A Fog Computing-based IoT Framework for Precision Agriculture

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Abstract

The challenge of analyzing and processing a huge amount of data is becoming increasingly important in this fourth industrial revolution era. In this scenario, Cloud Computing and Internet of Things (IoT) allow to build up an interconnected network of smart things. These two paradigms do not allow solving the Computing problems yet. Fog Computing aims at moving the processing abilities closer to the end users, avoiding an excessive exploitation of Cloud resources, further reducing computational loads. In this work, we propose a Fog-based IoT framework, which exploits the two-tier Fog and their resources, reducing the transmitted data to the Cloud, improving the computational load balancing and reducing the waiting times. The proposed Fog Computing approach is applied to the emerging area of precision agriculture, including all the techniques of agricultural land management. Furthermore, based on this framework, we have simulated and highlighted how the two-tier Fog Computing approach is able to reduce significantly the amount of transmitted data to the Cloud. We also propose and describe an application prototype, based on the previous framework, able to manage and monitor farmland, with a strong impact on both the business and environmental performance.

Keywords: Cloud computing, Fog computing, Internet of Things (IoT), LoRa technology, Precision agriculture

1 Introduction

The concept of Cloud Computing has been evolving over the years since its introduction. Although it was introduced from the mainframe model, the Cloud Computing concept expanded from ’60 and ’70 including not only a processors sharing, but also other concepts and technologies.

In 1961, John McCarthy at MIT’s centennial celebration stated that “Computing may someday be organized as a public utility just as the telephone system is a public utility”, thus imagining a future where Computing could have been distributed and organized on different systems of public access [1].

Cloud Computing regards both applications delivered as services over the Internet, and the hardware and systems software in the data center that provide those services [2].

The benefits of Cloud Computing have been discussed since a long time, but now we are witnessing the fourth industrial revolution related to the Internet of Things (IoT), the era in which “things” tend to gain more and more intelligence, becoming smart and being able to communicate with other “things”, integrating several technologies and communications solutions [3].

Therefore, the IoT paradigm is the key towards this revolution improving service levels and as a consequence the customer satisfaction, and meeting the demand of a new generation of empowered customers with smart products. IoT modeling constitutes a global network of interconnected and uniquely addressable “things”, merging various heterogeneous communication technologies, both wired and wireless [4].

IoT will not be seen as individual system, but as a critical, integrated infrastructure upon which many applications and services can run [5].

The extended use of heterogeneous sensors, involves a new challenge to extract useful information from a complex sensing environment [6]. Internet of Things is leading the research to investigate and develop novel and high-performance Computing architectures due to large amount of data analysis produced. Cloud Computing provides a solution to support dynamic scalability in many vertical areas such as smart city [7-9], smart home [10], smart agriculture [11], healthcare [12-13], smart grid and several context-aware environment of Wireless Sensor Networks (WSNs) [14].

However, the deployment of a large number of devices and sensors for IoT requires location awareness and low latency, which, currently, are missing in commercial Cloud Computing models. One of the main challenges of IoT is related to increasing amount of devices connected to the network which is

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going to further grow [15-16]. Therefore, Cloud Computing must be able in the near future to manage this large amount of data from the network that will probably lead to the reduction of available bandwidth and the subsequent increase of latency. IoT, along with actual and future challenges of Cloud Computing, claims for novel frameworks and paradigms, able to face the ubiquitous and pervasive nature of networks and the data-intensive Computing requirements [17].

Strictly linked to IoT, the new paradigm of the Fog Computing broadens the Cloud, extending some services also to the edge of network close to the end users, with the aim to reduce the network's computational load.

Thus, Fog Computing founded as a highly virtualized platform and applicable in many IoT scenarios, moves the processing abilities closer to the data source, proving useful to the smart grid, realizing more rapid M2M (Machine-to-Machine) communications, and even in the smart city context, shifting the decisions near the place where data are collected [18]. Therefore, in order to avoid a high exploitation of the Cloud resources, Fog Computing applications and services, allowing interaction between Cloud and Fog, in particular when it comes to data management and analytics [19].

