

ADlperf: A Framework for Application-driven IoT Network Performance Evaluation

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Abstract—The Internet of Things (IoT) is the convergence of the physical and the digital worlds. It enables a large spectrum of applications such as smart building, smart tracking, smart metering, predictive maintenance, remote control, augmented reality or video surveillance. The diversity of these applications has caused a profusion of the IoT communication technologies offerings for exchanging data between IoT devices and applications. The latter technologies come with different features in terms of range, throughput, latency, scalability, energy, etc. Each technology can fit several use cases and a use case can leverage several technologies. It is complex, yet critical, for an IoT architect to evaluate the adequacy and the limits of a network technology for a targeted application and to continuously optimize its configuration as the deployment evolves. This paper introduces ADlperf, a framework to simplify and systematize the evaluation of the performance of an IoT communication technology for a given IoT use case and context. The ADlperf approach pays special attention to the energy efficiency as well as to the ability of an IoT communication technology to properly scale up with the number of end-devices, with the ultimate goal of giving guidelines and tools for IoT architects to select the technology and configure the network that fulfill their application’s needs over time.

Index Terms—Internet of Things, Applications, Framework, Performance Evaluation, Simulation.

I. INTRODUCTION

The Telecommunication Standardization Sector of ITU (ITU-T) [1] defines the IoT as a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving inter-operable information and communication technologies. As a whole, the IoT forms a complex ecosystem for exchanging a large variety of information. The data can flow (i) from sensors to gateways and data center servers where collected data are processed and decisions made, and/or (ii) from the cloud or edge servers down to actuators, or more generally, to end-devices to transmit information or commands. Compared to traditional Internet devices, IoT devices often have limited memory, processing and network resources.

New connectivity technologies have emerged and continue to evolve to accommodate the specific needs of IoT traffic, devices and digital services. Solutions for long-range low-power communications include LoRaWAN [2], Sigfox [3],

Mioty [4], Wi-Fi HaLow [5], NB-IoT [6], LTE-M [7] while short or medium-range communication technologies comprise Zigbee [8] and Wi-Fi [9]. Each of these technologies has its own pros and cons, and most of them are evolving regularly. The profusion and diversity of technologies can be confusing and are disorienting IoT users but also IoT architects in charge of selecting and calibrating them. In such a context, decision-making can be a complex and risky task. These decisions can affect the entire initiative, both for the achievement of the objectives set and for its future. Under- or over-sizing an IoT system is often not an option as budget, capacity and performance can be highly constrained. Ultimately, the decision generally comes down to the best trade-off between cost, range, throughput and battery lifetime for the targeted IoT application. These decisions need visibility and forecasts that are difficult, time-consuming and error-prone if done by hand.

In this paper, we introduce ADlperf, a framework and associated tools to assist IoT architects in the evaluation of the ability of a network technology to meet the specific needs brought by a real-life IoT application. This approach defines and computes network- and energy-related key performance indicators (KPIs) that score the performance of a setting for a given topology and workload. To show the relevance of the method, we present the results of its application to two case studies inspired by IoT real-life.. Finally, we discuss how IoT architects can exploit the outcome of this evaluation framework.

The remainder of the paper is organized as follows. Section II provides a state of the art in IoT networks evaluation. Section III describes the proposed application-driven evaluation framework. We explore three real-life inspired case studies to showcase the potential of our framework in Section IV. A discussion on the obtained results and guidelines on how they can be used are provided in Section V. Finally, Section VI concludes this paper and gives perspectives.

II. RELATED WORK

IoT network technologies have been evaluated in many studies. For instance, in [10], the authors analyze the performance of LoRaWAN on four use-cases using the LoRaSim simulator with a modified MAC protocol. In [11], the authors use simulation to compare the reliability of LoRaWAN, Sigfox, and NB-IoT for the specific case of a smart water grid scenario. Another case in point is [12] wherein the authors compare the performance of Wi-Fi and cellular technologies in terms of throughput and latency in metro areas. We observe that, despite the abundance of IoT network research, there is a relative paucity for developing a reproducible and robust approach to systematically analyze the matching between an application and a network solution and its scalability. Most papers are indeed either restricted to the study of a single communication technology, or alternately, to only one application. Moreover, unlike fields like linear algebra and image processing, the IoT community lacks a reproducible approach to assess the performance of an IoT network technology in a well defined usage context.

