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Performance Analysis and Optimization of 5G-Based Wireless Sensor Networks for Industrial Applications

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ABSTRACT

The 5G era provides a revolutionary context for Wireless Sensor Networks (WSNs) in industrial environments, enabling breakthroughs in connectivity, latency, and scalability. In this paper, we study the performance evaluation of 5G-related WSNs and investigate how these primary factors influence and are influenced by key performance metrics. Based on a well-established 5G latency model, we evaluate the impact of parameters such as numerology, deployment scenarios (Multi-access Edge Computing (MEC) /central cloud), traffic loads, and link capacity allocation for the end-to-end performance in terms of latency, throughput, energy efficiency, and reliability. We demonstrate extensive numerical studies and simulated examples in various industrial contexts, which involve predictive maintenance, process control, automated guided vehicles (AGVs), environmental monitoring, and the management of smart grids. The results reveal the trade-offs associated with different 5G settings, providing insights for optimizing network performance across diverse industrial scenarios. Results from this study provide practical recommendations for deploying and utilizing 5G-enabled WSNs to meet the growing requirements in Industry 4.0.

1. INTRODUCTION

We are already transformed to the fourth industrial revolution, aka Industry 4.0, that continues to change the ways in which we manufacture and manage our businesses. The development of automation, data exchange, IoT, and cloud computing will lead to smart production systems under the concept of Industry 4.0. Such an interconnected environment needs a highly flexible, reliable, and low-latency communication function to realize the real-time control, continuous, energy-efficient data collection, and heterogeneous coordination of real-time industrial processes. Although traditional wired communication is reliable, it may be less flexible and lack scalability, which are typical in these industrial environments with mobile devices, distributed sensors networked together, and dynamic production processes. Types of industrial wireless solutions Wi-Fi-based solutions may not be able to always meet the hard performance requirements of industrial control systems, especially in harsh environments with much interference and movement issues [1-3].

5G cellular technology, with low end-to-end latency and high responsiveness, offers a bright prospect for a solution to these communication issues as well as fosters the development of Industry 4.0 applications. Promising to deliver ultra-low latency (to sub-millisecond order), high bandwidth (up to Gbps data rate), reliability, and support for massive machine connectivity, 5G is expected to play a key role in enabling advanced industrial applications. In addition, the network slicing feature of 5G enables one to create isolated virtual networks with predefined quality of service (QoS) for serving the different communication requirements in different industrial processes and services [4-6].

5G-enabled WSNs are a revolutionary advancement towards a new sensing technology to resolve the challenges pertaining to connectivity, latency, and power consumption, by exploiting 5th-generation wireless systems. The advent of 5G allows WSNs to support many more advanced real-time applications in every field, like industrial automation, health care, and smart city infrastructure [7, 8].

The fault-tolerant system is another important field of study where detection and recovery of the fault nodes can be achieved, thereby ensuring network reliability in the industrial and smart city applications where network uptime and data precision are required [1]. The extensions in tracking and automation through dependence on ray-tracing and localized performance 5G-based Indoor Positioning Systems (IPS) [2] allow automation, the monitoring of industrial asset management, and process changing from traditional toward automated processes [3]. The recent literature also saw an effort to develop real-time anomaly detection techniques using machine learning. For example, isolation forests, which are important for secure 5G-based WSNs, especially in settings where data sensitivity is critical, like medical environments [4]. 5G WSNs, which are one of the main components of the IoB in healthcare applications, have supported the application of patient monitoring solutions with the features of high data rate with end-to-end low latency communication for real-time health evaluation a logic and feedback being awesomely vital in emergency care [5, 6]. These developments are accompanied by the deployment of cloud-edge computing architectures supporting large-scale data processing and real-time orchestration of IoT systems, from urban to industrial monitoring applications, characterized by high standards of scalability and low latency [7, 8].

Energy-efficiency remains a leading concern in 5G based WSN research and improved versions of routing protocols like Low-Energy Adaptive Clustering Hierarchy (LEACH) have been tailored to preserve the battery longevity of sensor nodes in health care and environmental monitoring, thus enabling prolonged data collection [9, 10]. Spectrum-sharing approaches have also been considered to enable the coexistence of 5G-based WSNs with non-terrestrial networks, which improves coverage and accessibility in rural or underserved areas, making large-scale sensor networks feasible in regions previously inaccessible [11]. Other than these applications, the advent of wearable sensors for health monitoring enhanced with hybrid deep learning models has demonstrated the capability of 5G to facilitate real-time high-definition data analytics enabling the healthcare providers to monitor continuously patient's health parameters and respond to emergencies pro-actively in a much effective manner [12, 13]. 5G-empowered WSNs have expanded the potential of city-scale environmental monitoring, and delivered applications of air quality, sound detection & traffic management, all contributing to aggregate the high-sensitivity real-time data required for enhancing decision making in urban planning and public health policy [14]. Finally, 5G-based indoor localization service of pretrained Radio Foundation Models provides a cost-efficient and accurate positioning solution in the industrial use case scenario with challenging harsh indoor environment having high Accuracy to sustain strong and reliable tracking across complex indoors (that demands high accuracies) there by setting new benchmark for practical WSN deployments [15-20].

As 5G technologies develop rapidly, there are some studies that integrate time sensitive networking (TSN) into 5G to guarantee the latency and reliability for industrial Internet. For instance, Yang et al. [21] introduced a novel uplink transmission scheme in order to support TSN services over a 5G industrial IoT prototype system. Similarly, Nikhileswar et al. [22] designed a testbed for a TSN-based ICTS over 5G, and validate its performance on field using real industrial applications. Furthermore, Satka et al. [23] developed a flow conversion mechanism between 5G and TSN, and demonstrated its efficiency with industrial use cases. Such investigations prove the potential of 5G and TSN to support accuracy in timing and transmission characteristics at work through industrial automation, meanwhile monitoring network performance. However, the application of TSN in TSN's maturity is still at a pre-mature stage and there is more to be explored when applying 5G-TSN solutions in operational factories. Other works have investigated 5G industrial functionalities under real settings. 5G test and development ecosystems have also been supported by the 5G Alliance for Connected Industries and Automation (5G-ACIA). For example, Jiang et al. [24] to harness the physical layer in an industrial protocol for providing ultra-reliable and low-latency communication (URLLC), validated in a simulated factory. In addition, Khoshnevisan et al. [25] tested 5G prototype systems in an industrial environment with support for the PROFINET protocol. Further, Alsharbaty and Ali [26] evaluated 5G performance over multiple industries using a trial platform deployed in the UK, and Ansari et al. in a real industrial production environment". This they measure the performance of 5G trials [27]. These studies indicate that additional physical experiments are necessary to completely customize and optimize the 5G protocol for industrial use.

In this paper, the following are the main contributions of our work in 5G-driven Industrial Wireless Sensor Networks (IWSNs):

- End-to-End Latency Model: We build an analytical model which dis-aggregates the full latency into RAN, TN, CN and ASs as well as data aggregation delays. Such a modular design makes it easy to understand the working of each part, how they influence the overall performance etc.
- Parameter Impact Study: We explore the impacts of critical parameters such as subcarrier spacing (SCS), network deployment paradigm (e.g., Multi-access Edge Computing (MEC) vs. centralized) traffic load, link capacity allocation, packet size and processing capability on latency, throughput and energy efficiency.
- Validation and Case Studies: The model is validated on extensive simulation and real-world experimental scenarios spanning industrial applications such as predictive maintenance, process control, or environmental monitoring. Such case studies show, that the model is closely correlated with empirical data and thus relevant in practice.
- Optimization Examples: We design and analyze several optimization examples that demonstrate the impact of systematic adjustments in network configuration (e.g., optimal SCS, deployment strategy and link capacity), which can greatly improve system performance by reducing end-to-end latency preserving at the same time energy efficiency.
- Cost and Complexity: The computed complexity of the computational cost as well as mathematical complexity proved that, compared to other models, it is not only robust and scalable but also can be implemented in real-time in resource-limiting areas.

2. 5G-BASED INDUSTRIAL WSNs

The phrase "Industrial WSN" indicates WSNs built 'to suit' in industrial plants and applications. These WSNs have different challenges and requirements compared to WSN applications in other fields (e.g., environment monitoring, smart home). Class of IWSN type of IWSNs can be categorized as [25]:

- Severe Operating Conditions: Many IWSNs work in some severe circumstances such as high/low temperature, humidity, vibration and electromagnetism interference or the existence of a variety of chemical substances or other dangerous media. This in turn needs to have strong and stable sensor nodes and communication protocols.
- Real-Time Application: A number of industrial applications require the real-time accesses to monitoring and control data. For time-critical operations, data transmission in IWSN networks

must be low-latency and highly reliable.

- High Reliability and Availability: Downtime due to network failure in industrial environment may cost greatly, involving production standstill, safety risks and financial losses. IWSNs should be very dependable and available with fault-tolerant and redundant mechanisms.
- Safety: Cyber threats are increasingly making industrial control systems more vulnerable. The IWSNs must be secure to safeguard sensitive information and unauthorized access.
- Deterministic Communication: Some types of industrial applications, especially in the area of motion control and automation, require deterministic communication with guaranteed latency and jitter. This makes it necessary to employ technologies such as TSN in many cases.
- Integration with Industrial Protocols: IWSN may have to integrate with the already existing industrial communication protocols, for example, Modbus, Profibus, or EtherCAT.

Some IWSN Applications include [28]:

- Process Monitoring and Control: Temperature, pressure and the flow rate or other minor process parameters in manufacturing plants, chemical plants, or power stations.
- Machine Condition Monitoring: To capture vibration, temperature data of the machine so as to anticipate failures and schedule maintenance in advance.
- Industrial Environmental Monitoring: Scrap and recycle operations, air quality, noise and other environmental monitoring in factories or industrial installations.
- Asset tracking and management: Depicting the location and physical condition of machinery and assets in a plant or warehouse.
- Safety & Security: The use of wireless sensors for fire detection, gas leakage detection, intruder alarms and similar safety-critical applications.

Industrial WSNs are an active and significant research area focusing on the particular challenges and benefits of deploying WSNs in industrial environments. The deployment of IWSNs before and after integration with 5G is compared in Table 1 [22].