In this paper, we focused on a particular application area represented by Precision Agriculture which, in recent years, is expanding rapidly to become an essential concept in IoT scenario, due to the increasingly number of sensors and connected objects, which is estimated to grow even more rapidly. In fact, in 2050 the world population will reach 9 billion and, as a consequence, it will increase also the food production [20-21]. Precision agriculture includes all the techniques of farmland management, taking into account the inherent and induced soil variability and the specific needs of crops in order to increase production, minimize environmental damage and raising qualitative standards of the agricultural products [22-23].

The research study behind this work is to deal with the new challenges of IoT related to the computational loads due to the huge number of devices. For this reason, we propose a novel architectural model based on Fog Computing paradigm to transfer a part of processing abilities both to the gateway and sensor nodes, reducing the computational load of the Cloud and improving scalability, Quality of Service (QoS) and the performance of entire network [24, 39]. This framework results also more insightful looking at futures scenarios in which, not only the agriculture but also many vertical areas, will be composed of thousands of sensors that continuously transmit large amounts of data to the Cloud platforms. In terms of connectivity, we exploit new communication technologies suitable for IoT, named LoRa (Long Range) [25-26], a type of connectivity interposed between short-range multi-hop technologies, operating in the unlicensed frequency bands, and long-range cellular-based solutions which use licensed broadband cellular standards, named Low-Power Wide Area Networks (LPWANs) [27].

The rest of this paper is organized as follows. Section 2 highlights the new paradigm of Fog Computing and the reasons leading to this new approach. Furthermore, the same Section is focused on precision agriculture and its economic and environmental impact. Section 3 includes our Fog-based framework in the IoT scenario and the developed prototype related to precision agriculture. We also discuss, through some simulations, how the use of Fog Computing reduces the amount of data to the Cloud, and summarize all the achieved benefits of the proposed framework.

In the last section, we conclude with some considerations and discuss some future works for this project.

2 Materials and Methods

2.1 From Cloud to Fog

As defined in [28], Cloud Computing can be thought as an aggregation of Computing, providing on demand network access to computing, configurable and shared resources, which can be rapidly supplied and released with minimal management effort or service provider interaction.

A key requirement for a Cloud provider is the virtualization of resources in order to allow the required scalability of the Cloud, giving the users a perception of infinite resources [29], providing high storage capacity, high flexibility and high-computing performance [30].

Today we are going to the fourth industrial revolution related to the Internet of Things that consists of having an increasing amount of objects connected to the Internet with their own IP address, to exchange useful data to be processed and analyzed.

However, the transmission of all these data to the Cloud might be inefficient because of requiring high processing capacity and bandwidth, increasing the latencies and consequently negatively affecting the performance of the entire network and even leading technologies such as optical fiber or 4G connectivity having limitations caused by the cost of traffic and availability of bandwidth.

To support the Cloud, by a meteorological metaphor, originates "Fog Computing", an innovative paradigm which is an extension of the Cloud with the basic idea to transfer a part of processing to the edge of network, close to the end-users in order to solve some problems related to Internet of Things, e.g. the availability of bandwidth and the network's latencies.

Whereas Cloud Computing is based on large data centers away from the user, the Fog promises to bring more processing power in the network edge [19]. This is even more important for the devices themselves or local gateways, reducing the amount of data to be transmitted to the Cloud, allowing a highly virtualized platform in order to provide processing, analysis, storage, and networking services between end devices and data centers, other than supporting large-scale of sensor networks [18].

In Fog Computing paradigm any irrelevant information is filtered and discarded, whereas the most important ones are forwarded.

One of the main goals of Fog Computing is to exploit the available resource of the end devices to allow the network to have a better-distributed intelligence and enhance the performance.

In [31] Fog Computing is defined as "a scenario where a huge number of heterogeneous (wireless and sometimes autonomous) ubiquitous and decentralized devices communicate and potentially cooperate among them and with the network to perform storage and processing tasks without the intervention of third-parties. These tasks can be for supporting basic network functions or new services and applications that run in a sandboxed environment. Users leasing part of their devices to host these services get incentives for doing so".

As with the Cloud, Fog is predicated on the availability of computational, storage, and connectivity resources. Resources must be located within close physical proximity to users reducing questions associated with Cloud Computing. Fog nodes may take the form of servers or networking equipment with additional computational resources. They may even be integrated into wireless access points. Fog nodes will typically be located at the edge of the network, within close proximity to end-users. Figure 1 presents an example of Cloud-Fog architecture. In this case the Fog devices have the feature of location awareness and serve the sensors in their proximity.

