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Research article

Sustainable application-aware gateway deployment for massive IoT networks

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ABSTRACT

The growing development of massive Internet of Things (IoT) networks has a fundamental role in modern and sustainable technologies, such as smart cities and smart water systems. With increasing density and complexity of these networks, the need for sustainable and efficient solutions becomes more critical and challenging. This paper presents an application-aware strategy for gateway deployment in IoT networks, leveraging graph theory and graph signal processing techniques to integrate application-based information with network topology. The approach is validated through a focused case study in the context of water management systems. Specifically, our approach improves network coverage and reduces energy consumption by up to 70%. Our results demonstrate significant improvements in data extraction rates and overall network performance, highlighting the adaptability of the proposed graph-based Application Weighted Centrality (AWC) model for large-scale IoT scenarios. This work provides valuable insights into the sustainable deployment of IoT infrastructure, aligning technological advances with the specific needs of applications.

1. Introduction

Massive Internet of Things (IoT) networks are becoming fundamental for modern monitoring techniques, as they allow scalable and sustainable solutions in several domains, from smart cities to water management systems. IoT networks provide long-range connectivity, low power consumption, and cost-effective deployment, enabling communication among a large number of distributed sensors with minimal infrastructure [1]. According to recent studies [2], the number of connected IoT devices worldwide is expected to exceed 39 billion by 2030, with a significant portion relying on Low Power Wide Area Networks (LPWAN) technologies. This rapid growth highlights the need for efficient network planning and resource management. LPWANs have emerged as key enablers for IoT, providing reliable long-range communication while maintaining low energy consumption. Among the various LPWAN technologies, LoRaWAN (Long Range Wide Area Network) [3] has been widely used in the context of sensor monitoring, such as Water Distribution Systems (WDSs), thanks to its low energy requirements and wide coverage [4]. LoRaWAN operates on unlicensed sub-GHz frequency

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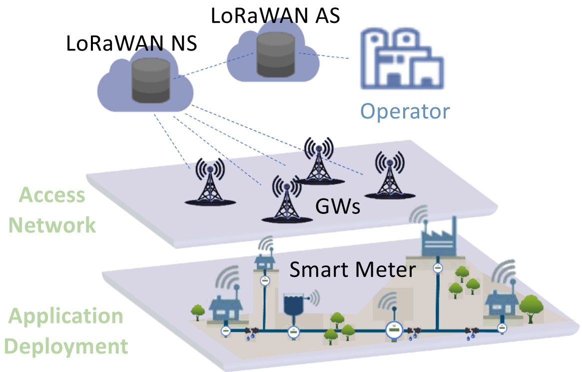

Fig. 1. Architecture for massive IoT WDS network.

bands and relies on the LoRa physical layer, which uses Chirp Spread Spectrum (CSS) modulation to achieve high link robustness and extended communication range while maintaining low power consumption [3]. A typical LoRaWAN network architecture can be defined as a star-of-stars topology. Sensor nodes, acting as smart meters in the WDS context, transmit data to gateways (GWs). These GWs relay the data to a Network Server (NS), which is responsible for managing network control aspects. Finally, the data are forwarded to the Application Server (AS), which operates within the application tenant domain [5]. LoRaWAN GWs have a fundamental role in massive IoT networks because they are key communication nodes that connect devices to the NS. Indeed, they enable efficient long-range communication between low-power devices and the NS, making possible IoT applications [6].

A key challenge in the design of massive IoT networks is the optimal placement of gateways, which directly affects energy efficiency, data delivery, and scalability. This requires a method able to integrate multiple levels, from network topology to application-level data requirements [7]. Although previous work has explored the placement of LoRaWAN GWs using heuristic or signal coverage models [8], they often overlook specific application requirements, which are critical in massive IoT scenarios with varying data criticality. Similarly, approaches that focus exclusively on energy optimisation or sparse measurement reconstruction [9] do not take into account differences in data priority or application requirements. Application-aware gateway deployment consists of configuring gateways to recognize, differentiate, and prioritize data packets based on their originating application. This can be achieved through various techniques such as deep packet inspection and edge computing capabilities. By understanding the context and requirements of each application, the gateway can make informed decisions about data routing, scheduling, and processing. This intelligent data management is particularly beneficial in scenarios with a high density of devices, specific application requirements, and the need for real-time or near-real-time responsiveness [8]. From a network planning perspective, application-awareness can be adopted to organize the number and position of the gateways in order to optimize the overall network coverage, leading to a more energy-efficient and sustainable infrastructure. Furthermore, another significant approach to network optimization involves leveraging sparse measurements [10]. This strategy allows for a reduction in the number of physical devices deployed, thereby decreasing costs and energy consumption, while still maintaining an adequate level of knowledge about the measurements within the network. By intelligently selecting a subset of sensor locations, it is possible to reconstruct the overall system behavior with acceptable accuracy.

In this work, we propose a general strategy for application-aware LoRaWAN gateway deployment that leverages graph theory and graph signal processing techniques. Unlike previous studies, our approach jointly considers the network's physical topology and the data characteristics associated with specific applications to inform gateway placement, addressing both coverage and application-level data priorities. While the methodology is broadly applicable to various domains such as smart cities and smart agriculture, we present a focused study on WDSs, specifically addressing scenarios where sparse measurements are available. As illustrated in Fig. 1, in our WDS context, smart meters transmit data to GWs, which then relay it to a NS for network management and subsequently to the Application Server (AS) for data utilization. The proposed approach demonstrates significant improvements in both energy consumption and data extraction rates, highlighting its potential for designing next-generation sustainable and efficient massive IoT networks. Although many IoT applications belong to different domains, they share common challenges that can be effectively addressed through application-aware strategies [11]. Indeed, each scenario involves data from a wide variety of sensors, which differ in data formats, transmission time intervals, and criticality levels. Generally, IoT devices in these scenarios are battery-powered, operating in environments where energy and bandwidth are limited. Consequently, the efficient use of these resources is necessary. Additionally, all IoT scenarios must address scalability needs, and the proposed GW deployment strategies must be able to manage a growing number of devices and an increasing amount of data [11].