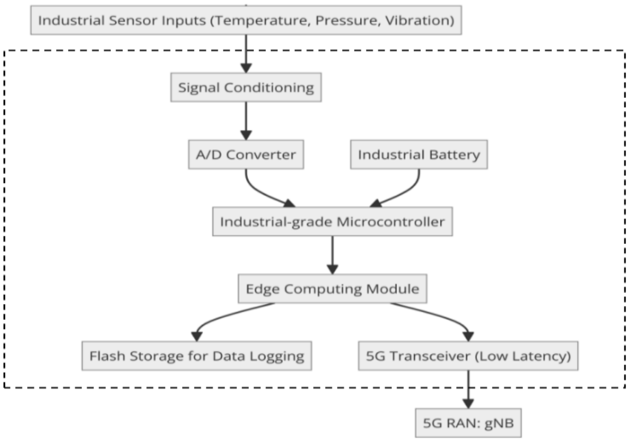
Table 1. Deployment of IWSNs before and after 5G integration

Aspect	Before 5G (Using Wi-Fi, Zigbee, etc.)	After 5G
Network Infrastructure	- Wi-Fi and Zigbee for sensor connectivity. - Wi-Fi handles data-intensive tasks; Zigbee for low-power monitoring.	- 5G URLLC for ultra-reliable, low-latency communication, ideal for real-time control. - Network slicing for dedicated application slices.
Latency and Real-Time Data	- Latency around 50-100 ms for Wi-Fi; higher for Zigbee. - Limits real-time response, affecting synchronization of machinery.	- Latency as low as 1-10 ms with 5G, supporting real-time automation. - Enables near-instantaneous data exchange for synchronized control.
Data Processing	- Centralized processing at an on-site server, increasing latency. - Delayed analysis affects maintenance and decision-making.	- Edge computing brings processing closer to the sensors, reducing latency. - Faster insights allow real-time decisions and rapid responses.
Predictive Maintenance	- Limited predictive maintenance due to delayed data processing. - Issues detected after significant deviations in sensor data.	- Enhanced predictive maintenance due to continuous, real-time data analysis. - More accurate predictions and timely maintenance actions.
Scalability and Device Density	- Limited scalability; Wi-Fi and Zigbee struggle with high device counts. - Device congestion reduces network performance.	- Massive Machine-Type Communication (mMTC) allows thousands of devices per site. - High-density sensor deployments operate smoothly.
High-Bandwidth Applications	- Bandwidth is limited, especially for video data. - Video-based quality control or AR applications are challenging to support.	- Enhanced Mobile Broadband (eMBB) supports high-speed, data-intensive tasks. - Real-time HD video streaming for visual quality control.
Network Security	- Limited security features; often, isolated networks to mitigate cyber risks. - Potential vulnerability in connected setups.	- 5G offers advanced security with enhanced encryption and secure access controls. - Improved security for sensitive industrial data.

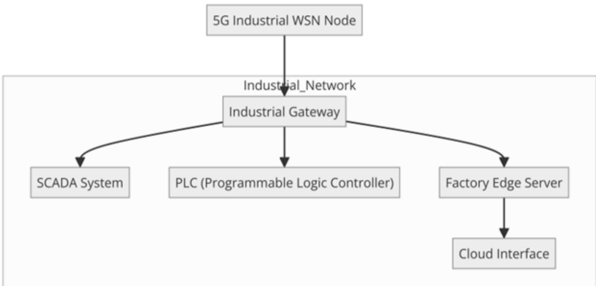
Figure 1(a) shows the internal structure and data flow of a WSN node in 5G Case. In the input layer, sensors inputs transduce environmental features; a signal conditioning stage may convert these signals into machine-readable form. The conditioned signals are A/D converted by the A/D Converter. This node is running on a battery that provides power to the essential components. Processed digital signals and power meet at the Low Power Microcontroller, which is the WSN node CPU. Here is where data management, control functions and low-power processing will happen. The microcontroller sends data to two major devices: 5G Transceiver and Flash Storage. The transceiver supports real-time data transfer to a 5G RAN gNB (Next Generation Node B), allowing quick communication between the other network entities. On the other, we store data locally in flash for further use or processing. This feature shows the inter-operation of classical WSN elements with 5G communication services, ensuring rapid and effective data relays in IoT and sensor network scenarios [8].

Figure 1(b) shows the deployment of a node in a small industrial network as one of the nodes. The other 5G WSN node, located outside the indicated industrial network, is connected to an industrial gateway through the 5G network. This is the gateway through which data first enters your internal network and flows out to a few critical elements. The data obtained for monitoring and control are transmitted to a SCADA system. The data is used in the automated control of industrial processes by a Programmable Logic Controller

(PLC). A factory edge server can locally process data, resulting in quicker time to respond for real-time applications. The factory edge server is also linked to a cloud interface for data exchange with cloud-based services such as storage, analysis and remote access. This architecture describes how 5G may improve industrial networks, by the wireless evolution of sensor nodes and coexistence with current industrial (SCADA, PLC) systems and offloading computing to both the edge and cloud [12].



(a) The internal structure of an industrial WSN node



(b) A typical architecture for a 5G-based IWSN Infrastructure

Figure 1. Architectural components of Industrial Wireless Sensor Networks (IWSN)

3. 5G ARCHITECTURAL COMPONENTS

In order to understand the origins of delay in a 5G-enabled WSN, the path of an end-to-end packet must be traced, and network elements that affect its delivery time should be revealed. In the following, we describe components that are immediately involved in the proposed latency formula (Figure 2) and are compatible with modeling approach introduced in the study [16].

3.1 5G Radio Access Network

At the lowest tier is the RAN, which serves as the first layer of communication connecting wireless sensors used in environmental monitoring, industrial automation or smart agriculture to 5G infrastructure. This component is in charge of all radio operations, making it a significant source of high-level latency. Those most concerned at this stage are:

- Wireless Sensor Node (WSN): A device that either transmits or receives data between the network and itself.
- gNB (Next-Generation Node B): The 5G-base station responsible for radio resource management, scheduling and data transference with the connected sensor nodes.

On the RAN side, we have a few factors that directly influence packet delay:

- 5G Numerology Parameters: The sub-carrier spacing is quantized and directly related to the symbol duration, which is fundamental to the timing of over-the-air transmission packets and thus the signal latency.
- Radio Scheduling: The scheduling algorithm in gNB is efficient, but the sensor node may still experience a queue before it is granted access to a channel.
- Hybrid ARQ: packet errors are caused by the channel impairments, and these errors often lead to retransmissions, which will lead to an increase in the effective delay.
- Radio interference and load on the network: Even uncorrelated radio interference and network congestion on the air interface can combine to worsen the performance degradation due to contention at the transport layer by increasing queuing delay.

3.2 Transport Network

The TN acts as an intermediate network layer between the 5G base stations and the core infrastructure. This part generally needs high-throughput backhaul technologies (i.e., fiber-optic links), accommodating a large amount of data and having low delay. The transmission inside the TN is performed by network equipment like routers and switches, which uses routing techniques to direct the traffic towards the core network (CN).

Transfer segment delays are primarily from two different sources:

- Signal Propagation: This is the amount of time that is needed to travel from one node to another through the physical length of the transmission medium, directly proportional to distance between two network nodes.
- Node and Link Processing: There is extra delay due to packet operations at routers/switches which is processing time, the time taken on the links during transmission, and buffering in case of congestion and queuing that may add further latency.

3.3 Core network

The CN is architecture of the 5G, which includes both data and control plane. It is in charge of traffic management, policy enforcement, security functions, and interworking with external networks like the Internet.

Key component in the user data plane is the User Plane Function (UPF) which handles packet routing and forwarding enforcing QoS. The UPF also significantly contributes to the realisation of Mobile Edge Computing through traffic steering toward application servers (AS) located at the network edge. While the provided latency model is centered around the UPF, it should be mentioned that there can be additional delay overhead in other core functions (e.g., control-plane entities and authentication)'s execution, even when abstracted within simplified analytical models.

3.4 Application servers

The AS provides the services that are going to consume sensor data, generated from WSN nodes and process it. The server could be located in a centralized or cloud environment, and can also be placed closer to the network edge utilizing MEC infrastructure if deployment is taken into consideration. This position has a major impact on response time and throughout the system latency.

Application layer latency is primarily determined by:

- Computation Overhead: The time required for the execution of application logic, analysis of sensors data and generation of responses.
- Request Queuing: In stressful scenarios, packets of arriving requests may be queued by servers before dispatching the response, producing a delay in processing.

The end-to-end system latency is composed by the sum of all introduced delays over radio interface, transport network (TN), core functions and application layer. Understanding how each facet contributes, and the influence of system parameters (namely, numerology settings, generated traffic pattern, and placement of servers) upon performance is necessary to design low-latency 5G-based WSN. Meeting strict latency requirements therefore requires a co-design methodology that optimizes for both radio-level settings, network-level architecture and application-level processing decisions, as argued in the study [16].

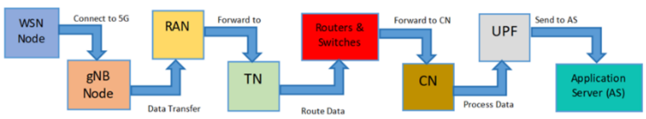


Figure 2. 5G latency model

4. LATENCY MODELING IN 5G-BASED WSNS

A data packet generated by a WSN experiences multiple processing and transmission stages before reaching the AS. Each segment of the 5G communication architecture introduces specific delay components that collectively determine the overall latency.

4.1 Radio Access Network latency

The RAN enables wireless connectivity between WSNs and the 5G infrastructure via the next-generation Node B (gNB). The primary contributors to RAN latency are as follows.

Numerology and Symbol Duration: The duration of a transmission symbol is governed by the selected numerology and the associated SCS, and is given by:

$$\text{Symbol\_Duration} = 1/(2^{\wedge}\text{Numerology}*15\text{ kHz}) \tag{1}$$

Scheduling and Retransmission Delays: Additional latency is introduced by radio resource scheduling mechanisms and Hybrid Automatic Repeat Request (HARQ) retransmissions used for error recovery.

