Minimal-Overlap Centrality for Multi-Gateway Designation in Real-Time TSCH Networks

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This article presents a novel centrality-driven gateway designation framework for the improved real-time performance of low-power wireless sensor networks (WSNs) at system design time. We target time-synchronized channel hopping (TSCH) WSNs with centralized network management and multiple gateways with the objective of enhancing traffic schedulability *by design*. To this aim, we propose a novel network centrality metric termed *minimal-overlap centrality* that characterizes the overall number of path overlaps between all the active flows in the network when a given node is selected as gateway. The metric is used as a gateway designation criterion to elect as a gateway the node leading to the minimal number of overlaps. The method is then extended to multiple gateways with the aid of the unsupervised learning method of *spectral clustering*. Concretely, after a given number of clusters are identified, we use the new metric at each cluster to designate as cluster gateway the node with the least overall number of overlaps. Extensive simulations with random topologies under centralized *earliest-deadline-first* (EDF) scheduling and *shortest-path* routing suggest our approach is dominant over traditional centrality metrics from social network analysis, namely, *eigenvector*, *closeness*, *betweenness*, and *degree*. Notably, our approach reduces by up to 40% the worst-case end-to-end deadline misses achieved by classical centrality-driven gateway designation methods.

CCS Concepts: • **Computer systems organization → Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

Additional Key Words and Phrases: Earliest-deadline-first (EDF), Gateway selection, Time-synchronized channel hopping (TSCH)

1 INTRODUCTION

Industrial wireless networks allow the development of a number of innovative applications, services, and systems (e.g. real-time monitoring) as one of the key enablers of the Industrial Internet of Things (IIoT). IIoT-driven systems supported by wireless technologies [20, 33] have been deployed ubiquitously due to many advantages, but mostly due to their superior flexibility and low infrastructure cost when compared to their wired counterpart. Particularly, *real-time wireless sensor networks* (RT-WSNs), i.e. WSNs with explicit requirements on the timely delivery of data, have appeared more recently, enabling a number of *time-sensitive* IIoT applications in automation and data management, most commonly for the purposes of system-wide monitoring and process control [25].

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1539-9087/2023/7-ART $15.00
https://doi.org/10.1145/3610583

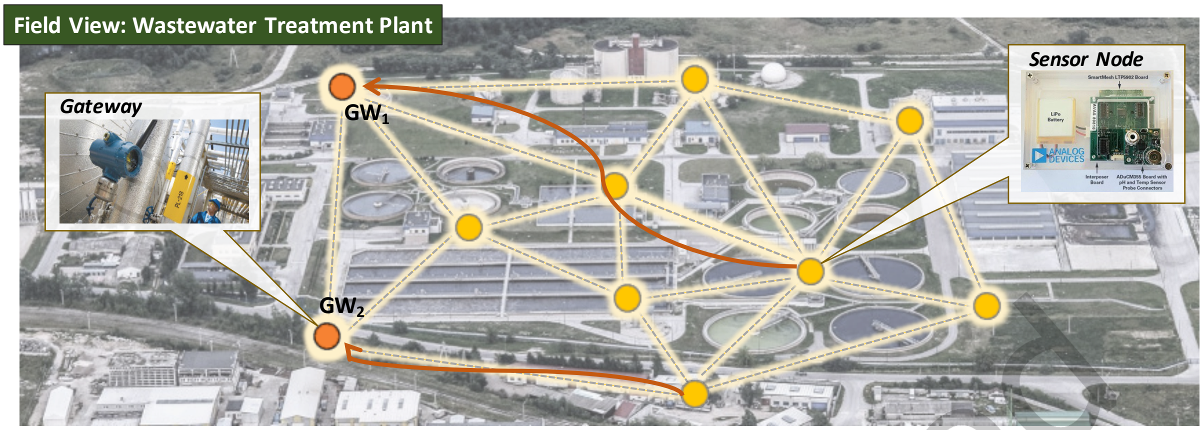


Fig. 1. A graphical representation for an RT-WSN at a wastewater treatment plant using several sensor nodes and two gateways, namely, GW_1 and GW_2. The orange lines represent data flow paths from the sensors toward the gateways.

Notably, their industrial scope has been broad, spanning from traditional oil and gas facilities [42] to the emerging additive manufacturing [41], automotive [36], health-care [11], and (even) smart marinas [2].

Typically, the primary RT-WSNs infrastructure is simple, consisting of a fixed set of field nodes (i.e, sensors and/or actuators) transmitting periodic and deadline-constrained sensory data flows toward one or multiple gateways (see Fig. 1). Gateways or managers are special nodes able to schedule the traffic and serve as bridges between field devices and the Internet or an intranet. In typical industrial settings, managers handle small wireless networks ranging from 10 to 100 nodes, while requiring wire-like reliability, i.e., 99.9% or better [44]. However, achieving high-performing RT-WSN is challenging due to the distinctive harsh (wireless) industrial conditions (e.g. due to external interference or fading) and dynamic multi-hop mesh topologies [37].

Proper physical, data-link, and network layer considerations are required to facilitate real-time communication, especially providing guarantees in terms of end-to-end (E2E) delays and reliability. Despite its limited bandwidth, Medium Access Control (MAC) layers such as Time-Synchronized Channel Hopping (TSCH) [10] offer salient features in this direction, both to achieve predictable and highly-reliable operation. TSCH is, in fact, one of the most popular standards for RT-WSNs, with plenty of literature dedicated to addressing major factors influencing *real-time* network performance [16, 25]. While research has been mostly devoted to scheduling and routing problems, other dimensions such as the proper selection or placement of the gateway node have recently emerged as important due to their not negligible impact on traffic *schedulability*, i.e. the network's ability to schedule packet transmissions within specific deadline constraints.

In this article, we target *judicious* RT-WSN gateway *designation* for improved *real-time* performance in terms of traffic schedulability. We claim that this proposition further stresses the relevance of this dimension in the design of RT-WSNs, complementing the more common approaches based on real-time scheduling [32] or routing [45]. While gateways in RT-WSNs are generally deployed in arbitrary positions (see e.g., [43]), gateways can also be *designated* among the existing nodes [47], i.e. elected without adding new ones, but being constrained by the actual nodes positions. In both situations, an arbitrary (random) or non-optimized gateway position can greatly influence the real-time network performance, e.g., in terms of E2E communication delays or schedulability, thus justifying the need for proper mechanisms to designate gateways[1].

This research is a follow-up of our recent study in [13] in which we first introduce the concept of *network centrality*[2] as an effective heuristic for gateway designation in RT-WSNs. Our prior work has shown that social network analysis (SNA) metrics are an appropriate criterion for gateway designation for remarkably increasing traffic schedulability *by design*. Despite the promising results, none of the *network centrality* metrics evaluated (eigenvector, closeness, betweenness, and degree) dominated over the other, nor achieved optimal *real-time* performance. A challenge we attempt to address herein.