The literature has shown that data variability contributes to exploiting application-aware network adaptation. In [12], an application-aware adaptive method for LoRaWAN networks is presented that enables devices to dynamically adjust their communication parameters. The proposed algorithm optimizes individual device performance based on application needs and environmental conditions, improving packet delivery ratio and energy consumption. Simulations demonstrate the method's ability to maintain overall network performance while satisfying specific application requirements over time [12].

Efficient *smart water management* is becoming increasingly critical due to increasing concerns about water scarcity [13]. Intelligent GW deployment plays a fundamental role in optimizing water usage and detecting anomalies. In a WDS, sensors monitor the

Table 1
Related works comparison in IoT gateway deployment strategies.

Works	Method	Dynamism	Massive IoT	QoS	DER	Energy efficiency	AWC
Tian et al. [21]	Greedy Algorithms	×	×	✓	×	×	×
Gravalos et al. [22]	ILP	×	×	✓	×	×	×
Rady et al. [23]	Machine-Learning	✓	✓	✓	×	×	✓
Ousat and Ghaderi [24]	MINLP	×	✓	✓	×	×	×
Matni et al. (2019) [18]	Machine-Learning	×	✓	✓	×	×	×
Hossain et al. [26]	Multiple cell deployment	×	×	✓	×	×	×
Ahmed et al. [19]	CN-V2N	✓	×	✓	×	×	✓
Loh et al. [20]	Graph-Based Placement	×	✓	✓	×	×	×
Matni et al. (2020) [8]	DPLACE	✓	×	✓	×	×	×
This work	Graph-Based AWC	✓	✓	✓	✓	✓	✓

QoS = Quality of Service; DER = Data extraction rate; Application-Aware Deployment = AAD; ILP = Integer Linear Programming; MINLP = Mixed integer nonlinear programming; CN-V2N = Cognitive Network for Vehicle-to-Network; DPLACE = Dynamic-Placement.

most important parameters, such as water levels in reservoirs, flow rates in pipes, and water quality. Although GWs themselves do not prioritize data autonomously, their deployment in areas with high-density sensor coverage ensures efficient routing of the most important information [13]. For instance, GWs placed near high-risk areas, such as water distribution points, can ensure that data indicating sudden pressure drops (which may suggest a leak) is transmitted promptly, while less urgent data, such as routine water level readings, can be transmitted at regular intervals. By situating GWs strategically across the network, our approach not only ensures efficient data routing but also facilitates application-aware monitoring, enabling predictive maintenance, resource optimization, and anomaly detection. This highlights the practical significance of application-aware gateway deployment in real-world IoT scenarios. Moreover, application-aware gateways facilitate *improved water resource planning*. By strategically placing GWs throughout the network, data from smart sensors can be aggregated and processed more efficiently. This enables better insights into water usage patterns, informing decisions on water allocation and conservation. More specifically, in the context of WDSs, the generation of faults, and consequently, the understanding of pressure gradient can aid network diagnosis to identify the sources that cause pressure transients and provide insight into the factors that contribute to faults in the WDSs [14,15]. Furthermore, it has been demonstrated that low-resolution sampling, such as every 15 minutes, often fails to capture fluctuations, including those in pressure measurements, which are vital for processing WDS assessments. Otherwise, high-frequency measurements of pressure make it possible to extract meaningful information about the causes that produce transients and give insights into how users contribute to pressure variability in WDSs [14,16]. Consequently, for a comprehensive and accurate assessment of hydraulic conditions, it is imperative to employ techniques to extract high-frequency and low-frequency water pressure according to the topology of the WDS. This allows for the detection and quantification of abrupt pressure fluctuations across a range of magnitudes. From a wireless network perspective, the increasing number of sensor measurements generates substantial data traffic, straining IoT network scalability and highlighting the limitations of meter processing and storage capabilities, thus driving our research.

The remainder of this article is organized as follows. Section 2 reviews related works and highlights the main contributions of the paper. Section 3 introduces the proposed application-aware gateway deployment method. Section 4 focuses on the study and evaluation of a massive IoT network, providing the large WDS scenario definition and presenting the experimental results. Finally, Section 6 concludes the paper with final remarks.

2. Related works and contribution

Several studies in the literature address this concern by evaluating the performance of LoRaWAN networks as traffic increases [17]. Moreover, the evaluation of the positions for the GWs remains a challenging problem, though there are physical constraints regarding the availability of sites where the equipment can be installed.

Works [8,18] proposed a gateway placement model specifically designed for dynamic IoT scenarios in LoRaWAN networks. Their approach clusters IoT devices based on similarity and estimates the required number of gateways using the Gap statistics method. K-means and Fuzzy C-means algorithms are then employed to determine gateway locations. The results demonstrate improvements in terms of quality of service (QoS) when compared to existing placement strategies. However, the models primarily focuses on device clustering and static optimization and does not explicitly address application awareness or sustainability aspects. In a different domain, Ahmed et al. [19] introduced a cognitive network architecture for vehicle-to-network (V2N) communications aiming to support ultra-reliable low-latency communications (URLLC). Their work leverages smart meters as distributed access points to enhance reliability and reduce latency. While this approach demonstrates the benefits of reusing existing infrastructure for improved performance, it focuses on vehicular communications rather than gateway placement optimization for LPWAN-based IoT networks, and energy-aware deployment considerations are not explicitly addressed. Interference-aware gateway placement has been studied by Tian et al. [21], who investigated optimized gateway positioning in transmit-only LPWA networks where gateways perform interference cancellation.

