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Effect of Event-Based Sensing on IoT Node Power Efficiency. Case Study: Air Quality Monitoring in Smart Cities

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ABSTRACT The predicted growth of urban populations has prompted researchers and administrations to improve services provided to citizens. At the heart of these services are wireless networks of multiple different sensors supported by the Internet of Things. The main purpose of these networks is to provide sufficient information to achieve more intelligent transport, energy supplies, social services, public environments (indoor and outdoor) and security, etc. Two major technological advances would improve such networks in Smart Cities: efficient communication between nodes and a reduction in each node's power consumption. The present paper analyses how event-based sampling techniques can address both challenges. We describe the fundamentals of the triggering mechanisms that characterise Send-on-Delta, Send-on-Area, Send-on-Energy and Send-on-Prediction techniques to restrict the number of transmissions between the sensor node and the supervision or monitoring node without degrading tracking of the sensed variable. At the same time, these aperiodic techniques reduce consumption by sensor node electronic devices. In order to quantify the energy savings, we evaluate the increase achieved in the average lifetime of sensor node batteries. The data provided by Smart City tools in the city of Santander (Spain) were selected to conduct a case study of the main pollutants that determine city air quality: SO_2, NO_2, O_3 and PM_{10}. We conclude that event-based sensing techniques can yield up to 50% savings in sensor node consumption compared to classical periodic sensing techniques.

INDEX TERMS Air quality monitoring, event-based sampling, sensor energy saving, smart cities technologies, wireless sensor network.

I. INTRODUCTION AND MOTIVATION

According to predictions, two-thirds of the world's population will live in cities by 2050 [1], [2]. Although there are several interpretations of the Smart City concept [3]–[10], the main goal is to achieve better use of public resources by means of digital and telecommunications technologies, increasing the quality of services offered to inhabitants, public administrations and businesses.

Sensing is at the heart of Smart Cities, and is used to monitor variables related to a plethora of applications for the environment, health care, transport and mobility, household energy consumption, security and surveillance, etc. [11]. Special mention should be made of battery-powered wireless sensor networks (WSN), due to their capacity for ubiquitous real-time sensing. A WSN can generally be described as a network of nodes that cooperatively sense and may control the environment, enabling interaction between individuals or computers and the surrounding environment [12]. However, WSNs present two constraints compared to classical wired networks: instability in communication and energetic autonomy [13].

The Smart City paradigm is supported by the Internet of Things (IoT), i.e. by a communication infrastructure that provides unified, simple and economical access to a profusion of public services, thus unleashing potential synergies and increasing transparency to citizens, companies and public administrations [14]–[17]. Some of the typical urban services that are enabled by the IoT paradigm include the structural health of buildings, waste management, noise monitoring, traffic congestion, energy consumption, smart parking, smart lighting, automation, the health impact of public buildings

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and air quality. Together with gateway and cloud solutions, sensor nodes comprise the basic IoT architecture, and some of the main associated challenges include protocols and standards, privacy and security, technological compatibility and power management [18]–[20].

The basic operation of a sensor node is as follows. A microcontroller receives data from the sensor and processes them accordingly. Then, the wireless transceiver (RF module) transfers the data to enable physical communication. In this process, the transmission of data is responsible for the greatest energy consumption [18], [21]. Multiple open source sensor nodes are available to the research community. Some of the most widely used sensor nodes are Mica2, TelosB, Stargate and IMote 2 [4]. Although technology based on microelectromechanical systems has achieved a reduction in sensor node consumption, their autonomy still depends on a battery; consequently, research on strategies to increase battery autonomy is of great interest. Unlike other networks, in WSNs it can be hazardous, very expensive or even impossible to charge or replace exhausted batteries, due to the hostile nature of the environment. There are several areas in which the challenge of energy autonomy in WSNs can be addressed: sensor node size and consumption, internal (battery) and external (ambient energy harvesting) energy sources, communication techniques (BLE, 6LoWPAN, LoRa, SigFox, etc.), duty cycling and data reduction [13], [22]–[24].

One of the main aspects to consider when evaluating node energy consumption is the choice of RF technology. In [25], an energy efficiency study is presented of the different wireless communication technologies applicable to IoT, analysing short-range (WiFi and ZigBee) and long-range (GSM, LoRa) technologies. The study found that the choice of transmission module is decisive for battery lifetime and that the communication technology ultimately depends on the distance range required by the application, besides other factors such as latency, number of messages to transmit, throughput and cost. The data reduction techniques proposed in the literature can be classified into three categories according to the data-handling step: production, processing and communication [26]. In [27], the backcasting method is implemented in the fusion centre to activate or not a node according to the correlation between the data sensed in the environment; the central node detects the data characteristics and sends the appropriate sampling rate to sensor nodes. The work [28] deals with the algorithm Adaptive Frequency based Sampling to regulate sampling frequency of sensor nodes in different clusters dynamically following the change of signal frequency. The key idea is to measure periodic signal frequency online in different clustered region, afterwards adjust signal-sampling frequency following with minimal necessary frequency criterion. The work considers an adaptation mechanism based on the frequency not on the level of the tracked data. In [29] authors propose an adaptive sampling algorithm based on temporal and spatial correlation of sensory data for clustered WSNs. This strategy is interesting for sophisticated collection processes of sensory data, which consume more energy than traditional transmission processes. That is the case of image and video acquisitions, but not of air quality monitoring.