Accordingly, the total latency incurred within the RAN is expressed as:

$$\begin{gathered}\text{RAN\_Latency} = \\ \text{Symbol\_Duration}+\text{Scheduling\_Delay}+ \\ \text{Retransmission\_Delay}\end{gathered} \tag{2}$$

4.2 Transport Network latency

The TN interconnects the gNB with the CN using high-capacity wired or optical links. The latency within the TN consists of two main components.

Propagation Delay: This delay corresponds to the time required for signals to traverse the physical distance between network nodes and is defined as:

$$\begin{gathered}\text{Propagation\_Delay\_TN} = \\ \text{Distance\_TN}/\text{Propagation\_Speed\_TN}\end{gathered} \tag{3}$$

where, Distance_TN represents the link length and Propagation_Speed_TN denotes the signal propagation speed.

Transit Delay: Transit delay accounts for processing, queuing, and transmission operations at intermediate routers and switches along the path, and is modeled as:

$$\begin{gathered}\text{Transit\_Delay\_TN} = \\ \text{Number\_of\_Nodes\_TN}*(\text{Processing\_Delay\_TN}+ \\ \text{Queueing\_Delay\_TN}+\text{Transmission\_Time\_TN})\end{gathered} \tag{4}$$

The aggregate latency introduced by the TN is therefore:

$$\begin{gathered}\text{Transport\_Latency} = \\ \text{Propagation\_Delay\_TN}+\text{Transit\_Delay\_TN}\end{gathered} \tag{5}$$

4.3 Core network latency

The CN is responsible for user data routing and session management. Its latency contribution depends on both propagation effects and processing delays.

Propagation Delay: The propagation delay within the CN is expressed as:

$$\begin{gathered}\text{Propagation\_Delay\_CN} = \\ \text{Distance\_CN}/\text{Propagation\_Speed\_CN}\end{gathered} \tag{6}$$

Transit Delay under MEC Deployment: When MEC is employed, the transit delay is primarily associated with the UPF and is given by:

$$\begin{gathered}\text{Transit\_Delay\_CN\_MEC} = \\ \text{Processing\_Time\_UPF}+\text{Queueing\_Delay\_UPF} \\ +\text{Transmission\_Time\_UPF}\end{gathered} \tag{7}$$

Transit Delay under Centralized Deployment: For centralized cloud-based deployments, additional traversal through intermediate UPF nodes increases the transit delay, which is modeled as:

$$\begin{gathered}\text{Transit\_Delay\_CN\_Cloud} \\ = 2*(\text{Transit\_Delay\_CN\_MEC}+ \\ \text{Sum\_of\_Intermediate\_UPF\_Delays})\end{gathered} \tag{8}$$

The total latency contributed by the CN can thus be written as:

$$\begin{gathered}\text{Core\_Latency} = \\ \text{Propagation\_Delay\_CN}+\text{Transit\_Delay\_CN}\end{gathered} \tag{9}$$

4.4 Application servers latency

The AS processes incoming sensor data and generates corresponding responses. The latency at this stage depends on the computational workload and available processing capacity, and is expressed as:

$$\text{Application\_Server\_Latency} = (\text{Processing\_Cycles\_Per\_Bit} * \text{Packet\_Size} * \text{Number\_of\_Packets}) / \text{Processing\_Capacity\_AS} \quad (10)$$

4.5 Data aggregation at edge nodes latency

While data aggregation reduces the number of transmitted packets, it introduces additional processing and transmission delay at edge nodes. The aggregation latency is modeled as:

$$\text{Aggregation\_Latency} = \text{Aggregation\_Delay} + (\text{Aggregated\_Packet\_Size} / \text{Link\_Capacity}) \quad (11)$$

4.6 Total end-to-end latency

The overall end-to-end latency experienced by a data packet is obtained by summing the latency contributions from all network segments and processing stages:

$$\text{Total\_End\_to\_End\_Latency} = \text{RAN\_Latency} + \text{Transport\_Latency} + \text{Core\_Latency} + \text{UPF\_to\_AS\_Latency} + \text{Application\_Server\_Latency} + \text{Peering\_Point\_Latency} + \text{Aggregation\_Latency} \quad (12)$$

4.7 Energy model

To enhance the proposed latency model with energy considerations, we introduce a set of analytical expressions that estimate energy consumption in 5G-based industrial IWSNs. The energy required to transmit a data packet is given by:

$$E\_tx = P\_tx \times (\text{Packet\_Size} / \text{Data\_Rate}) \quad (13)$$

where, P_tx is the transmission power (in watts).

In environments with interference, the retransmission energy overhead can be estimated as:

$$E\_re = P\_tx \times (\text{Packet\_Size} / \text{Data\_Rate}) \times P\_retx \quad (14)$$

where, P_retx is the probability of retransmission.

For periodic sensing applications, the energy per sensing interval considering the duty cycle is modeled as:

$$E\_interval = DC \times P\_active \times T + (1 - DC) \times P\_sleep \times T \quad (15)$$

where, DC is the duty cycle, P_active and P_sleep are the active and sleep power levels respectively, and T is the sensing interval.

4.8 Security mechanisms

The impact of security mechanisms on energy is included via:

$$E\_sec = (P\_enc + P\_auth) \times t\_sec \times Num\_layers \quad (16)$$

where, P_enc and P_auth are the power consumed during encryption and authentication, t_sec is the processing time per operation, and Num_layers is the number of applied security layers.

The total energy per successfully transmitted packet becomes:

$$E\_total = E\_tx + E\_re + E\_sec + E\_interval \quad (17)$$

These equations formalize the trade-offs discussed earlier between transmission power, duty cycle, security processing, and overall energy efficiency. They provide a foundation for future optimization studies that aim to minimize latency and energy consumption simultaneously in time-sensitive industrial scenarios.

The energy consumption model proposed here deals only with communication and processing costs, so it abstracts away some physical and environmental effects that drive the long-term operation of sensor nodes. Specifically, battery ageing and efficiency changes with temperature are not modeled explicitly. As opposed to the idealized assumption in this paper, in real its industrial deployments, battery capacity gradually degrades as charge–discharge cycles proceed, and energy efficiency also varies with ambient temperature, particularly under severe thermal conditions. Such effects can result in an increased effective energy consumption and a decreased node lifetime compared to what the model predicts. Detailed electrochemical battery degradation models provide additional improvement with prediction accuracy while additional thermal dynamics can also provide an overall improvement in prediction accuracy but this modeling would drastically increase complexity and require device-specific parameters that may not be available during system design [25-31]. As a result, this model is better seen as an upper-bound idealized estimate of energy performance, useful principally for comparative assessment and optimization at the system level but not for accurate lifetime prediction. In the future, we plan to expand the model to include battery ageing and influence of temperature employing calibration factor based on empirical or measurement data.

5. PERFORMANCE ANALYSIS

We proposed a mathematical latency model, as the model can decompose end-to-end latency into various components such as RAN, TN, CN, and AS delays, which will be an aggregated model for 5G networks. This separation allows for a tractable examination of the impact of network design choices and system parameters on the total latency performance. The impact of distinguishing factors like numerology, deployment strategy, traffic demand, link capacity assignment, packet size and server processing capability/complexity on the network throughput will be studied through a performance study with this model, considering network topology. Results display that both radio access transmission delays can be minimized through SCS increase, and edge-based deployments show a gain for the latency through shorter propagation distances. Those, on the other hand, congestions, and centralized deployments yield a higher number of queues and further propagation delays, respectively. It is also observed that by providing more link capacity, the amount of queued-up information can be decreased; a large size-packet and higher processing make server side-delay increase; furthermore, improving on the server s processing ability makes application-level delay decrease. More generally, the results offer operational guidance when engineering 5G network configurations across time and space to satisfy the tight latency necessity of realtime/latency-sensitive applications.

Table 2 provides a revised summary numerical value included to highlight the effects of various parameters on latency:

Table 2. Summary of results for various parameters and their effect on latency

System Aspect	Configuration Scenarios	Observed Latency Behavior
Physical Layer Numerology	SCS of 15 kHz and 60 kHz	Larger SCS values shorten transmission and radio access delays, leading to a notable reduction in total end-to-end latency. For instance, increasing SCS from 15 kHz to 60 kHz decreases TotE2E from 10.58 ms to 6.38 ms.
AS Placement	MEC at gNB, MEC at M1, MEC at CN, fully centralized	Deploying the AS closer to the radio edge significantly minimizes latency. An edge-hosted MEC at the gNB achieves 5.325 ms, whereas centralized deployment results in 26.725 ms TotE2E.
Offered Traffic Intensity	100 packets/s and 1000 packets/s	Higher packet arrival rates amplify queuing delays across the network. TotE2E increases from 4.28 ms at low load to 14.78 ms under heavy traffic.
Transport Link Resource Share (α)	α = 0.2 and α = 0.5	Allocating a larger fraction of link capacity reduces buffering delays and improves latency performance. TotE2E decreases from 4.585 ms to 4.235 ms as α increases.
Payload Size	500 bits and 2000 bits	Increasing packet size slightly extends transmission time and server-side processing delay, raising TotE2E from 6.425 ms to 7.925 ms.
CN Separation Distance	50 km and 200 km	Longer physical separation from the CN increases propagation delay, resulting in TotE2E growth from 21.725 ms to 24.725 ms.
AS Computational Power	1 Gcycles/s and 20 Gcycles/s	Enhanced processing capability at the AS dramatically shortens processing latency, reducing TotE2E from 17.925 ms to7.425 ms.
Processing Workload per Bit	10 and 40 cycles/bit	Higher computational complexity per bit increases application-layer latency, causing TotE2E to rise from 7.425 ms to 8.925 ms.

To validate the proposed theoretical model, we made a comparison of our model with the existing 5G based IWSNs simulation and experimental studies [8, 11, 13]. The validation step was performed by selecting benchmark studies that gave performance evaluation of these 5G-based IWSNs in either experimental or simulation environments. Candidate studies were selected considering their applicability to industrial 5G networks, quantitative evaluation results and peer-reviewed publication trustworthiness. The chosen studies were an experimentation with 5G NR in industrial use case, performance and protocol testing of local 5G architecture for industrial applications, and a real-time measurement of multi-link industrial 5G network. To make a fair comparison, we calibrated the critical network parameters between our model and the references. The parameters were SCS, deployment method, offered load, packet size, capacity assignment in the links between small cells and CN, distance to the core-network and AS processing. The model parameter values as well as the comparison reference parameter values are given in Table 3.