The authors derived analytical regions where collided packets can be successfully decoded and proposed greedy algorithms for gateway placement. Their results show improved packet delivery ratios due to reduced contention. Nevertheless, the work assumes

specific interference cancellation capabilities and does not consider application requirements or heterogeneous traffic demands. An optimization-based approach was presented by Gravalos et al.[22], who formulated the gateway placement problem as an integer linear programming (ILP) model with explicit QoS constraints. Their method minimizes the total network cost while ensuring required service levels. Although optimal solutions can be obtained for small-scale scenarios, the computational complexity of ILP formulations limits scalability in large and dynamic IoT deployments. Furthermore, Rady et al. [23] addressed gateway deployment in LPWANs by distinguishing between network-aware and network-agnostic scenarios. Machine learning techniques such as K-means clustering and spatial algorithms were used to estimate gateway locations, while link assignment was formulated as an optimization problem. Their study highlights that naïve deployment strategies, such as placing gateways at the highest altitudes, may significantly degrade performance. While their work contributes valuable insights into cost-efficient deployment, it does not explicitly integrate application-level requirements or sustainability-driven objectives into the placement process. In paper [24], LoRa network planning is formulated as a joint optimisation problem that considers gateway placement and spreading factor assignment. The proposed solution is scalable to large networks and demonstrates improvements in throughput and energy efficiency compared to the traditional Adaptive Data Rate (ADR) mechanism. However, the approach primarily focuses on network-level optimisation and does not explicitly account for application-specific requirements, nor does it support highly dynamic scenarios.
Finally, a graph-based gateway placement approach was introduced in Loh et al. [25] with the objective of reducing collision probability and improving reliability in LoRaWAN deployments. By modeling the network as a graph and focusing on collision-aware placement, the proposed method achieved up to 40% reduction in the number of required gateways and up to 70% reduction in collision probability compared to baseline approaches. Additionally, the authors discussed scalability by decomposing large networks into smaller sub-problems. However, the approach primarily targets collision mitigation and does not explicitly integrate application awareness or sustainability metrics into the placement process.

Table 1 compares recent studies on IoT gateway deployment strategies, considering key aspects such as dynamism, support for massive IoT, QoS, data extraction rate (DER), energy efficiency, and Application-Aware Deployment (AAD). It is evident that most traditional works, based on greedy algorithms [21], ILP [22], or multi-cell deployment [26], focus primarily on QoS, while lacking support for dynamism, scalability for massive IoT, DER, energy efficiency, or AAD. More recent approaches, such as those based on machine learning or CN-V2N [19,23], introduce dynamism and partial support for massive IoT and AAD, but remain limited in other aspects.

The method proposed in this work, called Graph-Based AWC, is the only one covering all the considered aspects, integrating dynamism, support for massive IoT, QoS, DER, energy efficiency, and AAD, thus demonstrating a comprehensive and versatile approach for WDS. Our approach incorporates SWI-FEED [7], this framework is a holistic and innovative solution for the evaluation and optimisation of smart SWDSs in massive IoT scenarios. Unlike existing methodologies, which tend to treat hydraulic and wireless simulation separately, SWI-FEED achieves bidirectional integration between the application and network levels, recognising their critical interdependence. The architecture combines the EPANET hydraulic simulation engine [27], integrated via the Python Water Network Tool for Resilience (WNTR) [28] package, to model the behaviour of the water network and generate application datasets (e.g. pressure and flow) with the ns-3 network simulator [29], specifically implemented to analyse the performance of communications in large-scale LoRaWAN networks. This integration allows for the evaluation of crucial impacts such as energy consumption, wireless network performance, and the effectiveness of optimisation algorithms (e.g., for leakage detection and optimal gateway placement). The framework is therefore ideal for defining and testing sustainable strategies that balance water management with communication energy efficiency in real-world, large-scale scenarios.

The key contributions of this work, which extend beyond the specific WDS use case, are:

(i) a novel WDS modeling approach grounded in graph signal processing, capable of jointly representing network topology and application-level requirements;
(ii) the formulation of a new AWC metric for identifying optimal GW placement, adaptable to different application-specific weighting functions;
(iii) a validation of the proposed method on a realistic WDS scenario, demonstrating its ability to ensure accurate monitoring while significantly reducing the energy consumption of IoT devices; and
(iv) the release of a publicly available synthetic dataset[1], created through EPANET and ns-3 simulations, which captures realistic network conditions.

Although gateway deployment based on dynamic variables may seem counterintuitive, since gateway positions generally remain static once chosen, the literature [8,19,23] demonstrates that this approach can yield significant benefits. Furthermore, as in the case of WDS, dynamic variables such as node pressure or water flow follow predetermined patterns linked to user behavior [30], thereby supporting the adoption of a dynamic AAD approach. For example, Parra et al. [31] studied the temporal evolution of flow and pressures, where a clearly quasi-periodic pattern with a period of about 24 h can be observed. This behavior indicates a cyclic dynamics of the system, most likely related to daily variations in water demand. A daily pattern (24 h) of the average pressure was also observed in the Eani water supply network [32], where the periodic trend of the average water pressure values ranges from 73.7 to 119 psi. In light of these periodic patterns reported in the literature, the proposed approach justifies the use of water network pressure to identify the optimal placement of GWs within a WDS.

[1] https://github.com/WITS-Restart/WDN-IoT-Dataset-Workbench

Lastly, while we tested our approach in a WDS context, the dataset structure is versatile and can facilitate testing different LoRaWAN deployment and communication strategies across a wide range of application domains.

