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QoS Performance Evaluation for Wireless Sensor Networks: The AQUASENSE Approach †

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Abstract: The AQUASENSE project is a multi-site Innovative Training Network (ITN) that focuses on water and food quality monitoring by using Internet of Things (IoT) technologies. This paper presents the communication system suitable for supporting the pollution scenarios examined in the AQUASENSE project. The proposed system is designed and developed in the SimuLTE/OMNeT++ simulation for simulating an LTE network infrastructure connecting the Wireless Sensors Network (WSN) with a remote server, where data are collected. In this frame, two network topologies are studied: Scenario A, a single-hop (one-tier) network, which represents a multi-cell network where multiple sensors are associated with different base stations, sending water measurements to the remote server through them, and Scenario B, a two-tier network, which is again a multi-cell network, but this time, multiple sensors are associated to local aggregators, which first collect and aggregate the measurements and then send them to the remote server through the LTE base stations. For these topologies, from the network perspective, delay and goodput parameters are studied as representative performance indices in two conditions: (i) periodic monitoring, where the data are transmitted to the server at larger intervals (every 1 or 2 s), and (ii) alarm monitoring, where the data are transmitted more often (every 0.5 or 1 s); and by varying the number of sensors to demonstrate the scalability of the different approaches.

Keywords: wireless sensor network; water quality monitoring; simulation

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1. Introduction

Water is considered one of the scarcest natural resources on our planet [1]. It directly impacts our lives, as it is vital to humankind, animals, and plants [2]. Thus, the alteration of water quality caused by, for example, industrial waste or climatic changes, is a significant concern. Its quality might be a source of life or death [3]. Promptly detecting the pollution and locating its source is vital in environmental protection. Considering the multiple advantages offered by the technology, the Wireless Sensor Network (WSN) is adopted in pollution-monitoring works. WSNs are suitable for monitoring the physical and chemical characteristics of water remotely [4–7]. In this paper, we describe our contribution to the AQUASENSE project in designing and assessing the performance of a WSN-based end-to-end system for water quality monitoring through computer simulations.

In such a context, a simulation framework built in SimuLTE/INET/OMNeT++ [8–10] is developed, tailored to two scenarios to evaluate the performance of a remote pollution monitoring service through a 4G/LTE-enabled WSN. The first scenario builds on a multi-cell network architecture, in which multiple sensors are associated with different LTE base stations (eNBs) and transmit their water quality measurements directly to the remote server. The second scenario still builds on the multi-cell network architecture. Still, multiple sensors are associated with local aggregators and communicate using short-range technology (e.g., Wi-Fi or ZigBee). The aggregators coordinate their local network of sensors, collect and aggregate their water measurements, and transmit them to the remote server through LTE base stations (eNBs), with which every aggregator is associated. For the above scenarios, we provide valuable performance results regarding the network's Quality of Service (QoS) under different conditions.

2. Previous Work

Our main goal was to design a good quality model that evaluates our project best. Accordingly, following the indications of the most referenced network architectures reviewed by Farmanullah Jan et al. ([11] and the references therein), who provided an in-depth literature review on Water Quality Monitoring Systems based on Internet-of-Things (IoT-WQMS), in [12], we already developed a performance comparison of the most suitable communication technologies.

In our previous work, with the help of the WinProp software simulation framework [13], we compared the performance of three long-range communications technologies to support an IoT-based network reporting data from the sensing devices spread along rivers of the Abruzzo region in Italy to a remote central station, where they are collected and analyzed. More in detail, we jointly assessed the radio signal coverage and the maximum achievable data rate for (i) 4G/LTE, (ii) NB-IoT, and (iii) LoRa communications technologies. In particular, the transmitting antennas' were placed at different heights above the ground or the river's water level.

Our results demonstrated that 4G/LTE outperforms the other two technologies since it achieves the highest throughput and allows adding value services, such as video surveillance over simple data chunks reporting. Nevertheless, 4G/LTE is limited in coverage: the best performance results are achieved near the base stations, i.e., in urban/suburban areas, while the rural regions need more radio signal quality. On the contrary, the LoRa and NB-IoT technologies achieve outstanding connectivity for large regions far from the base stations. However, this performance is paid with a reduced capacity of the medium to support the mentioned added value service.