Most monitoring applications based on sensor networks rely on a time-based philosophy whereby readings are carried out with a given sampling frequency [30]. To minimise the associated problems, upcoming standards (IEEE 802.3az, 802.11ah, etc.) introduce discontinuous transmission/reception cycles with short wake-ups and large sleep ranges. A further step is proposed in [31], whereby interconnecting devices exchange data only when a particular event (alarm) has been triggered, and both distributed and centralised strategies are evaluated by simulation. Regarding the receiver node, if a prediction model of the sensed process is provided, some of the data can be predicted instead of measured at the inter-sampling times [23], [32]. A compression and transmission strategy with the objective of prolonging lifetime of sensors while guaranteeing a desired reconstruction accuracy of the tracked data is described in [33]. Sampling compression, data compression and communication compression are the pillars of the strategy to prolong the lifetime of IoT networks for monitoring applications while satisfying given QoS constraints. The proposal contributes to reduce the energy consumed by the transceiver but demands a high-energy cost due to computational complexity even when the sensed data are not transmitted. In aperiodic sampling schemes, sampled data are only transmitted when a threshold is violated, which means that fewer sampled data are transmitted, thus achieving better resource utilisation [34]–[36].

In the context of Smart Cities, WSN and IoT, the present study examines the event-based sensing approach, i.e. the sensed variable is only transmitted when a relevant change is detected, without degrading signal tracking at the remote monitoring node. This ensures low computational cost and significant savings in sensor node power consumption what increases battery lifetime. This paper evaluates the effect of different measurement-based sampling techniques on reducing the consumption of commercial sensor nodes. To this end, a case study is conducted of the city of Santander (Spain) using the periodic data on several environmental pollution parameters provided by this Smart City's services. For a detailed quantitative analysis of IoT node power consumption, an assessment is conducted of the commercial electronic devices comprising the main node parts (sensor, microprocessor and communication module) to ensure that the contribution of different event-based techniques to IoT node battery lifetime is quantitatively evaluated. The results are then compared with those obtained by means of the classical time-based alternative. Lastly, the study conclusions are presented.

II. OVERVIEW OF EVENT-BASED SENSING ALTERNATIVES

Event-based sensing forms part of the event-driven paradigm, which has aroused considerable research interest in recent years. It is especially interesting in the context of wireless

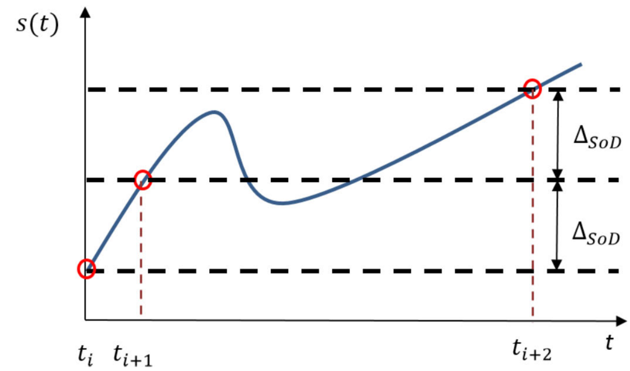

FIGURE 1. **Send-on-Delta sampling mechanism.**

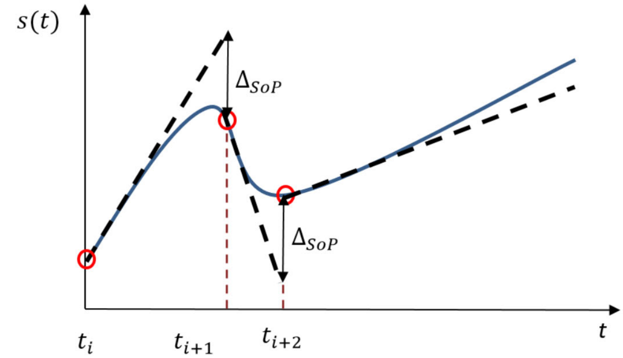

FIGURE 2. **Prediction-based Send-on-Delta sampling mechanism.**

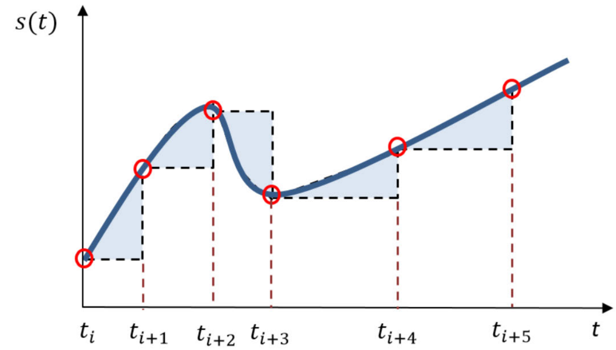

FIGURE 3. **Send-on-Area sampling mechanism.**

networked sensor and control systems due to its capacity to reduce interactions between spatially distributed nodes, in contrast to classical periodic sampling [34], [37]. Basically, event-driven sampling reduces sensor node use while maintaining satisfactory observation accuracy.

