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

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***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 ºC 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.

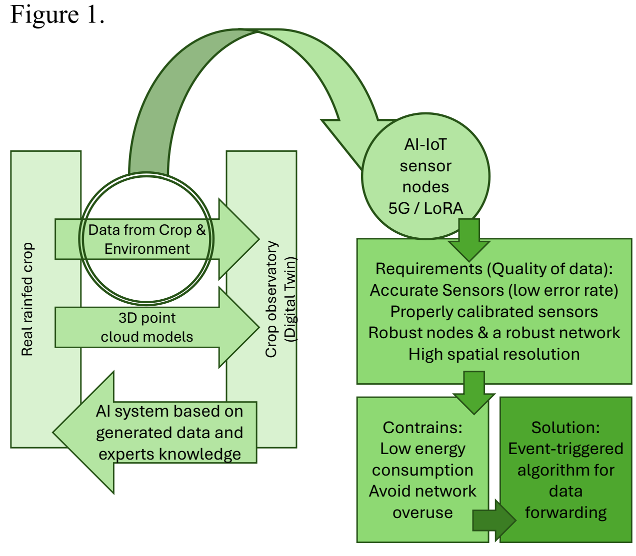

Figure 1. Framework of the proposal and requirements of event-triggered algorithms.

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

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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)

$$Metric = \frac{\frac{\widehat{E1}+\widehat{E2}}{2}+\hat{p}}{2} \quad (1)$$

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.

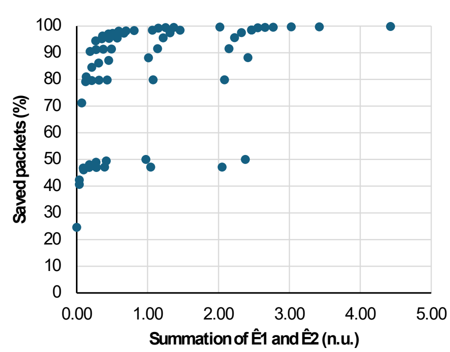

Figure 2. Comparison between the summation of errors and saved packets for a node with two soil moisture.

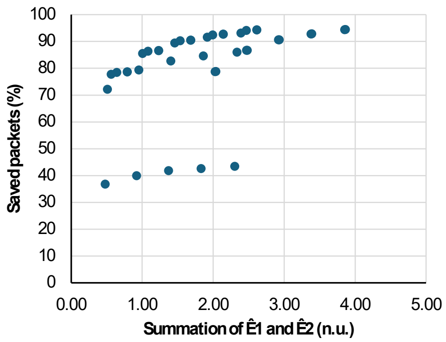

Figure 3. Comparison between the summation of errors and saved packets for a node with soil moisture and temperature sensors.

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.

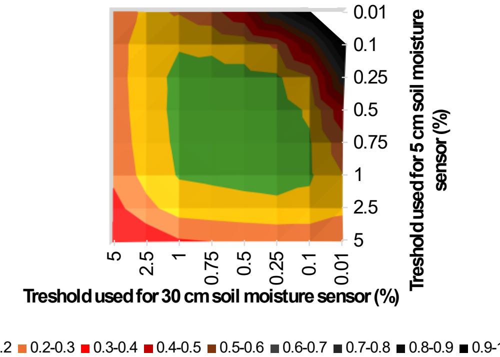

Figure 4. Metric values for the combined thresholds in the case of the node with two soil moisture sensors.

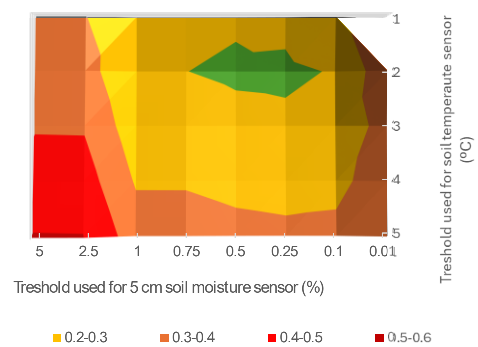

Figure 5. Metric values for the combined thresholds in the case of the node with the soil moisture and soil temperature sensors.

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.

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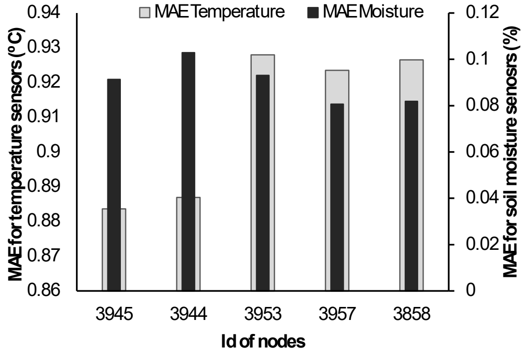

Figure 6. MAE for temperature and moisture data in other cases when optimised thresholds are used.