Contributions. We present a novel *centrality-driven* single- and multi-gateway designation framework for RT-WSNs with improved real-time performance. We deal with alike foundational questions of the work in [13], but solve the gateway designation problem by proposing a new flow-informed metric termed *minimal-overlap centrality* based on the reduction of path node-overlaps in shortest path routing. This metric requires knowing the routing approach beforehand to compute the overall overlapping degree resulting from the encountering of all active flows in the network elements. The metric is inspired by the minimal-overlap routing protocol [14], which reduces path overlaps among flows using a greedy heuristic that weights links based on the flows' node-overlaps. By contrast, this work reduces the network global overlapping degree by judiciously choosing as gateway the node that *minimizes* the overall number of overlaps. While a schedulability-optimal choice could be made using enough computational power, we explore a less demanding approach that does not require fully assessing network schedulability to achieve optimal or near-optimal real-time performance.

We also extend the idea to multiple gateways with the aid of the unsupervised learning method of *spectral clustering* [29], as in [15]. Concretely, at each cluster, we use the *minimal-overlap centrality* to designate as gateway the node which produces the least overall number of overlaps. Note clustering is used here for gateway designation only, being orthogonal to traffic scheduling and routing that operate globally across the network.

To the best of our knowledge, this work represents the first extensive study of a centrality-driven single- and multi-gateway designation framework specifically designed to reduce end-to-end deadline misses in RT-WSNs. Without loss of generality, we consider RT-WSNs operating under the TSCH (time-synchronized channel hopping) mode of the IEEE802.15.4e standard, a popular medium access control (MAC) layer common to several WSN standards (e.g. WirelessHART, ISA100.11a, 6TiSCH, etc.) offering salient real-time features.

Organization. The remainder of this article is organized as follows. Section 2 discusses related work. Section 3 summarizes the system model, including the network, flow and performance models. Section 4 described the proposed framework. Section 5 reports and discusses extensive empirical results and validation of the proposed framework. Finally, Section 6 gives concluding remarks and future work directions.

2 RELATED WORK

Table 1 shows a non-exhaustive review of gateway designation methods based on their goal and underlying principle of operation. It highlights in bold those terms which are closely related to the approach proposed here, namely, *network centrality*, *clustering*, and *schedulability*. In the following, we discuss in more detail how these ideas appear in prior work for both the single and multiple gateway designation categories.

Single-gateway designation. Prior work has already addressed the problem of how to properly designate a node for the role of gateway, i.e. among the existing nodes in the infrastructure, to choose the one which is more

[1]Although we consistently use the term *gateway* to refer to nodes enabling seamless communication with external entities (e.g. a host application), the problem addressed here assumes the gateways also play the role of *sinks* (or even edge-computing nodes), thus used to centrally (and *timely*) gather data transmissions from sensors, e.g., for further processing or storage.
[2] a relative measure of the importance of the node according to its position in the network.

Table 1. Gateway Designation Methods for RT-WSNs

Category	Goal	Concept	Reference
Single Gateway Designation	Timeliness	**Network Centrality**	[47]
	Energy Efficiency	Load Balancing	[34]
	System Throughput	Flowchart	[24]
Multi-Gateway Designation	Latency	Optimization	[8]
	Schedulability	**Clustering**	[9]
	Reliability	Routing	[48]

suitable according to a given key performance indicator. These works have often targeted specific metrics such as energy efficiency [34], timeliness [47], etc., or composite trade-offs [24], e.g. with the goal of reducing load and interference[4]. Moreover, a great part of related work has considered optimization-based problems [35], yet often relying on positions or distance-based inputs to find a suitable solution. This, however, is typically deemed as a different problem called gateway *placement*. Recently, we have proposed a (position-agnostic) *network centrality*-driven gateway designation method for real-time WSNs [13] with improved performance in terms of *schedulability*. The concept of network centrality has been applied in previous research on wireless networks to solve several problems, namely, for information dissemination in Delay-Tolerant Networks (DTN) [27] or for reducing traffic congestion in Information-Centric Networking (ICN) [7] to improve, for instance, caching and content delivery. Centrality has also been applied in wireless networks for network modeling or protocol design, namely for routing [30], topology control [40], security [26], among others. Nevertheless, the notion of centrality for gateway designation has been considered in few works only (e.g. [47]). Specifically, Xing et al. [47] proposed a method for gateway designation for improving information timeliness, however, without specifically targeting *real-time* performance guarantees, e.g. schedulability.

Moreover, although prior centrality-based gateway designation methods have been shown to improve the real-time performance of WSNs, optimal performance was far from being reached. In short, knowledge of the routing approach allows computing the overall overlapping degree resulting from the encountering of all active flows in the network elements and the node that minimizes the overall number of overlaps is selected as gateway.

Multi-gateway designation. Previous works in the literature demonstrated that using multiple sinks or gateways increases parallelization of flows and improves traffic timeliness in WSNs (e.g. [21, 38]). Similarly, several studies (e.g. [8][9][48]) in the field have focused on the problem of selecting a subset of nodes as gateways for a WSN. Chen et al. [8], for example, have shown that the minimum gateway designation problem with latency and reliability guarantees in a TSCH network is NP-hard. The authors proposed a method to address this problem that jointly considers RPL routing and DeTAS [1] scheduling, but they didn't target schedulability. Dobslaw et al. [9] explicitly addressed *schedulability* as a QoS constraint by proposing a complete cross-layer configuration for industrial WSN that considers, among others, the possibility of adding multiple sinks. This work - as many others in related literature - relied on actual node positions for finding an appropriate gateway or sink designation/placement, in this case, based on the popular k-means clustering. This approach, however, is not applicable when physical positions are unknown, and when the only information available is the logical network topology; as in our case. Other studies have addressed alike problems (e.g. [22, 28]), either from the perspective of clustering and/or from the viewpoint of multi-sink placement, targeting common delay or reliability issues; yet, often ignoring the cornerstone aspect of real-time performance, i.e. *schedulability*, and/or assuming a match among physical and logical topologies. To tackle these downsides, our recent work in [15] provided a novel combination of network centrality and spectral clustering [29] - which rely only on topology in the form of an adjacency matrix - to designate multiple gateways in WSNs, yet offering an improvement over a random benchmark.

