IoT Devices Overhead: A Simulation Study of eHealth Solutions over a Hospitals' Network

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Abstract: As Internet of Thing (IoT) applications for eHealth gain momentum, one aspect becomes critical: the underlying network infrastructure. The efficient operation of interconnected devices hinges upon a robust and reliable network architecture, that can present formidable barriers to IoT's potential. In this paper we analyze the capacity of a typical hospital network infrastructure to implement new eHealth solutions, given the number of devices required in a average setup. We use the IFogSim Simulator to model a network setup for a hospital, selecting parameters for the devices from state-of-the-art solutions. This work is an important investigation on the overload a collection of IoT devices may cause in a common network setup, and could be used for planning ahead the installation of eHealth solutions. Our results show that a realistic arrange for IoT solutions might impact significantly the network flow, energy consumption and processing time. Also, the number of gateways reflects on the working capacity of the general system, turning from a distribution point to a bottleneck. The environment provides a reliable representation, allowing the extrapolation of the scenarios.

1 INTRODUCTION

The advent of the Internet of Things (IoT) has ushered in a new era of technological advancements, revolutionizing various sectors, including healthcare. The integration of IoT technologies within the healthcare domain, known as eHealth, has introduced novel and transformative opportunities to enhance patient care, streamline clinical processes, and optimize resource utilization (Gupta and Quamara, 2020). In particular, the installation of IoT devices in health clinics and hospitals holds the promise of real-time monitoring, data-driven decision-making, and improved patient outcomes.

As the number of IoT devices in healthcare grows, so does the potential for network congestion and performance issues (Puliafito et al., 2019). Developing countries often grapple with limited network bandwidth, intermittent connectivity, and inadequate infrastructure (Wu et al., 2019).

Effective resource allocation within eHealth networks is essential to prioritize critical data and tasks. Network overheads, for characteristics as latency and packet loss, can jeopardize the ability to provide real-time care, potentially leading to adverse patient outcomes. Also, scalability is a significant concern, as the infrastructure must accommodate more devices without degradation in performance (Puliafito et al., 2019). Other aspects that require attention, but that are beyond the scope of this paper are legal regulations, security, privacy, data volume and devices variety.

This study focuses on analyzing the impact of IoT devices on network performance. A realistic simulation environment is created with IFogSim (Mahmud et al., 2021), incorporating various IoT devices, such sensors, gateways, and data processing units. Simulation techniques assess the potential network bottlenecks, latency issues, and data transfer constraints that could emerge in real-world scenarios (Castane et al., 2019).

To assess the network overhead, a variety of scenarios is designed, considering factors such as the number of IoT devices, data transmission rates, and traffic patterns. Performance metrics includes network latency, energy consumption, and processing time, measured under different workload conditions. he experiment also seeks to validate the effective-

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ness of the IFogSim framework in evaluating scenarios within an eHealth context.

The experimental results demonstrate how varying the number of IoT devices, network overload, bandwidth, and energy usage impacts the performance of simulated eHealth IoT system. Also, it helps observing the scalability and efficiency of computer networks in health facilities when supporting IoT-based monitoring services.

Through these scenarios, the experiment validate IFogSim's ability to accurately provide insights into system behavior under different conditions.

Subsequent sections of this paper are organized as follows: in Section 2 the related works are presented and compared. Section 3 presents methodology, materials and modifications made on IFogSim. Section 4 shows the results and discussion on the experiments finds. Finally, in Section 5 are described the conclusion and future directions of this research.

2 RELATED WORK

The integration of Internet of Things (IoT) technologies in health facilities has revolutionized patient monitoring services, leading to improved healthcare outcomes. However, the deployment of IoT devices introduces additional computational and communication requirements, potentially increasing the overhead on computer networks (Gupta and Quamara, 2020). The study in (Premkumar and Santhosh, 2022) highlights insufficient eHealth readiness among managers and healthcare workers. It emphasizes the importance of careful planning, execution, and monitoring of eHealth initiatives to overcome obstacles and threats.

There are several studies on the use of computer supported technologies for fast diagnostic, precise monitoring and data availability. In (Lv et al., 2022) is proposed a intelligent system for prevention of infectious diseases. It uses edge algorithms to generate a model for low cost prevention strategies and enhanced security. The authors present a generous evaluation of their model, failing to demonstrate how the security of patients is guaranteed.