In WSN event-triggered sampling, aperiodic or asynchronous sampling schemes update information only when a relevant change in the measurement is detected. The triggering mechanism can be activated in the sensor node (measurement-based or threshold-based sampling) [37], [38] or in the remote centre (variance-based sampling) which requests the measurement [39], [40]. The most well-known measurement-based sampling patterns are: Send-on-Delta (SoD) [38], Send-on-Area (SoA) [41], Send-on-Energy (SoE) [42] and Send-on-Prediction (SoP) [43].

The simplest event-based sampling method is the SoD or constant amplitude difference sampling; this sampling technique updates the measurement when it reaches a given difference with the previous sample sent. Where s(t) is a continuous-time signal to be sensed, the new sampling instant t_i is obtained when the signal deviates from the last sampled update $s(t_{i-1})$ by a threshold level Δ_{SoD},

$$t_i = \min\{t > t_{i-1} || s(t) - s(t_{i-1})| = \Delta_{SoD}\}. \tag{1}$$

Thus, the lower the Δ, the higher the number of samples and the resolution of the signal tracking (see Figure 1).

Previous works [43] and [44] present an improved version of prediction-based Send-on-Delta (SoP). In this case, s(t) is only updated if it deviates from the predicted value $\widehat{s}(t)$ based on the most recent updated sample $s(t_{i-1})$ by the threshold Δ_{SoP},

$$t_i = \min\{t > t_{i-1} || s(t) - \widehat{s}(t)| = \Delta_{SoP}\}, \tag{2}$$

where $\widehat{s}(t)$ is the predicted value at t derived from the truncated Taylor series expanded at t_{i-1} (see Figure 2):

$$\widehat{s}(t) = s(t_{i-1}) + \dot{s}(t_{i-1})(t - t_{i-1}) + \frac{\ddot{s}(t_{i-1}))}{2}(t - t_{i-1})^2 + \ldots. \tag{3}$$

where $\dot{s}(t_{i-1})$ and $\ddot{s}(t_{i-1})$ are the first and second time-derivatives respectively.

An extension of SoD is integral sampling or SoA [41]. The triggering criterion is to sample when the integral of the absolute difference between the current signal value $s(t)$ and the last sample $s(t_{i-1})$, accumulated over the interval $(t_i - t_{i-1})$, reaches the threshold Δ_{SoA},

$$t_i = \min\{t > t_{i-1} | \int_{t_{i-1}}^{t_i} |s(t) - s(t_{i-1})| dt = \Delta_{SoA}\}. \tag{4}$$

This sampling technique is depicted in Figure 3.

A further extension of previous schemes is the SoE paradigm [42]. Following this criterion, a new trigger appears when the energy of the difference between the signal value $s(t)$ and the most recent updated sample $s(t_{i-1})$, accumulated over the interval $(t_i - t_{i-1})$, reaches the threshold Δ_{SoE}:

$$t_i = \min\{t > t_{i-1} | \int_{t_{i-1}}^{t_i} (s(t) - s(t_{i-1}))^2 dt = \Delta_{SoE}\}. \tag{5}$$

A graphical representation of this sampling mechanism is sketched in Figure 4.

III. CASE STUDY: AIR POLLUTION MONITORING IN SANTANDER

Clean air is one the main city staff challenges to guarantee a sustainable and healthy future. Around 91% of the world's population lives in places where air pollution levels exceed World Health Organisation (WHO) limits [45]. For this reason, we focus on air pollution as a case study to evaluate the benefits of our smart sensing proposal.

Santander is a benchmark Smart City in Spain. Examples of smart sensor network applications in Santander

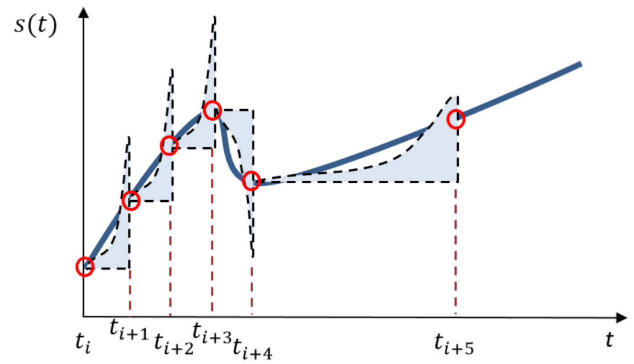

FIGURE 4. SoE sampling mechanism.