Novelty. To the best of our knowledge, this is the first position-agnostic framework for single- and multi-gateway designation specifically designed to enhance real-time performance in WSNs. We contribute with a new metric termed *minimal-overlap* centrality able to reduce the overall number of path overlaps in the network, which in turn impact positively on traffic schedulability. We then built upon the work in [15] to extend the minimal-overlap insight to multiple gateways by combining our new metric with spectral clustering [29]. We show by extensive simulations that with this combined approach our metric is able to outperform classic centrality metrics showing up to $\sim 40\%$ better traffic schedulability under particular configurations, and up to about $\sim 200\%$ more schedulable network flows than when considering a worst-case node selection.

3 SYSTEM MODEL

3.1 Network Model

The wireless sensor network is abstracted as an undirected graph $G = (V, E)$ where V is the set of vertices or nodes and E is the set of edges or links between those nodes. The order of the graph G is denoted as $N = |V|$, of which a set of $N - k$ nodes act as field nodes (e.g. sensors) while the rest of k nodes are designated as gateways. All nodes can perform the sensing, relaying or gateway functions, are provided with adequate power sources, and are connected wirelessly forming a wireless mesh network (see Fig. 1). We then assume full knowledge of the network topology (i.e. the graph G) in the form of an adjacency matrix representing binary connectivity with lossless links. Topology tracking can be assumed as a native in-built centralized service that can be further implemented, e.g., as in [3].

Multiple access is governed using TSCH protocol which uses fixed-size TDMA slots combined with multi-channel hopping. TSCH allows concurrent transmissions over up to $m = 16$ different radio-frequency channels with global synchronization. A time slot interval, here $t_s = 10$ ms, allows the transmission of a single packet and receiving the corresponding acknowledgment. All packet transmissions are considered centrally managed using a global earliest-deadline-first (EDF) scheduling [3] policy and a (hop-count) shortest-path routing algorithm.

3.2 Real-Time Flow Model

We consider a subset of $n \leq N - k$ field nodes as sensor nodes, thus required to transmit periodically their sensing data toward any of the k designated gateways (destinations). These messages need to reach their corresponding gateways before specific timing constraints, i.e. deadlines. We denote as $F = \{f_1, f_2, \dots, f_n\}$ the set n of *real-time flows* potentially transmitting an infinite number of deadline-constrained messages, periodically. Each of the n flows is characterized by a 4-parameter tuple (C_i, D_i, T_i, ϕ_i), where C_i represents the transmission time between the source node s_i and any of the k gateway destinations. T_i is the transmission period, D_i is the (relative) deadline, and ϕ_i is the multi-hop routing path. The γ^{th} transmission of each periodic flow f_i is released at time $r_{i,\gamma}$ such that $T_i = r_{i,\gamma+1} - r_{i,\gamma}$. Then, according to the EDF scheduling policy, each of these flow instances $f_{i,\gamma}$ is constrained to reach the gateway before its absolute deadline $[d_{i,\gamma} = r_{i,\gamma} + D_i]$.

3.3 Performance Model

We consider the schedulability assessment framework in [17] to evaluate the real-time performance of our TSCH-based network under global EDF. The method is a state-of-the-art supply/demand-based schedulability test leveraging the concept of *forced-forward demand-bound function* (FF-DBF) [5] from multiprocessor scheduling theory. Essentially, this method evaluates if the *supply-bound function* (SBF), here the minimal transmission

[3]We assume both routing and scheduling are always computed offline, thus do not generate further network traffic during normal operation.

capacity offered by an RT-WSN with m channels, is equal or larger than the upper-bound of the FF-DBF network demand when adapted to WSNs (FF-DBF-WSN) [18].

Formally, (1) presents the traffic schedulability test for RT-WSNs, where $\text{sbf}(\ell)$ is such that satisfies the conditions in (2), and the FF-DBF-WSN is defined in (3).

$$\text{FF-DBF-WSN}(\ell) \leq \text{sbf}(\ell),\ \forall \ell \geq 0. \tag{1}$$

$$\text{sbf}(0) = 0 \wedge \text{sbf}(\ell + h) - \text{sbf}(\ell) \leq m \times h, \forall \ell, h \geq 0. \tag{2}$$

$$\text{FF-DBF-WSN}(\ell) = \underbrace{\frac{1}{m}\sum_{i=1}^{n} \text{FF-DBF}(f_i, \ell)}_{\text{CHANNEL CONTENTION}} + \underbrace{\sum_{i,j=1}^{n}\left(\Delta_{i,j} \cdot \max\left\{\left\lceil \frac{\ell}{T_i} \right\rceil, \left\lceil \frac{\ell}{T_j} \right\rceil\right\}\right)}_{\text{TRANSMISSION CONFLICTS}} \tag{3}$$

Note that the expression for FF-DBF-WSN is composed by two terms, namely, *i*) **channel contention** and *ii*) **transmission conflicts**. The former – in the left parcel of (3) — represents the mutual exclusive condition for allocating concurrent transmissions on multiple channels, equivalent to the FF-DBF expression for multiprocessors scheduling [5]. The latter – in the right parcel of (3) – models the delay contribution due to multiple flows encountering at a common half-duplex node. Eq. (4) defines $\Delta_{i,j}$ as a delay factor representing the node-path overlapping between any pair of flows f_i and $f_j \in F$ (with $i \neq j$), as in [46].

$$\Delta_{i,j} = \sum_{\alpha=1}^{\delta(ij)} Len_{\alpha}(ij) - \sum_{\beta=1}^{\delta'(ij)} (Len_{\beta}(ij) - 3) \tag{4}$$

where $\delta(ij)$[4] indicates the total number of overlaps between the flows f_i and f_j of which $\delta'(ij)$ are the ones larger than 3. The length of the α^{th} and β^{th} path overlaps between f_i and f_j are termed $Len_{\alpha}(ij)$ and $Len_{\beta}(ij)$, respectively, with $\alpha \in [1, \delta(ij)]$ and $\beta \in [1, \delta'(ij)]$. Note that this expression considers the fact that after 3 hops slots can be reused, not causing further transmission conflicts.

Table 2 summarizes the main symbols of the performance model.

Table 2. Table of Performance Model Symbols

Symbol	Definition
FF-DBF-WSN	Forced-forward demand-bound function for WSNs
SBF	Supply bound function
ℓ	Length of the interval of evaluation
Δ_{ij}	Delay factor between f_i and f_j
$\delta(ij)$	No. of overlaps between f_i and f_j
$\delta'(ij)$	No. of $\delta(ij)$ larger than 3
m	No. of channels
h	A scalar

[4]Note that $\delta(ij)$ is trivially calculated by counting the number of nodes that belong to the path of f_i and to the path of f_j at the same time.