3. Application-aware gateway deployment method

To enable sustainable LoRaWAN GW deployment in massive IoT networks, we introduce a graph-based method that integrates both the network topology and the application-layer information. The methodology, designed to dynamically reflect application priorities and traffic distribution by adapting sensor transmission schedules (i.e., their duty cycles) based on the relevance of their measurements, thus optimizing the operational behavior of the sensor nodes themselves, is based on three main principles:

(i) modeling the physical network as a graph to capture topological relationships between sensors;
(ii) adapting the transmission scheduling of sensors based on application-level values;
(iii) selecting gateway positions through graph centrality estimates that incorporate both structural and application-specific information.

We model the network as an undirected graph $\mathcal{G} = (N, E)$, where each node $i \in N$ represents a smart meter located at coordinates (x_i, y_i), and each edge $(i, j) \in E$ denotes a connection between sensors, such as pipes in WDSs. The network structure is encoded in the adjacency matrix $A = [a_{ij}]$, with $a_{ij} = 1$ if a connection exists between nodes i and j, and 0 otherwise.

To quantify the monitoring relevance of each node, we define a weight based on the deviation of the measured value p_i from the network average:

$$w_i = \left| p_i - \frac{1}{N} \sum_{j=1}^{N} p_j \right| \tag{1}$$

where p_i denotes the value of the parameter measured by each sensor i, and N represents the total number of smart meters present in the network.

In the considered scenario, we leverage the application layer data to dynamically adjust the transmission time of smart meters. Indeed, the Duty Cycle (DC) of a sensor refers to the proportion of time the sensor is actively measuring compared to the total time it is in operation. It is typically expressed as a percentage and indicates how frequently the sensor is active compared to when it is idle. The weight w_i is then used to assign a proportional DC to each node $DC_i = \alpha \cdot w_i$, where α is a dimensionless scaling factor taking into consideration network parameters and the fixed range of DC values. This adaptive scheduling increases the sampling resolution in areas with higher variability, resulting in a non-uniform traffic distribution across the network.

This adaptive DC allocation has direct implications for network planning, as it requires the GW deployment to align with the resulting traffic patterns. Areas with smart meters configured with lower DC values and therefore transmitting more frequently will generate higher local traffic. To handle this increased load and reduce the risk of collisions in the LoRaWAN network, a higher density of gateways or a more strategic placement approach is needed in these zones. Although LoRaWAN provides long-range coverage, its performance degrades under high traffic due to increased collisions and longer time-on-air, especially when high Spreading Factor (SF) values are used [33]. Deploying additional gateways or optimizing their placement reduces the distance between devices and GWs, allowing for lower SFs and improving the capture effect, thus enhancing network reliability [34].

To account for both topological and application-level priorities in the GW deployment, we define an Application Weighted Centrality (AWC) metric:

$$AWC_i = \frac{\sum_{j=1}^{N} g(w_i \cdot a_{ij})}{\sum_{j=1}^{N} g(w_j)} \tag{2}$$

where $g(\cdot)$ is a normalization or smoothing function. Higher AWC scores indicate nodes that are both topologically central and connected to sensors with high application relevance. Gateway locations are selected by ranking nodes according to their AWC_i score and choosing the top M nodes that satisfy three key constraints: full sensor coverage, a Data Extraction Rate (DER) above a threshold τ, and a minimum spatial separation $d_{\min}$ between selected gateways to ensure efficient reuse of radio resources. Our complete procedure is summarized in Algorithm 1, which integrates all key steps: network setup, graph construction, score computations, adaptive duty cycle evaluation, and final gateway selection.

It is worth noting that while the gateway selection process (Algorithm 1) relies on a ranking-based procedure, it operates as a greedy heuristic rather than a strict global optimization. Specifically, selecting the top M nodes based on their AWC score does not inherently guarantee global feasibility for all constraints. Instead, the algorithm iteratively traverses the ranked list of candidates, validating and enforcing the coverage, minimum DER, and spatial reuse distance ($d_{\min}$) constraints at each step. In addition, the DER constraint implicitly captures traffic-related effects that arise in massive IoT deployments. Under moderate traffic conditions (e.g., around 30 packets per hour per device), gateway performance may be affected by channel contention and packet queuing due to multiple devices accessing the medium. By verifying the minimum DER requirement during the selection process, the algorithm avoids gateway configurations that would lead to excessive load and packet accumulation, thus indirectly accounting for traffic-induced performance degradation. By adopting this heuristic framework, the proposed method provides a highly scalable and computationally efficient solution suitable for massive IoT scenarios, effectively balancing application-aware requirements with network topological and traffic-related constraints.