Several papers have tackled the issue of selecting the most adequate network technology for an IoT application. For instance, [13] compares between LoRaWAN, NB-IoT, Wi-Fi HaLow [5] and Sigfox on the following metrics: data rate, loss, cost, power consumption, bandwidth, coverage and SNR. However, the performance of each technology in terms of these metrics does not take into account the targeted scenario the network technology is used for. A similar remark can be made about [14] and [15], where the selection is done using approximately the same metrics, but with different network technologies. In addition, other works like [16] do not consider the energy consumption criteria which is important in the IoT domain. Hence, the evaluation process has its limitation since an IoT technology can be very efficient for an application in a given context and inadequate for another one. Therefore, we argue that a well defined evaluation method for effectively studying IoT network performance in realistic context is lacking.

III. ADI PERF EVALUATION FRAMEWORK

In this section, we describe ADIperf, our application-based IoT network performance evaluation framework. It consists in two types of inputs, an instrument and a set of outputs. These four building blocks are: (i) an application scenario specification (input), (ii) network setup characteristics (inputs), (iii) an evaluation tool (instrument) and (iv) a set of network metrics (outputs) to assess the performance of the IoT network technology on the selected scenario. Figure 1 gives an overview of our evaluation framework, with highlighting its inputs and outputs. We detail each of these components in the sections below.

1) **Application scenario specification:** To characterize an IoT application, we define a scenario by a list of parameters an architect can specify. These parameters are of four types: (i) the end-devices characteristics: their number, their relative

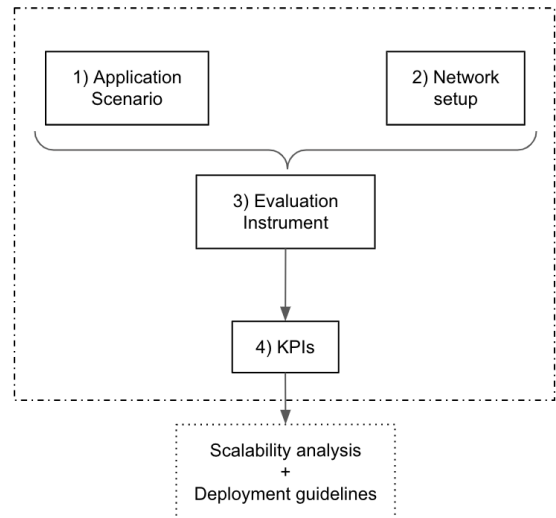


Figure 1: Overview of ADIperf building blocks.

location and their batteries capacity, (ii) the transport protocol (*e.g.*, UDP/TCP, etc.), (iii) the traffic type and (iv) the workload (defined by the message size and the inter-messages period).

We propose to classify the IoT traffic types by (i) their direction: upstream (from end-devices to gateways or the cloud) or downstream (from the cloud or gateways to end-devices) and (ii) their profile: periodic or stochastic (for sporadic or bursty traffic). The periodic traffic corresponds to a fixed data rate, while the stochastic traffic has a variable rate. Although some applications have bidirectional traffic, we observe that a majority of IoT applications have unidirectional data flows. Table I categorizes the different IoT traffic types. We illustrate each traffic type by possible applications. The "overload" IoT traffic types 5 and 6 of Table I, though not corresponding to realistic traffic, are proposed to evaluate the IoT technologies in extreme conditions, giving us an insight on the technologies limits. Figure 2 shows a classical IoT system architecture where the end-devices can either be sensors or actuators, depending on the traffic direction, upstream or downstream respectively.

2) **Network setup:** The IoT network setup is defined by (i) the network technology PHY and MAC layers, (ii) the propagation model, (iii) the radio frequency, (iv) the bandwidth, (v) specific radio parameters (*e.g.* Spreading Factor SF, Modulation and Coding Scheme MCS) and (vi) the network topology, with the number of gateways and their location. Depending on the network topology, some parameters may be null. For example, there will be no gateway in a mesh topology. Even though we focus, in the tested use-cases, on networks with a star topology, the framework can be also applied to a mesh topology. Depending on the chosen evaluation tool, some parameters like, for instance, the propagation model can be defined by the user (in case of analytical models and simulation) or be fixed by the evaluation environment (in case of real experiments).

Traffic type	Traffic profile	Traffic direction	Examples
1	Periodic	Upstream	Telemetry, Geolocation...
2	Periodic	Downstream	Webcast, Virtual Reality...
3	Stochastic	Upstream	Video Surveillance, Cloud gaming...
4	Stochastic	Downstream	Notifications, Alerts, Remote commands...
5	NA	Upstream	Overload
6	NA	Downstream	Overload

Table I: Traffic types characteristics.