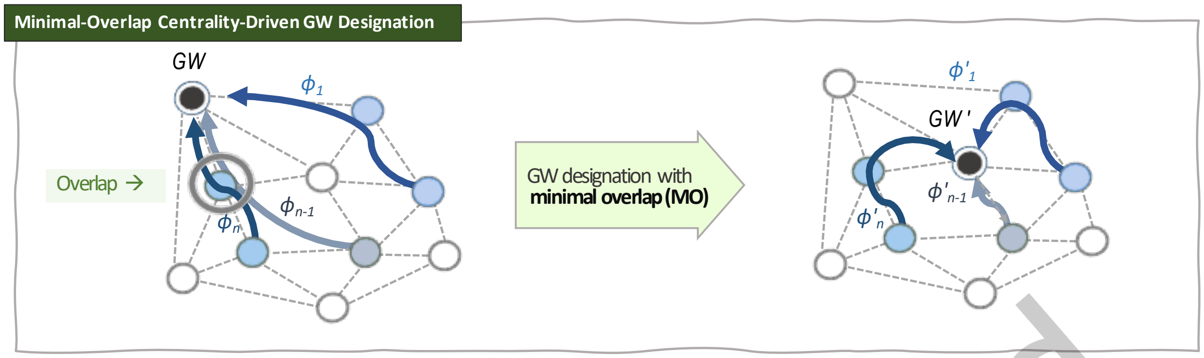


Fig. 2. A graphical representation of the minimal-overlap centrality-driven single-gateway designation strategy.

4 MINIMAL-OVERLAP NETWORK CENTRALITY FOR GATEWAY DESIGNATION IN RT-WSNS

Given the network, flow and performance models presented in Section 3, we consider the problem of how to *judiciously* designate one or multiple nodes as gateways for improved WSN traffic schedulability. In this direction, and resorting to the notion of *network centrality*, we propose a new metric that characterizes the relationship between gateway designation and node-path overlaps. We recall that our framework is intended to be used at system design time, assuming full knowledge of the network topology (graph) in the form of an adjacency matrix. The proposed metric is then used to designate as gateway the node with the highest centrality score. Similarly to [15], we also extend the framework to multiple gateways with the aid of the unsupervised learning method of *spectral clustering*. Classical network centrality metrics are considered for benchmarking purposes.

4.1 Minimal-Overlap Network Centrality

In the following, we address the single-gateway designation problem illustrated in Fig. 2 by proposing a new metric termed *minimal-overlap* (MO) network centrality. This metric is built upon the computation of the overall *path overlapping* resulting from the superposition of all flow routes in the network when directed to a given node $v_q \in V$. The metric represents the relative importance (centrality) of the node v_q w.r.t. the other nodes in the network in terms of node-path overlaps. A higher score indicates a higher overlapping degree at that node. Formally, the MO centrality metric is presented in (5).

$$MO(v_q) = \frac{1}{\sum_{i,j=1 \wedge i \neq j}^{n} \Delta_{i,j}^{q} + 1} \tag{5}$$

where the factor $\Delta_{i,j}^{q}$ is the node-path overlap contribution from flows f_i and f_j when their routes ϕ_i and ϕ_j are directed toward node v_q, and n is the number of flows in the set F. Note that we consider a subset of $n < N$ nodes are message sources (i.e. sensor nodes) transmitting periodic data toward a single gateway. The rest of $N - n - 1$ act as relays only. Without loss of generality, we also assume all the routes are computed using a hop-count-based *shortest-path* algorithm (e.g. Dijkstra, as in [19]).

4.2 Classical Network Centrality Metrics

For comparison, we assess four of the most common network centrality metrics in network science, namely, i) *eigenvector*, ii) *closeness*, iii) *betweenness* and iv) *degree*. These metrics are deemed as near optimally correlated for the purposes of benchmarking [39]. For completeness, we revisit their formal definitions as follows:

4.2.1 ***Eigenvector Centrality (EC).***
This metric quantifies how *influential* a specific node is w.r.t. others in a given network, a concept also known as *transitive influence*. This means a node with an EC score that is higher than another is connected to many other nodes which themselves also are highly scoring nodes. The score can be determined from the analysis of the principal eigenvector extracted from the adjacency matrix representing the network topology. Formally, the EC for a given node $v_q \in V$ can be expressed by (6):

$$EC(v_q) = \frac{1}{\lambda_{max}(A)} \cdot \sum_{j=1}^{N} a_{j,q} \cdot x_j \tag{6}$$

where $\lambda_{max}(A)$ is the largest eigenvalue of the adjacency matrix $A = [a_{j,q}]_N$, $a_{j,q}$ is the matrix element at row j and column q, x_j is the jth value of the eigenvector x of graph G, and N is number of nodes in the network.

4.2.2 ***Closeness Centrality (CC).***
This metric quantifies the level of *proximity* (or *closeness*) a specific node has w.r.t. the rest of nodes in the network. For a given node $v_q \in V$, CC is defined as the inverse of the sum of the geodesic distances from v_q to all the other nodes. Formally, the CC metric is presented in (7) as follows:

$$CC(v_q) = \frac{1}{\sum_{p \neq q} distance(v_p, v_q)} \tag{7}$$

where $distance(v_p, v_q)$ is the shortest path distance between the nodes v_p and v_q, with $p \neq q$, $\forall\, v_p \in V$. Note that, for simplicity, we consider in this work only hop-count-based shortest paths.

4.2.3 ***Betweenness Centrality (BC).***
This metric quantifies how many shortest-path routes pass through a specific node in the network. For a given node $v_q \in V$, the metric can be computed as the fraction between the number of shortest paths of any pair v_r and v_s ($\forall\, v_r, v_s \in V \wedge\ r \neq s \neq q$) passing through node v_q, and the total number of shortest paths in the network. Eq. (8) formally presents the BC metric:

$$BC(v_q) = \sum_{q \neq r} \frac{sp_{r,s}(v_q)}{sp_{r,s}} \tag{8}$$

where $sp_{r,s}$ is the number of shortest paths between any pair of nodes v_r and v_s, and $sp_{r,s}(v_q)$ is the number of those paths passing through node v_q.

4.2.4 ***Degree Centrality (DC).***
This metric quantifies the number of links, edges or one-hop neighbours a specific node has. For a given node $v_q \in V$, DC can be formally presented as in (9):

$$DC(v_q) = \frac{degree(v_q)}{N - 1} \tag{9}$$

where $degree(v_q)$ denotes the number of links or edges of v_q directly connected to other nodes and $N = |V|$.

4.3 Clustering-Aided Multi-Gateway Designation

We built upon the work in [15] to extend our minimal-overlap centrality-driven framework to multiple gateways. This prior work consists on first clustering the network with *spectral clustering* (SC)[29], which does not require knowledge of nodes positions, just adjacency, and then applying a *classical* centrality metric (EC, CC, BC or DC) to designate a gateway inside each cluster. This novel combination of *spectral clustering* and network centrality is applied to our framework in its original fashion, but using MO as the centrality instead. The end goal is to demonstrate MO outperforms classical centrality metrics also for the multi-gateway designation case.

