, and IARIA's partners to further distribute the work.

Table of Contents

Evaluation of Event-Triggered Algorithm to Minimise Differences From Real Values to Digital Twin and Balancing Energy Efficiency Applied to Rainfed Crops

Alberto Ivars-Palomares[1], Lorena Parra[2], Jaime Lloret[1], Sandra Sendra[1], Pedro V. Mauri[3]

[1] Instituto de Investigación para la Gestión Integrada de Zonas Costeras Universitat Politècnica de València,
C/ Paranimf, 1, 46730, Grao de Gandia, Valencia, Spain;

[2] Departamento de Producción Agraria, Escuela Técnica Superior de Ingeniería Agronómica, Alimentaria y de Biosistemas, Universidad Politécnica de Madrid, 28040 Madrid, Spain;

[3] Instituto Madrileño de Investigación y Desarrollo Rural, Agrario y Alimentario (IMIDRA), Finca "El Encin", A-2, Km 38, 28800 Alcalá de Henares, Madrid, Spain;
email: aivapal@epsg.upv.es, lorena.parra@upm.es, jlloret@dcom.upv.es, sansenco@upv.es, pedro.mauri@madrid.org

Abstract—**The quality of data is essential when it is used for digital twin purposes. Nevertheless, in rural areas with limited energy, the periodicity in data forwarding can be challenging. This paper assesses an event-triggered algorithm based on the variation between the current sensed data and the last sent data. Specifically, thresholds are optimised to determine the data forwarding for a rainfed agriculture monitoring network. The thresholds are optimised using a metric that combines the energy efficiency and quality of data in terms of the percentage of packets saved and the error between the real value and the digital twin value. This has been conducted for soil moisture sensors located at different depths and soil temperature sensors. Once the thresholds have been optimised, with values of 2 ℃ for soil temperature and 0.25 % for soil moisture sensors, the saved packets are considered. These thresholds are applied to other similar nodes located in different areas. The results indicate that while the amount of sent packets is similar, ranging from 953 to 1269, the errors are highly variable. The saved packets represent a saving in packets that ranges from 82 to 86 %. This can be explained by the differences in temperature and soil moisture changes and trends among different sensors located in different places. Thus, these results suggest that adaptable tresdhols should be provided that automatically adapt to the conditions of the monitored site.**

Keywords- Soil moisture; soil temperature; agriculture; sensor.

I. INTRODUCTION

In dryland agriculture, where irrigation is impossible, management activities rely exclusively on environmental monitoring to anticipate crop needs, estimate yields, and predict pathogen attacks [1]. However, due to the energy limitations inherent to remote sensors—powered by batteries or small solar panels—continuous measurements and transmissions threaten the autonomy of the network [2]. Typical rainfed crops include cereals, such as wheat and barley, pulses, olives, and dryland vineyards, whose growth and health are highly dependent on variations in humidity and temperature.

Digital twins emerge as a strategic tool by integrating sparse field data, weather forecasts, and process models to estimate unobserved variables and forecast future states, thus compensating for informational gaps [3]. Their capabilities are further enhanced with Artificial Intelligence (AI) techniques, enabling real-time optimisation of parameters, such as irrigation, fertilisation, soil moisture, and quality, particularly relevant in water-scarce or sustainable agriculture contexts [4].

Moreover, different digital twin modelling approaches—from physical and agent-based to hybrid and spatial models—are used to monitor key crop variables, such as soil moisture and climatic conditions [5]. Recent projects integrate these models with soil sensors, Global Positioning System (GPS) data, and predictive algorithms, enabling precise recommendations and simulations that optimise water and pesticide use [6]. In this regard, recent initiatives have expanded applications in Mediterranean dryland systems [7], developed frameworks for sustainable water management [8], applied hybrid AI–sensor models for pathogen prediction in vineyards [9], and implemented Geographical Information System (GIS)-based approaches to map soil heterogeneity in olive groves [10].