Considering all the above, we believe, in this paper, that the most exciting scenarios to study are identifying pollutants in urban and suburban areas, i.e., where most people live. Accordingly, the suitable solution for our project is to focus on the 4G/LTE communication technology [14] due to its maturity, its overall coverage, i.e., the availability of base stations, and in general its capacity in terms of guaranteeing radio connections of good quality (low packet loss rate and latency, and generally high throughput). We then assess the system's performance to support different network topologies.

3. The Study

3.1. System Level Simulator

The simulator builds upon INET/SimuLTE over the OMNeT++ Discrete Event Network Simulator. OMNeT++ is an extensible, modular, component-based C++ simulation library and framework primarily developed for building network simulators.

SimuLTE is an innovative simulation tool enabling complex performance evaluation at the system level for LTE and LTE Advanced networks in the OMNeT++ framework. It simulates the data plane of the LTE/LTE-A Radio Access Network and Evolved Packet Core. SimuLTE implements eNBs and User Equipment (UE) as OMNET++ compound modules. These can be connected with other nodes (e.g., routers and applications) to compose networks, as shown, e.g., in Figure 1.

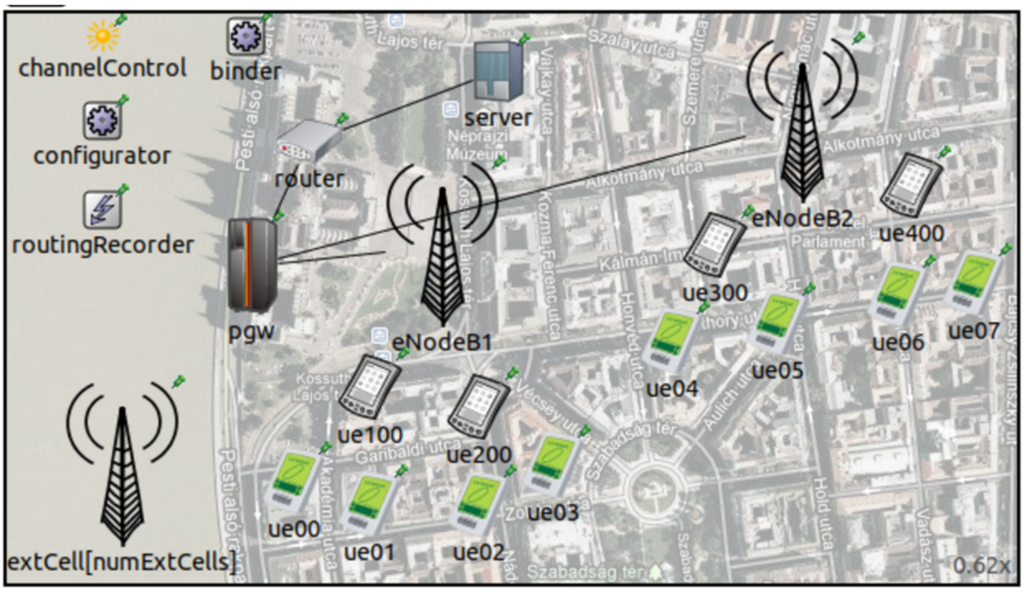

Figure 1. Design mode of the NED file in the OMNeT++ environment represents a system with four sensors and two aggregators (6 UEs) attached to an eNb each.

3.2. The Scenarios

The first scenario is a one-tier network architecture including communication between two parties, the sensors, and the server as is shown in Figure 2(left). The sensors are deployed along a river; each is assigned to a base station and communicates with the server through the LTE network. The challenges in this scenario are to measure the propagation of a pollutant in a river and the reaction (alarm) on the server side, taking into consideration the QoS of the network in two conditions: periodic monitoring and alarm reaction. In systematic monitoring, each sensor sends the river's water measurements at a specific time interval. The server continuously checks the measurements, i.e., it compares them against some given thresholds, and when this comparison indicates the presence of a pollutant, it enters into the alarm condition by sending back a command to all the sensors to start sending their data more often (i.e., lowering their sampling and sending time interval) to track the pollutant appropriately while it flows along the water.