include traffic management, irrigation optimisation for parks and gardens, waste management and air pollution [46]. For mobile environment monitoring, besides measuring parameters at static points, devices located on vehicles are used to collect data on environmental parameters such as SO_2, NO_2, O_3 and PM_{10}, associated with given parts of the city. About 150 devices are installed on public vehicles such as buses, taxis and police cars. The accessibility of data on these parameters via the Smart Santander platform enabled us to use them as a proof-of-concept to validate the benefits of event-based sensing in Smart City applications. Here, we analyse air pollution measurements collected throughout October 2018 and compare the effect of the different event-based strategies on the number of transmissions over the wireless sensor network and on IoT node consumption in comparison with 15 min periodic updating in Santander [46].

WSN applications are usually implemented in digital devices and algorithms are processed in discrete time instead of in continuous time. In our case, we discretize Equations (1)-(5) regarding the before mentioned event-based sampling methods. We choose the same Δ value for a fair comparison among the aperiodic sensing techniques. Therefore, the i-th triggering time t_i is calculated, by the tracking error between the sampled signal s_k and the last sent s_{i-1} to the remote node, as follows:

$$\text{SoD:} \quad i = \min\{k > i-1 | |s_k - s_{i-1})| \geq \Delta\}. \tag{6}$$

The discrete integration for SoA and SoE is periodically evaluated by the summation and it is sample normalized.

$$\text{SoA:} \quad i = \min\{k > i-1 | \sum_{j=i-1}^{k} |s_j - s_{i-1}| \geq \Delta\}. \tag{7}$$

$$\text{SoE} \quad i = \min\{k > i-1 | \sum_{j=i-1}^{k} (s_j - s_{i-1})^2 \geq \Delta^2\}. \tag{8}$$

The signal predictor formulation derives from the linear discretization of the Taylor expansion:

$$\begin{aligned} \text{SoP:} \quad i &= \min\{k > i-1 | |s_k - \widehat{s}_k)| \geq \Delta\}, \\ \widehat{s}_k &= s_{i-1} + (s_{i-1} - \overline{s}_{i-1})(k - (i-1)), \end{aligned} \tag{9}$$

where $\overline{s}_{i-1}$ is the previous sample to the transmitted s_{i-1}.

TABLE 1. Comparison of different sampling strategies using number of updates and mean absolute error as performance parameters.

Effect of event-based sensing applied to air quality measurement Data source [46], October, 2018						
Air pollutant		Periodic	SoD	SoA	SoE	SoP
PM_{10} , Santander,	Updates	2976	335	648	537	632
$\Delta = 5\mu g/m^3$	MAE	0.000	1.523	0.510	0.752	1.654
SO_2 , Santander,	Updates	2976	75	556	366	182
$\Delta = 2\mu g/m^3$	MAE	0.000	0.997	0.153	0.237	0.646
NO_2 , Santander,	Updates	2976	301	861	577	754
$\Delta = 20\mu g/m^3$	MAE	0.000	7.097	3.560	4.681	6.699
O_3 , Reinosa,	Updates	2976	303	801	547	571
$\Delta = 10\mu g/m^3$	MAE	0.000	3.727	1.624	2.252	3.593

To evaluate aperiodic sampling performance, we calculated the tracking error of the different aperiodic sampling techniques compared to the periodic one using the mean absolute error (MAE),

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |s(t_i) - s(t)|, \tag{10}$$

where N is the size of the dataset. The threshold established by the designer implies a trade-off between the number of system updates (with the consequent energy costs) and the tracking error of the signal. We set a reference threshold equal to 10% of each air pollutant critical value, taking into account the recommendations of the World Health Organisation [47]: $\Delta_{PM_{10}} = 5\mu g/m^3$, $\Delta_{SO_2} = 2\mu g/m^3$, $\Delta_{NO_2} = 20\mu g/m^3$ and $\Delta_{O_3} = 10\mu g/m^3$.

Table 1 summarises the effect of different sampling strategies applied to air quality measurements registered in the Santander region in Spain (Santander and Reinosa cities) [46]. The number of updates and MAE are the parameters selected to evaluate the performance of each alternative.

We use the periodic sampling method as the relative performance reference (MAE = 0) with 2976 updates (31 days x 24 hours/day x 4 updates/hour). For all the air pollutants under study, the SoD method yields the lowest number of wireless channel accesses and the SoA the best tracking error. However, from the designer's point of view, there are intermediate alternatives balancing updates number and tracking error.

Figure 5 shows the Santander City PM_{10} data periodically sampled over one month, as well as the updates performed by the different event-based sampling alternatives. In this figure, it can be appreciated how in the zone around sample 2500, when the signal has low variation, only the SoA and SoE techniques generate new triggers due to their cumulative character in which sampling errors are integrated over time.