Wireless Sensor Networks (WSNs) form the backbone of monitoring infrastructures in these scenarios [11]. The design of WSNs—considering communication protocols, sampling frequency, and power management—is critical to balancing data quality and energy consumption. However, deploying Digital Twin (DT) in agriculture faces significant challenges in data acquisition due to environmental heterogeneity (geographic and climatic variability) and high sensor installation and data transmission costs, which hinder adoption, especially in rural or hard-to-reach areas [12]. Furthermore, there are concerns regarding infrastructure investment, technical complexity, data privacy, environmental impacts (e-waste), and technological access disparities in rural zones [13].

Event-triggered algorithms are a practical approach to saving energy in WSNs. Instead of sampling and transmitting data at fixed intervals, sensors activate only when significant changes or events occur, reducing unnecessary transmissions [14]. These algorithms can adjust sampling rates based on battery levels or data importance, preserving energy while maintaining meaningful data streams [15].

Evaluating the performance of these strategies requires metrics that quantify information loss due to skipped transmissions [16]. Unlike packet loss metrics, these focus on discrepancies between the DT's estimated data and the actual environmental state, with standard measures including the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

The aim of this paper is to evaluate the performance of an event-triggered algorithm to balance energy consumption due to sent packets and errors in information stored in a digital twin in the framework of an agriculture project. The algorithm will be optimised by adjusting the thresholds used to define data forwarding. The algorithms will be applied to different nodes which are part of a WSN for a rainfed agriculture field. These sensor nodes include soil moisture sensors and soil temperature sensors.

The rest of the paper is structured as follows: Section 2 summarises the current uses of event-triggered algorithms. The proposal and used metrics are fully described in Section 3. Meanwhile, Section 4 analyses the obtained results. Finally, the conclusions are outlined in Section 5.

II. RELATED WORK

Several studies have explored event-triggered sampling techniques to reduce energy consumption in WSNs for agricultural monitoring. Lozoya et al. demonstrated a soil moisture monitoring system where sensor nodes transmit data only upon detecting significant changes, achieving substantial energy savings compared to periodic sampling [15].

Similarly, Gatschet designed and evaluated a multi-hop communication protocol based on event triggers, which selectively forwards data only when local environmental events occur, enhancing energy efficiency and reducing network traffic [17]. Yu et al. investigated event-triggered distributed state estimation, where sensors send updates only when the estimator error exceeds a threshold, balancing estimation accuracy with communication overhead in precision agriculture applications [18].

Recently, Li et al. developed an event-triggered routing protocol (EEWRP) that combines energy-efficient forwarding with selective transmission, prolonging network lifetime while maintaining data fidelity [19].

Furthermore, Wright and Davidson clarify the distinction between models and digital twins, highlighting metrics, such as MAE and RMSE to assess data fidelity, helping evaluate the impact of reduced sensing on digital twin accuracy [16].

The OpenTelemetry Metrics Data Model provides a standardized framework for defining and comparing data quality and information loss metrics, facilitating consistent evaluations across different deployments [20].

Regarding event-triggered algorithms applied to digital twins, Viciano-Tudela et al. proposed an algorithm where variations in all measured values are compared with the last transmitted values to determine whether data should be sent;

even if only one variable changes, all variables are sent [21]. Originally applied to water quality monitoring nodes, this work is adapted to soil monitoring nodes, with more stable variables and metrics to optimize the transmission thresholds.

The main differences between existing proposals and the present work are the use of algorithms for soil data and their use for the digital twin. The spatial and temporal heterogeneity in soil data strongly differs from other media.

III. PROPOSAL

In this section, the description of the proposed algorithm, along with the system in which it has been implemented, is shown. First of all, the overview of the system is detailed. Then, the studied parameters and sensors used for their monitoring are described. Finally, the proposed algorithm is depicted.