The article (Steele and Lo, 2013) addresses the challenges of limited bandwidth in rural and remote areas for traditional telehealth applications, proposing ubiquitous computing as a solution, highlighting their potential to address healthcare challenges in such regions.

The work of (Mishra et al., 2022) argues that interoperability is the most challenging aspect of the health care industry. The authors propose a system to access, analyze, and enhance communication of patient health information while ensuring data privacy and security. Their framework is proposed with limited functionalities and further research is expected.

The paper (Banday and Bhat, 2022) introduces a eHealth model tailored for Neglected Tropical Diseases (NTD). This type of disease is prevalent on developing countries and such system would greatly benefit patients otherwise relegated by the major research centers. Also, developing countries lack well structured networks, helping understand why the overload prediction is necessary prior to the installation of complex eHealth solutions.

The work in (Ahmed et al., 2020) presents a solution using Genetic Algorithm (GA) to optimize energy consumption in Cloud IoT with numerical simulations demonstrating that the proposed approach achieves better energy efficiency in handling task requests, although they don't consider the impact of the number of devices per interaction.

An IoT-enabled deep learning framework for breast image classification is shown in (Gezimati and Singh, 2023), achieving high accuracy, sensitivity, and specificity, demonstrating its potential in healthcare applications, pointing to another example of IoT capacities. However, detailing on the network and power impact could be beneficial to potential adopters.

The authors in (Su et al., 2022) propose a edge computing-based network architecture to improve the performance of wireless body area network (WBAN) for healthcare applications. They argue for better Quality of Service (QoS) and Quality of Experience (QoE) namely with latency and low energy, but their findings for those metrics are not described. Simulation has also been used to model other types of complex scenarios.

The work on (Puliafito et al., 2020) describes a solution to overcome flaws on mobility and service migration for fog computing. Their results encourage new approaches on resource provision projections.

The rise in connected IoT devices results in a significant increase in data volume, demanding real-time responses and incurring high bandwidth costs.Various studies focus on data collection strategies, including remote monitoring, pre-processing, compression, and filtering, to alleviate bandwidth demands (Vilela et al., 2020).

To the best of our knowledge, there are no similar approaches to evaluate the impact of eHealth solutions on computer networks. We aim to contribute to the literature with a model to estimate the capability of installation of IoT devices and predict the network behavior.

3 METHODS

Developing countries often grapple with limited network bandwidth, intermittent connectivity, and inadequate infrastructure, that can impede the deployment and functionality of IoT devices (Yousaf et al., 2021). This paper aims to shed light on these challenges and propose using the IFogSim simulator, a cutting-edge tool designed to simulate and analyze the deployment of IoT devices to eHealth environments. Fog computing, characterized by decentralized data processing at the edge of the network, holds promise in alleviating the strain on centralized cloud resources and addressing network-related challenges (Puliafito et al., 2019).

The necessity to address these challenges has given rise to the application of simulation tools, such as IFogSim, to comprehensively assess the deployment of IoT devices in healthcare settings. This section presents arguments for the use of IFogSim, elucidating its setup, importance, capacities, and the expected results it offers in terms of optimizing IoT deployments for enhanced eHealth outcomes. This not only enhances the likelihood of successful deployments but also helps preemptively identify and address network-related bottlenecks.

The simulated environment's classification as eHealth is primarily defined by the integration of multiple IoT virtual devices. These devices are specifically tailored to monitor ambient temperature and humidity, crucial parameters managed across two distinct levels adhering to regulatory protocols and hospital quality benchmarks. This infrastructure enables the leveraging of information technologies to ensure ongoing quality assurance and safety measures for both staff and patients, aligning with the World Health Organization's (WHO) delineation of eHealth.

To evaluate the installation of IoT devices in healthcare institutions, two simulators were analyzed: IFogSim and IotSim Osmosis (Alwasel et al., 2021), both implemented as extension to CloudSim (Calheiros et al., 2011). The three simulators have very similar characteristics as they have resources and tools necessary to research, including computational network modeling and integration of IoT sensors.