4.3.1 ***Spectral Clustering***. Several clustering algorithms (e.g. survey in [49]) have been proposed in the literature. In this work, we resort to *Spectral Clustering (SC)* due to its superior performance as demonstrated in comparative studies (e.g. [31]) and since this algorithm family does not rely on the node's position but rather the graph structure. The relatively high time complexity [5] and the need to preset the number of clusters are two of the main drawbacks of this class of clustering methods. In short, SC resorts to the eigendecomposition of the graph Laplacian matrix (L) to find solutions based on the relaxation of graph cut problems. Specifically, we use the direct k-way SC algorithm proposed by Ng, Jordan and Weiss [29] to identify groups of widely separated nodes represented by k connected subgraphs (or clusters). The Ng-Jordan-Weiss (NJW) algorithm uses eigenvectors of the normalized Laplacian (L_{norm}) which can formally be obtained as follows:

$$L_{norm} = D^{-1/2} \cdot L \cdot D^{-1/2} \tag{10}$$

where D is the degree matrix, and $L = D - A$ is the Laplacian, with A being the adjacency matrix of the graph. Algorithm 1 presents a high-level pseudo-code for the NJW SC method.

Algorithm 1 NJW Spectral Clustering [29]

Input: a graph G and the target number of clusters k
Output: a partition of k clusters $\Pi = \{G_1, G_2, ..., G_k\}$

1: Find the first k eigenvectors u_1,u_2,...,u_k of L_{norm} and sort them in the columns of U'
2: Build matrix $U = [u_{ij}]_{n \times k}$ based on U' by normalizing each row of U' using $u_{ij} = u'_{ij} / \sqrt{\sum_k u'^2_{ik}}$
3: Let the i^{th} row of the matrix U represent node v_i from graph G
4: Apply k-means algorithm (or an equivalent method) to U and find a k-way partitioning $\Pi' = \{G'_1, ..., G'_n\}$
5: Form the final partition Π assigning every node v_i to the cluster G_ℓ, if the i^{th} row of U belongs to G'_ℓ in Π'

4.3.2 ***Multi-Gateway Designation***. As shown in Fig. 3, we leverage a centrality-driven multi-gateway designation framework resorting to the SC algorithm to partitioning the network. The approach requires computing a centrality metric *per cluster* after a number of k clusters has been identified. This means selecting as gateways of each cluster the node with the highest centrality score. Differently from the work in [15] – that uses *classical centrality* metrics –, here we use the MO centrality instead. MO centrality is used with the interpretation of being a *cluster centrality* metric. This requires considering each cluster G_ℓ as a subgraph of G which can be characterized by its cluster adjacency matrix A_ℓ and the number of nodes in the cluster N_ℓ, with $\sum_{l=1}^{k} N_\ell = N$. As in [15], we can trivially adapt the centrality expressions in Equations (5), (6), (7), (8) and (9) to reflect these formalities. We summarize these adaptations in Table 3[6] for completeness.

Particularly, for the MO centrality, we reformulate the expression in (5) for clusters as follows:

$$MO^\ell(v_q) = \frac{1}{\sum_{i,j=1 \wedge i \neq j}^{n_\ell} \Delta_{i,j}^{q} + 1} \tag{11}$$

[5]While solutions to further reduce the time complexity of SC exist in the literature (see e.g., [23]), the time complexity will be a potential issue only in the case of large datasets, e.g., with millions of samples or nodes. In contrast, we target here a typical industrial network setting with no more than 100 field devices per each controller or gateway [44]; thus resulting in a marginal increase of the processing time".

[6]*Notation*: $degree(v_q)$ denotes the number of edges of node v_q that are directly connected to any of the rest $N_\ell - 1$ nodes in G_ℓ; $sp_{r,s}$ is the number of shortest paths between any pair of cluster nodes v_r and v_s, and $sp_{r,s}(v_q)$ is the number of those paths passing through node v_q; $distance(v_p, v_q)$ is the (hop-count) shortest path distance between nodes v_p and v_q, with $p \neq q$, $\forall\ v_p \in V_\ell$, where V_ℓ is the set of vertices or nodes of cluster G_ℓ; x_j is the j-th value of the eigenvector x of the subgraph G_ℓ, and $\lambda_{max}(A_\ell)$ is the largest eigenvalue of the cluster's adjacency matrix $A_\ell = [a_{j,q}]_{N_\ell \times N_\ell}$, with $a_{j,q}$ being the matrix element at the row j and column q.

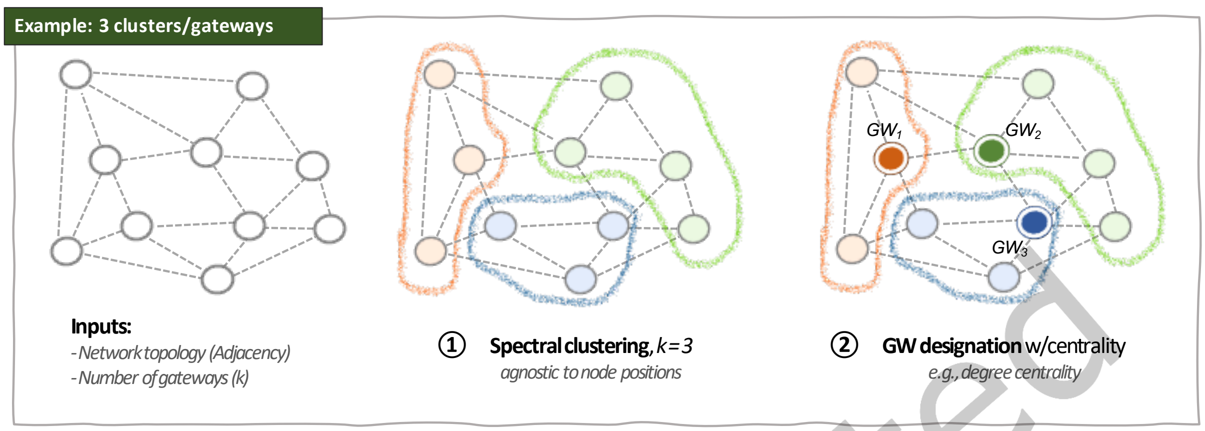


Fig. 3. A toy example of the centrality-driven multi-gateway designation framework in [15] for $k = 3$ clusters/gateways.

where $n_\ell < n$ is the number of sources which flows are directed to node $v_q \in G_\ell$. Note that v_q as well as all the n_ℓ sources belongs to the same cluster G_ℓ. $\mathrm{MO}^\ell(v_q)$ denotes the MO cluster centrality for a given node $v_q \in G_\ell$.