To better appreciate the effect of different event-based sampling techniques we present Figure 6. It shows a zoom of the first 50 samples, in the upper graphic the signal captured by the sensor and the prediction applied with SoP are presented, in the middle graphic we show the sampling instant regarding each sampling method and finally in the lower graphic

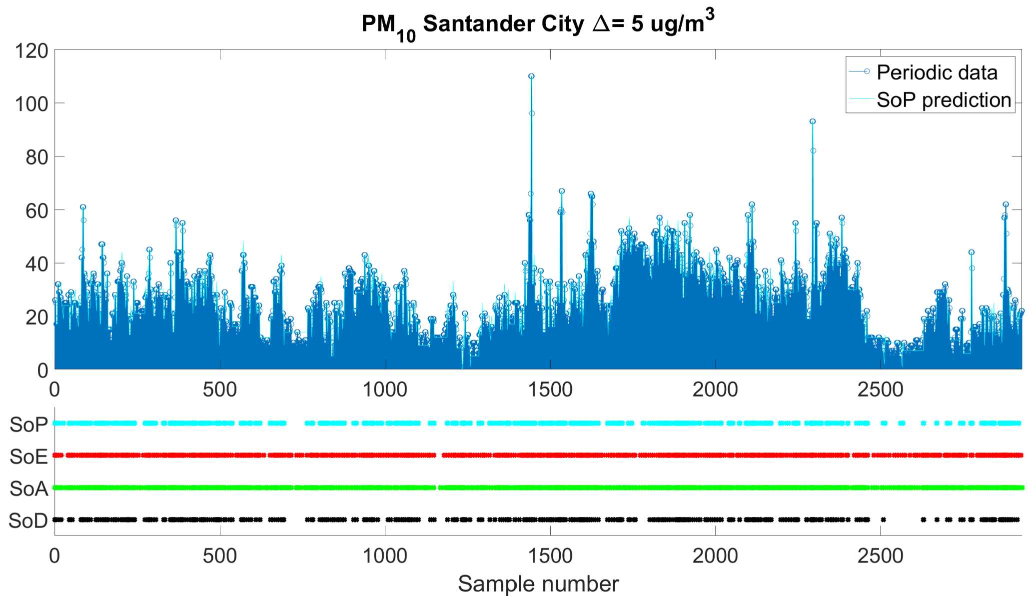

FIGURE 5. ***PM_{10}*** **periodically sampled data in Santander City and updates performed by the different event-based sampling strategies (SoP, SoE, SoA and SoD).**

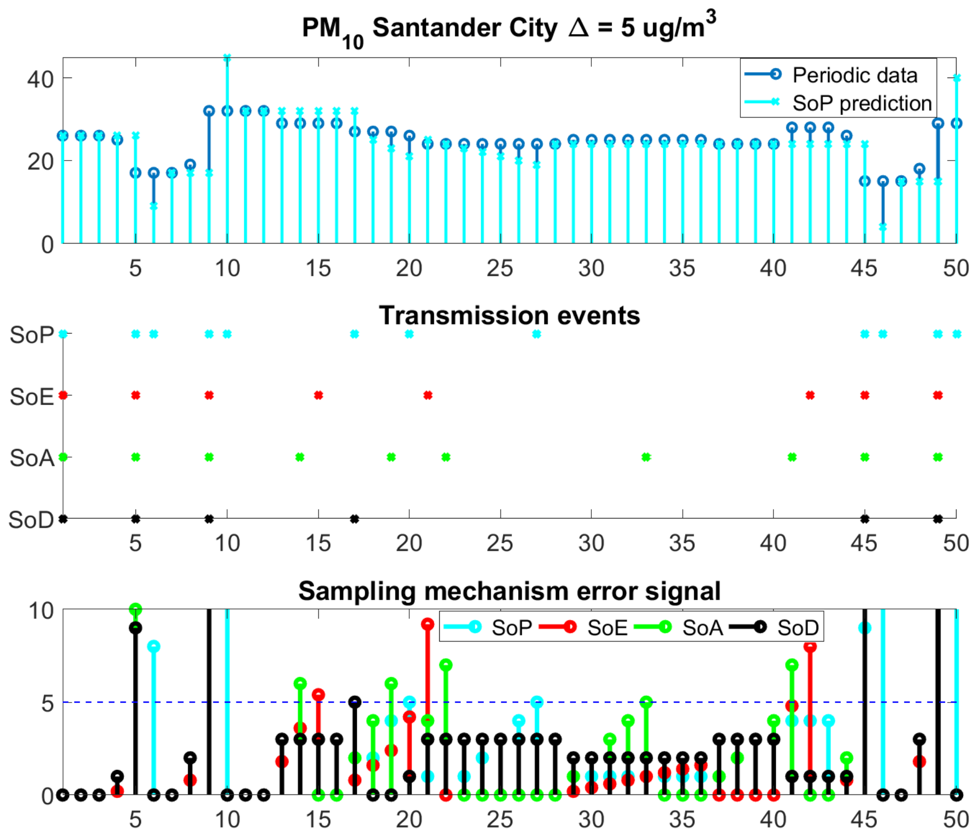

FIGURE 6. **First 50 periodic samples of** ***PM_{10}*** **recorded in Santander City and updates performed by the different event-based sampling strategies.**

the evolution of the sampling error periodically evaluated according to the different triggering mechanism. As can be appreciated, SoD only takes into account the last transmitted sample and SoP the slope of the signal in the last triggering instant; however SoA and SoE accumulate the error signal and its quadratic value respectively.