Initially, IoTSim Osmosis stood out due to its large number of examples and base data provided by the developer, easing the understanding of its structure, in addition to assisting in system configuration. It was used to structure and simulate the modeling of a computational network, to send data from sensors to processing at the edge and cloud layers. However, when carrying out a deeper analysis of the simulator, modeling the desired eHealth scenarios became unfeasible, as the framework is tailored for cloud continuum applications. It is suited for IoT environments, however its structure was found to be more rigid, with static simulation features and harder to adapt. It has fewer protocols and device emulation support, and limitations in scalability for large-scale IoT deployments. Additionally, it may face challenges in accurately replicating certain environmental factors or hardware interactions (Al-Khafaji, 2022).

Changing the focus to IFogSim paid of, as it has a simulation element for low-level infrastructure, enabling end-to-end modeling from user-level applications to edge computing of IoT environments, including sensors and actuators.

3.1 The Simulator

The IFogSim simulator provides a realistic framework to model and assess the network overhead in healthcare environments (Mahmud et al., 2021).

The framework is designed to emulate the deployment of IoT devices within fog computing environments, offering an invaluable platform for assessing the intricate interplay between devices, network infrastructure, and data processing. Leveraging the principles of edge computing, IFogSim enables the modeling of dynamic interactions among devices, fog nodes, and cloud resources. It facilitates the prediction of performance metrics, network latency, and data transfer efficiency, thus providing a holistic perspective on the real-world implications (Mahmud et al., 2021).

IFogSim considers the distribution of processing tasks across fog nodes and cloud servers. It accounts for mobility patterns of IoT devices and offers insights into data processing latency (Mahmud et al., 2021). It offers a controlled and repeatable environment for experimentation and to take informed decisions before physical implementation.

Furthermore, IFogSim accommodates the modeling of mobility patterns, network topology, and data dissemination strategies, allowing for a comprehensive analysis of IoT ecosystems (Mahmud et al., 2021).

Despite the significance of these factors in computer network design, we focused our experiments exclusively on analyzing network topology. Mobility and location principles were deliberately excluded, earmarked for future investigations. As a result, our experiment centered solely on devices within the hospital's physical confines.

IFogSim offers a controlled yet intricate platform for evaluating IoT device deployments in healthcare settings. Difficulties were encountered in understanding the simulator classes and behavior, indicating that better documentation and code refactoring are welcome to future releases.

3.2 Models Development

Development of the simulated environment follows the code available as examples in IFogSim packages (Mahmud et al., 2021). The implementation is derived from the *TwoApps* example, which implements the simulation of two virtual reality game applications (VR Games) aimed to verify its performance. The new model is named **OneApp**, consisting of a single application for an automated hospital environment with IoT devices and a limited structure of data communication resources at its digital network.

The main class is *createApplication*, responsible for adjusting the network parameter and processing load as the sensors generates data. Additionally, the class also adjusts the transmission costs between layers, e.g. networking usage and processing time for the sensors to transmit information to IoT devices.

The simulator has an general topology to indicate the type of equipment created and the network structure. However, the main class assigns the relation among the devices. Therefore, the devised module describes the connections so that each Iot device is linked to four different sensors. Here are also modeled the gateways, proxy server and cloud environment, with the respective connections and data flow.

The modules developed operates according to the scheme represented in Figure 1. The sensors transmit data to the IoT devices, which redirect them to the gateways. Each gateway acts as an intermediary, routing data to a cloud server, where it is processed and transmitted back to the IoT devices. The organization represents a simplified hierarchy of real world implementation for and eHealth installation on a health clinic.

To emulate the sensors, versatile models like the DHT22 were chosen for utilization in hospital environments, as well as the sensors ZMPT101B and SCT-013 for monitoring equipment's electrical networks. This approach allows for comprehensive analysis of environmental conditions and equipment performance (Woo et al., 2018). The strategic choice of sensors facilitates detection of system failures and overloads, especially in settings with numerous interconnected devices, providing assessment of interoperability and equipment stability.

The description of the equipment modeled in the simulator, along with its parameters is presented in Table 1. To fill the missing information in the technical sheets, the examples provided at (Mahmud et al., 2021) were useful in estimating values, such as the energy consumption of some equipment. The respective references for each machine configuration are listed.