A. Proposal overview

In the project AGRICULTURE 6.0 framework, a digital twin has been proposed for rainfed crops. This digital twin aims to provide a valuable tool for farmers to remotely monitor and assess the effects of different actions in their production fields. Additionally, the visualisation of this data can be highly valuable for multiple actors, having a great variety of benefits from collecting valuable scientific data to becoming a tool for social education. Thus, it is necessary that data from the digital twin clearly identifies and reflects the tendency of data in real fields. Nevertheless, the restrictions on energy consumption of sensor nodes demand the application of even-triggered algorithms to reduce energy consumption. The global framework of the project and its relation with energy-efficient algorithms can be seen in Figure 1.

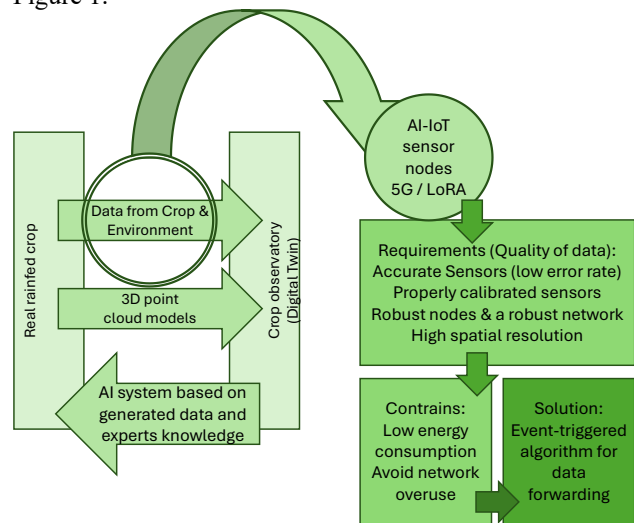Figure 1. Framework of the proposal and requirements of event-triggered algorithms.

B. Sensors and monitored parameters

In rainfed crops, the available water content in the soil becomes critical to evaluate the potential yield or the harvest

moment. Thus, it is one of the key aspects to be evaluated. Nevertheless, soil moisture is variable over time and in space, both horizontally and vertically. In the top part of the soil, the water moisture changes throughout the day due to dew and evapotranspiration. Moreover, changes in soil composition and local orography strongly affect soil moisture distribution. Therefore, monitoring soil moisture at a single point is inadequate when generating a digital twin, since it does not reflect the soil moisture variance in the field.

Commercial sensors provided by Plantae have been used to collect data presented in this paper. Two types of sensors have been used. On the one hand, one sensor can monitor soil moisture at 5 and 30 cm depth has been used. On the other hand, 6 sensors monitor soil moisture and soil temperature. Sensors have been configured to gather and forward data every 20 minutes. A total of 7 sensors have been deployed in a rainfed field during a growing season. The data used in this paper corresponds to 100 days of data, from February to May.

C. Algorithm and metrics

The algorithm evaluated in this paper has been previously described in [19]. It is an event-triggered algorithm that compares the current value of sensed variables with the last sent value to each digital twin. The gathered value must be forwarded when the variation between the data stored in the digital twin and new data from reality surpasses a given threshold. Even though only one of the monitored parameters has surpassed the threshold, all values (soil moisture at 5 cm and soil moisture at 30 cm or soil moisture at 5 cm and soil temperature at 5 cm) will be sent.

The novelty in this case is the adjustment of threshold values to minimise the energy consumption while keeping an adequate representativity of real data in the digital twin. We will consider these values for soil moisture at 5 cm, soil moisture at 30 cm and soil temperature at 5 cm.

We will include the number of sent packets, the percentage of packets saved, the average relative error, and the accumulated error as metrics. The number of sent packets is the accumulated packets each sensor sent when the event-triggered algorithm indicated that a variation occurred and data should be sent. The percentage of packets saved is the number of sent packets divided by the number of packets when no algorithm is used, which is the number of times that data are gathered. Average error is the average of the differences between the real value and the value of the digital. Finally, the accumulated error is the sum of the individual errors.