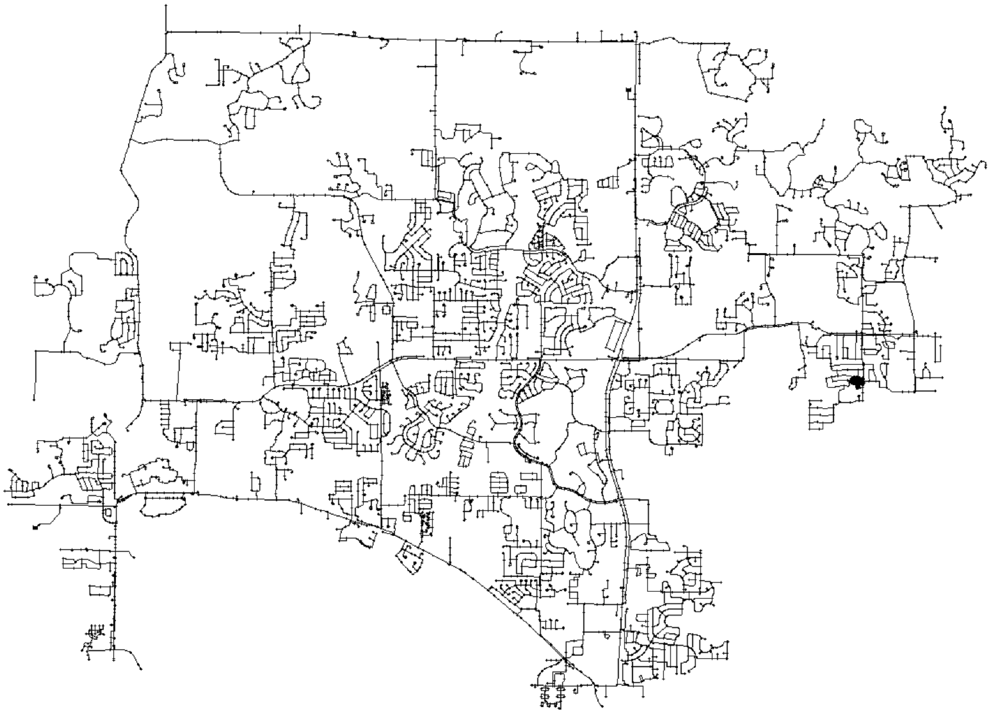

Fig. 2. Realistic Massive-IoT WDS used for performance evaluation.

4. Focused study and evaluation on massive IoT network

In this section, we present a case study on WDSs to demonstrate the importance of optimal GW deployment. Although IoT sensor placement has gained growing interest for optimal monitoring [35,36] and leak detection [37], the GW deployment is still poorly investigated and is typically limited to the network perspective [25]. However, optimal GW deployment is fundamental for several reasons: first, suboptimal deployment increases the risk of packet collisions and data loss; second, it directly impacts the number of required GWs, with significant implications for energy consumption and overall system efficiency.

This study proposes an innovative GW deployment strategy based on graph theory, designed to minimize the number of GWs while ensuring adequate network coverage. Although the method is demonstrated in the context of WDSs, it is not restricted to this domain. The approach can be generalized to other massive IoT networks that leverage high-level application information to guide gateway placement, particularly in scenarios where measurement time resolutions vary across the network and are not uniformly distributed.

4.1. Large WDS scenario definition

For proof-of-concept validation, smart meter deployment is derived from a real WDS. Fig. 2 shows the realistic Massive-IoT WDS used to evaluate the proposed AWC approach. Specifically, the WDS comprises a network of interconnected links and nodes, in which links model pipes, pumps, and valves, whereas nodes represent junctions, tanks, and reservoirs. The network model is derived from a real-world infrastructure available in the OpenWater Analytics public repository [38]. In the considered scenario, each node and pipe is equipped with an IoT sensing device based on LoRaWAN technology (e.g., flow meters and pressure sensors), enabling large-scale monitoring in a Massive-IoT setting. Each node can be configured with an hourly demand pattern, simulating user consumption over time, while the pipes convey water based on the hydraulic head difference between nodes. Thanks to the WNTR library integrated within SWI-FEED, the hydraulic simulation allows analyzing the temporal evolution of key hydraulic quantities, such as flow rate, pressure, water velocity, and volumetric flow, across the entire network, which in our case consists of $N = 4419$ junctions, $M = 3$ reservoirs, and $P = 5066$ pipes.

LoRaWAN simulations, incorporating the Adaptive Data Rate (ADR) algorithm for dynamic SF adjustment [39], are used to evaluate the performance of the gateway placement method (detailed in Section 3). This method leverages graph theory and application data to optimize Duty Cycles (DC) and gateway selection to analyze for Data Extraction Rate (DER) and energy consumption of the network. Fig. 3 shows the deployment of GW distributions for the considered network topology. In particular, the strategy of GW distribution takes into account the centrality of nodes weighted by both their location and the pressure value within each node, i.e., by contextual features as explained in the previous subsection. Moreover, the figure illustrates the pressure experienced by the node

Algorithm 1 Application Weighted Centrality (AWC) for GW placement.

Input: Set of nodes N with coordinates (x_i, y_i), measurements p_i, constraints on DER and reuse distance
Output: Set of selected GW locations $\mathcal{G}^* \subseteq N_{all}$

Step 1: Network Setup Import sensor positions from application model
$N \subseteq N_{all}$ from application model with $(x_i, y_i) \in \mathbb{R}^2$
Set coverage (cov(g)), performance (DER), and reuse distance $d_{\min}$ requirements
Ensure:
- Coverage: $\forall s \in N, \exists g \in \mathcal{G}^*$ s.t. $s \in \mathrm{Cov}(g)$
- DER $\geq \tau$
- $\|g_i - g_j\| \geq d_{\min}, \quad \forall g_i, g_j \in \mathcal{G}^*$

Step 2: Graph Construction Build graph from WDS topology
$\mathcal{G} = (N, E)$ from network topology
$A = [a_{ij}]$ where $a_{ij} = 1$ if $(i, j) \in E$, else 0

Step 3: Compute Scores Estimate node relevance using topology and data
for $i = 1$ to $|N|$ **do**
Compute deviation-based weight:
$w_i = \left|p_i - \frac{1}{N}\sum_{j=1}^{N} p_j\right|$
Application Weighted Centrality:
$$AWC_i = \frac{\sum_{j=1}^{N} g(w_i \cdot a_{ij})}{\sum_{j=1}^{N} g(w_j)}$$
end for

Step 4: Adaptive Duty Cycle Computation Derive the DC from the deviation-based weight through the input parameter α:
$DC_i = \alpha \cdot w_i$

Step 5: Gateway Selection Iteratively select top M locations verifying constraints
Rank N by AWC_i descending
$\mathcal{G}^* \leftarrow$ top M nodes satisfying constraints in Step 2
return $\mathcal{G}^*$

in the network. This is depicted using a color scale, with each color corresponding to a different pressure level as indicated by the color bar.