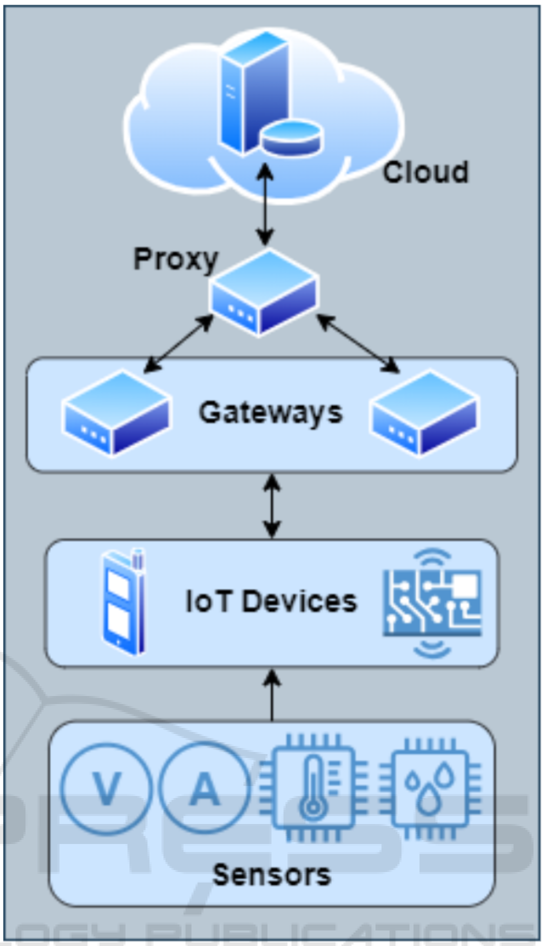

Figure 1: Infographic of components organization, modeled on IFogSim. The data is collected on sensors, either direct on patients or on the environment. It is transmitted to IoT devices, and next sent to gateways. The last route the data to cloud servers, responsible for heavier computations.

After consolidating the data relating to the devices, the configuration of the simulator is ready to model a hospital network. This process served as an initial foundation to execute the experiments with variations to validate its portrayal of the real world.[1]

3.3 Materials

The experiment environment was configured on IFogSim version 2 (Mahmud et al., 2021). The toolkit offers the following options: mobility-support, migration management, microservice orchestration, dynamic distributed clustering and healthcare scenarios.

[1] Code available on github.com/GabrielKrauss/iFogSim-IoT.

Table 1: Devices description in the IFogSim simulation. Each device is modeled according to the specification in the reference.

Device type	Specification	
Gateway	Raspberry Pi 4 (RaspberryPi, 2019)	
IoT Device	ESP32 (Google, 2023)	
Cloud Host	Intel Xeon E5-2696 v4 @ 2.20GHz (PassMark_Software, 2023)	
Proxy	EGW-5200 (Dell, 2022)	
Sensors	Temperature	DHT22 (Aosong_Eletronics, 2023)
	Humidity	DHT22
	Voltage	ZMPT101B (InnovatorsGuru, 2023)
	Current	SCT-013 (DataSheet39.com, 2023)

As test-bed for the experiments were used a desktop computer with Intel Core i5-10400 CPU @ 2.90GHz, 8 GB-RAM, 240 GB SSD. The Operation System is Windows 10 64 bit.

3.4 Experiment Design

Having defined the setup for the simulator, it's necessary to choose parameters to compose an evaluation scenario. The parameters are listed in Table 2. We chose to analyze the network behavior at different configurations of the number of IoT devices, the amount of energy consumption and the network usage. These details are fundamental for infrastructure estimation and could greatly impact on the performance of an complex eHealth system.

Clearly, there are many other parameters that could be analyzed into a eHealth environment. Our aim is to focus on network occupation and energy usage as those are the functional basis of computational communication.

Table 2: Experiments detailing for 8 different scenarios. Labels: MJ = Mega joules, MB = Megabytes.

Energy Consumption (MJ)	IoT Devices	Network Usage (MB)	Experiment ID
Idle = 25 — Busy = 90	150	100	1
		1000	2
	300	100	3
		1000	4
Idle = 50 — Busy = 180	150	100	5
		1000	6
	300	100	7
		1000	8

MegaJoules is the standard energy unit in iFogSim, serving as a reference for various measurements like power (Watts), electron volts (eV), calories (cal), and kilowatt-hours (kWh). They also aid in converting work requirements for infrastructure components. However, experiment execution times in the simulator may not always match real-world times due to virtual time control mechanisms.

The eHealth scenario depicts a standard configuration commonly found in healthcare settings, adhering to parameters outlined by the WHO. Data bursts are configured to mirror communication intervals across multiple devices concurrently, assessing the system's ability to respond effectively.