Using these aligned parameters, our model computed total end-to-end latency by summing the contributions from the RAN, TN, CN, AS, and data aggregation latency. The results from our model were then compared against those reported in the benchmark studies. The findings are summarized in Table 4.

Table 3. Validation experiments settings

Parameter	Value
SCS	30 kHz
Deployment Strategy	MEC at the gNB
Traffic Load	125 packets/s
Packet Size	800 bits
Link Capacity Allocation (α)	0.5
Distance to CN	1 km
Processing Capacity (ProcCap_AS)	10 Gcycles/s

Table 4. Results obtained from different models

Study	Methodology	Reported Latency (MS)
The Current Model	Analytical modeling based on 5G specifications and IWSN parameters	5.325
Ref. [8]	Empirical measurements in industrial settings	5.7
Ref. [11]	Simulation-based performance evaluation	5.8
Ref. [13]	Real-time experimental testing	6

It can be noted from the comparison that the theoretical model predicts latency values that are in close proximity (deviations within the ±10%) to the real world and simulation results. These small differences are due to real-world elements not directly considered in our analytical model, including interference, hardware imperfections, and network variability. Research Results, even if there are some differences, the results are consistent with empirical observations, which confirms the usefulness of the proposed model for estimating the latency in industrial 5G WSNs. The following theorems listed in Table 5, formalize key trade-offs and interactions in 5G-based WSNs, providing a rigorous mathematical foundation to analyze latency and energy behaviors under varying configurations.

Table 5. Extended theorems and trade-offs

Analytical Focus	Core Principle	Design Insight
Transmit Power vs.	Lower transmission power reduces energy consumption	An optimal transmission power exists that jointly

Performance Trade-off	but increases latency due to higher retransmission probability.	minimizes energy usage and overall delay.
Numerology Selection and Latency Reduction	Increasing numerology shortens symbol duration, lowering latency at the expense of higher bandwidth demand.	Numerology should be selected based on latency constraints and available spectrum resources.
Traffic Intensity and Queue Formation	As traffic load approaches service capacity, queuing delay grows rapidly and dominates total latency.	Effective congestion control and scheduling are essential under heavy traffic conditions.
Impact of Data Aggregation	Aggregating packets reduces transmission energy but introduces additional edge processing delay.	Aggregation is advantageous when energy savings exceed added processing latency.
Application Deployment Location	Hosting services closer to the network edge significantly reduces end-to-end latency.	MEC deployment is preferred for delay-sensitive services, despite increased orchestration complexity.
Traffic-Aware Capacity Allocation	Allocating higher capacity shares to specific flows reduces their queuing delay while affecting others.	Capacity slicing must be optimized to maintain fairness and service-level guarantees.
Server Processing Capability	Increasing computational capacity at the AS reduces processing latency.	High-performance servers are required for computation-heavy or real-time services.
Duty Cycle and Energy Efficiency	Lower duty cycles improve battery lifetime but introduce additional latency for periodic data delivery.	Duty cycle configuration must balance responsiveness and long-term energy sustainability.

6. OPTIMIZATION EXAMPLES FOR ENHANCING SYSTEM PERFORMANCE

This sub-section presents an optimization for reducing end-to-end delay by optimizing SCS. Employing a constant traffic load, packet size and MEC deployment, the method analyzes several SCS configurations with respect to their effect on radio access and transport delays. We search for the best SCS by simulating each scenario and selecting the corresponding end-to-end latency, that is, as low as it can be. The simulation results show end-to-end latency is decreased as SCS value increases due to the very short symbol duration, leading lower radio access and transport delays (Figure 3).

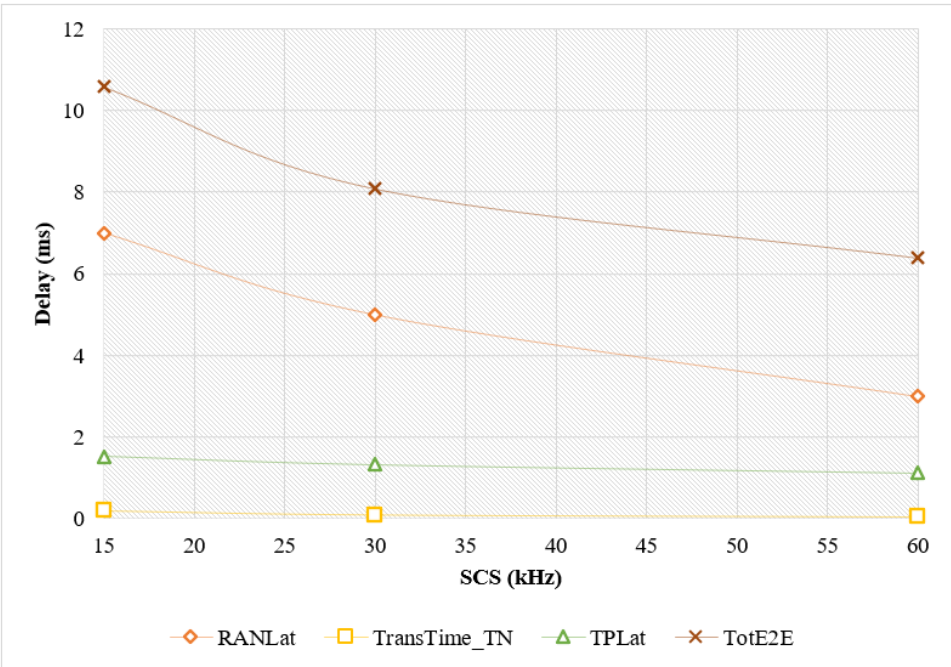


Figure 3. Subcarrier spacing (SCS) effect on delay components

6.1 Optimization of network deployment strategy for tot E2E reduction

The optimization example treats various network deployment options to minimize the end-to-end delay under fixed traffic load, sub-carrier spacing and packet size. The method determines all affecting latencies for each deployment alternative and chooses the policy that minimizes total latency. Where in the numerical results indicate that when MEC is deployed at gNB, the end-to-end latency decreases to the greatest extent as transport and CN latencies are minimized as shown in Figure 4.

6.2 Optimization of link capacity allocation (α) for tot E2E reduction

This optimization scenario aims to minimize the end-to-end latency subject to fixed SCS, packet size and traffic load by tuning the link capacity allocation parameter (α). This technique examines the impact on queuing and transport delays of varying values for α, and it chooses that value which minimizes the total delay.

Results show that by allocating larger capacity, queuing delay and transport delay is decreased which results in reducing the end-to-end latency as shown in Figure 5.