We can observe that the horizontal axis indicates how the nodes are extended geographically on the area (location awareness), whereas the vertical axis indicates the feature of the Fog Computing paradigm, that a part of the processing moves to the edge of the network, encouraging a distributed intelligence among end nodes.

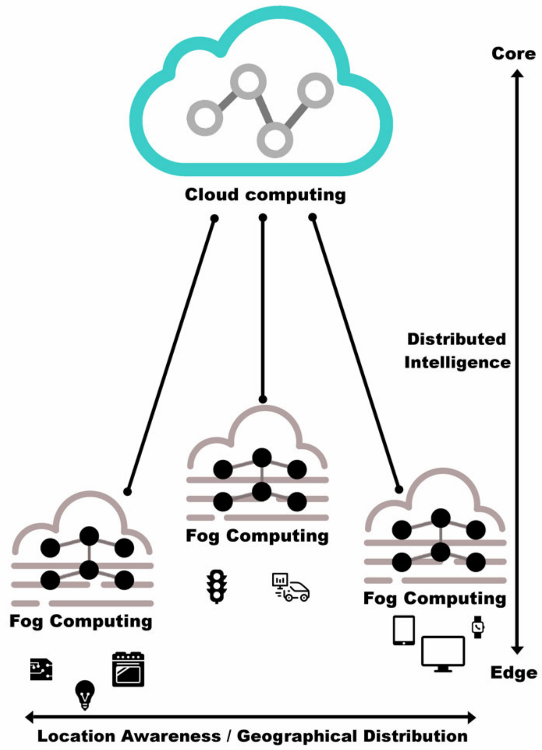


Figure 1. Fog Computing scenario: the network has a distributed intelligence extended to the edge while the end devices present location awareness and geographical distribution

2.2 Precision Agriculture

The term "Precision Agriculture" (PA) indicates a group of concepts of agronomic management based on observation and response to variations that exist within growing areas (e.g. soil, moisture, organic matter, etc.) and actions aimed at optimizing the crop.

In an agricultural land we can address soil conditions, weather, sun exposure, and topography very different among them. In the case of small sized fields, farmers may manually and easily change treatments in different areas. However, with the enlargement of the fields and the intensive agricultural mechanization, it has become increasingly difficult to take into account the variability of the field without a revolutionary development in information technology [32].

2.2.1 Variability in Agriculture

In agriculture, any plot is characterized by a certain variability involving all the parameters of the soil. The variability observed in the field is the result of interaction between a spatial component and a time component [33]. Thus, we can distinguish between two different concepts of variability, in space and time respectively.

The spatial variability is the ability of a given parameter to occur with a different intensity in the various areas, oscillating around the measurable average value inside them.

The temporal variability can be defined as the ability of a given parameter to assume a different intensity over the time at the same point within the area.

The study of the spatial and temporal variability aims at identifying and quantifying the intensity of one or more parameters and to characterize its main components.

The final target is to determine plots of areas, which are stable over the time, and identify individual parts of them where the productivity factors are different from the other areas.

2.2.2 Impact of Precision Agriculture

One of the most ambitious and interesting aspects that emerge from PA is, therefore, an attempt to combine two apparently divergent goals: maximize productivity by reducing both the environmental and economic costs.

To pursue this target, a detailed knowledge of cultivation parameters, topographic and weather-environmental is required. Therefore, fertilization and irrigation are two crucial moments, which involve the cultivation process, and optimizing these steps can be a useful tool to improve quality and quantity of the crop yields, also reducing the environmental impact.

By an economic perspective, the Information and Communication Technologies (ICTs) for PA provides the farmers with the possibility to change the distribution and timing of fertilizers according to the spatial and temporal variability of field. Thus, it will be possible to carry out economic analyses based on the variability of crop yield, getting an accurate risk assessment.

Further economic savings may come from the appropriate use of the irrigation of the fields in fact, dosing correctly the amount of water in the various areas will produce a considerable water saving.

With regards to the environmental aspect, precision agriculture represents a smart tool to achieve a precise and targeted use of fertilizer in such a way as to have a substantial reduction of the use of chemicals.