A combined metric is proposed to assess the best configuration and threshold for the algorithm. This metric combines the normalised average error of both parameters measured by a sensor and the normalised percentage of sent packets. The formula can be seen in Eq. (1)

$$Metric = \frac{\frac{\widehat{E1} + \widehat{E2}}{2} + \hat{p}}{2} \tag{1}$$

where Ê1 and Ê2 are the normalised errors of parameters 1 and 2, and p̂ is the normalised percentage of sent packets.

D. Metric value optimisation process

Different thresholds will be considered for the different sensors to assess the best thresholds to optimise the metric. Values assumed for the thresholds to calculate metrics are given in Table 1.

TABLE I. VALUES FOR THE THRESHOLDS TO CALCULATE METRICS

Table Head	Temperature	Soil Moisture
1	5	5
2	4	2.5
3	3	1
4	2	0.75
5	1	0.5
6		0.25
7		0.1
8		0.01

The maximum admissible threshold for temperature is 5ºC, while for soil moisture is 5%. Minimum assessed thresholds will be given by the resolution of the sensors, which are 1 ºC for temperature sensors and 0.01 % for the soil moisture sensors. Metrics will be calculated for one node with temperature and moisture sensors, and the node with both soil moisture sensors.

IV. RESULTS

In this section, the obtained results are presented and analysed. First of all, the errors obtained and the number of packets sent to the sensor nodes used for the metric calculation are shown. Then, the results in metrics are analysed to determine the optimised values to be used as thresholds. Finally, the comparison between real field data and other sensors' digital twin is provided.

A. Trade-off summation of normalised errors and percentage of saved packets

First of all, we present in Figure 2 and Figure 3 the trade-off between the obtained summation of normalised errors Ê1 and Ê2 and the percentage of saved packets. These values have been calculated for the node with two soil moisture sensors, Figure 2, and one node with soil temperature and soil moisture sensors, Figure 3.
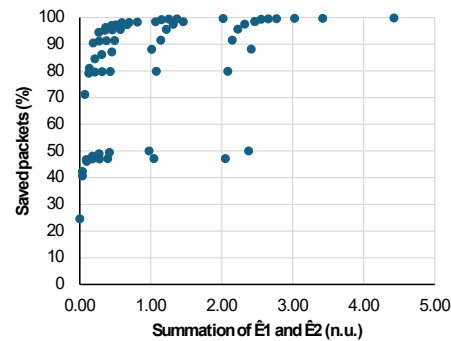

Figure 2. Comparison between the summation of errors and saved packets for a node with two soil moisture.
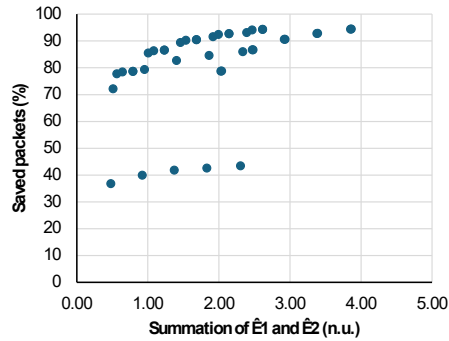
Figure 3. Comparison between the summation of errors and saved packets for a node with soil moisture and temperature sensors.

Both graphics show similar trends, indicating that the lowest errors are achieved with the lowest percentage of saved packets. This indicated the need to use the proposed metric to assess the best threshold configuration. Meanwhile, some differences can be seen. While errors approach 0 in the case of the node with soil moisture sensors, the node with soil moisture and temperature sensors has higher errors. This is caused by the different bit resolution of the temperature sensor, which causes greater errors.