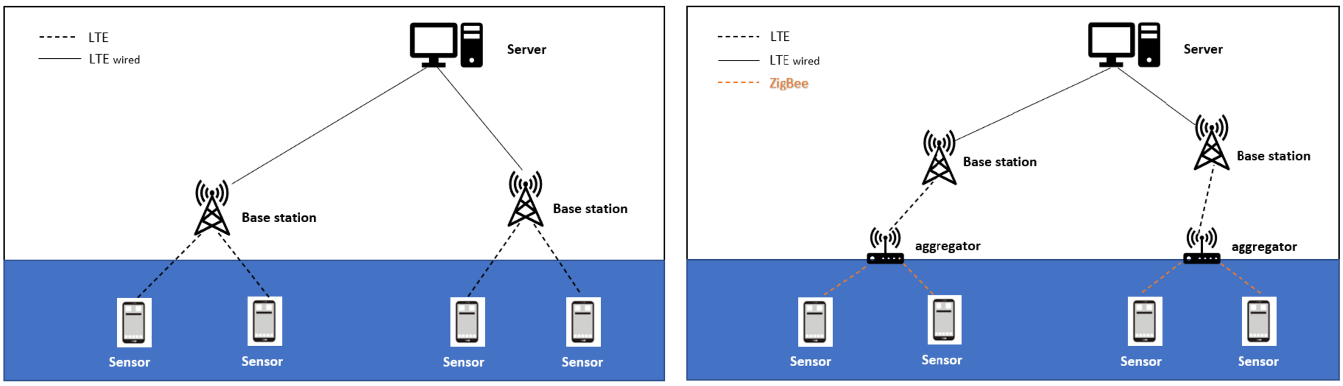

Figure 2. (**left**) Scenario A, one-tier architecture: the sensors are connected directly to the server through the base stations. (**right**) Scenario B, two-tier architecture: the sensors are connected to an aggregator, and the aggregators are connected to the server through base stations.

The second scenario is a two-tier network architecture including communication between three parties, (i) the sensors, (ii) the aggregators, and (iii) the server, as Figure 2(right) shows. The aggregators collect all the data from the sensors transmitted through ZigBee, aggregate them, and then send them to the server, again through LTE. In this case, we simulate pollution through a river to investigate the server's reaction considering the QoS of the network, again in the two conditions as before. The difference with the previous scenario is that when the server detects anomalies in the measurements, it cannot reach the sensors directly; instead, it sends a message to the aggregators, which coordinate their group of sensors to lower their sampling and transmission interval.

3.3. Pollution Simulation

The primary goal is to simulate the effect of a pollutant on the sensors' measurements and then its propagation along the river. In our simulation, we adopted a simple U-shape model in which the presence of the pollutant leads to a temporary decrease in the pH measurement of the sensor while the pollutant flows along the river. We imagine placing and ordering the sensors toward the water flow. Accordingly, as the pollutant flows along the river, the sensor s_1 will start reporting a reduction in its pH measurements to the server at time $t = T_1$. At time $t = T_1 + \Delta T$, UE2 starts sensing the reduction in its measurements too. The interval $\Delta T > 0$ depends on the river water's speed (assumed as constant, for the sake of simplicity) and the distance between the sensors. To make the simulation more realistic, we adopt a model of the pH sensor based on which the value of a sensor reading is assumed to be affected by an error (Equation (1)):

$$pH_{read} = pH_{ideal} + N(0, \sigma) \tag{1}$$

where pH_{read} is the reading value of the WSN node which will be transmitted, pH_{ideal} is the value generated according to our U-shape model of the pollutant as described above, and $N(0, \sigma)$ represents the error as a random value according to a Gaussian distribution having 0 mean and standard deviation σ (e.g., $\sigma = 0.01$).