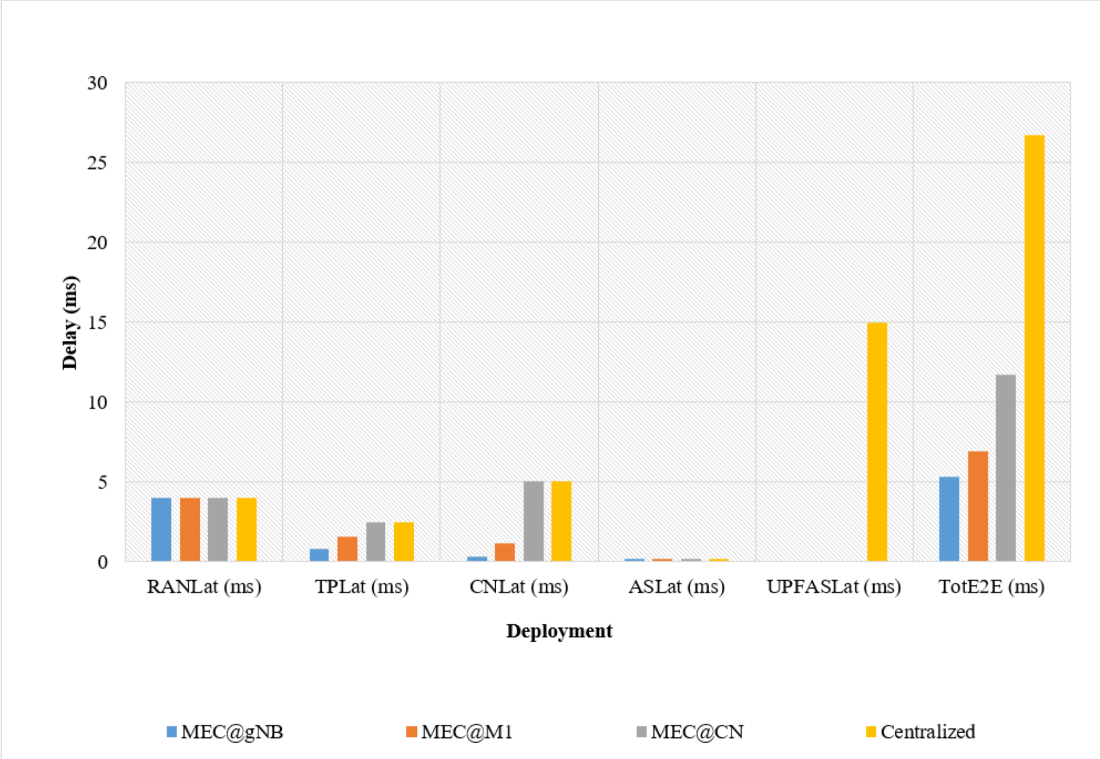


Figure 4. Deployment strategy effect on delay components

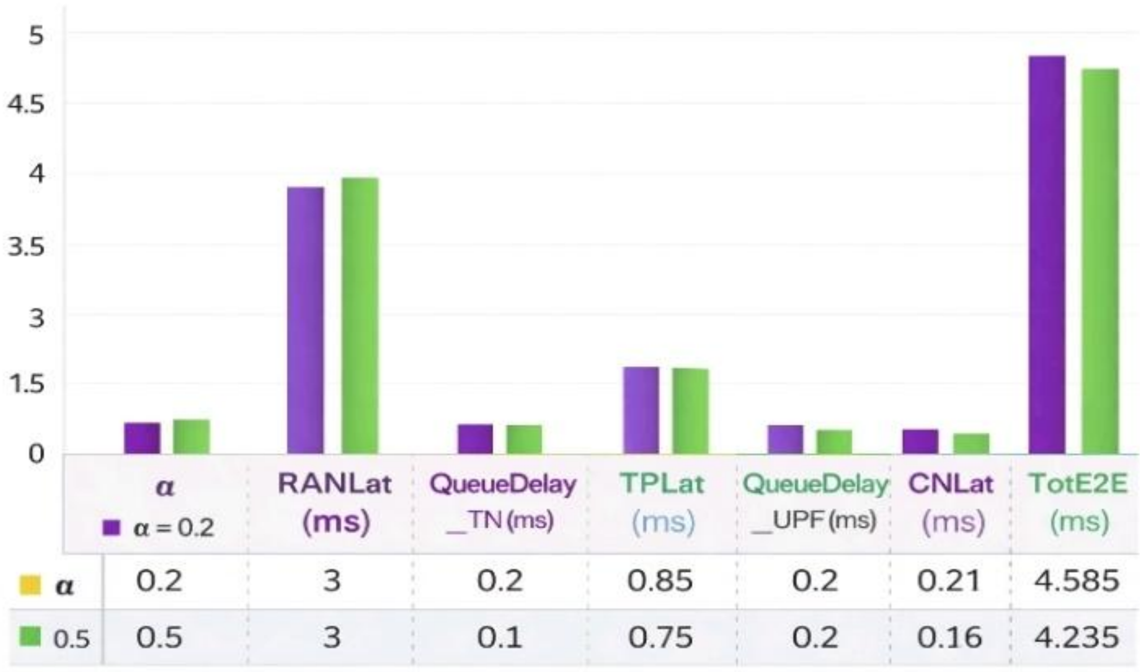


Figure 5. Link capacity allocation (α) effect on delay components

6.3 Optimization of duty cycle for maximizing battery life

In this example, we consider a low-power sensor node and the challenge of tuning its duty cycle to maximize its battery life. One way is to evaluate multiple duty-cycle options for a given packet size, battery capacity, and transmission power, and estimate the energy and battery life consumption. The results suggest that the battery lifetime is significantly enhanced for lower duty cycle, which shows the energy saving versus sensor activations compromise (Figure 6) [28-34].

6.4 Optimization of transmission power for energy efficiency

This optimization example examines transmission power control to reduce energy consumption while preserving reliable communication. Using fixed packet size, transmission distance, and duty cycle, the approach evaluates multiple power levels and selects the configuration that minimizes energy usage while ensuring a packet success rate above 95%. The results show that a moderate transmission power provides the best trade-off between energy efficiency and communication reliability, see Figure 7 [29-34].

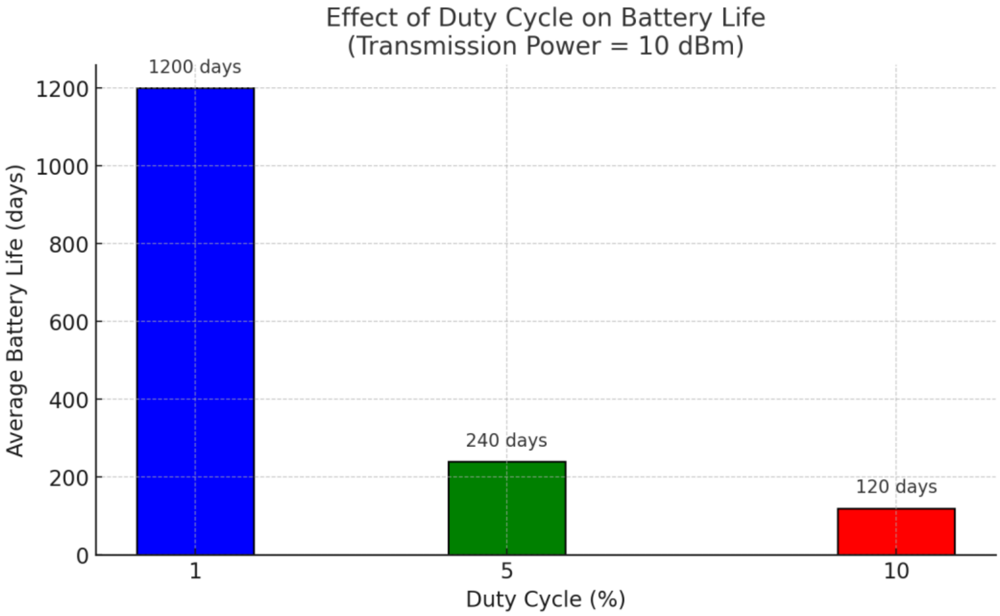


Figure 6. Duty cycling effect

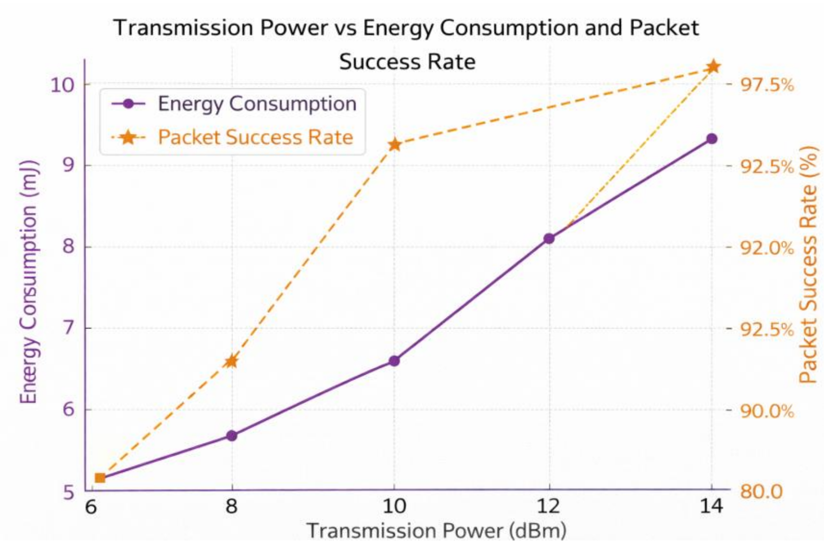


Figure 7. Transmission power effect

In response to the dynamic wireless network and to shed lights on learning-based optimization, we present a future-preparatory adaptive optimization framework for 5G-enabled industrial scenarios. The structure of the framework is an opportunistic base discretized in time, which starts with assigning a set of baseline system parameters (e.g., network load, network architecture, slice setup and radio resource allocation). The basic latency terms, i.e., RAN latency, transport latency and CN latency are calculated based on the analytical models introduced in this section.

At each time instance, the system state is described by observations on a number of measurable variables such as traffic load now, measured channel quality, length of queue and slice utilization and remaining energy. From the value of such a state, the optimization agent determines control decisions like SCS, link capacity assignment, transmission power and slice priority. We measure the effect of these actions through a refinement of the end-to-end latency and energy consumption. A reward function is then designed to penalize large latency, packet loss and energy consumption to drive the optimization process towards achieving low-latency and energy-efficient operating points.

Reinforcement learning methods, like Q-learning or deep Q-networks, may be used to approximate a mapping from states to control actions by interacting with the environmental model in an iterative way. The learning process itself adheres to the standard observe–act–reward–update loop and under typical assumptions of bounded rewards, sufficient exploration, and diminishing learning rates it hone in. The environment dynamics are characterized by stochastic traffic arrivals, interference and channel variation modeled as probabilistic processes using discrete event simulation for numerical evaluation.

A simulation environment built using SimPy, MATLAB, or python scientific libraries can be introduced for simulating the time evolution of a network and to evaluate how well we learned our policies. Furthermore, queuing-theoretic models are employed to verify the simulated latency behavior analytically under some simplifying assumptions. Such a joint analytical-and-learning-based framework offers a solid foundation for dynamic optimization while ensuring tractability and clarity, as well as supports systematic characterization of adaptation policies to industrial 5G setups.

7. COST AND COMPLEXITY ANALYSIS OF THE PROPOSED MODEL

The proposed model offers an analytical tool to optimize latency, throughput, and the energy efficiency in 5G-based IWSNs. It is to provide closed-form solutions for important performance metrics, including total end-to-end latency (TotE2E), SCS tuning and resource allocation with low computational complexity suitable for real-time analysis. To evaluate on a single network configuration the model needs about 20-30 arithmetic operations and can be computed in less than 1 ms on an average laptop (Intel i7, 2.6 GHz). This efficiency makes the rapid study of many configurations feasible: as an example, the evaluation of 100 different configurations with a combination of 10 SCS and 10 link allocation parameters (α values) can be made in less than 100 milliseconds.

Table 6. A comparison table summarizing the proposed mathematical modeling features alongside other recent academic works

Evaluation Dimension	Proposed Study	PSAP-WSN Scheme [30]	AI-Driven Framework [31]	Fog-Assisted VANET Model [32]	DL-Based Routing Protocol [33]
Latency Representation	Comprehensive end-to-end delay formulation separating RAN, transport, core, AS, and aggregation delays.	Delay modeling centered on authentication and security operations in 5G-WSNs.	Latency minimized through AI-enabled D2D coordination rather than explicit modeling.	End-to-end latency evaluated for vehicular scenarios using fog offloading.	Delay behavior analyzed within routing mechanisms optimized for 5G-WSNs.
Analytical Formulation	Rich mathematical framework combining queuing models (M/M/1, M/D/1), transmission, and energy equations.	Mathematical analysis mainly focuses on queuing delays in authentication procedures.	Lacks explicit analytical expressions; relies on learning-based optimization.	Incorporates propagation, queuing, and computational delay equations.	Delay estimation embedded within adaptive deep learning routing models.
Numerology Consideration	Explicitly models SCS and symbol duration effects on RAN-related latency components.	Numerology effects are not addressed.	Not considered in the model.	Not directly analyzed in relation to latency.	Considered indirectly through throughput–latency interaction.
Energy Awareness	Detailed energy consumption modeling including transmit power, duty cycle behavior, and sleep states.	No formal energy consumption model included.	Energy efficiency achieved implicitly via AI optimization strategies.	Energy usage modeled for both fog infrastructure and sensor devices.	Routing decisions aim to prolong network lifetime.
Architectural Scope	Evaluates centralized, MEC-based, and hybrid deployments and their impact on latency and energy.	Primarily protocol-oriented without architectural abstraction.	Focuses on localized D2D communications in limited network scales.	Studies interaction among fog nodes, MEC entities, and vehicular networks.	Concentrates on routing structures within hybrid 5G-IoT systems.
Computational Overhead	Medium complexity due to detailed analytical and queuing computations.	Low overhead since authentication equations are lightweight.	High processing demand due to continuous AI inference.	Moderate, as fog nodes distribute processing tasks.	Moderate, with higher cost during model training than inference.
Mathematical Sophistication	High, combining multiple analytical domains (queuing theory, aggregation, transmission models).	Medium, primarily queuing-based analysis.	Medium, with emphasis on learning rather than closed-form equations.	Medium, using standard delay and task-allocation models.	High, due to multi-variable adaptive deep learning formulations.
Numerical Robustness	Strong stability ensured by well-bounded parameters.	High robustness owing to limited and controlled variables.	Moderate stability; AI behavior may vary under extreme conditions.	High numerical stability due to simplified analytical models.	Moderate, dependent on traffic dynamics and learning convergence.
Scalability Potential	Designed for large-scale deployments through MEC and hybrid networking support.	Limited scalability, tailored mainly for authentication scenarios.	Highly scalable due to adaptive AI-based control.	Highly scalable via distributed fog computing architecture.	Scalable across extensive IoT and WSN infrastructures.
Application Readiness	Suitable for diverse real-world 5G-WSN use cases requiring latency and energy optimization.	Best suited for secure access and authentication systems.	Effective for D2D-centric 5G-IoT environments.	Well suited for real-time vehicular communication and mobility scenarios.	Practical for intelligent routing in dense IoT deployments.