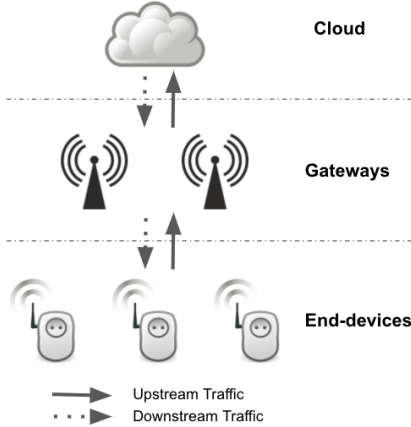


Figure 2: Classical high-level overview of an IoT architecture.

3) **Evaluation instrument:** In theory, the performance evaluation could be realized through different instruments: experimentation, simulation or analytical modelling. These instruments have their own advantages and drawbacks. Depending on their requirements, users can choose between one or several of these evaluation instruments. If real performance results are expected, experimentation will be preferred. For example, the architect will run a real test if he needs to precisely estimate the battery power consumption under a given workload. If a scalability analysis is considered, analytical modelling or simulation is very likely more appropriate. An IoT architect will often conduct studies combining several evaluation tools to get precise at-scale results.

4) **IoT-relevant KPIs:** Now, we propose to define IoT relevant key performance indicators (KPIs) as evaluation outputs: (i) attained throughput, (ii) latency, (iii) success rate, (iv) power consumption, (v) energy efficiency ratio, (vi) battery lifetime, and (vii) scalability index.

Attained throughput, latency and success rate are classical networking performance parameters. Attained throughput represents the overall speed of the network at conveying data or the data rate delivered to each IoT device. Latency is the time that a packet takes to transit from its source to its destination. The success rate (a.k.a. packet delivery ratio) is the ratio of the packets successfully received from all the sent packets. Note that from the IoT application perspective, a message is the fundamental data unit while the packet is the classical network

data unit. There may be several packets in one application message. But for the sake of simplicity and without loss of generality we assume a message corresponds to one packet here.

Energy is highly important in the IoT industry where end-devices often have limited power supply and are equipped with a battery. Power consumption represents the rate at which energy is consumed over a period of time. It can be measured on the overall network or on each IoT end-device. In this work, we define the energy efficiency ratio as the amount of bytes that each transmitter can successfully transmit to the receiver using a single joule of energy. The higher this quantity, the more energy efficient the IoT technology is. The battery lifetime gives an indication on the IoT system's lifetime without recharging batteries. The energy consumption due to the sensing is often neglected compared to transmission costs in IoT systems [17].

We call "scalability index" the maximum number of devices that can be connected to a single gateway without deteriorating the performance in terms of IoT metrics. It gives an indication on the deployment cost.

IV. APPLICATION OF THE EVALUATION FRAMEWORK

In this section, we apply our framework to two different use cases: telemetry and video surveillance. We evaluate the adequacy and the performance of the Wi-Fi and LoRaWAN network technologies, for these use cases. We use simulation in the ns-3 environment as the evaluation instrument.

Let's consider first the following telemetry use-case: an IoT architect has to design a WSN-based (Wireless Sensors Network) service to count passengers in urban trains, where sensors are placed over each door. The counting service will operate near real time to optimize the passenger flows. A typical train will have up to twenty wagons and a length going up to 1000m. In this case, the key questions the IoT architect would have is how many gateways should be installed as well as how frequently messages can be exchanged with a 99% reliability.

The second use case is related to video surveillance. We consider a large event gathering a large crowd (Olympic games, trade fairs, concerts, etc.) where a camera-based surveillance system is needed. For mobility, installation time and logistic reasons, the only possible solution is to adopt a wireless connectivity. This means that cameras have to be placed at specific locations, while being self-powered with batteries. Video frames will then be transmitted to a server through a wireless network. A crucial challenge for IoT architects is to know how long will the batteries last, depending on the number of the cameras and the video quality. Moreover, it would be interesting for them to know how many cameras should be placed, at what distance from each other to avoid collisions. The energy efficiency ratio is also studied as it represents the energy consumption behaviour in an interesting way.

All these answers have a critical impact, especially on the financial view point, since they may give the maximum

number of gateways, sensors or cameras that can be installed, they can also inform on how often the batteries will have to be changed, etc. We explore these questions in the following, using ADIperf to analyze costs and scalability. In order to provide actionable result, we vary parameters that are critical from the application perspective (message size, message period, etc.), as well as the number of end-devices.

We would like to emphasize the fact that there may be several parameters which are not taken into account in what follows. However, we consider that the considered parameters are enough to have an interesting overview of the behaviour of a network technology for a given application.

A. Case study A: Telemetry on LoRaWAN

This example is devoted to the case of a telemetry application deployed over LoRaWAN. The sensors collect data before exchanging them to the gateway for further processing.