The simulation utilizes a discrete model of the spatial distribution of IoT devices within hospital settings. The primary aim is to analyze the distribution of devices across different scenarios while considering communication between devices, gateways, and the backend cloud environment, for a comprehensive examination of network dynamics.

To have results that reflect the real world, the simulator parameters were classified into two categories: constant values and random values, as detailed in Table 3. To ensure consistency of results, the experiments were executed ten times before calculating the results' statistics.

The simulation incorporates transmission latency of IoT devices. As outlined in Table 3, random intervals are generated during runtime, based on device granularity and network architecture (Figure 1). This approach brings approximation of communication behaviors and network performance, considering the devices' hierarchical positions and immediate data link access.

4 RESULTS

Having defined the parameters and scenarios for the experiments, and after performing ten executions of each scenario, the results were collected and are presented in this section.

The reliability of the data collected is assessed by standard error measured. The small dispersion of the scenarios indicates consistency and stability in the results.

In Figure 2, it is possible to observe that the number of IoT devices is one of the main contributors to the increase in the total value. The network occupation is heavier when the number of devices is higher, as one would expect. For the size of application defined in the network usage and for the energy consumption by device, the total network consumption does not seem to change significantly. The principal aspect to impact on the overall network occupation is the number of tasks involved, as well as the complex data information throughout the system.

In the Figure 3 it is observed that the energy consumption of IoT machines is mainly responsible for the total energy expenditure. Therefore, when doubling the number of IoT products, total energy consumption shows a proportional growth. The same pattern occurs with the energy cost of these equipment, as evidenced by the difference between experiments 1-2 and 5-6. Despite that the cloud environment is significantly more powerful than the other de-

Table 3: Parameters specification for the experiments. Labels: MIPS = Millions of Instructions per Second, MBPS = Megabits per second, GB = Gigabytes, MJ = Mega joules, ms = milliseconds.

	IoT Device	**Fog Gateway**	**Cloud**	**Proxy Server**
Quantity	150 - 300	2	1	1
Speed (MIPS)	1500	92500	6890500	2376800
RAM (GB)	4	64	32	4
Uplink (MBPS)	150	1000	16000	10000
Downlink (MBPS)	150	1000	16000	10000
Busy Power (MJ)	90 - 180	107.3	1716.8	107.3
Idle Power (MJ)	25 - 50	83.4	1331.2	83.4
Random Values (interval)				
App CPU Usage (MB)	Sensors Latency (ms)	Gateway Latency (ms)	Proxy Latency (ms)	IoT Device to Gateway Latency (ms)
50 - 500	0.1 - 0.6	1.0 - 15.0	1.0 - 4.0	1.0 - 4.0

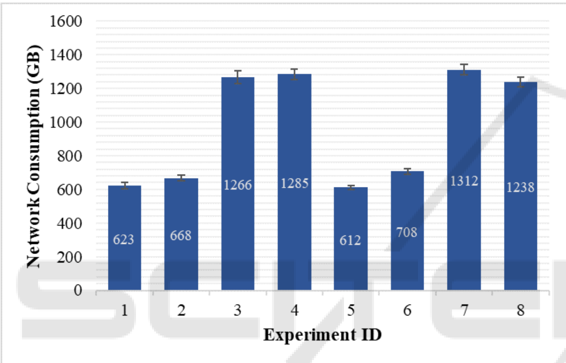

Figure 2: Total network consumption per scenario, in Gigabytes. The task setup is the main influence for this result.

vices, its energy usage is remarkably smaller than the IoT devices, for example. Also, its use remains stable throughout every scenario, indicating that the processing jobs didn't demand scaling up the servers.

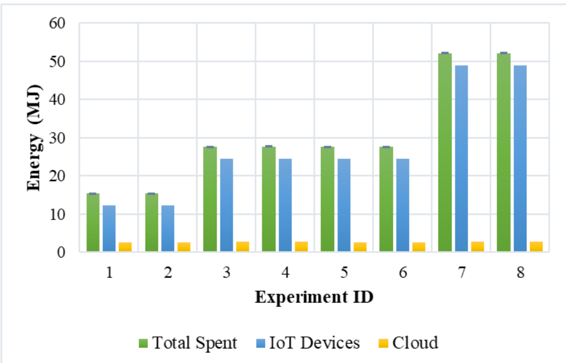

Figure 3: Energy consumption by type of device, displayed by scenario.