B. Values of the calculated metric

In this subsection, we analyse the obtained values for the metric for both nodes. The optimisation has reached the lowest value of the metric. In Figure 4, we display the values for the soil moisture sensors. In this graphic, it is possible to see the different impacts on the metrics for the thresholds used for both soil sensors. We can identify that the impact on the metric is different for each sensor. The impact is greater for the sensor located at 5 cm, as can be seen if we compare the value of the metric of the two pairs of thresholds. For example, when treshodls of 5 and 2.5 are used (5 cm sensor and 30 cm sensor), the metric value is 0.39, while when the treshodls are 2.5 and 5, the metric decreases to 0.34. This tendency is also reflected in the lowest values of the thresholds. The metric for thresholds 0.01 and 0.1 is 2, and for 0.1 and 0.01 is 2.1. These results make sense given the greater variability of the sensor located at 5 cm. Thus, this is the sensor that requires a greater accuracy in the digital twin and thus a lower threshold. Nevertheless, when reaching the centre of the distribution of the metric, when thresholds are 0.75 to 0.25, the tendency is the opposite. The optimised thresholds according to the metric are 0.75 and 0.25 for 5 cm and 30 cm soil moisture sensors. In this case, the value of the metric is 0.053.

The obtained metric values for the node with soil temperature and soil moisture sensors can be seen in Figure 5. As stated before, the errors are higher in this case, and thus, the values of metrics are greater than in the case of the node with the two soil moisture sensors. The minimum value for the metric is 0.185, which is almost three times the metric achieved with the other node. This metric is achieved when thresholds are set at 2 for the temperature sensor and 0.25 for the soil moisture sensor.
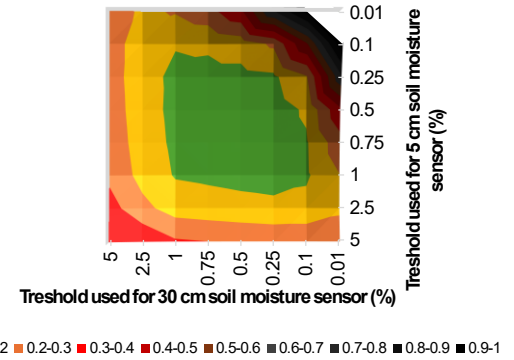

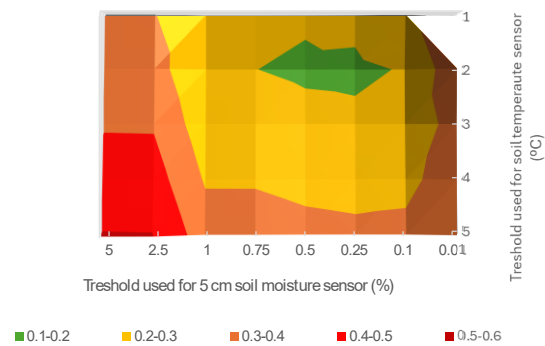Figure 4. Metric values for the combined thresholds in the case of the node with two soil moisture sensors.

Figure 5. Metric values for the combined thresholds in the case of the node with the soil moisture and soil temperature sensors.

C. Application of the optimised threshold for other nodes

Following, the obtained errors in terms of MAE and Mean Relative Error (MRE) for each parameter in the other sensors are shown. Concerning the MAE, Figure 6 shows that there are high differences in temperature MAE among different nodes and apparently low differences in moisture MAE.

Nevertheless, when data is analysed as MRE, see Figure 7, it is possible to see that these differences are strongly intensified. There is one particular sensor for which the MREs are lowest. Obtained MRE for the node used to optimise the thresholds are 0.52 and 9.8 % for soil moisture and soil temperature; for this particular node, the values are 0.08 and 0.92 %. This might indicate that the location in which this sensor is placed has different characteristics. Thus, for an efficient use of trehsodols in event-triggered algorithms for data management, these should be adjusted and adapted to the different situations.