The application scenario is defined as the following: We let the number of sensors vary from 1 to 15,000 and we position them uniformly at a distance ranging from 100 to 3,000 meters from the gateway. Each sensor is equipped with a battery of 2,400 mAh capacity powered by 3.3 V ([18]). The traffic type corresponds to the type 1 (periodic and upstream) of Table I. Regarding the workload, the size of packets (a.k.a. payload) is set to 23 bytes unless specified otherwise, and we consider three possible periods for the rate at which sensors generate their packets: 300, 600, and 900 seconds. For the network setup, we consider that the sensors communicate using LoRaWAN, on the 868 MHz frequency band with a bandwidth of 125 KHz. We use the log-distance path loss model for the propagation model of the radio waves. To evaluate the influence of the SF (Spreading Factor) over the KPIs, we consider two of its value: 7 and 9. The network has a star topology with one gateway. As mentioned before, we used simulation as the evaluation instrument.

To evaluate the performance parameters for this example, we run simulations of 3600 seconds using ns-3. Although the official release of ns-3 does not include methods to estimate the energy costs incurred by LoRaWAN communications, Magrin et al. provide an ns-3 module [19] to do so. The power consumption of the NIC (Network Interface Card) is obtained thanks to a state machine whose states and associated drawn currents are given in Appendix (Table IV). Having set this module, we are then able to obtain the KPIs for this network.

Figure 3 shows the results provided by our framework for case study A. As shown by Figure 3a, the success rate remains relatively high until a couple of thousands of sensors regardless of the specific configurations in use for the SF and the packet generation periods. More precisely, we observe that the success rate tends to drop faster when the periods between successive packets are short and when the SF is large (i.e., when sparser modulations, which keep the radio channel busy for a longer time, are in use). Note that we did not represent the packet latency as the latter does not depend on the number of concurrent sensors. Indeed, unlike Wi-Fi, LoRaWAN does not belong to the listen-before-talking

SF \ Period (s)	Energy consumption (mJ)		Battery lifetime (Years)	
	7	9	7	9
300	250	442	13	7
600	134	229	25	14
900	94	158	36	21

Table II: Case study A: Energy consumption per device over 3600 seconds and battery lifetime for LoRaWAN simulations.

protocols and does not include packet retransmissions so that the packet latency is not workload-dependent. For an SF of 7 and 9 and a packet of 23 bytes, the packet latency is equal to 72 and 230 ms, respectively. These values are typically compliant with the performance requirements of telemetry systems. Figure 3b represents the energy efficiency ratio for LoRaWAN in our example of telemetry for a success rate larger than 50%. We notice that the energy efficiency ratio tends to deteriorate with the number of concurrent sensors due to the increasing probability of collisions that reduce the number of bytes successfully conveyed. We can also note the Spreading Factor has a stronger impact on this metric than the period. The use of a small SF is more energy efficient than using a higher SF.

Table II reports the energy consumption by each sensor over the 3600 seconds of simulation as well as the corresponding expected lifetime of their battery given their capacity. As expected, we observe that using a smaller SF (i.e., more robust modulation) for the packet transmission results in a longer battery lifetime. The table also shows that depending on the selected period between packet generations, battery lifetime may range from a decade to several tens of years.

We conclude this case study by observing that the scalability index is more impacted by the Spreading Factor than by the packet generation period. Still, a LoRaWAN based telemetry system can handle between 3,000 and 15,000 stations.

Figure 4 represents an illustration of ADIperf on the Case Study A, with an instantiation of the four building blocks.

B. Case study B: Telemetry on Wi-Fi

In our second example, we consider a telemetry system in which Wi-Fi is used to send data from the sensors (end-devices) up to the access point (gateway).

For the application scenario, the sensors are located in the vicinity of the gateway and their number can vary from 1 to 60. We consider that their batteries have capacity of 5,200 mAh powered by 12 V. The used transport protocol is UDP. The traffic originating from the sensors also matches type 1 of Table I. For the workload, we assume two possible sizes for the packets: 23 and 1,000 bytes as well as 3 possible periods for the rate at which packets are generated by each sensor: 6, 60, and 360 seconds. For the network setup, we resort to the log-distance path loss model to represent the radio propagation model. Cameras will use the 802.11ac amendment of the IEEE 802.11 standard on the 5 GHz with a channel width of 80MHz, a single spatial stream, without frame aggregation