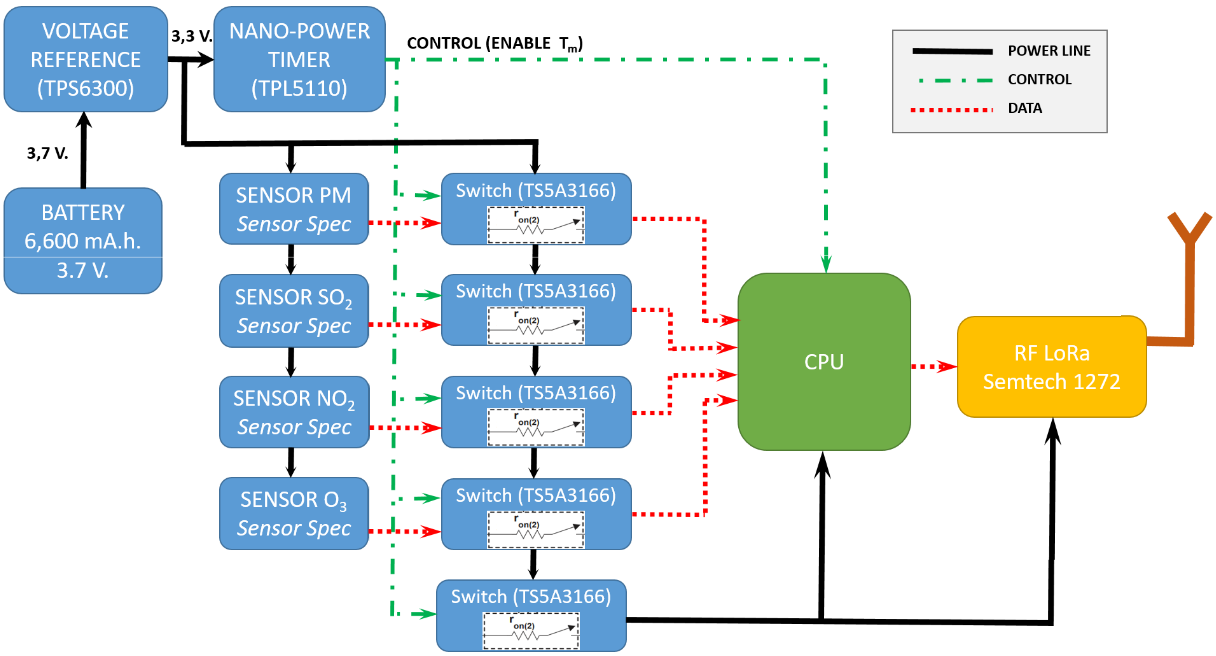

FIGURE 7. Electronic architecture of IoT nodes for air quality monitoring in Smart City applications.

IV. IoT NODE CONFIGURATION FOR AIR QUALITY MEASUREMENT

The goal of this paper is to quantify the effect of event-based sensing strategies on IoT node power efficiency using air quality monitoring in Smart Cities as a case study. Having described the event-based sensing strategies, we now present the IoT node electronic configuration that enabled us to evaluate power consumption and battery lifetime. As mentioned previously, the main elements of an IoT node are the sensor, digital processor and communication module.

In general, Smart City applications are insensitive to latency because the data volume is moderate and delays in message delivery are negligible, indicating that range and consumption are priority challenges for selecting the communication module. Taking this and recently published studies on LoRaWan [48], [49] into account, the LoRaWan was selected for this study.

Unlike short-range technologies (Wifi or Zigbee), in which consumption by commercial electronic devices is significant, with LoRaWan, consumption by these same devices is not a discriminating factor [50]–[52]. The Semtech 1272 module was chosen for this study because it has been one of the most widely used devices in previous research [53]–[57]. The consumption of LoRaWan devices depends on several factors: configuration of the physical layer parameters (Spreading Factor [SF], Bandwidth [BW] and Code Rate [CR]), data rates, transmission with or without acknowledgement, payload size, bit error rate (BER), number of collisions and the LoRaWan device class (class A, B or C) [49], [54]–[56], [58]. The combination of the parameters SF, BW and CR determines the range and transmission rate, as well as the overload for data detection. Therefore, power consumption depends on configuration and the device class. In the context of Smart Cities and energy consumption, we selected a class A module from the Semtech 1272 family, because class A devices have the lowest power consumption. For Smart City applications, its nominal consumption is about 30 mA [52]–[54], and each transmission takes approximately 3 seconds [57]–[59].