The number of packets in the nodes used to evaluate the performance of the optimised thresholds is 1246, 995, 1269, 1022, and 953 for nodes 3945, 3944, 3953, 3957, and 3858. Suppose a saving in packets from 82 to 86%. Thus, the differences in MRE are not caused by differences in the number of sent packets.
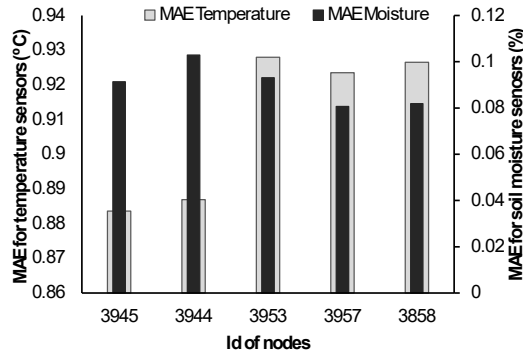
Figure 6. MAE for temperature and moisture data in other cases when optimised thresholds are used.
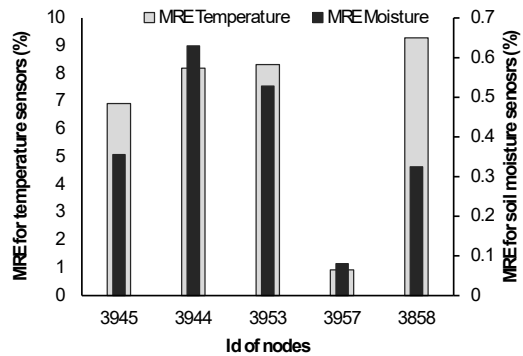

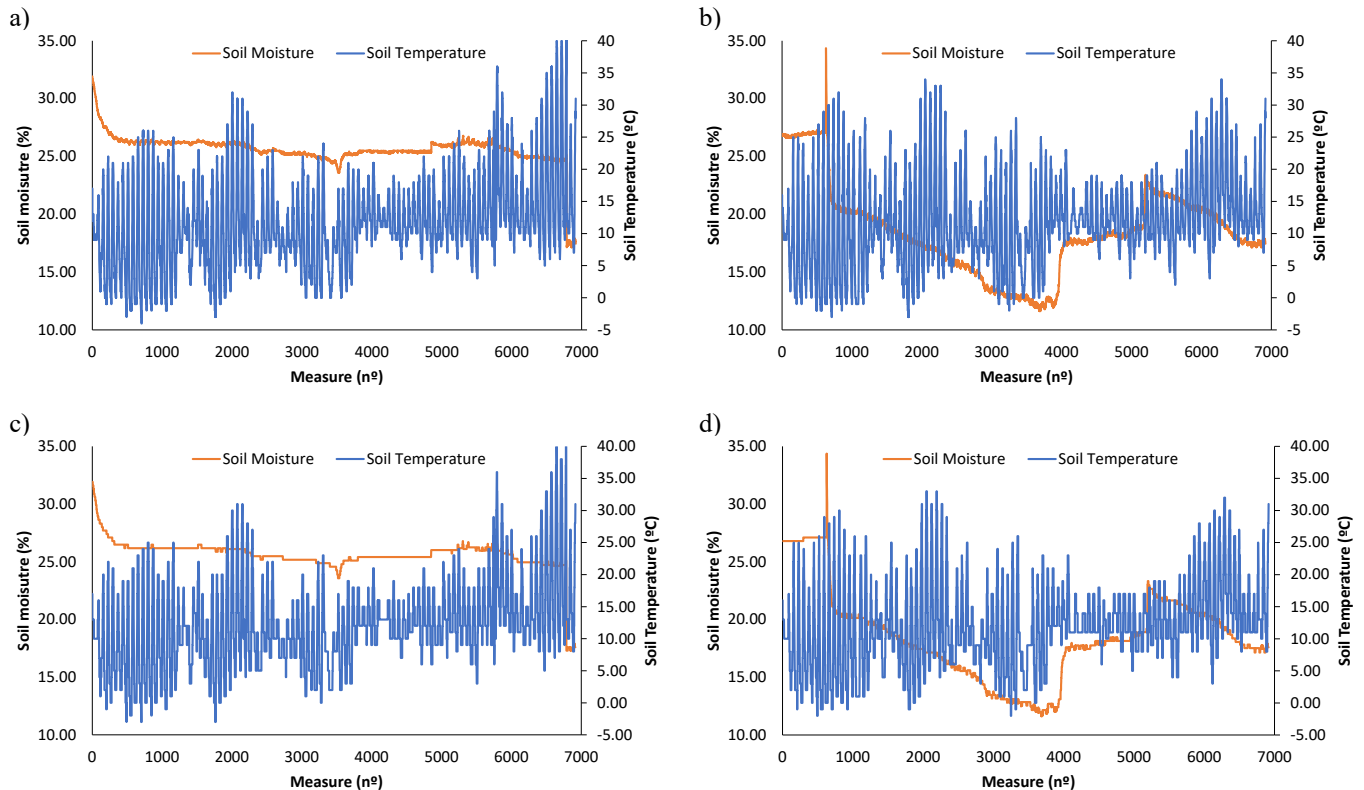Figure 7. MRE for temperature and moisture data in other cases when optimised thresholds are used.