For the total execution time, Figure 4 shows that the number of devices is again the most significant factor, due to the reduced number of gateways compared to the amount of information transmitted by IoT equipment, which ends up overloading the processes and delays the information traffic. Furthermore, the Figure 5 shows the difference in magnitude between the transmission time and the total simulation time is very large, which demonstrates the insignificance of this factor for the scenarios setup. There were found no significant influence for traffic delays, even though there were variations for that parameter. Therefore, information processing time is the main agent for the results obtained.

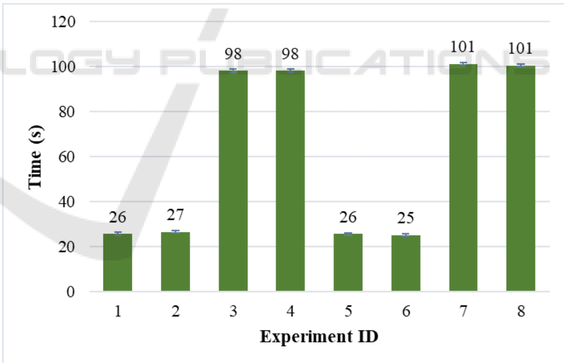

Figure 4: Total experiment run time, by scenario.

From the results obtained, it is evident that the values implemented in the simulator, as specified in Table 2, have a linear impact on the results of the network and energy consumption. In other words, when doubling the number of IoT devices, it is clear that the output value comes considerably closer to twice what was expected. However, this phenomenon does not manifest itself in the same way in time results: when the initial quantity is doubled, the difference in results is approximately four times greater in relation to the expected value. These results indicate that depending on the network topology for the eHealth

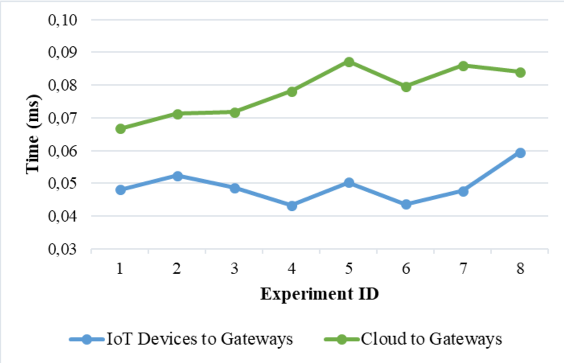

Figure 5: Network delay for scenario. The lines shows that the communication on the edge of the network is slightly faster, but not much significant to the overall results.

IoT system, the critical parameter of execution interval can suffer, generating risks for the patients and medical team. The integration of IFogSim as a simulation framework presents a pivotal step forward in the realization of IoT applications for eHealth.

The simulation focus on network infrastructure and cloud computing, to assess the impact of IoT deployment, especially in applications like temperature and humidity sensing. This analysis aids planning resource management in the eHealth framework. Given simulation nature, the devices, including gateways, endpoints, proxies, and cloud components, are characterized broadly and configured with varying parameters. This configuration enables an evaluation of how the factors influence the response variables.

5 CONCLUSIONS

The convergence of IoT and eHealth holds immense promise for transforming healthcare delivery. However, the challenges posed by network infrastructure, particularly in developing countries, necessitate innovative solutions to ensure the optimal functioning of IoT devices. This paper presents a model of computational simulations of IoT device installations to preemptively address network-related challenges.

The results validate the accuracy of the simulation and provide insights for designing IoT healthcare environments. Our findings demonstrate that a typical number of devices might greatly impact on the results, specially regarding execution time and energy expenditure, that can be crucial for life monitoring devices and general costs. Even though there are machines with far superior setups, the number of devices (costumary for eHealth setups) impacts the electric consumption.

Overall, our contributions are a better understanding of the implications of IoT implementation in health facilities, specifically regarding the associated network overhead, specially in areas with uneven or limited bandwidth capacities. Also, the modifications to IFogSim classes enrich the capacity of the simulator to model real life scenarios.

In future works we aim to further investigate the network occupation and energy costs with more complex scenarios. Factors as network technology and carbon emission can be evaluated, so the simulation provides more complete representation for eHealth services deployment. Other simulators could also be used for comparison purposes.

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