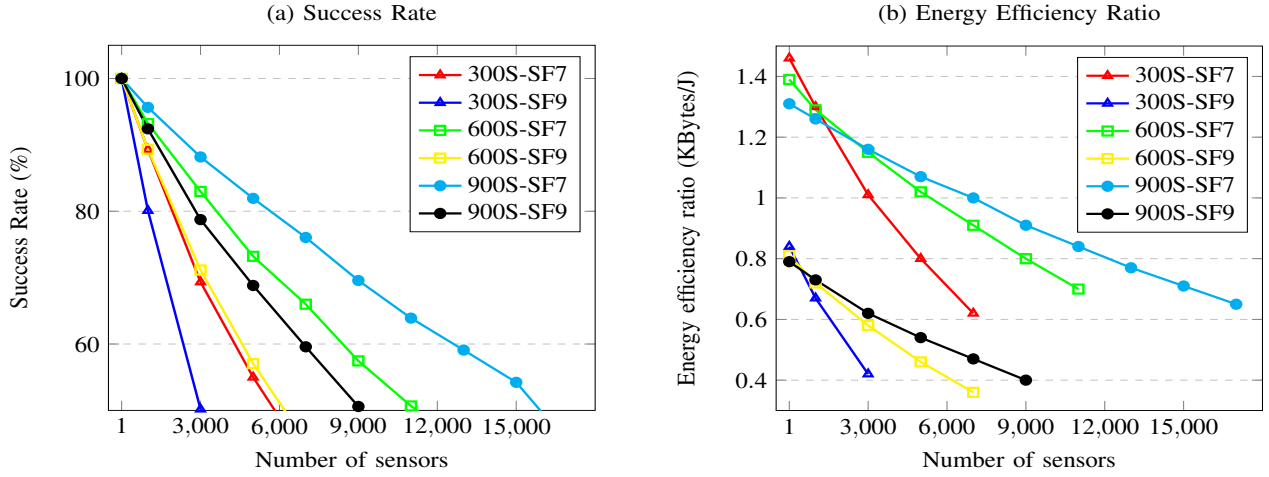


Figure 3: Case study A: Key Performance Indicators (KPI) for telemetry on LoRaWAN.

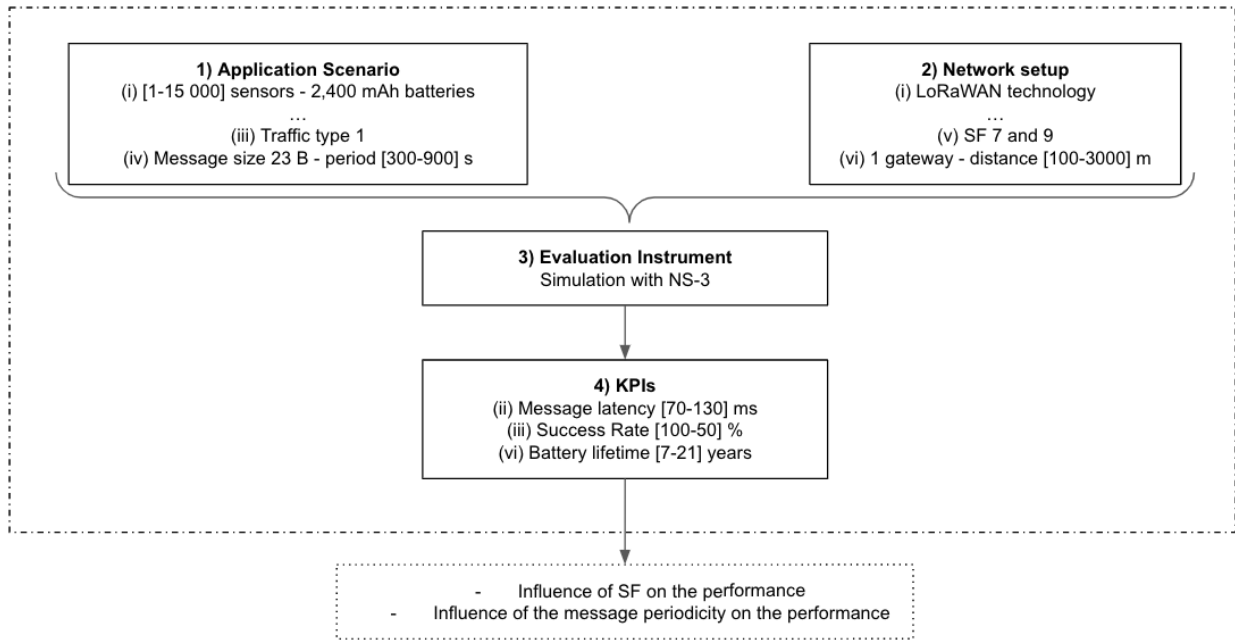


Figure 4: Illustration of the evaluation framework for case study A.

and long guard intervals. We set the MCS (Modulation and Coding Scheme) value to a value of 9. The network also has a star topology with one gateway. We also use ns-3 to evaluate the performance of the considered network. Performance parameters such as the attained throughput, packet latency, and success rate are rather straightforward to obtain from the simulator execution.