With regard to the selection of sensors, it should be noted that their consumption could have a significant impact on total node consumption. This circumstance is accentuated in the case of sensors used for air quality measurement in IoT Smart City applications [60]. These sensors are generally characterised by high consumption related to the required pre-heating to provide stable measurements. Depending on the manufacturer, consumption varies from 50 ÂţW to 180 mW. In addition, several hours are required in some cases to reach the optimum operating temperature, rendering such sensors unfeasible for IoT applications. For our study, we analysed gas (SO_2, NO_2, O_3) and particle (PM_{10}) sensors from Spec Sensors. These present the lowest consumption of all similar commercial products (45 ÂţW maximum), a lower pre-heating time (60 min recommended) and a response time of less than 30 seconds [61].

The microcontroller decides when to take sensor measurements and sends the information via SPI to the LoRa radio communication module. The microcontroller selected for this study was the ATmega328 [62], one of the most popular digital processors in research on IoT applications [53], [63], [64]. It takes 5 seconds to perform the measurement, process it and send it to the LoRa RF module for transmission.

TABLE 2. Current consumption and timing parameters of the IoT node electronic devices per measurement cycle.

ELECTRONIC DEVICE	Current consumption (mA)	Active time per measurement cycle (s)
Voltage reference TPS6300x	0.04	900
Analog Switch TS5A3166	0.00	900
SO_2 Spec Sensors	0.01	900
NO_2 Spec Sensors	0.01	900
O_3 Spec Sensors	0.01	900
PM Spec Sensors	0.01	900
Nano-Power System Timer TPL5110	0.00	900
CPU ATmega328(Active4MHz,VCC=3V)	2.50	5
RF LoRa Semtech 1272	30.00	3

How does the sampling strategy affect node consumption, and therefore node battery lifetime? To answer this question, we propose the electronic node configuration shown in Figure 7, which quantifies the improvements of aperiodic sampling strategies.

As can be seen, besides the three main components of an IoT node (sensor, microcontroller and RF module), we also used one 3.3 V voltage regulator TPS63060 [65], five analogue switches TS5A3166 [66] and one nano-power system timer TPL5110 [67]. The voltage regulator powers all IoT node components. The five switches maintain those components with the highest consumption (microcontroller and LoRa transmission module) deactivated (Off state) in the time intervals without measurement, and activates them (On state) every time of measurement (T_m = 15 min). The sensors are always powered because, as indicated above, they require about 60 min warm-up before providing stable measurements [61].

Table 2 presents the nominal consumption and active time over each measurement cycle of the electronic devices comprising the node architecture, for a measurement cycle of 15 minutes (900 s). The sensors, voltage reference, timer and switches are permanently powered; however the microcontroller is only activated every 15 minutes to perform and process measurements for 5 s, and the LoRa RF module is only activated to perform data transmission to the IoT target for 3 s. To calculate the average consumption we apply

$$I_m = C_{m\_permanent} + C_{m\_CPU} + C_{m\_LoRa1272}, \quad (11)$$

where $C_{m\_permanent}$ is the consumption of the electronic elements that require permanent power: the TPL5110 timer, TS5A3166 switches and TP63000 voltage reference; so that

$$C_{m\_permanent} = C_{TPS6300} + 5\,C_{TS5A3166} + 4\,C_{Sensors} + C_{TPL5110}. \quad (12)$$

The average consumption of the CPU ($C_{m\_ATmega328}$) and the LoRa RF module ($C_{m\_LoRa1272}$) depends on the number of measurements taken (one every 15 minutes, or 2,976 per month) and the number of transmissions respectively:

$$C_{m\_ATmega328} = \frac{N_{meas\_month}\, C_{ATmega328}\, t_{ATmega328}}{s_{month}}, \quad (13)$$

TABLE 3. Effect on energy saving of event-based sampling alternatives compared to periodic sampling by Santander Smart City tools [46].

PM_{10} Santander City $\Delta = 5\mu g/m^3$	Periodic	SoD	SoA	SoE	SoP
Number TX/month	2976	335	648	537	632
Average Consumption (mA)	0.19	0.10	0.11	0.11	0.11
Battery Lifetime (month)	46.44	86.72	78.63	81.32	79.01
Consumption saving (% respect to Periodic)	-	46.45	40.95	40.23	41.23

SO_2 Santander City $\Delta = 2\mu g/m^3$	Periodic	SoD	SoA	SoE	SoP
Number TX/month	2973	75	556	366	182
Average Consumption (mA)	0.19	0.09	0.11	0.10	0.10
Battery Lifetime (month)	46.46	94.82	80.85	85.84	91.31
Consumption saving (% respect to Periodic)	-	51.00	42.54	45.88	49.12