We validate the proposed methodology by analyzing the overall network performance in terms of DER and energy consumption. We consider the following different load conditions:

(i) *Static DC:* all smart meters are set to transmit at an identical DC. Under these circumstances, the data transmitted by each smart meter results in an average interval time of 120 seconds. Given a payload size of 50 bytes and a time on air ranging between 0.12 and 2.8 seconds, which corresponds to data packets sent using SF7 and SF12, respectively, and a final rate of 30 packets/hour.

(ii) *Adaptive DC:* the smart meter experiences a transmission interval time that varies between 120 and 420 seconds, as determined by the aforementioned formula for w_i computation, obtaining a different transmission rate in the range from 8.6 to 30 packets/hour. It's important to note that the packet transmission rate does not precisely match the effectiveness of sensor measurements. This discrepancy is due to the potential implementation of a buffer that collects a certain number of measurements and then pushes the entire window of data in a single packet transmission.

(iii) *Optimized devices activation:* to enhance efficiency in sensor network deployments, the optimized devices activation condition leverages findings from GraphSmart (GS) [35] to reduce the number of active sensors, enhancing savings in both energy consumption and network traffic, preserving useful information for the data analysis. In our specific experiments, we obtained a reduction of 50% of the active devices. In order to highlight the effect of AWC we compare the optimized gateways placement obtained with a fixed grid gateway positioning.

4.2. Experimental results

This subsection focuses on assessing strategies for GW deployment in alignment with the WDS pressure and node positions. Before implementing our IoT gateway deployment strategy, we conducted a thorough analysis of pressure variations in the nodes of the water distribution network. Fig. 4 illustrates the pressure evolution for the representative node with ID 400, observed over approximately 10 days (240 hours). The pressure profile exhibits regular fluctuations of around $2.5 - 3\,m$, with peaks occurring during nighttime or periods of low demand, when water consumption is reduced and the network pressure recovers, and minima in the early evening

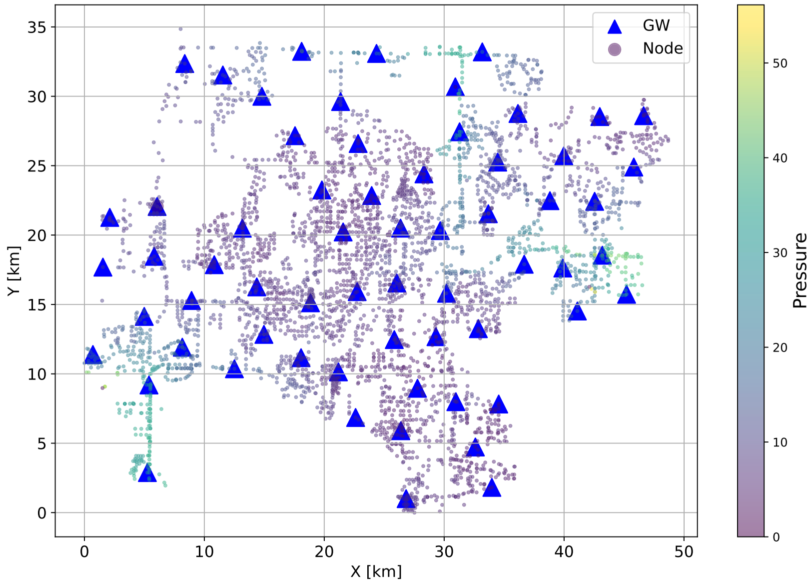

Fig. 3. Massive IoT topology used for the evaluation of the proposed approach and the respective GW deployment with the AWC approach.

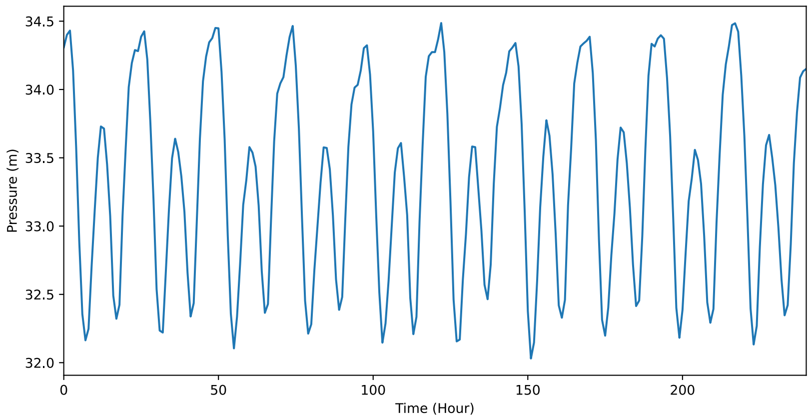

Fig. 4. Pressure evolution at the node (ID 400) over 10 days.

and early morning ($\approx 32.3\ m$) due to increased consumption and higher head losses along the pipelines. These findings confirm that node pressure is strongly influenced by user consumption patterns, as widely reported in the literature [30–32,40]. Consequently, the observed pressure trends confirm the feasibility and suitability of our algorithm for WDSs, making it an effective tool for optimizing network management through IoT devices. Fig. 5 presents a comparative analysis of the Data Extraction Rate (DER) under various LoRa gateway deployment strategies and device Duty Cycle (DC) configurations, plotted against an increasing number of gateways (No. of GWs). The lowest performance result is obtained with *Grid Static DC* configuration (green dash-dotted line, cross marker). This scenario, representing a uniform grid gateway topology with a constant DC for all network devices, yields a DER of approximately 37% with 63 gateways, incrementally rising to around 64% with 117 gateways. A first improvement is achieved by introducing *Grid Adapt DC* (green dashed line, diamond marker) to increase the DER by approximately 18 percentage points above the Grid Static DC at 63 gateways (from 37% to 55%). The deployment of gateways using the AWC technique provides a more substantial performance improvement (*AWC Static DC*, blue dash-dotted line, circle marker), where DER at 63 gateways is approximately 56%, significantly outperforming both grid-based scenarios. Further performance enhancement is realized by implementing an adaptive DC within the AWC framework (*AWC Adapt DC*, blue dashed line, inverted triangle marker). This configuration shows a DER of approximately 71% with 63 gateways. This is an increase of about 15 percentage points over the AWC Static DC and a substantial 34 percentage points over the baseline Grid Static DC at the same gateway count. The adaptive DC mechanism, which assigns variable DCs potentially based on sensor-read values to prioritize devices with more critical data, clearly demonstrates its efficacy here. Finally, the integration of the GraphSmart (GS) algorithm [35] leads to the highest observed DER values. Employing GS in the AWC Static DC configuration (*AWC Static DC GS*, red solid line, triangle marker) also boosts performance, about 65% DER with 63 gateways and up to about 88% with 117 gateways. The optimum configuration, *AWC Adapt DC GS* (red solid line, square marker), applies all the sophisticated