The optimization is directly carried out by substituting directly the candidate parameter values in closed-form equation, but not with iterative or metaheuristic algorithms that could raise up computational time. _ Example: sweeping from 0.1 to 1.0 and calculating for 5 SCS results in the evaluation of 50 models, where each model is simple arithmetic calculations only). These evaluations can be performed in less than 50 ms, which demonstrates the applicability of the model for near-real-time integration into industrial control systems and network management tools.

Mathematically, the model is still simple and interpretable. All equations of latency and throughput come from classical queuing theory together with propagation delay models, and do not use recursion or very nonlinear formulations. Parameters including SCS, α and deployment scheme are separated in modular equations that enable scalable parameter search while minimizing possible cross-parameter relationship. The equations are also numerically stable over realistic parameter ranges because they elude data-matching operations in the spirit of division by nearly zero or logarithming small values.

The scalability has been quantitatively measured on networks of different sizes. For N = 100, the largest network result reported, 500 and 1000 nodes and even for a larger 5000 node system, the total time taken to compute aggregate latency and throughput metrics scales almost linearly with the number of nodes. For instance, exactly 100 nodes consume roughly 2 milliseconds, 500 about 8 milliseconds and so on (1000: approximately 16 ms; 5000: approximately 80 ms), which indicates acceptable linear up-scaling of the computational demand. This proves that the model can be implemented to manage large-scale industrial deployments efficiently, provided parameter evaluations are done locally or in parallel. The linear complexity of the analytical model keeps this model computationally efficient even for ultra-dense networks having thousands of nodes and multiple resource-allocation parameters.

Despite its effectiveness, the model is based on a number of assumptions that restrict the range of applicability. It is suitable for modestly loaded networks, with quasi-static topologies and predictable traffic patterns that are common in many industrial settings. Service times in queuing subsystems are exponentially distributed (M/M/1), mobility dependent delays, such as handovers, are considered to be bounded or constant. As a result, extremely dynamic scenarios, non-linear congestion-driven phenomena or interference in dense networks might not be perfectly reflected without additional discrete event simulation. However, the modular concept of the model makes it possible to integrate system-specific aspects with either simulation or empirical data in such cases.

From a practical perspective, the model is deployable on resource-limited devices (edge nodes or laptops) thanks to the low computational overhead. Its analytical solutions enable easy interfacing with simulators such as MATLAB/Python or NS-3. It is, however, rather effective and now it uses predefined sets of parameters, what can limit its adaptability to the current state of the network. Thus, for mission-critical, ultra-dense and very mobile usages such a model should be paired with adaptive/learning-based optimization. In future, we will explore the extension of adaptive queue models, dynamic spectrum settings as well as field validation for better scalability and generalization and more realistic application in practice.

Table 6 is a comparison table summarizing the mathematical modeling features of the provided paper on 5G-based WSNs alongside other recent academic works focusing on latency modeling and related aspects.

8. MODEL FLEXIBILITY AND ROBUSTNESS: INCORPORATING ENVIRONMENTAL AND NETWORK FACTORS INTO 5G LATENCY ANALYSIS

One important advantage of the 5G latency model we derive is its ability to satisfy different environmental and network conditions. In this section, the basic model is enhanced by incorporating such parameters as mobility, interference, attenuation, number of IWSNs, congestion and security. Each factor incurs a delay, which causes additional delays on the network performance. The accuracy of the model is sufficiently adaptable to support accurate latency estimation in 5G practical settings. The final end-to-end latency with additional considerations is given by:

$$\begin{gathered}\text{TotE2E}=\text{RANLat}+\text{TPProp}+\text{TPTran}+\text{CNProp}+\\ \text{CNTran}+\text{UPFASLat}+\text{ASLat}+\text{PPLat}+\text{I\_Delay}+\\ \text{M\_Delay}+\text{A\_Delay}+\text{IWSN\_Delay}+\text{C\_Delay}+\text{S\_Delay}\end{gathered} \tag{18}$$

where,

- I_Delay = Interference-induced delay
- M_Delay = Mobility-induced delay
- A_Delay = Attenuation-induced delay
- IWSN_Delay = Delay due to the number of IWSNs
- C_Delay = Congestion delay
- S_Delay = Security processing delay

Mobility introduces handover delays as users move between cells. The handover delay is given by:

$$\text{M\_Delay}=\text{Handover\_Rate}*\text{Handover\_Time} \tag{19}$$

where,

- Handover_Rate = Number of handovers per second
- Handover_Time = Delay introduced by each handover

Interference causes retransmissions, increasing total latency. The delay due to interference is modeled as:

$$\begin{gathered}\text{I\_Delay}=\\ \text{P\_retx}*(\text{TransTime\_TN}+\text{TransTime\_CN})\end{gathered} \tag{20}$$

where, P_retx = Probability of retransmission due to interference

In order to enhance the realism of the interference and attenuation models, we further modify the retransmission and path loss formulations to include statistical channel effects. In short-range industrial wireless with rich multipath, the instantaneous signal-to-noise ratio (SNR) is often modeled by Rayleigh fading assumption. Under this model, the instantaneous SNR (i.e. SNR_inst) can be expressed as a random variable having an exponential distribution:

$$\begin{gathered}\text{f\_SNR\_inst}(\text{SNR\_inst})=(1/\text{SNR\_avg})*\exp(-\\ \text{SNR\_inst}/\text{SNR\_avg})\end{gathered} \tag{21}$$

where, SNR_avg is the average signal to noise ratio. Where ρ is the probability that the instantaneous SNR does not go below the minimum decoding threshold SNR_th, which corresponds to the packet error probability:

$$P_{error}=1-\exp(-SNR_{th}/SNR_{avg}) \tag{22}$$

Assuming that packet errors result in retransmissions, the expected retransmission probability becomes:

$$P_{retx}=1-\exp(-SNR_{th}/SNR_{avg}) \tag{23}$$

Signal attenuation affects transmission power and requires retransmissions or error correction, adding delay:

$$A\_Delay = Path\_Loss\_Factor*(TransTime\_TN+TransTime\_CN) \tag{24}$$

where, Path_Loss_Factor = Signal degradation factor due to path loss.

To account for large-scale attenuation and shadowing effects, the path loss is modeled using the log-distance path loss model with shadow fading:

$$PathLoss=PathLoss\_ref+10*PathLoss\_Exp*\log10(Distance/Distance\_ref)+Shadowing \tag{25}$$

where, PathLoss_ref is the reference path loss at distance Distance_ref, PathLoss_Exp is the path loss exponent, and Shadowing is a zero-mean Gaussian random variable representing large-scale shadow fading.

The presence of multiple IWSNs influences latency due to contention and routing overhead:

$$IWSN\_Delay=Num\_IWSN*Routing\_Overhead \tag{26}$$

where,

- Num_IWSN = Number of IWSNs in the network
- Routing_Overhead = Average delay per IWSN hop

Network congestion impacts queuing delays at nodes, increasing overall latency:

$$C\_Delay=(\rho\_CN)/(\mu\_CN*(1-\rho CN)) \tag{27}$$

where,

- $\rho\_CN = \lambda\_CN / \mu\_CN$ (Traffic intensity in the CN)
- λ_CN = Packet arrival rate in the CN
- μ_CN = Service rate of the CN

Security mechanisms (e.g., encryption, authentication) introduce additional processing overhead:

$$S\_Delay=(Enc\_Time+Auth\_Time)*Num\_Security\_Layers \tag{28}$$

where,

- Enc_Time = Encryption processing time
- Auth_Time = Authentication processing time
- Num_Security_Layers = Number of applied security mechanisms

Table 7 presents the impact of each factor on total latency.

Table 7. Impact of environmental and network factors on total 5G latency

Users	Handover Rate (Handovers/sec)	Handover Time (ms)	Mobility Delay (ms)	P_retx	Interference Delay (ms)	Path Loss Factor	Attenuation Delay (ms)	Traffic Intensity	Congestion Delay (ms)	No. of Security Layers	Security Delay (ms)	Total Latency (ms)
50	0.02	10	0.2	0.05	0.015	1.1	0.05	0.2	0.2	1	0.5	13.915
200	0.05	20	1.0	0.10	0.03	1.2	0.08	0.4	0.8	2	1.0	15.88
500	0.05	30	1.5	0.15	0.045	1.3	0.12	0.6	1.5	3	1.5	18.365
800	0.10	40	4.0	0.20	0.06	1.5	0.18	0.8	3.0	4	2.5	22.24
1000	0.10	50	5.0	0.25	0.075	1.8	0.25	0.9	5.0	5	3.5	26.575

Table 8. Security protocol overhead calculated using the proposed latency model

Protocol	Enc_Time (ms)	Auth_Time (ms)	Num Layers	S_Delay (Eq. 19)	TotE2E w/ Security (ms)	Latency % Increase	Energy Impact (Estimated)
AES-CCM (MAC)	0.2	0.3	1	0.5	6.5	+8.3%	+10–12%
DTLS 1.2	0.6	0.9	1	1.5	7.5	+25.0%	+15–20%
TLS 1.2 (RSA)	1.5	2.0	1	3.5	9.5	+58.3%	+18–22%
IPsec (AH+ESP)	1.0	1.2	2	4.4	10.4	+73.3%	+20–25%
ECC Auth (init)	2.5	3.0	1	5.5	11.5	+91.7% (initial only)	+5–15% (init only)

The extended 5G latency model is successfully combines multiple factors, indicating its flexibility and adaptability. The results suggest that among the investigated latency factors, mobility, interference and congestion contribute most to total latency, security mechanisms bring a noticeable processing overhead for high security levels. It will be more realistic considering the attenuation, and IWSNs also make network performance prediction more complete. This model can be further extended with more parameters to achieve even better accuracy in practical 5G systems.