To estimate the energy cost of communications, we use the ns-3 module that was developed based on the energy model of Wu et al. [20]. The power consumption of Wi-Fi communications is also estimated thanks to a state machine, which maps values of drawn current to each possible state of the Wi-Fi NIC. The associated drawn currents are also provided in Appendix (Table V). We calibrated the drawn current

parameters of each state using the experiments provided by Serrano et al. in [21]. Through this model, which is embedded within ns-3, we are able to compute the power consumption of any sensor resulting from its Wi-Fi communications. We can also easily obtain the energy efficiency ratio as well as the expected battery lifetime.

For a total number of sensors between 1 and 60, the simulation results show that the success rate for the packet transmission is kept to 100% and that the packet latency remains at its lowest level (below tens of milliseconds and then much lower than the typical requirements for telemetry). These results owe to a total workload having its maximal value at 0.07 Mbps (with 60 sensors, packet size of 1,000 bytes and a periodicity of 6 seconds) when the radio channel

supports a data rate of 50 Mbps. The power consumed by Wi-Fi for each sensor (due to the exchange of communication with the access point) amounts to nearly 47 J for a simulation time of 3600 sec regardless of the number of concurrent sensors. Interestingly, this value also remains about the same for the different combinations of packet sizes and periodicity. This underlines the important energy overhead brought by Wi-Fi resulting from the lack of sleep state in most 802.11 implementations (unlike LoRaWAN) and, to a lesser extent, from the frequent receptions of beacons sent by the access point every 100 ms. Having computed the consumed power resulting from the Wi-Fi communications, we can derive the expected battery lifetime, which we find to be approximately 200 days.

Given that we arguably tested what could be the upper bounds for the packet size and periodicity for the purpose of telemetry applications, we can conclude that Wi-Fi will do network-wise (provided that its radio range is enough) but that the batteries of sensors will typically last less than a year unless they have some form of self-harvesting capabilities or are on electric supply.

Then, we compute the energy efficiency of Wi-Fi using packets of larger sizes. Table III reports the energy efficiency ratios obtained for a packet size of 23 bytes as well as those measured when the packet size is set to 1,000 bytes for three different rates of packet generation (i.e., periods of 6, 60 and 360 seconds). As expected, we observe that the energy efficiency ratio grows significantly with the size of packets (and decreases with the period between packet generations). Regardless of the considered period for the time between packet generation, increasing the packet size by 43 fold (from 23 to 1,000 bytes) approximately results in a 30 fold increase of the energy efficiency ratio.

Interestingly, we observe that the values obtained here are worse than those obtained for LoRaWAN with a packet size of 23 bytes but that they somehow reach the same efficiency as Wi-Fi if the latter uses packets of size 1,000 bytes with a period of 60 s. This observation may resonate with the work of Abedi et al. in which the authors showed that Wi-Fi may be more energy-efficient than Bluetooth [22].

Packet size (Bytes)	Period (sec)		
	6	60	360
23	0.44	0.04	0.007
1,000	13.67	1.36	0.21

Table III: Case study B: Energy efficiency ratio (KBytes/joule) with Wi-Fi for different sizes of packets and packet generation rates.

C. Case study C: Video surveillance on Wi-Fi

In this example, we study how Wi-Fi can be used to support the communication exchanges in a video surveillance application. Such a scenario is expected to be strongly supported by IoT networks [23]. Each camera (end-device) generates a stream of video frames that are sent upwards to

the access point (gateway) and then transferred to a back-end server. We do not explore this use case on LoRaWAN as the minimum bandwidth requirement for video traffic (a minimum of 1Mbps) is not met with a low power technology like LoRaWAN (providing a maximum of 27kbps).

The application scenario is defined as the following: Cameras are located in the proximity of the gateway and their number varies from 1 to 60, with the same batteries as for Case Study B and also with UDP as transport protocol. Note that this traffic corresponds to type 3 from Table I. For the workload, we consider three different rates for the application rate: 2, 5, and 8 Mbps that can be viewed as three different codecs, corresponding to real video traces [24] having frames of different sizes, with a fixed FPS (Frames per Seconds) of 30. The same network setup parameters are used as for Case Study B, with the only difference that the MCS takes a value either of 6 or of 9. The former MCS represents a medium value for the data rate of the radio channel while the latter represents a high value. Simulation with ns-3 is also used as the evaluation instrument.