3 Results and Discussion

We propose an architectural model based on Fog Computing paradigm exploiting the full potential and resources of the peripheral devices considering two Fog layers.

The main services provided at the Fog layer will be the use of clustering algorithms to identify homogeneous areas in order to help the user to manage the entire agricultural land, forecasting analysis to predict possible diseases that can affect the plantations and the alert management to detect abnormal events.

We also simulated and compared the data traffic sent to the Cloud and data storage in both cases with a Fog Computing approach and with a traditional Cloud approach, without exploiting Fog.

At the end of this section, we describe our prototype implemented with the aim to provide a useful tool to manage agricultural environments, such as fields and greenhouses with the goal to optimize the crop, reducing costs and environmental impact.

3.1 The Fog-based Framework

As shown in Figure 2, we present a three-tier architecture composed by M2M platform, gateway and sensor nodes. M2M platform represents the Cloud service, able to provide Data Storage, Data Visualization, Network Management and Data Report.

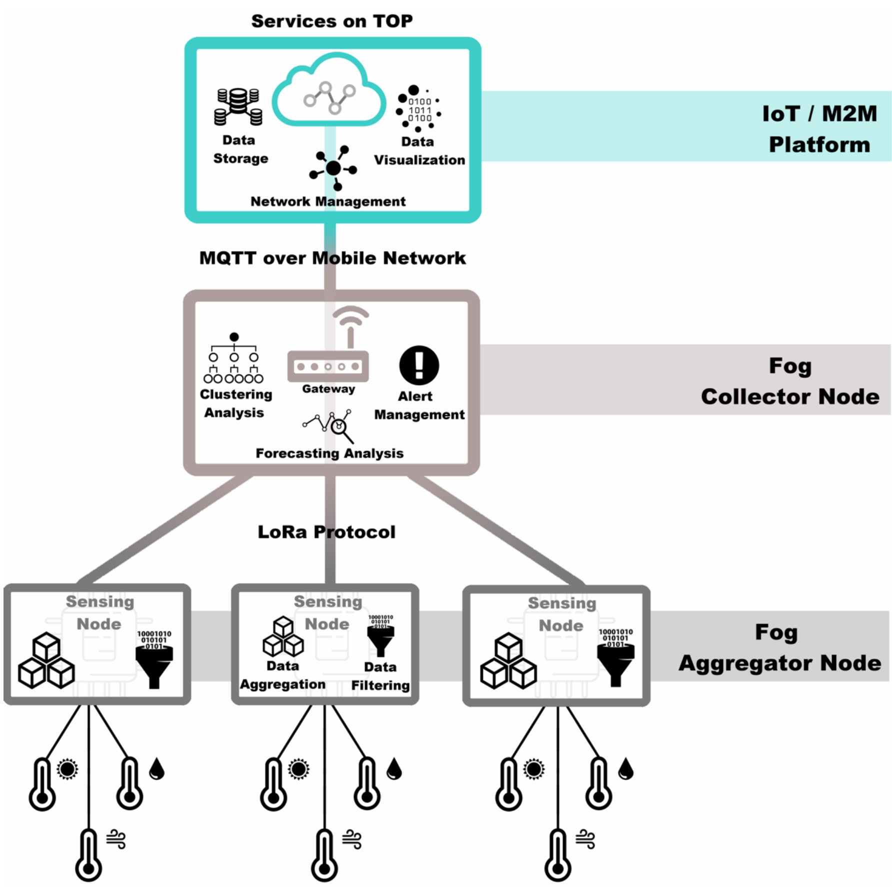


Figure 2. Proposed framework in precision agriculture scenario exploiting the Fog Computing paradigm

Fog Collector Node (FCN) and Fog Aggregator Node (FAN) compose the underlying layers.

FCN is represented by a gateway, which performs some relevant task, such as clustering analysis, alert and actuation management and forecasting analysis, in order to reduce both important computational load to the Cloud and time response of some events.

FAN is represented by sensor node. It implements an algorithm which performs data filtering and data aggregation processes in order to reduce the amount of data sent to the Cloud, other than the energy consumption.

Communication among layers was determined using the efficient protocols and technologies suitable for IoT both saving resources and to reach far away areas.