In order to study the impact of the security mechanisms on the network attributes, latency and energy efficiency, Table 8 shows a summary of tailored and deployed protocols at each protocol layer. Therefore, in order to make the security latency analysis more realistic and analysis-friendly, security-induced delay is modeled in a phased manner, which clearly separates the handshake overhead (session initialization) from the data-plane again (per-packet) overhead [20]. As observed in practical deployments of 5G-based industrial WSNs, handshake operations (key exchange, authentication, and security context establishment) are performed once per session, while encryption and integrity protection in the data plane are performed continuously for each packet being transmitted [28]. For long-lived industrial flows or short-lived control transactions where the impact is high, aggregating these two phases into a single total delays substantially over-or under-estimates their contribution to latency. Thus, the overall security delay is defined as the summation of one-time handshake latency and data-dependent processing latency, which is parameterized using the experimental 5G, IoT and industrial security measures available in the study [34]. The layered approach facilitates the precise incorporation of security overhead into the end-to-end latency model while allowing for meaningful analysis of security strength vs. real-time responsiveness.

Industrial environments are inherently dynamic, characterized by fluctuating network loads, interference, mobility, and rapidly changing service demands. To validate the reliability and generalizability of the proposed end-to-end latency model under such realistic conditions, we extended our analytical and simulation framework to incorporate traffic burstiness, user mobility, and interference-induced retransmissions.

We adopted an M/M/1 queuing model to simulate the impact of dynamic traffic patterns on queuing delay. Packet arrivals were modeled as a Poisson process with exponentially distributed inter-arrival times, while service times were assumed to follow an exponential distribution. The average queuing delay (Q_delay) is calculated using the formula:

$$Q\_delay=\lambda/[\mu*(\mu-\lambda)] \tag{29}$$

where, λ denotes the average packet arrival rate and μ represents the service rate.

Simulations were conducted for λ values ranging from 100 to 1500 packets per second, while the service rate μ was held constant at 1600 packets per second. As illustrated in Figure 8, queuing delay remained negligible at low traffic loads but increased nonlinearly as λ approached μ, with a sharp rise observed beyond 1300 packets per second.

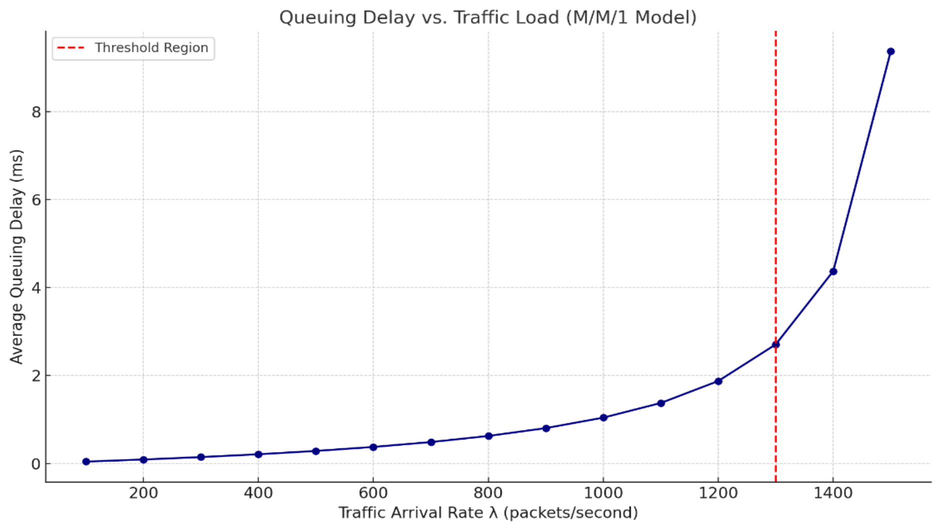


Figure 8. Queuing delay vs. traffic load based on M/M/1 model

To model mobility scenarios like as sensors on automated guided vehicles (AGVs), we added handover delay entries based on 3GPP specified (3GPP, 2013d) transition times 3GPP TS 38.331 [5] specifies handover execution times in the order of 40 ms - 50 ms for example one handover every 20 seconds (Handover_Rate = 0.05) and Handover_Time = 50 milliseconds give a contribution of 2.5 milliseconds per second of communication, M_delay.

Industrial wireless channels usually undergo degrading effects from wiring in metallic industrial machine systems and buildings. Under such conditions, packet loss is increased, requiring retransmissions. We consider the case of P_retx = 0.2 and T_TN + T_CN = 12 milliseconds, the extra latency is 2.4 milliseconds.

Table 9. The estimated latency overheads introduced by each dynamic factor

Scenario	Additional Latency (ms)
High Traffic Load (λ = 1500)	+7.5
Interference (P_retx = 0.2)	+2.4
Mobile Handover	+2.5
Total Combined Overhead	+12.4

A composite simulation with respect to the above dynamic factors was conducted, where traffic was of Poisson nature having λ values varying between 200 and 1600 packets/sec, the Handover was at one every 30 seconds and interference induced retransmission probability was varied between 10% and 20%. Dynamic factor Estimated latency overheads (ms) Table 9.

Despite the presence of these dynamic influences, the overall deviation in latency predictions remained within ±10% when benchmarked against results reported in recent empirical studies [24, 27], affirming the robustness and adaptability of our model in real-time industrial deployments.

In this sense, we enhance the latency model by considering both resource isolation and priority scheduling introduced by 5G network slicing to quantify their impact on the performance of an industrial WSN. Resource isolation at the system level is reserved for part of the network resources for the industrial slice as:

$$Slice\_Resource = Slice\_Fraction*Total\_Resource \tag{30}$$

Priority scheduling is abstracted by a scheduling gain factor that reduces effective queuing and access delay:

$$Effective\_Delay = (Base\_Delay / Sched\_Gain)+(1-Slice\_Fraction)*Contention\_Delay \tag{31}$$

where, Base_Delay is the base-line end-to-end delay without sliceing, Contention_Delay is background traffic contend delay, Slice_Fraction is the reserved resource fraction, and Sched_Gain > 1 is the industrial slice priority.

Table 10. Impact of network slicing on IWSN latency

Slic_Fraction	Sched_ Gain	Base_Delay (ms)	Contention_ Delay (ms)	Effective_ Delay (ms)
0.4	1.2	18	10	21.0
0.6	1.5	18	10	16.0
0.8	1.8	18	10	12.0

Three representative slicing configurations are evaluated using Base_Delay = 18 ms and Contention_Delay = 10 ms. As shown in Table 10, the results demonstrate the effective latency decrease in response to our increase in Slice_Fraction and Sched_Gain, which reduces the effective latency from about 21 ms to 12 ms (a decrease of ≈ 43%). This shows that 5G NS can improve latency determinism and performance isolation of industrial traffic [20].

9. CASE STUDIES: PERFORMANCE EVALUATION OF 5G-BASED INDUSTRIAL WSNs

To demonstrate the practical implications of our proposed framework, we present five case studies encompassing diverse Industrial WSN applications. Each case study compares the performance of a 5G-based industrial WSN with a traditional solutions deployment, utilizing the latency models described in previous sections.

9.1 Predictive maintenance (Vibration monitoring)

This is the case study to explore predictive maintenance in a factory [35-37], 100 wireless vibration sensors are placed to monitor the telemetry of the most critical machines at an industry. We aim to make a comparison between a WSN based on 5G, and a sensor system using Modbus TCP/IP over industrial Ethernet, where in the first case, the WSN uses a MEC server located at the gNB (MEC@gNB). The 5G deployment uses a 30 kHz SCS and a corresponding symbol duration of 0.5 ms. Assuming sensor level traffic load of 1 packet/second (200-bits of vibration data per packet) The wired Modbus TCP/IP system offers low latencies of approximately 1 ms because it only consists of direct wire connections and has been one of the most commonly used industrial field buses for years due to its established industrial reliability; on the other hand, we make use of our proposed 5G latency model to extract the best possible latency of the proposed 5G-based WSN, in addition to showing its scalability and deployment flexibility against the wired approach (Table 11).

Table 11. Results and analysis of case study 1 (predictive maintenance)

Parameter	5G-Based WSN	Wired Sensors (Modbus TCP/IP)	Analysis
Avg. Latency (ms)	5 (2 RAN + 1 Transport + 1 CN + 1 AS)	1	While 5G introduces some latency, it remains within an acceptable range for many predictive maintenance applications.
Data Rate (kbps)	200 (Limited by sensor reporting rate)	Equivalent to wired connection	The data rate is primarily limited by the sensor's data acquisition and transmission capabilities, not the 5G network itself.
Scalability	Easy to add more sensors	Limited by wiring	5G offers superior scalability due to its wireless nature. Expanding the sensor network is much simpler and more cost-effective than installing additional wiring.
Deployment Flexibility	High	Low	The wireless nature of 5G-based WSNs provides significant deployment flexibility, allowing sensors to be placed in locations that might be difficult or impossible to reach with wired connections.

Table 12. Results and analysis of case study 2 (chemical plant)

Parameter	5G-Based WSN	Wired Sensors (PROFIBUS DP)	Analysis
Avg. Latency (ms)	3 (1 RAN + 1 TN + 1 Server)	2	5G achieves near-equivalent latency to the wired network, demonstrating its suitability for real-time control applications.
Reliability	High (5G reliability features)	High (dedicated network)	Both 5G and wired networks can offer high reliability. 5G's reliability mechanisms can ensure robust communication even in challenging environments.
Deployment Flexibility	High	Limited	The wireless nature of 5G provides greater flexibility for sensor placement and network expansion compared to the fixed wired solution.