Table 3. Cluster Centrality Metrics.

Metric	**Definition**
Degree	$DC(v_q) = \frac{degree(v_q)}{N_\ell - 1}$
Betweenness	$BC(v_q) = \sum_{q \neq r} \frac{sp_{r,s}(v_q)}{sp_{r,s}}$
Closeness	$CC(v_q) = \frac{1}{\sum_{p \neq q} distance(v_p, v_q)}$
Eigenvector	$EC(v_q) = \frac{1}{\lambda_{max}(A_k)} \cdot \sum_{j=1}^{N_k} a_{j,q} \cdot x_j$

5 PERFORMANCE EVALUATION

We resort to the joint system model described in Section 3 to assess the performance of the single and multi-gateway designation methods presented in Section 4. We perform UUniFast-like [6][12] simulation with random task sets of random flows and random topologies, and then sample the output process for performance assessment. In the following subsection, we present the simulation setup for each of the components of the system model (i.e. wireless network, real-time flow and performance models). The main results are given and discussed in Section 5.2.

5.1 Simulation Setup

5.1.1 ***Wireless network.*** We consider 1000 network topologies built upon the synthetic generation of random graphs. Each graph is generated using a sparse uniformly distributed random matrix with a target (average) node density of $d = \{0.1, 0.5, 1.0\}$. The dimension of the random matrix is $N \times N$, where $N = 75$ is the total number of

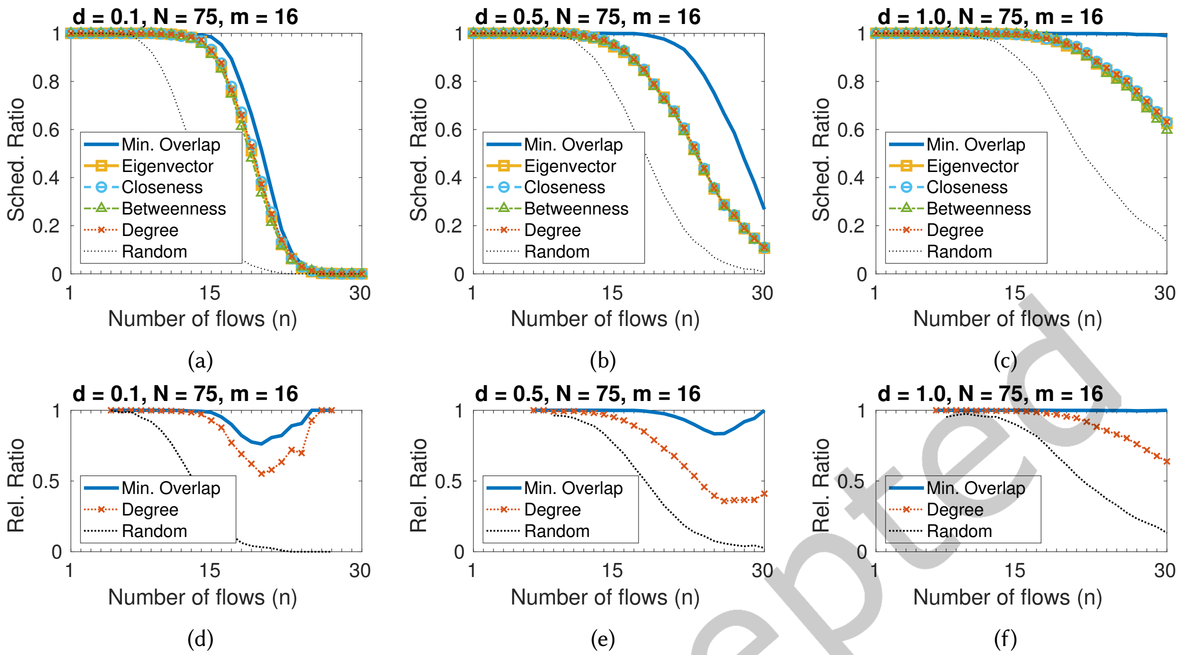


Fig. 4. **Top**: Schedulability ratio of 1000 random topologies for varying number of flows with target density 0.1 (*a*), 0.5 (*b*) and 1.0 (*c*) resorting to gateway designation methods based on i) classical network centrality metrics (e.g. eigenvector centrality) and ii) the proposed minimal-overlap network centrality. **Bottom:** the deviation in terms of schedulability from the best and worst possible gateway assignments. A random selection is included as a benchmark.

nodes in the network including $k = \{1, 2, 3\}$ gateways. All graphs represent TSCH-based WSNs in multi-channel operation with up to $m = 16$ channels and time slots of $ts = 10$ ms.

5.1.2 ***Real-time flows***. We consider a subset of $n \in [1, 30]$ nodes acting as *source nodes* while the rest are relays and/or gateways. Source nodes are selected randomly from the set of field nodes, i.e. excluding the k gateway(s). All flows are consistently generated according to the real-time model in Section 3, following a 4-tuple parameter (C_i, D_i, T_i, ϕ_i). Each of these flows is directed to only one gateway through its (hop-count-based) shortest path ϕ_i. C_i is computed by multiplying the time slot duration ts with the length of the routing path (i.e. the number of hops). T_i is randomly generated in the form 2^η, with $\eta \in \mathbb{N}$ in the range $[4, 7]$ as done in similar works with stricter (industrial) application requirements (e.g. [45]), thus leading to harmonic periods. This implies a super-frame duration (or hyper-period) of $H = 2^7$ slots, i.e. $H = 1280$ ms. All deadlines (D_i) are assumed to be equal to the respective flow periods, i.e. $D_i = Ti$, thus forming an implicit-deadline model.

5.1.3 ***Performance assessment***. We resort to the schedulability test in (1) to asses the real-time performance of the network, which assumes a global EDF scheduling policy. In all the cases, we consider an interval equal to the hyper-period ($\ell = H$) for the assessment. Concerning $\Delta_{i,j}$, network topologies are used to directly compute node-path overlaps. Recall clustering is used here only to assist the gateway designation process, being orthogonal to traffic scheduling and routing that operate globally across the network. This implies all experiments are performed allowing routing paths to use any link on the network, accounting for the eventual path overlaps in the computation of the schedulability.