NO_2 Santander City $\Delta = 20\mu g/m^3$	Periodic	SoD	SoA	SoE	SoP
Number TX/month	2973	301	861	577	754
Average Consumption (mA)	0.19	0.10	0.12	0.11	0.12
Battery Lifetime (month)	46.46	87.70	73.94	80.33	76.23
Consumption saving (% respect to Periodic)	-	47.02	37.17	42.17	39.05

O_3 Reinosa City $\Delta = 10\mu g/m^3$	Periodic	SoD	SoA	SoE	SoP
Number TX/month	2973	303	801	547	571
Average Consumption (mA)	0.19	0.10	0.12	0.11	0.11
Battery Lifetime (month)	46.44	87.64	75.21	81.07	80.48
Consumption saving (% respect to Periodic)	-	47.02	38.26	42.72	42.30

$$C_{m\_LoRa1272} = \frac{N_{TX\_month}\, C_{LoRa1272}\, t_{LoRa1272}}{s_{month}}. \quad (14)$$

where s_{month} is the number of seconds per month, N_{meas_month} the number of measurements per month, N_{TX_month} the number of transmissions per month, $C_{ATmega328}$ and $C_{LoRa1272}$ the nominal consumption of the CPU and RF module respectively, finally $t_{ATmega328}$ and $t_{LoRa1272}$ represent their active times.

Working with the expressions from (11) to (14), average consumption in the case of periodic transmissions is 77.5 μA for the permanently powered elements, 100 μA for the CPU connecting every 15 minutes to capture and process measurements and 100 μA for the LoRa RF module. The average total consumption for periodic transmissions is 190 μA.

The consumption study was performed assuming the use of a rechargeable lithium-ion battery (Li-Ion) of 6600 mA-h with a 3.7 V nominal voltage, similar to that used by Waspmote Libelium modules [68]. Battery lifetime ($B_{lifetime}$) depends on the nominal charge and on the average current supplied to the electronic devices it supports. The following expression is used to quantify this lifetime:

$$B_{lifetime} = \frac{Charge_{battery}}{I_m} = \frac{6,600mAh}{I_m}. \qquad (15)$$

To evaluate sensor node performance according to the different sampling strategies, several parameters are considered: number of transmissions per month, average consumption, battery lifetime, percentage of transmission savings compared to periodic sampling and tracking error. Table 3 summarises the comparative study applied to four pollutant emissions registered by Smart City tools in the Santander region in Spain (Santander and Reinosa cities): a) PM_{10}, b) SO_2, c) NO_2 and d) O_3. Table 3 confirms that, independently of the air pollutant, the less updates number on the wireless channel the more energy saving at the sensor node. Besides, for the designed electronic implementation the average consumption saving achieves values between 37% and 51%, what means an increase close to the 100% in the battery lifetime.

V. DISCUSSION AND CONCLUSION

Numerical and graphical paper results focus on different items to compare the effect of periodic and aperiodic (SoD, SoA, SoE and SoP) sampling strategies to remotely monitor changes over time in air pollutants in a Smart City. Air quality guidelines [47] list four common air pollutants: inhalable particles with diameters up to 10 micrometres (PM_{10}), ozone (O_3), nitrogen dioxide (NO_2) and sulphur dioxide (SO_2). For this study we used the periodically sampled data available for Santander and Reinosa cities [46]).

In the present study, the triggering threshold (Δ) was equal to 10% of the critical values given by the World Health Organisation [47]. Using the same threshold and comparing the sampling techniques based on the difference between the sensed signal and the last transmitted one (SoD, SoA and SoE), Send-on-Delta yields the highest transmission savings with respect to periodic sampling, but also the highest tracking error assessed by the MAE factor (see equation (10)). SoA offers the best sampling accuracy but the price to pay is a high number of transmissions. The designer can select intermediate alternatives with SoE and SoP.

On top of that, the main contribution of the paper is to quantify the triggering mechanisms effect on the saving consumption of the sensor node proposed for this Smart City application. From an electronic point of view, the permanently powered devices (sensors, voltage reference, switch and timer) only require a low current but their contribution to total consumption can be significant for high inter-sampling times. Of all the devices integrating the electronic design shown in Figure 7, the key one to understand the global consumption is the RF module. The evaluated hardware arquitecture clearly illustrates the interest of aperiodic sampling mechanisms, providing consumption saving rates up to 50% and extra battery lifetimes that can even duplicate the current ones with classical periodic sensing.

Summing-up, classical periodic sampling is not the best alternative for measuring air quality in Smart Cities. As has been analyzed, most of the asynchronous or aperiodic solutions help reduce the number of transmissions and extend sensor node battery lifetime.

In future work, we intend to apply predictive techniques based on artificial intelligence as triggering mechanisms for aperiodic sensing. The idea is to transfer the main computational load to a remote center instead of the current local processing at the multiple sensor nodes, this way we will try to go on increasing the efficiency of battery-powered IoT networks.

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