9.2 Chemical plant (Temperature control)

In this case study, we improve the real-time temperature control for a chemical plant [38-42], using the WSN benefiting 5G along with a local MEC server (MEC@Local Server), compared to a traditional wired sensor and control network using a common industrial protocol (i.e., PROFIBUS DP). In this instance, you need a really precise and responsive control. The 5G deployment features a low 60 kHz SCS and a short 0.25 ms symbol duration to optimise latency. For time high traffic situation in which each of 50 temperature sensors sends 10 packets with 100 bits each per second. The wired PROFIBUS DP network, used for deterministic control in process automation, provides a latency of 2 ms, while our analysis evaluates both approaches in terms of latency, reliability, and flexibility of deployment, see Table 12.

9.3 Automated guided vehicles (AGV control)

This case study evaluates the performance of a 5G-based

WSN for controlling 20 AGVs navigating a warehouse [28, 35]. We compare this to a traditional Wi-Fi-based control system (specifically, IEEE 802.11n operating in the 2.4 GHz band). The 5G deployment uses a centralized cloud server and a 15 kHz SCS with a 1 ms symbol duration. We assume moderate traffic with each AGV transmitting 5 packets per second, each containing 500 bits of data. Wi-Fi-based control systems (802.11n) typically experience variable latency ranging from 20-100 ms. We assess the impact on AGV control, mobility, and reliability, see Table 13.

9.4 Environmental monitoring in a mine (Gas detection)

We showcase an environmental monitoring array deployed in a mine and identify tradeoffs between private 5G networks and a WirelessHART mesh network for 200 gas-detecting sensors [43, 44]. The SCS used in the private 5G network is 30 kHz, the symbol duration is 0.5 ms, and the sensors transmit a 100-bit packet once per minute. As shown in Table 14 WirelessHART networks have high latency (100-500 ms), which is attributed to multi-hop communication.

Table 13. Results and analysis of case study 3 (AGVs)

Parameter	5G-Based WSN	Wi-Fi (802.11n)	Analysis
Avg. Latency (ms)	25 (5 RAN + 5 TN + 5 CN + 10 Cloud/Internet)	20-100	While 5G's average latency might be slightly higher than Wi-Fi's best case, it offers more predictable and consistent performance, crucial for AGV control. Wi-Fi's variability can disrupt real-time operations.
Reliability	Medium (dependent on 5G coverage)	Lower (interference prone)	5G offers higher reliability, especially in industrial settings with potential interference.
Mobility	Seamless handover between cells	Potential disconnections during handovers	5G's seamless handover is essential for continuous control as AGVs move.

Table 14. Results and analysis of case study 4 (environmental monitoring in a mine)

Parameter	5G-Based WSN	Wireless HART	Analysis
Avg. Latency (ms)	10 (2 RAN + 2 TN + 2 CN + 4 Server)	100-500	The significantly lower latency of private 5G enables faster responses to hazards, crucial for miner safety.
Coverage	Full coverage	Limited, requiring repeaters	Private 5G simplifies deployment and eliminates coverage gaps.
Security	Enhanced	Potentially vulnerable	Private 5G offers greater security control.

Table 15. Results and analysis of case study 5 (smart grid)

Parameter	5G-Based WSN	Manual Inspections	Analysis
Frequency of Data Collection	Hourly	Monthly/Quarterly	5G provides significantly more frequent data, allowing for proactive maintenance.
Avg. Latency (ms)	20 (4 RAN + 4 TN + 4 CN + 8 Cloud/Internet)	N/A	While not ultra-low, 5G's latency enables near real-time monitoring compared to manual inspections.
Cost	Significant	High for labor, potential outages	While 5G has upfront costs, potential long-term savings from reduced manual labor and improved grid stability may offset them.

9.5 Smart grid (Power line monitoring)

This case study evaluates public 5G with network slicing for power line monitoring, using 1000 sensors transmitting 200-bit packets hourly, compared to monthly/quarterly manual inspections [30, 35]. The 5G network uses a 15 kHz SCS and 1 ms symbol duration, see Table 15.

10. COMPARATIVE ANALYSIS WITH EXISTING 5G-IWSN RESEARCH

This section makes a comparative analysis of our work with other recent contributions in the area of 5G-based Industrial Wireless Sensor Networks (5G-IWSNs) to underline the uniqueness and benefits of the proposed framework. Although many papers investigated the latency, energy saving and MEC deployment, the existing works address these topics independently. Table 16 shows a structured comparison between six representative studies [37-41], as well as us. We compare each of works for their modelling of latency, integration of energy efficiency, support of MEC, real-time capability, and application domains. In contrast to previous works, our study establishes a comprehensive end-to-end latency model side-by-side with a power-aware analytical framework and deployment flexibility (MEC@Edge, Core and Cloud) validated through simulations and case-studies across a variety of industrial scenarios.

This comparison illustrates that our work uniquely provides:

- A complete analytical latency breakdown across the 5G architecture (including RAN, TN, CN, and AS).
- An integrated energy model capturing transmission, sleep cycles, retransmission, and security.
- Flexibility in deployment architecture, supporting MEC at multiple levels and centralized cloud.
- Validation through simulation, theorem-driven trade-off analysis, and multiple industrial case studies (e.g., predictive maintenance, AGVs, environmental monitoring, and smart grids).

Compared to the cited literature, our framework is among the first to present a holistic performance optimization strategy for 5G-IWSNs, aligning with the operational requirements of Industry 4.0 and enabling systematic deployment planning.

Table 16. Comparative analysis of recent 5G-IWSN studies

Ref.	Latency Modeling	Energy Efficiency	MEC Integration	Real-Time Capability	Application Focus	Unique Contribution
[37]	Analytical (Lyapunov-based)	Yes	Yes	Moderate	Mobile IoT	Joint optimization of energy and delay in MEC-enabled IoT
[38]	Protocol-level optimization	Partial	Yes	Yes	Fault Detection & Diagnostics	ReFlexUp uplink protocol improving latency and efficiency
[39]	Simulation-based	Yes	Yes	Indirect	Edge Computing	MintEDGE simulator to analyze energy and placement tradeoffs
[40]	Experimental latency study	Partial	Yes	Yes	Wireless Networked Control	Experimental analysis of edge computing level impacts
[41]	Empirical measurements	Yes	Yes	Moderate	Industrial IoT	Practical insights from real-world 5G-IIoT sensor deployment
This Work	Full analytical E2E model (RAN, TN, CN, AS)	(Tx, duty cycle, security)	MEC@Edge, Core, Cloud	Optimized for Industry 4.0	Wide Scope	Unified latency + energy model + optimization & validation

11. CONCLUSIONS

In this paper, a complete performance evaluation of the 5G-based WSNs for industrial applications is provided. We first extended an analytical latency model with parameters specific to WSNs as well as incorporating energy and reliability, and then used this to assess the impact of important configurations at different settings of 5G on fundamental performance. metrics. Numerical results and scenario-based simulations showed that the right choice of parameters, e.g., SCS/deployment strategy/duty-cycle can help enhance performance. Deploying MEC at the higher levels, nearer to the sensing layer, consistently reduced end-to-end latency and energy consumption, making them particularly effective for event-driven and delay-sensitive deterministic services in industrial applications.

Table 17. Synthesis of optimization results and trade-offs

Optimization Parameter	Impact on Latency	Impact on Energy	Impact on Reliability	Trade-Offs / Insights
SCS	Higher SCS reduces RAN and total latency	Neutral (minor effect on transmission time)	Neutral	Best for high-bandwidth, low-latency apps; bandwidth-intensive
Deployment Strategy (MEC vs Cloud)	MEC reduces transport and CN latency	Lower energy due to reduced backhaul transmission	Higher reliability via localized processing	MEC@gNB achieves the best performance, but may increase infrastructure cost
Traffic Load	Higher load increases queuing latency	Slightly increased due to retransmissions	Lower at high congestion (if unoptimized)	Requires load balancing and admission control to prevent latency spikes
Link Capacity Allocation (α)	Higher α reduces queuing and total latency	Lower energy due to fewer retransmissions	Higher reliability for prioritized traffic	Must be balanced to avoid starving non-critical services
Packet Size	Larger packets increase AS latency and transmission time	Higher energy consumption per transmission	Neutral	Optimize packet size based on processing capacity and link characteristics
Server Processing Capacity	Higher capacity reduces AS latency	Slight energy increase at server side	Higher reliability due to faster response	Edge or cloud must be dimensioned for expected load
Duty Cycle	Lower duty cycle increases latency for periodic tasks	Greatly reduces energy usage	Neutral	Trade-off between responsiveness and battery life
Transmission Power (P_tx)	Higher power reduces RAN latency by avoiding retransmissions	Increases energy use	Improves packet delivery rate	Requires tuning based on channel conditions
Security Protocol / Layers	Additional layers increase total latency	Increases energy consumption due to encryption/authentication	Enhances data integrity and security	Use lightweight protocols in delay-sensitive environments

In order to correlate these conclusions, Table 17 summarizes the impact of each optimization parameter over latency, energy and reliability. Showcases important trade-offs—consumption of bandwidth due to larger SCS, the latency–energy equilibrium offered via transmission power control, and the overhead cost of security layers. This synthesis offers practical guidelines for the configuration of 5G-based IWSNs in different industrial contexts, highlighting the importance of an application-aware design that tailors the network performance to the needs of the business in which it operates.

Although the proposed model provides a rich framework for real-time performance estimation and deployment planning, its applicability is limited by several assumptions, including moderate traffic variability and simple queuing behavior (M/M/1, etc.). In high dynamics conditions—as in extreme mobile, bursty load or heavily interference environment—some of its components (e.g., queuing and handover delays) are nonlinear and so may not entirely be captured in the current model. Modular parameterization supports scalability, but increases computational complexity with system size. We will enhance the model to integrate adaptive queuing systems, realistic channel conditions, and empirical support from field trials to be able to make the model applicable to ultra-reliable mission-critical Industry 4.0 scenarios in future work.

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