D. Comparison of data in the digital twin with real values.

Finally, the comparison of real data with information stored in the digital twin for the nodes 3957 and 3953 is presented in Figure 8. Figures 8 a) and 8 b) represent the real data for the location of nodes 3957 and 3953, respectively. Meanwhile, information of subfigures 8 c) and 8 d) represents the data stored in the digital twin for both locations (3957 and 3953). It is possible to see that the differences between real data and information stored in the digital twin are minimal.

In this case, a potential explanation of the differences observed in previous values of MAE and MRE can be provided when visualising the data. In location 3957, the variation of soil moisture has been minimal compared with the location of node 3953. Since the value of soil moisture has been more stable, variations are expected to occur slowly, and values have become stable over time. This might provoke that MAE and MRE for soil moisture have been strongly decreased. The trend in temperature is not as visible as in the case of soil moisture, but fewer changes occur, explaining the lower MRE and MAE in temperature. Combined with the highest value of soil moisture, this situation is highly compatible with a node located in a region at the bottom of a depressed area. In these areas, soil moisture tends to accumulate, and surrounding orography reduces the variation of temperature, mainly in the winter, by protecting the area from the cold winds.

With this information, it is clearer that the location of the node is remarkable and should be considered for the event-triggered algorithms.

a)

b)

c)

d)

Figure 8. Example of data in the real field and in the digital twin.

V. CONCLUSIONS AND FUTURE WORK

Having high-quality data in digital twins is necessary to obtain accurate models and predictions. Nevertheless, the quality of data has a direct impact on sensor energy consumption. Thus, adequate energy management should be conducted by event-triggered algorithms.

This paper analysed the importance of optimising the thresholds used in the event-triggered algorithms and provided a metric to balance errors and energy efficiency. In addition, our results suggest that establishing a general threshold for all the nodes that share the same sensors might not be the best solution, and having adaptable thresholds can improve the results obtained.

In future work, we will propose and evaluate different methodologies to automatically recalculate these thresholds at the edge. Moreover, the integration of this information with data received from multi-point cloud and other inputs for the digital twin will be assessed.

ACKNOWLEDGMENT

REFERENCES

[1] P. Angin, M. H. Anisi, F. Göksel, C. Gürsoy, and A. Büyükgülcü, "Agrilora: A digital twin framework for smart agriculture," Journal of Wireless, Mobile Networks, Ubiquitous Computing, and Dependable Applications, vol. 11, no. 4, pp. 77–96, 2020.

[2] A. Khanna and S. Kaur, "Evolution of Internet of Things (IoT) and its significant impact in Precision Agriculture," Computers and Electronics in Agriculture, vol. 157, pp. 218–231, 2019.