Currently, the most widely used protocol to connect things is ZigBee, which is an IEEE 802.15.4 standard. Networks exploiting this protocol use a mesh topology and operate mainly in the 2.4 GHz and sometimes in the 868/915 MHz unlicensed frequency bands. Nodes communicating over ZigBee, covering distances ranging from a few meters up to roughly 100 meters, according to the features of the environment [27].

Therefore, to communicate between the sensor node and the gateway we have chosen *LoRa* [25-26], the innovative wireless technology that allows long distance communication, low bit rate and low power consumption, more suitable for IoT and M2M applications (see Table 1). In this way we can have only one gateway to handle large agricultural lands exploiting a star topology.

Table 1. LoRa VS ZigBee comparison

	LoRa	ZigBee
Standard	LoRaWAN	IEEE 802.15.4
Frequency-Band	ISM 868 MHz and 915 MHz	ISM 2.4GHz, 868 MHz and 915 MHz
Topology	Star	Mesh
Range	2-5 km (Urban) 10-15 Km (Rural)	10-100m
Data Rate	0.3 - 50 kbps	250 kbps
Battery	Over 10 years	Some year

Whereas the communication between gateway and M2M platform is via the MQTT protocol (Message Queuing Telemetry Transport) [34], considered one of the most reference standard for IoT communication. MQTT is a messaging protocol for publishing and subscribing suited to working with limited power computing and connectivity of embedded products.

MQTT protocol is less complex than HTTP, having few message types and a lower message size [35]. It supports connections with edge nodes under constrained environments (low-speed wireless access) due to the poor mobile network coverage in some rural areas. Thus, it results more suitable than AMQP protocol [36]. Furthermore, MQTT performs better in the low throughput scenario with a single device and offers lower latency than CoAP protocol [37].

The data to the Cloud will be sent in JSON or XML format over Mobile 4G/3G Network.

FAN is connected to sensors that monitor both the soil (temperature, humidity) and the plants (fruit diameter, leaf wetness). It is programmed to acquire data from the sensors connected to it and send them to the gateway via LoRa technology. Table 2 shows the sensor's accuracy used in our project.

Table 2. Sensor's accuracy

Sensor	Accuracy
Humidity Sensor (808H5V5)	< ±4%RH (25°C, range 30 ~ 80%) < ±6%RH (range 0 ~ 100%)
Temperature Sensor (MCP9700A)	±2°C (range 0°C ~ +70°C) ±4°C (range -40°C ~ +125°C)
Humidity+Temperature Sensor (SHT75)	±0.4°C (range 0°C ~ +70°C), ±4°C (range -40 ~ +125°C) ±1.8%RH
Fruit Diameter Dendrometer	±2μm
Solar Radiation Sensor PAR (SQ-110)	±5%

Before to transmit the data, FAN implements a data filtering process in such a way that the values of the data collected by the sensors belong into an acceptable range, according to the design of the sensors. For example, the humidity values cannot exceed 100%. However, the values, which are out of range, may appear due to various factors (e.g. measurement errors or compromised sensors, faulty sensor values etc.). If the data value is out of range, these defective sensory data are discarded and if these discarded data exceeds a certain threshold, the FAN sends an alert to FCN to notify a potential anomaly for the specific sensor node.

The next step is the Data Aggregation process. One per-hour value will be transmitted to the gateway as result of the average of the previous values or, if the samples present certain variability, also the min and max values of the series will be sent. These values may constitute useful information for a further analysis carried out at the upper levels.

To assess the variability of the samples, we compare the coefficient of variation with a threshold, which usually has a value equal to 0.5.

Therefore, rather than sending the data read at each time by the sensors, the sensor node transmits an aggregate value, reducing the network traffic and hence energy consumption.

Figure 3 shows the algorithm performed within Fog Aggregator Node.