5.2 Simulation Results

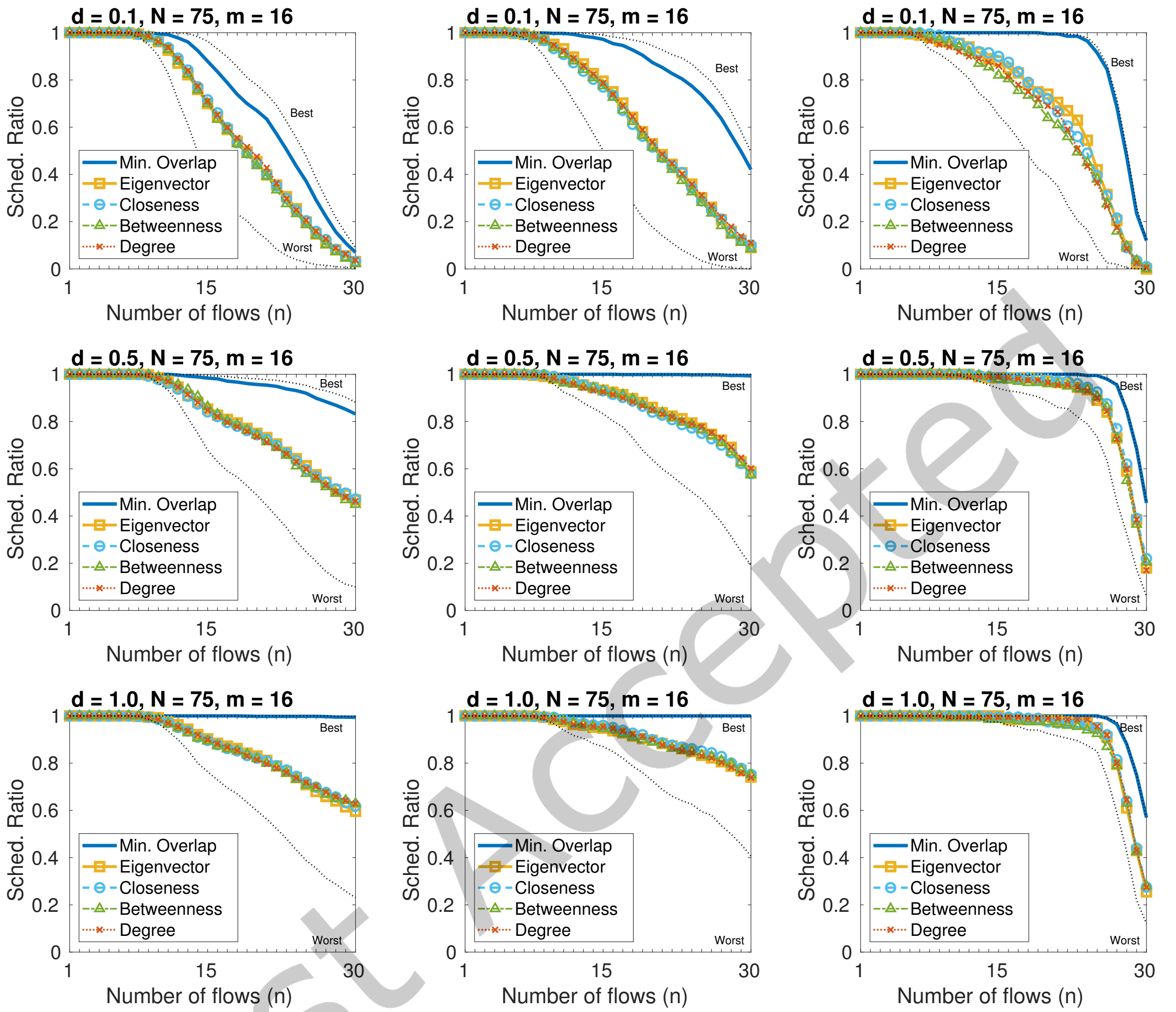
5.2.1 ***Schedulability Ratio, k=1***. Figs. 4a, 4b, 4c present schedulability ratio results for the case of single-gateway designation (i.e., $k = 1$) for varying number of network flows $n \in [1, 30]$ and different network densities $d = \{0.1, 0.5, 1.0\}$, respectively. Different centrality metrics were used as criterion to designate a single gateway. In specific, our minimal-overlap metric is compared against the classical eigenvector, closeness, betweenness and degree, as well as versus a random assignment. As expected, the schedulability ratio decreases for larger numbers of flows in all configurations due to the larger channel contention and transmission conflicts. Conversely, higher network density increases the number of potential paths between any given pair of nodes, thus favoring schedulability.

The results also show that the minimal-overlap gateway designation method achieves higher schedulability for all numbers of flows and densities when compared with a method based on classical centrality metrics. We argue this is caused by the minimal-overlap method ability's of decreasing, by design, the number of overlapping paths. This, in turn, allows for reducing transmission conflicts, thus improving the timely delivery of data messages. As expected, the proposed *minimal-overlap* method is also clearly superior to random selection, further demonstrating the significance of judicious gateway designation.

We also analyze how the proposed method deviates from the system's optimal gateway election in Figs. 4d, 4e, 4f. The metric *relative ratio* is defined as the ratio between the schedulability ratio of a given method to the schedulability ratio of the best and worst performing nodes in the network, with a value of 1 denoting best and 0 the worst performance. The results show the performance of the proposed method is only slightly below the best method, having the maximum degradation of ~24% for a density of 0.1 and 20 simultaneous flows. We highlight this degradation is lower for larger densities (e.g. $d = 0.5$) - becoming negligible for highly connected networks (e.g. $d = 1.0$) - since the overall overlapping degree decreases for increasing density, which was also confirmed by previous studies [14]. Additionally, these results reveal the performance improvements of the proposed method are, in general, able to increase for higher density and higher number of flows when compared with other centrality-based gateway designation methods or random gateway selection.

5.2.2 ***Schedulability Ratio, k>1***. Fig. 5 presents different schedulability ratio results for the *minimal-overlap* multi-gateway designation framework when compared to classical centrality-driven methods. Also, both the best and worst possible gateway selections at each cluster are presented (in dotted lines) for comparison. Overall, these results show that our minimal-overlap framework is always dominant over all the classical metrics assessed while achieving optimal (best) or near-optimal real-time performance, especially when the node density is increased. As expected, it is also shown to be clearly superior to the worst-performing gateway selection at each cluster.