3.4. Scenarios Implementation

3.4.1. Network A: One-Tier Architecture

In this scenario, the involved entities are S sensors in the water, E eNodeB cell towers of the LTE network, and the server. The sensors monitor the river water's pH and periodically sends the information to the server. In the alarm condition, when the server starts receiving data indicating pollution from a sensor s_i, it notifies all the subsequent ones (s_j, $j = i + 1, ..., S$) to begin transmitting more often for better tracking the pollutant.

3.4.2. Network B: Two-Tier Architecture

In this scenario, the S sensors in the water are organized in G groups, each coordinated by an aggregator. The aggregators are connected to E eNodeB cell towers of the LTE network, and the server. As before, the sensors monitor the water's pH, then they transmit the measurements to the aggregator. The aggregator collects the data, aggregates them into a report containing the average, the standard deviation, and the maximum and minimum values of such measurements, and transmits them to the server. In this scenario, the alarm condition involves the server sending commands to aggregators to increase how often they transmit when an alteration in the data is detected. At the same time, the server requests a change in the format of the aggregators' packets from sending aggregated statistics to sending all the (node ID, pH value)-pairs for each node that the aggregator coordinates.

3.5. Simulation Setup

The parameters for the networks A and B mainly consist of the following:

- Network A: $E = 2$ eNBs and $S = 6$ sensors. The sensors are equally distributed to the eNBs and directly transmit packets to the server every $t^A_{per} = 1$ s in the periodic and $t^A_{ala} = 0.5$ s in the alarm conditions.
- Network B: $E = 2$ eNBs, $G = 2$ aggregators and $S = 6$ sensors (equally distributed between the aggregators). The sensors always transmit data to the aggregator every 1 s.

In the periodic condition, the aggregators communicate to the server every $t^B_{per} = 2$ s, while in the alarm condition, they transmit to the server every $t^B_{ala} = 1$ s.

Then, we simulated two scenarios for each network and conditions: (i) varying the number of sensors, i.e., S = {3; 6; 10; 40; 50}, each generating packets at the application layer with a fixed size of P = 40 B, and the number of aggregators G = {1; 2; 2; 4; 5} for the network B, respectively, and (ii) varying the packet's size P, i.e., P = {40; 80; 120; 400; 800; 1000; 2000} bytes, with the number of sensors referred in the two networks above.

The performance indices considered in these simulations are the End-to-End (E2E) delay (from the sensor to the server) and the goodput, i.e., the valuable sensor's measurement data that reach the collector application on the server in the unit of time. For those two indices, we computed their average over all the packets received by the server.

Finally, the default simulation run lasts five minutes.

4. Results

Figure 3 shows the resulting E2E delay and goodput in all the simulated cases. In agreement with the LTE protocol and network architecture, which grants to the communicating nodes some so-called resource blocks available in a shared way, the trends we obtained from these results confirm our expectations. Nevertheless, from this figure, a couple of conclusions can be drawn: (i) the LTE network supports well the alarm condition since its end-to-end delay is lower than the periodic condition for all the cases of S and P; (ii) network B scales much better than network A, particularly as a function of P, where the mean E2E delay stabilizes at values less than 15 ms for the periodic condition and around 10 ms for the alarm condition as the packet size increases above 400 B, as compared with network A cases, whose trend keep increasing; and (iii) when either the number of sensors or the packet size grows, the goodput increases with a pretty stable linear trend. The results suggest that a WSN network, where multiple nodes transmit data to a sink node that sends only the aggregated report to the server, is much more reliable and predictable regarding LTE network performance results.