We now turn to the simulation results summarized in Figure 5. First, looking at Figure 5a, we observe that Wi-Fi can sustain up to 8 or 9 cameras when each of them generates a stream of 8 Mbps. Beyond 9 cameras, the success rate rapidly decreases with packets being dropped as the radio channel activity increases. Using a lower video codec like 5 Mbps and 2 Mbps allows to expand the maximum number of supported cameras to 15 and 30, respectively. Interestingly, we notice that the value of MCS does not impact much the results here. As expected, the packet latency increases with the number of cameras connected to the access point (see Figure 5b). Although it rapidly increases with the number of cameras, its absolute value remains relatively low and does not affect the good behavior of the system even for a total of 40 cameras. Because a video surveillance system with a success rate below 60% can be considered as a non-functional system, we limit our analysis in Figures 5c and 5d to cases where the number of cameras leads to a success rate larger than 60%. Figure 5c indicates that the number of successfully delivered bytes per joule over Wi-Fi mostly depends on the number of concurrent cameras as its value can decrease 10 fold, ranging from a bit more than 15 MBytes per joule when there is only one camera with MCS 9 and a video rate of 8 Mbps up to less than 3 MBytes per joule for a total of 29 cameras with MCS 6 and a video rate of 2 Mbps. Finally, Figure 5d represents the estimated lifetime of the battery. The results demonstrate the importance of having a low video rate to improve the battery lifetime especially if the number of cameras remains relatively low, say no more than 10.

Overall, we observe with this case study that the scalability index (the maximum number of cameras that can be connected to a gateway without degrading the performance) strongly depends on the rate of the video data stream, and much less on the selected MCS. A Wi-Fi based video surveillance can handle between 5 and 20 cameras, which can live on their battery for a month or two [25] depending on the used codecs.