Fig. 5a show the results for $k = 2$ gateways, Fig. 5b the case for $k = 3$ and Fig. 5c for $k = 5$. In general, these results confirm the expectation that an increase in the number of gateways (and clusters) also favors schedulability. These results can also be compared with those in Fig. 4, equivalent to the case with $k = 1$. As shown in a prior study [15], increasing the number of gateways reduces significantly worst-case network demand (i.e. contention and conflicts), impacting positively the overall network schedulability. On one hand, having a larger number of gateways allows reducing the mean path length between source and gateway as flows are directed towards a closer sink, which reduces channel contention. On the other hand, dividing the network into a number of clusters, ensures higher flow isolation, which reduces transmission conflicts. These benefits can be observed, for example, when comparing the case of using classical metrics in Fig. 5a with the case of using MO in Fig. 5b for $d = 0.5$, which allows passing from about 10 to 30 schedulable flows with 99.9% of schedulability, representing an improvement of $\sim$ 200% w.r.t. the same framework, same configuration, but with only one more cluster/gateway. A similar effect can be observed in Fig. 5b for $d = 0.1$ but with much lower gains, due to the reduced node density. The case of $d = 1.0$ is included Fig. 5b and Fig. 5a for comparison, confirming the validity of the approach for higher densities. Note these density-related effects are consistent with the plots for the



(a) $k = 2$ (b) $k = 3$ (c) $k = 5$

Fig. 5. Average schedulability ratio of 1000 random topologies for a varying number of flows when using (a) $k = 2$, (b) $k = 3$ and (c) $k = 5$ gateways. The solid blue line curves show the results for our minimal-overlap centrality used as a cluster centrality metric and when compared against classical centrality metrics. Best and worst performing nodes are also shown as benchmarks.

single-gateway designation case, which can be explained because by offering more diversity paths (due to higher node density) we favor schedulability, which is especially convenient for our *minimal-overlap* approach (see Fig. 6 for additional insights in terms of densities and number of overlaps). Despite these positive results, the benefits in schedulability of increasing the number of clusters are also limited by the network load and size. In

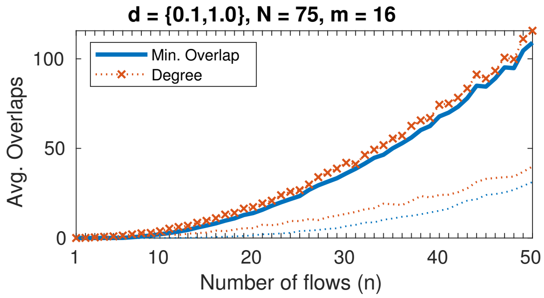


Fig. 6. Average number of overlaps of 100 random topologies when varying network flows for two gateway designation methods (minimal-overlap and degree) and two extreme densities, namely 0.1 (solid line) and 1.0 (dotted line).

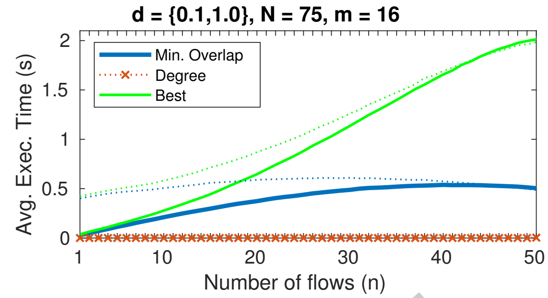


Fig. 7. Execution time for different gateway designation methods, namely, minimal-overlap, degree and best, considering up to 50 network flows and two extreme target densities, namely 0.1 (solid line) and 1.0 (dotted line).

Fig. 5c we see that schedulability suffers a sudden drop at about 25 flows, after which the results with 5 clusters can even be worse than using less clusters, thus holding a trade off for high network loads.

5.2.3 ***Computational Cost***. Fig. 7 depicts the average execution time for the different single-gateway designation methods and the optimal gateway designation. Regarding the classical centrality-based designation method, we solely present the result for degree centrality for visual clarity and because this has the lowest execution time among all metrics. We also present results for two extreme density values of 0.1 (solid line) and 1 (dashed lines). The setup for this experiment used MATLAB R2020b on Ubuntu 18.04 LTS on a laptop with an Intel Core i7-6500U CPU at 2.5GHz and 4GB of DD3 RAM.

The results confirm the low execution time of the degree-centrality gateway designation. On the other hand, minimal overlaps designation considerably decreases the execution time when compared to optimal gateway designation, particularly for higher number of flows. Note that the optimal method uses extensive search with full schedulability analysis for each case, while the MO metric just requires computing the number of overlaps in the network given a set of flows. The results also show that the density has a minimal impact on the average execution time. Overall, the proposed method provides a good trade-off between achievable schedulability ratio (near optimal) and computational cost (up to one-quarter of the value of the optimal method). Note these results are higher than if obtained by cluster, considering the reduced number of nodes and flows in each cluster.

5.2.4 ***Limitations***. Despite the promising results of the MO framework performance under varying network conditions, the overall approach may benefit from future studies that further evaluate the validity and applicability of the proposed approach in real-world settings. Not only in terms of time complexity and real-time performance but also in terms of energy consumption, throughput, latency, scalability, etc. Particularly, in terms of scalability, simulations have shown that increasing the number of gateways while keeping greater network loads holds a trade-off, thus requiring proper design. This, however, enables the possibility to compute how many gateways will satisfy a given schedulability requirement under a given load, which translates into an opportunity. Likewise, although the proposed framework may require considering some additional capabilities on normal nodes to become gateway-enabled (e.g., hardware components), the benefits of an improved real-time performance may justify the costs and complexity of deployment. Overall, while these limitations exist, they do not diminish the potential value and contributions of the proposed minimal-overlap multi-gateway designation framework.

6 CONCLUSIONS

This paper has presented a novel single- and multi-gateway designation method for enhanced real-time performance in RT-WSNs. The single-gateway designation approach based on minimizing the number of path node-overlaps has shown to be substantially effective in terms of improved traffic schedulability while offering lower execution times w.r.t. the optimal case. The multi-gateway extension also showed considerable improvements in terms of real-time network operation, while generalizing the single case in a straightforward fashion. Notably, both methods outperform classical centrality-driven single- and multi-gateway designation methods in up to 50% and 40% better traffic schedulability, respectively. In the future, we are interested in further benefiting from the use of this framework at run-time, for example, as a potential solution for fast leader node selection in dynamic networks of mobile robots (i.e. robot swarms). Furthermore, we will investigate the performance impact of having only a subset of nodes as gateway candidates due to computational or energy constraints. Other aspects to consider in the future are the impact of time-varying channel conditions and retransmissions.

ACKNOWLEDGMENTS

This work was partially supported by National Funds through FCT/MCTES (Portuguese Foundation for Science and Technology), within the CISTER Research Unit (UIDB/04234/2020); by the Operational Competitiveness Programme and Internationalization (COMPETE 2020) under the PT2020 Agreement, through the European Regional Development Fund (ERDF); also by FCT and the ESF (European Social Fund) through the Regional Operational Programme (ROP) Norte 2020, under PhD grant 2020.06685.BD.

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