Algorithm implemented into Fog Aggregator Node

Input

1: th_df : Data filtering threshold to detect anomaly of sensor nodes;
2: th_cv: Coefficient of Variation threshold;
3: N: Number of sensed data;

Data filtering process

4: **while** sensed data < N **do**
5: **if** sensed data is out of range of acceptable values **then**
6: Discard data;
7: Increment counter variable of discarded data;
8: **else**
9: Store data in local database;
10: Increment counter variable of sensed data;
11: **end if**

12: **if** discarded data > th_df **then**
13: Send alert to FCN;
14: **end while**

Data aggregation process

15: Calculate the average μ of the samples;
16: Calculate the standard deviation σ;
17: Calculate coefficient of variation $cv = \frac{\mu}{\sigma}$
18: **if** $cv < th\_cv$
19: Send the average value;
20: **else**
21: Send the average, min and max values;
22: **end if**

Figure 3. Data filtering and data aggregation process

To evaluate the time complexity of the algorithm we can observe that the first part (data filtering process), from lines 5 to 13, involves a constant complexity and it is executed N times due to the while loop defined between lines 4 and 14. Thus, the overall time complexity of the data filtering process is *O(N)*.

The second part, that is the data aggregation process, which performs the computation of average and standard deviation of the input data, has a *O(n)* complexity. It is noted that $n \le N$ since the data filtering process can discard some data. The rest of the statements implies a constant complexity.

Therefore, we can state that the time complexity involved by the entire algorithm, with respect to the number of sensed data, is *O(N)*.

FCN implements a middleware able to receive data from FAN by LoRa technology, store the received data in local RDBMS, transmit data to the Cloud in MQTT over mobile 4G/3G network and, periodically, perform the following tasks.

Cluster Analysis: as explained in [38], we use a hierarchical agglomerative clustering to subdivide the field into homogeneous parts. In this way, the user can assess the field variability and exploits it to maximize the crop, e.g. dosing the proper amount of fertilizer or water depending on the clustering of the various areas.

The clustering algorithm is periodically performed and then the results are transmitted to the platform via MQTT protocol in JSON or XML format.

Forecasting Analysis: the collected data and cluster analysis will be exploited by the data mining algorithms to facilitate and enhance the development of predictive models useful for sustainable agricultural management, in order to predict the occurrence of plant diseases and take the most suitable actions. Furthermore, the weather forecast will be used to better manage irrigation and save water.

Alert Management and Actuation: in presence of certain conditions, e.g. the soil moisture level falls below a certain threshold due to high temperatures or because the system does not work appropriately, the actuator, such as automatic irrigation, will be activated. Therefore, FCN will send the actuation command and then will notify the Cloud of the event. In fact, the actuation takes place at the edges of the network close to the field devices, without the need that the command comes from the Cloud.

Figure 4 shows a flow diagram to explain our framework based on Fog Computing paradigm, where is highlighted the communication and the main tasks performed by FAN and FCN.

Figure 4. Flow diagram which describes the Fog logic

3.2 Expected Benefits

The proposed framework presents the following benefits:

Computational load balancing: the distribution of business logic among different levels of the architecture allows having a more balanced computational load saving considerable Cloud resources, which will perform less activities despite the more overhead due to data stored among the end devices.

Reduction of waiting times: when a real-time event occurs, it is processed locally, closer to the field devices such as the actuation process management, without necessarily reaching the Cloud but just sending notifications on related actions and sending notifications about the taken actions. Therefore, it will be the gateway to have a responsibility to begin the actuation.

Reduction of hardware costs: bringing business logic at a lower level allows the use of cheaper radio antennas that enable the use of communication mechanisms developed specifically for IoT. Although ensuring a throughput of some Kb, these communication mechanisms do not affect the overall performance of the system, thanks to the thoroughness with which the same intelligence is distributed.

3.3 Simulation and Evaluation of Data Traffic and Data Storage

To evaluate the usefulness of the proposed architecture, we carried out two kinds of simulations such as transmitted and stored data to the Cloud.

Our simulations have been performed in a network composed by ten sensor nodes (FAN), the gateway (FCN) and the Cloud platform and we have evaluated the amount of transmitted and stored bytes to the Cloud in three different scenarios:

- Cloud Computing architecture,
- 1-tier Fog architecture,
- 2-tier Fog architecture,

In order to facilitate the evaluation processes, we simulated both gateway and Cloud within the same host.

Table 3 shows some parameters of the data traffic simulation.