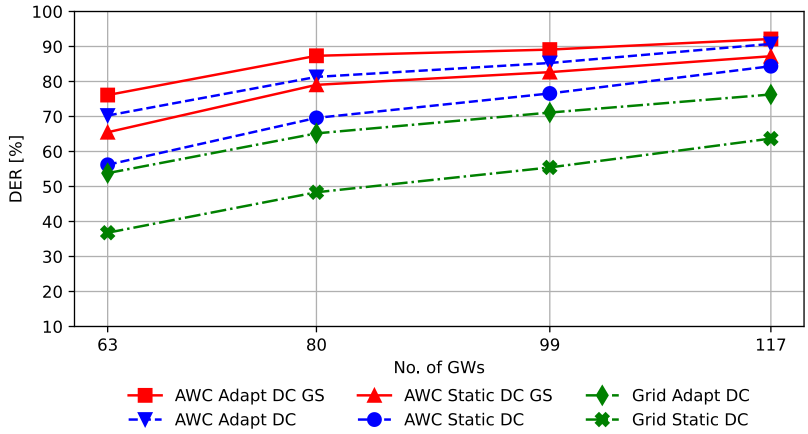

Fig. 5. Comparison of Data Extraction Rate with AWC deployment, in static and adaptive DC traffic scenarios.

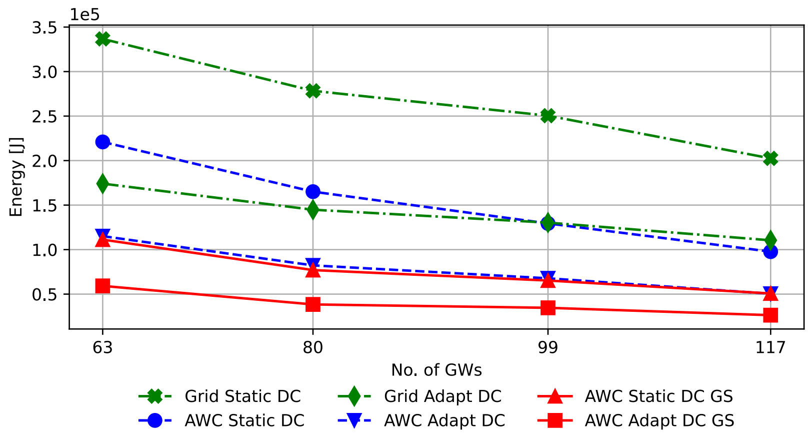

Fig. 6. Daily network energy consumption versus the number of installed GWs in both AWC and grid deployments when static and adaptive DC is used.

methods. It achieves a DER close to 76% even with the fewest gateways (63), representing an approximate 5 percentage point gain over the AWC Adapt DC (without GS) and a remarkable 39 percentage point improvement over the initial Grid Static DC baseline. This configuration consistently delivers the highest DER, exceeding 90% with 99 or more gateways.

The evaluation of daily energy consumption for the considered network and scenarios is depicted in Fig. 6, highlighting the benefits of utilizing the proposed AWC, adaptive DC and GS techniques. This combination significantly reduces the energy expended by nodes during data transmissions. For instance, with the maximum deployment of 117 GWs, static DC deployment with grid gateway topology consumes approximately 200 kJ, whereas AWC deployment with adaptive DC allocation can achieve a reduction to around 50 kJ. If we also consider the adoption of GS, the energy consumption reaches less than 45 kJ. Overall, a reduction is achieved up to 77% in daily network energy consumption when comparing one of the proposed solutions, such as AWC Adapt DC GS (red curve with square markers in Fig. 6), with the conventional GW deployment with grid topology (green dotted curve with "×" indicators), highlighting the effectiveness of the proposed joint optimisation strategy in reducing transmission-related energy expenditure. As validation of the discussed insights, the results provided indicate that although the coverage area of the LoRaWAN GW is in the order of 10 km, the actual number of deployed GWs is also influenced by the current traffic originating from the devices. This is clearly illustrated in the figures, where there's a noticeable trend of decreasing energy consumption and a concurrent increase in the DER. This is primarily because, as the density of GWs escalates, the ADR assigns lower SF values to the end devices. Consequently, determining the optimal number of GWs should take into account these two factors, in addition to the effective path loss experienced by the devices.

It is interesting to note that the analysis performed in terms of both DER and Energy also reveals that satisfactory results can be achieved with just 80 gateways. This significantly reduces the network complexity, with 30% of less gateway usage.

To further demonstrate the physical effectiveness of the proposed strategy, we evaluated the network coverage in terms of out-of-range devices (i.e., nodes experiencing a 0% reception rate). Table 2 compares the number of isolated nodes when using a standard Grid placement versus the proposed AWC strategy across the 4419 total nodes.

The AWC approach demonstrates a clear advantage in moderate and realistic deployment scenarios. For instance, with 48 and 63 GWs, the AWC strategy nearly halves the number of disconnected devices compared to the Grid deployment. Notably, an optimal

Table 2
Comparison of out-of-range nodes between Grid and AWC deployment strategies across a total of 4419 nodes.