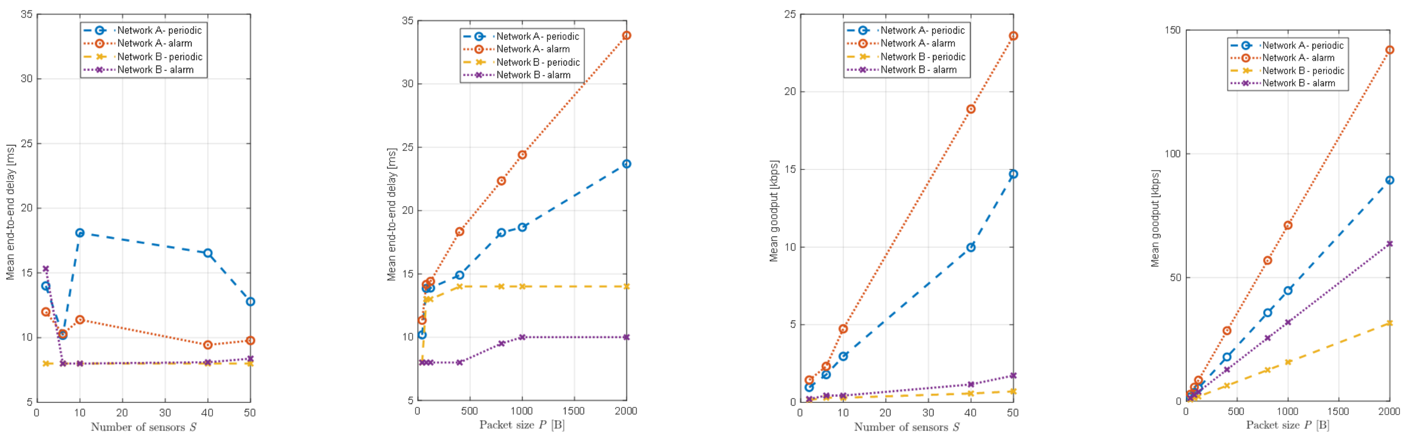

Figure 3. Mean end-to-end delay and goodput. From (**left**) to (**right**): E2E delay against S; E2E delay against P; goodput against S; and goodput against P.

The figure also presents an unexpected trend in the delay for network A for both periodic and alarm cases. For instance, we found a mean E2E delay of 18 ms for ten sensors in the periodic case, but for fifty sensors, we obtained only 12 ms, even though the expected network load in the second case is five times higher than in the former. The reason for this is that while we increased the number of sensors S, we were forced to also increase E, i.e., the number of the eNBs. Accordingly, the fewer sensors each eNB serves, the lower the E2E delay and, consequently, the lower the network load. To make this more evident, we ran the same experiment with ten sensors two times, the first time, with $E = 2$ eNBs and five sensors each, and the second time with $E = 3$ eNBs and three, three, and four sensors, respectively. The results are shown in Table 1.

Table 1. Network A: Mean E2E delay for periodic case as compared to the number of eNBs and different distribution of sensors.

E	*S*	**Mean E2E Delay [ms]**
2	(5 + 5)	18.10
3	(3 + 3 + 4)	13.68

Overall, comparing the alarm results with the periodic conditions, the absolute values show an increase of roughly 40% and 60% in the maximum E2E and goodput, respectively. This is due to the increased traffic generated by the sensor nodes, which flows through the LTE network. Once again, these results confirm that the LTE resources support well the traffic generated by the AQUASENSE WSN, and thus, the expectations already anticipated in our previous work [12] are met.

5. Conclusions

This paper gave an overview of the work conducted in the frame of the AQUASENSE project concerning the design, development, and analysis of a communication system. These communication systems are evaluated through computer simulations using SimuLTE for simulating an LTE network infrastructure connecting the WSN with a remote server, where data are collected. In this frame, two network topologies are studied: (i) network A, which represents a multi-cell network, where multiple sensors are associated with different base stations, sending water measurements to the server, and (ii) network B, which is again a multi-cell network, but this time multiple sensors are associated to local aggregators, which collect and aggregate the measurements and send them to the remote server through LTE base stations. For these topologies, the end-to-end delay and the goodput are evaluated as representative performance indices in two conditions: (i) periodic monitoring, where the data are transmitted to the server at larger intervals; and (ii) alarm monitoring, where the data are transmitted more often. The performance of the two scenarios described above demonstrates that when we use the aggregators to collect the data from the sensors, the network's QoS is higher. In particular, an intelligent implementation of how the aggregators provide the information to the server in normal and alarm conditions dramatically helps achieve efficient monitoring and accurate pollution event detection.

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