Table 3. Simulation parameters for data traffic

	From FAN To FCN	FROM FCN TO CLOUD
Protocol Type	LoRa	MQTT
Packet Size	110 Bytes	750 Bytes
Data Transmission Frequency	Per-Hour (1-2 tier) Per-Minute (cloud architecture)	Per-Hour (1-2 tier) Per-Minute (cloud architecture)
Devices Number	10 FAN	1 FCN

In 1-tier Fog architecture, the pre-processing is done only in the FAN that senses data from the sensors exploiting the algorithm explained in Figure 3, which then are transmitted to the gateway, transforming them into MQTT format to be sent over the mobile network to the Cloud platform.

In 2-tier Fog architecture, when FCN receives data from FAN, every hour it applies the hierarchical agglomerative clustering algorithm by identifying the homogeneous areas in the field and applying a further data aggregation.

Following the three approaches, Figure 5 compares the amount of transmitted bytes per day, whereas Figure 6 compares the amount of stored data to the Cloud calculated in one month.

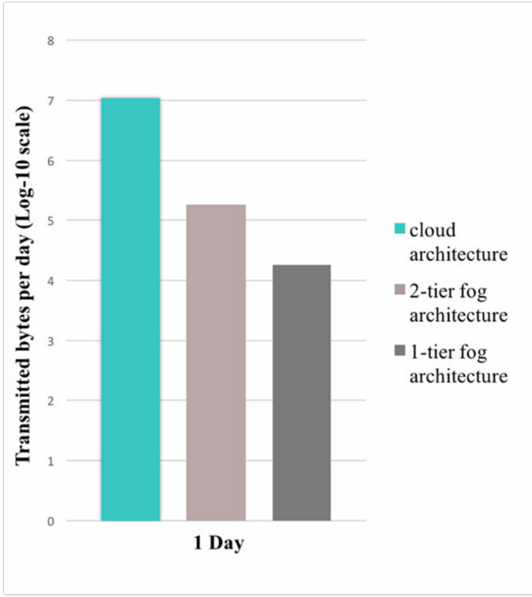


Figure 5. Transmitted data (bytes-per-day) to the Cloud using the three different approaches represented in Log-10 scale

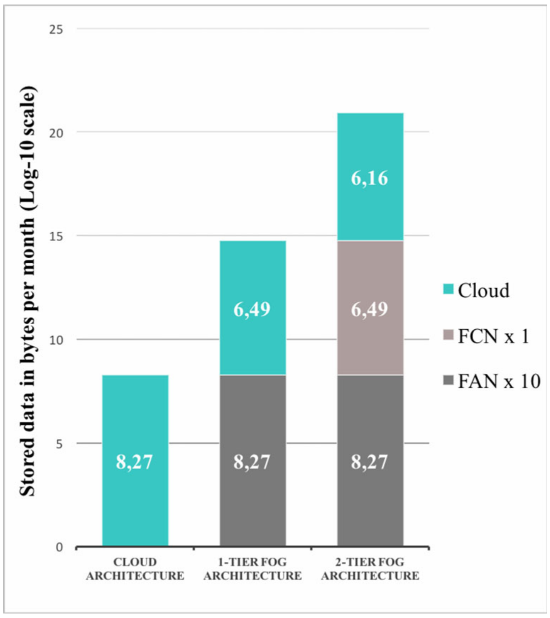


Figure 6. Stored data (bytes-per-month) in the Cloud using the three different approaches represented in Log-10 scale

The overall quantity of transmitted and stored data to the Cloud is calculated as follows:

$$Bytes_{tx\backslash stored} = Packet \backslash Doc_{size} * Min_{day\backslash month} * Devices_{num} \quad (1)$$

$$Bytes_{tx\backslash stored} = Packet \backslash Doc_{size} * Hour_{day\backslash month} * Devices_{num} \quad (2)$$

Eq. (1) is used in the Cloud architecture, while Eq. (2) is used in 1-tier and 2-tier architecture. The differences among 1-tier and 2-tier is the devices number, since in 2-tier architecture we consider only one device (gateway) sending an aggregate value as result of cluster analysis.

In both simulations we have used a log-10 scale for y-axis to better showing the values, compressing them in a more readable scale.

According to the first graph and exploiting the Fog Computing paradigm, we can observe that the amount of transmitted data presents a sharp reduction in relation to the traditional Cloud Computing architecture.