No. of GWs	Grid Out-of-Range	% (Grid)	AWC Out-of-Range	% (AWC)
48	885	20.03%	482	10.91%
63	478	10.82%	203	4.59%
80	147	3.33%	123	2.78%
99	56	1.27%	15	0.34%
117	10	0.23%	42	0.95%

trade-off is achieved at 99 GWs, where the AWC strategy ensures near-total coverage (only 15 isolated nodes, or 0.34%) by intelligently clustering gateways in areas with higher data variability and topological importance.

While a massive over-provisioning of gateways (e.g., 117 GWs) allows the purely geometric Grid approach to slightly outperform AWC in terms of raw physical coverage (0.23% vs 0.95% out-of-range nodes), this comes at the cost of deploying unnecessary infrastructure. AWC prioritizes the coverage of high-value data sources and high-traffic areas, proving that intelligent, application-aware placement can achieve higher functional coverage with a smaller, more sustainable hardware footprint.

5. Discussion and broader applications

The results presented demonstrate the significant benefits of the Graph-Based AWC approach in optimizing LoRaWAN GW deployment for massive IoT, particularly within the context of WDSs. Beyond the specific case study considered, the approach exhibits a broader potential applicability across different domains where efficient data utilization and resource optimization represent key challenges. In *smart agriculture*, *application-aware* approaches optimize the collection and transmission of data from farm sensors that monitor soil conditions and crop health [41]. An optimal placement of LoRa gateways reduces interference and ensures timely responses, such as irrigation [42]. Strategically placed GWs offer key benefits such as *resource optimization*, helping to extend sensor battery life and reduce maintenance needs. They also enable *data-driven insights* by efficiently transmitting sensor data to the cloud, minimizing the need for manual monitoring and enhancing large-scale smart farming operations. Precision agriculture takes advantage of application-aware resource optimization for sensor networks [43]. Recognizing that different applications like soil monitoring or pest detection have varying data and energy needs, specific methodologies can be adopted that dynamically adapt network parameters to these specific requirements. By tailoring communication protocols and data processing to individual application profiles, resource utilization can be achieved, ensuring reliable data delivery, ultimately supporting the goals of sustainable and efficient smart farming practices [43]. In *smart cities*, IoT technologies optimize resource management and public services, with *application-aware* LoRaWAN GWs improving system efficiency and responsiveness. Smart cities generate a wide range of data streams from applications such as smart lighting, waste management, air quality monitoring, and traffic control [44]. GW traffic can be managed through intermediate edge or fog servers, prioritizing or rerouting urgent data, such as accident alerts, while scheduling routine updates like parking availability for later transmission [19].

The high efficiency achieved is intrinsically linked to the nature of WDS, where key application parameters such as pressure and flow have well-defined, quasi-periodic patterns that are strongly correlated with predictable user consumption behaviour [30,32]. This prior knowledge of application dynamics enables the adaptive duty cycle mechanism to effectively predict areas of high data variability and prioritise gateway coverage accordingly. However, this heavy reliance on predictable application behaviour is a fundamental limitation in terms of generalising the current implementation. In scenarios characterised by highly stochastic or rapidly changing data patterns (e.g., dynamic traffic monitoring in a smart city or urgent real-time industrial monitoring [45]), the static pre-computing of AWC scores based on an average model may be less effective. Furthermore, applying this methodology to new domains requires significant effort in modelling application-level data characteristics and understanding their temporal predictability. To further enhance the general applicability of the AWC approach and overcome its current limitations, future research should explore dynamic adaptation mechanisms, potentially integrating machine learning techniques such as time-series forecasting to account for short-term fluctuations in application parameters [30]. Additional efforts may investigate alternative weighting functions tailored to specific operational objectives, as well as extend the validation of the graph-based AWC framework to non-periodic smart city scenarios characterized by less predictable traffic patterns [45]. Furthermore, integrating physical and operational constraints, such as building layout and radio resource availability, into the selection algorithm would help improve the practical feasibility and real-world sustainability of the proposed methodology, ensuring that the theoretically optimal AWC configuration can be effectively translated into sustainable infrastructure planning.

6. Conclusion

Application-aware LoRaWAN gateway deployment offers significant advantages in massive IoT networks. This research demonstrates a methodology for application-aware LoRaWAN gateway deployment, leveraging graph theory and graph signal processing to address the critical challenges of sustainability and efficiency in massive IoT networks. The proposed approach, based on Application-Weighted Centrality (AWC), validated through a realistic Smart Water Management scenario, has demonstrated the optimization of gateway placement by strategically considering application-specific data traffic patterns. Moreover the exploitation of GraphSmart techniques allows to reduce the number of devices maintaining the quality of application monitoring and reducing the number of active devices. Our results highlight significant improvements in both energy efficiency, with reductions of up to 70% observed, and significant increase of Data Extraction Rate (DER). Beyond the specific context of WDS, the adaptability of the AWC model and the graph-based framework suggests broader applicability to various massive IoT deployment scenarios. This work contributes a valuable data-driven strategy for network planning, aligning infrastructure deployment with application needs for more sustainable and effective IoT ecosystems.

CRediT authorship contribution statement

Fabrizio Giuliano: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization; **Antonino Pagano:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation; **Domenico Garlisi:** Software, Resources, Project administration, Methodology, Formal analysis, Conceptualization; **Tiziana Cattai:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology; **Francesca Cuomo:** Supervision, Resources, Project administration, Funding acquisition.

Data availability

Data will be made available on request.

Declaration of competing interest

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

Antonino Pagano reports was provided by UNIVERSITA' DEGLI STUDI DI PALERMO and CNIT. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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