[3] L. Wang, "Digital twins in agriculture: a review of recent progress and open issues," Electronics, vol. 13, no. 11, pp. 2209, 2024.

[4] X. Song, X. Li, P. Wu, Y. Zhang, and J. Zhao, "AI-driven digital twins for precision agriculture water management," Applied Sciences, vol. 15, no. 8, pp. 4228, 2024.

[5] T. Y. Melesse, "Digital twin-based applications in crop monitoring," Heliyon, vol. 11, no. 2, 2025.

[6] S. Banerjee, A. Mukherjee, and S. Kamboj, "Precision agriculture revolution: Integrating digital twins and advanced crop recommendation for optimal yield," arXiv preprint arXiv:2502.04054, 2025.

[7] G. Espadas-Aldana, "Life cycle assessment method to support the waste valorisation pathway in French olive oil circular production," Doctoral dissertation, Institut National Polytechnique de Toulouse-INPT, 2022.

[8] R. Ahsen et al., "Harnessing digital twins for sustainable agricultural water management: A systematic review," Applied Sciences, vol. 15, no. 8, pp. 4228, 2025.

[9] F. Portela et al., "A systematic review on the advancements in remote sensing and proximity tools for grapevine disease detection," Sensors, vol. 24, no. 24, pp. 8172, 2024.

[10] S. Chiappini, "Precision agriculture by proximal and remote sensing: from the 3D modelling and tree metrics computation to the analysis of rural landscape," 2023.

[11] J. Lloret, M. Garcia, D. Bri, and J. R. Diaz, "A cluster-based architecture to structure the topology of parallel wireless sensor networks," Sensors, vol. 9, no. 12, pp. 10513–10544, 2009.

[12] R. Zhang, H. Zhu, Q. Chang, and Q. Mao, "A comprehensive review of digital twins technology in agriculture," Agriculture, vol. 15, no. 9, pp. 903, 2025.

[13] A. Katharria et al., "Information fusion in smart agriculture: Machine learning applications and future research directions," arXiv preprint arXiv:2405.17465, 2024.

[14] M. Garcia, S. Sendra, J. Lloret, and A. Canovas, "Saving energy and improving communications using cooperative group-based wireless sensor networks," Telecommunication Systems, vol. 52, no. 4, pp. 2489–2502, 2013.

[15] C. Lozoya, A. Favela-Contreras, A. Aguilar-Gonzalez, L. C. Félix-Herrán, and L. Orona, "Energy-efficient wireless communication strategy for precision agriculture irrigation control," Sensors, vol. 21, no. 16, pp. 5541, 2021.

[16] L. Wright and S. Davidson, "How to tell the difference between a model and a digital twin," Advanced Modeling and Simulation in Engineering Sciences, vol. 7, no. 1, pp. 13, 2020.

[17] T. Gatschet, "Event-triggered multi-hop communication for wireless sensor networks," Master's thesis, ETH Zurich, 2020.

[18] D. Yu, Y. Xia, L. Li, and D. H. Zhai, "Event-triggered distributed state estimation over wireless sensor networks," Automatica, vol. 118, pp. 109039, 2020.

[19] Y. Li, P. Xu, W. Chen, and H. Zhang, "An event-triggered energy-efficient wireless routing protocol for fault monitoring of wind turbines," ICCK Transactions on Internet of Things, vol. 2, no. 3, pp. 55–62, 2024.

[20] D. G. Blanco, Practical OpenTelemetry, Apress, 2023.

[21] S. Viciano-Tudela, D. Carrasco, L. Parra, S. Sendra, and J. Lloret, "Design, deployment, and testing a device with edge computing energy efficiency algorithm for water quality monitoring," in 2022 Seventh International Conference on Fog and Mobile Edge Computing (FMEC), pp. 1–8, IEEE, Dec. 2022.