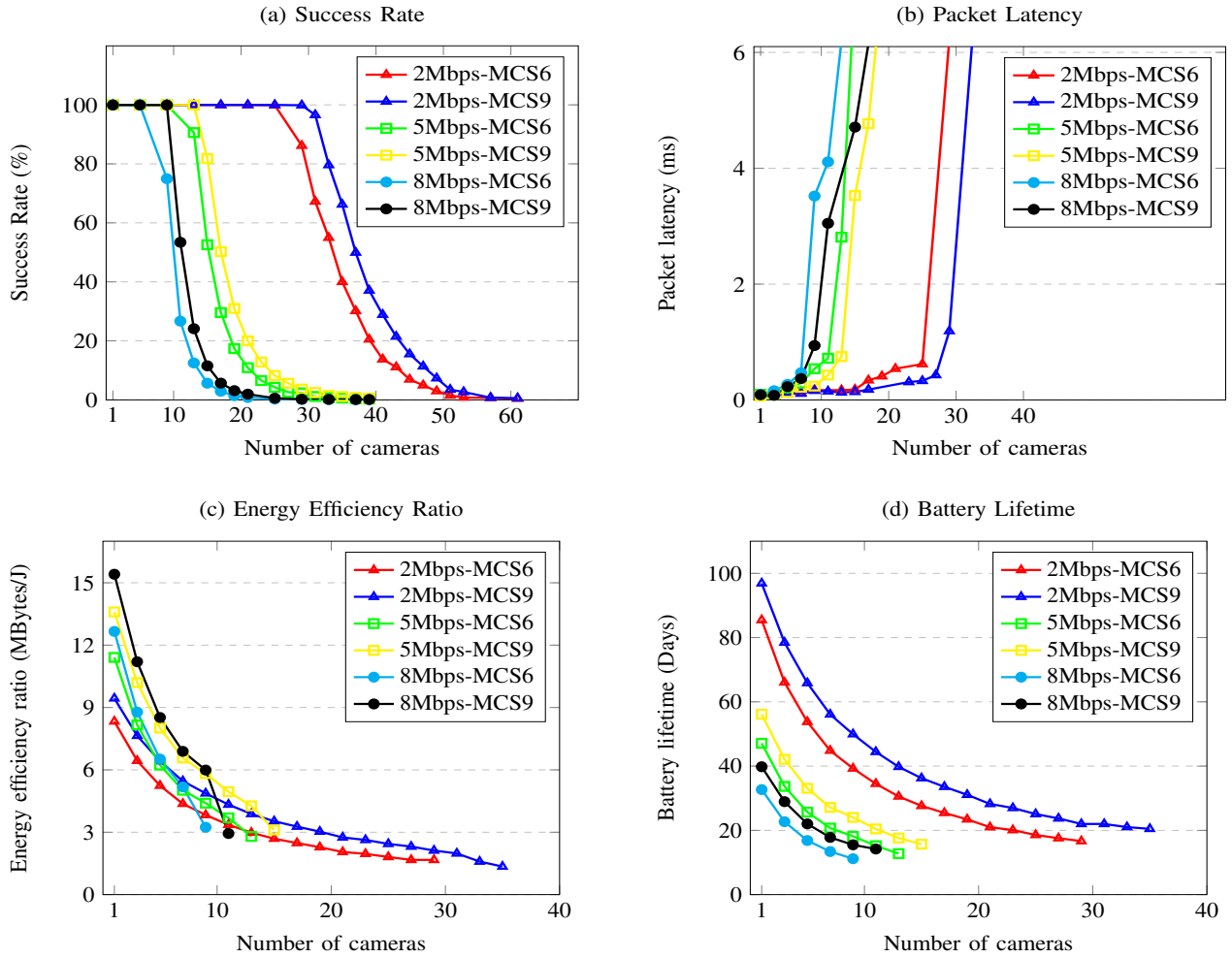


Figure 5: Case study C: Key Performance Indicators (KPI) for video surveillance on Wi-Fi.

V. DISCUSSION

The results of the previous section regarding telemetry, have confirmed the superiority of LoRaWAN setup in terms of scalability. Up to thousands of sensors can be managed by a single gateway. Our results show that, despite being almost an order of magnitude more energy-efficient (in terms of Bytes successfully transmitted per joule) than LoRaWAN when the end-devices have a lot of data to exchange, Wi-Fi is significantly overpowered by LoRaWAN for the battery life of their end-devices (not mentioning its shorter radio range) in the case of a telemetry application. Then the key guidelines for deploying a train passengers metering system using LoRaWAN would be:

- If the distance between the gateway and sensors is not very large, lower than a thousand meters, then privileging lower SFs will ensure more reliability and less energy consumption. This will be for example the case for the train passengers metering solution.
- Message periodicity should be carefully set since it may strongly influence the performance and longevity of the

system. Charts provided by the framework will be used to guide the decision.

Note that for both LoRaWAN and Wi-Fi, ADIperf can consider other kinds of radio channels (more noisy for example) by using different propagation models [26]. This would be an other round of experiments that the architect would run to refine its configuration with respect to the environmental context.

On an other side, an IoT architect looking for a network setup for a video surveillance application may select Wi-Fi for its strong reliability. The following guidelines can be generated from the previous evaluation results:

- One Wi-Fi access point can manage at least ten cameras.
- The greater the MCS, the better the performance will be.
- Favoring low mean data rates for the video streaming may strongly influence the scalability and lifetime of the system, even though the quality of the video may suffer from it.
- The architect will have to use the results to derive the best compromise between the required video quality and battery lifetime.

VI. CONCLUSION

We have presented a framework to evaluate the performance of the network technologies for IoT applications where multiple end-devices exchange data via gateways. The framework includes the definition of a scenario and of its KPIs as well as their evaluation. We used two typical use cases, inspired by real-life IoT applications, to illustrate the applicability of our framework on different network technologies. We paid special attention to the energy efficiency as well as to the ability of an IoT communication technology to properly scale up with the number of end-devices. The provided application-based evaluation results highlight the importance of having a holistic approach when evaluating the good fit of a communication technology its field context. For the sake of reproducibility, we made the code repositories for our numerical results available in [27] and [28].

As future work, we intend to enhance the evaluation framework with a larger set of metrics and network technologies and to explore emerging IoT use-cases, which correspond to cellular technologies such as 5G/6G. We will also extend our framework using decision-making tools to facilitate the comparison of multiple technologies (e.g., NB-IoT, Sigfox, 5G) and to select the best alternative. We believe that our work can simplify the life of IoT architect and thus contribute to facilitate the deployment and adoption of IoT.

VII. ACKNOWLEDGMENT

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APPENDIX

Tables V and IV indicate the numerical values we used throughout this paper to compute the energy consumption of the Wi-Fi NIC and LoRaWAN NIC, respectively. The values of Table V were selected calibrating the state machine against the measurements provided by Serrano et al. in [21]. The corresponding parameter values are given in Appendix (Table V). The values of Table IV are those given by default in the ns-3 module for the LoRaWAN consumption by Magrin et al. [19].

State	Drawn current value (mA)
Tx	77
Rx	28
Idle	1
Sleep	0.015

Table IV: Drawn current values for each state of the machine state used in ns-3 simulations to evaluate the power consumption of LoRaWAN communications.

State	Drawn current value (mA)
Tx	107
Rx	40
CCA Busy	1
Idle	1

Table V: Drawn current values for each state of the machine state used in ns-3 simulations to evaluate the power consumption of Wi-Fi communications.

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