Exploiting the 2-tier Fog Computing architecture, the amount of transmitted data to the Cloud will be further reduced, missing a part of information respect of the measure of the individual sensor node. Therefore it will be sent a measurement range for each cluster of nodes since, in this context, it may not be significant to have information on the parameters measured by each node, but it might be enough to have information about overall features of a specific area. To evaluate the stored data in the Cloud, we used a NoSQL database, considering that each stored document related to the normal sensors measures has size of 425 bytes, while each document regarding cluster analysis has a 2 KB size.

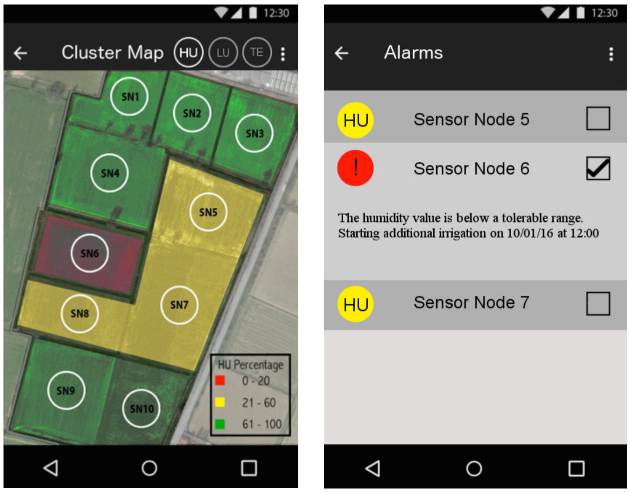
Observing the second graph shown in Figure 6, we can see a decrease in the amount of stored data in the Cloud because of the distribution on both the FAN and the FCN. As a consequence, the overall amount of stored data will be higher in 1- or 2-tier approaches, due to data duplication in both the two aggregators.

3.4 Prototype

We have developed an application prototype to provide useful services for the optimal management of the agricultural lands. Figure 7(a) illustrates the subdivision of the field into clusters in order to monitor the field.

The clustering allows identifying homogenous areas that, in this case, are grouped by soil moisture values, exploiting the hierarchical agglomerative clustering. In particular, we can observe three different clusters and the presence of a cluster composed by only SN6 node with a lower soil moisture value.

Figure 7(b) shows all the alarms produced by some sensor nodes. In fact, SN6 produces an alarm to notify a case where there is a low percentage of humidity. As explained in Figure 4, the FCN will send a command of the additional irrigation to the FAN and will notify the successful operation to the Cloud. The yellow alarm denotes another type of anomaly related to likely faults to the specific sensor nodes due to amount of discarded data during the filtering process. Specifically, we observe potential faults for the humidity sensors of SN5 and SN7, so that the user can perform an accurate control of the specific sensor node and, if necessary, replace it.



(a) The field is divided into clusters grouped by soil moisture value

(b) Alarm notification produced by sensor nodes

Figure 7. Application prototype to manage agricultural lands

4 Conclusion

In this paper we presented a Fog Computing solution in an IoT scenario where the computing is peripherally distributed, balancing the computational load. As application area, we consider the precision agriculture, a field of growing interest in research community, due to its potential impact on performance in terms of management, environmental and economic outcomes. The proposed framework considers two Fog layers, performing respectively different tasks based on them computational capabilities. Thus, FAN nodes are responsible for data filtering and aggregation, whereas clustering analysis, alert and actuation management tasks are carried out by FCN. Based on this framework, we have simulated and highlighted how the two-tier Fog Computing approach is able to reduce significantly the amount of transmitted data to the Cloud.

Among the achieved benefits exploiting this framework and the implemented prototype, the most valuable are the load balancing, due to the Fog Computing approach, and the reduction of waiting times in the actuation phase of an event. The realized application prototype will allow us managing agricultural lands, thanks to the clustering mechanism, and tracking easily the alarm notifications from the sensor nodes.

Future works will be focused on exploiting data gathered through the prototype and perform data analysis applying data mining algorithms, preventing plants disease and improving the quality of the crop. Moreover, we will work to strengthen the reliability of the measures through the robustness and sensitivity analysis.

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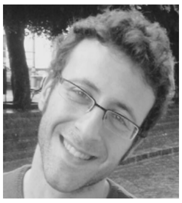

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