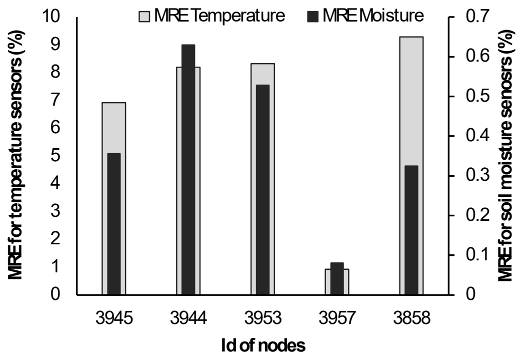

Figure 7. MRE for temperature and moisture data in other cases when optimised thresholds are used.

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.

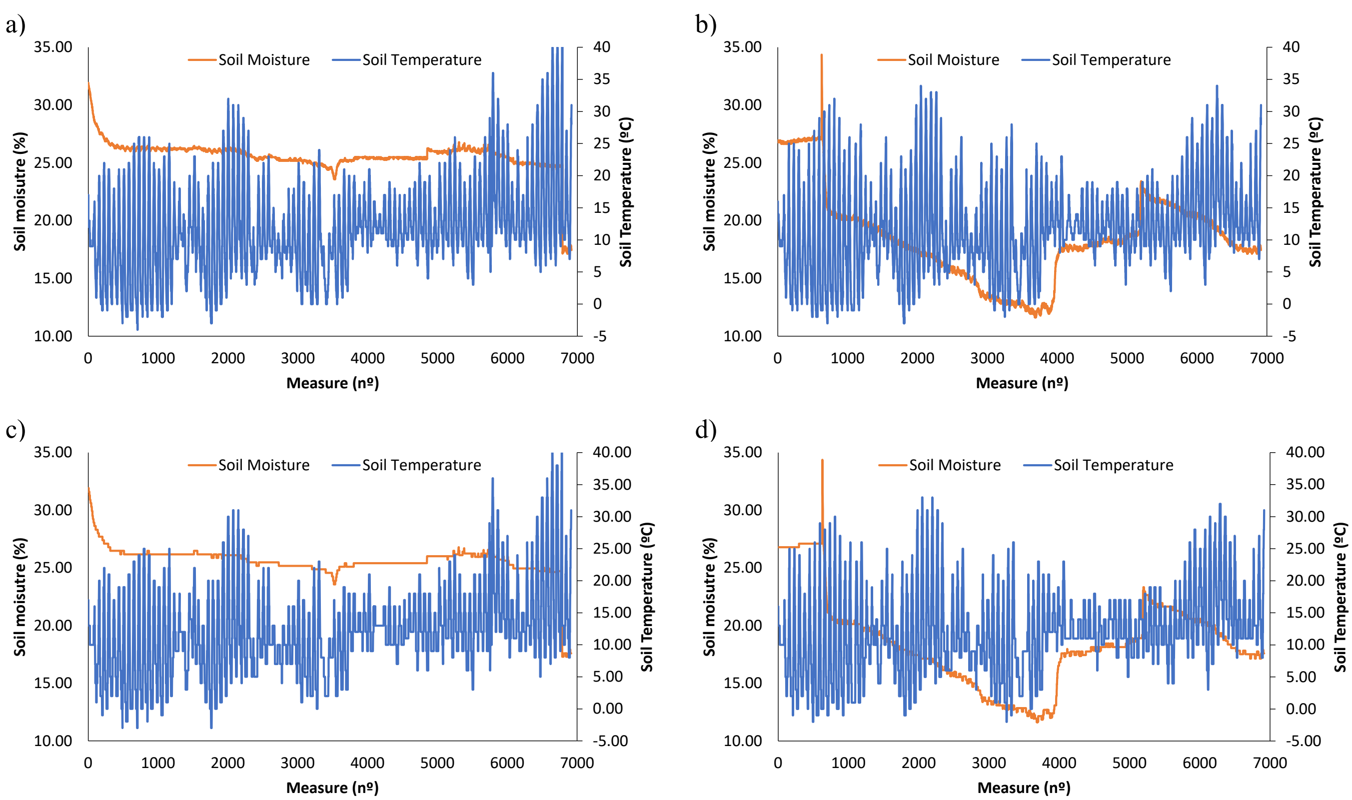

Figure 8. Example of data in the real field and in the digital twin.

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.

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