An IoT-based System for Landslides Warnings Using a Real Time Slope Monitoring Model

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ABSTRACT

This work presents an IoT-based system for remote monitoring of landslides. The solution uses a Wireless Underground Sensor Network (WUSN), a cloud computing platform and an App to implement a real time monitoring scheme. The sensor network runs on Arduino components connected through Wi-Fi modules, and is responsible to collect soil moisture rates. Then, the collected data is sent to a cloud computing environment in order to ensure a robust and secure storage. Moreover, the cloud platform runs a model for triggering an alarm when a potential landslide is detected. Finally, an App aimed to data visualization in real time and landslides warning is also presented. The proposed work enables a real time end to end solution, once it starts with the data collected by the humidity sensors and finishes with the data visualization by the citizens, which is very suitable for Smart Cities and Internet of Things (IoT) environments. The system was evaluated through real tests and simulated scenarios. The results show the sensor network accurately measured the soil moisture and the landslides monitoring model was able to send warnings consistently.

KEYWORDS

INTERNET OF THINGS, SMART CITIES, LANDSLIDES MONITORING, SENSOR NETWORK, CLOUD COMPUTING

1 INTRODUCTION

The landslides are an usual phenomenon in Brazil, due to the tropical weather with great amounts of rain, mostly on summer. Besides that, there are several mountainous terrains along the country which are occupied by legal and illegal buildings. These occupations increase the risk of landslides, once the original vegetation was removed from those areas. As shown in [1], in the year of 2020 over 8 million people, whose live in 2.4 million of habitations located in 872 cities, remain in areas with potential risk of landslides.

Despite some states and cities present safety protocols to evacuate people in critical rainy scenarios, as can be seen in Rio de Janeiro's protocol described in [2], most of these action plans are not efficient and do not provide public data visualization in real time. This inefficiency occurs due to the monitoring model of these approaches, which are based on simple pluviometric rates thresholds, and do not consider other relevant factors that trigger a landslide, such the soil humidity. These approaches analyze the weather forecast information and the pluviometric rates collected from rain sensors spread on different locations around the cities. More to the point, the data is not collected only from hills and slopes mapped as risky areas, but the most areas in the cities, which leads to a ineffective model to predict landslides on as specific location and to evacuate people as well.

This work address an end to end landslides remote monitoring, based on an IoT scheme. The proposed solution uses a Wireless Underground Sensor Network (WUSN) to collect data directly from the target areas. To this end, humidity sensors are deployed in the soil of mountainous terrains previously mapped as risky areas by the local authorities. Then, in order to ensure a robust and secure storage, the data collected by the underground sensor network is sent to a cloud computing platform. The cloud computing platform also is responsible for running the model designed to detect the eminence of a landslide, enabling early warnings for the local population through an open access App.

The monitoring model proposed in this work is aimed to predict a landslides in real time, and is based on the Safety Factor (SF) metric, which considers several elements related with landslides, such as slope degree angle, soil density, vegetation type, among others. Therefore, the system is able to run in a proactive manner with a high level of accuracy, avoiding that people remain in risky areas when a landslide is about to begin. The App is designed for mobile devices (smartphones and tablets) where the data could be displayed in real time using a friendly interface.

The main goal of this work is to enable a landslide monitoring in risky areas by everyone interested (authorities and citizens). The solution is designed to the context of Smart Cities and IoT environments, implementing an autonomous solution driven to data visualization in real time and landslides warnings. Besides that, the proposed system is generic enough to provide a sustainable and low cost deploy in any interested cities and locations with landslide issues. This work is organized as follows: The Section 2 presents the related work. The proposed solution is described in Section 3. In Section 4 a simulated evaluation of the monitoring model is presented. Finally, the Section 5 describes the conclusion and points for future work.

2 RELATED WORK

A typical Wireless Sensor Network (WSN) is an *ad hoc* network, composed by sensor devices that have the capacity to collect data, in different contexts (military, medical, home/industrial automation, and so on), and autonomously transmit them using a wireless infrastructure. The sensors are devices with processing and energy constraints [3]. The energy of sensor nodes is supplied by a battery

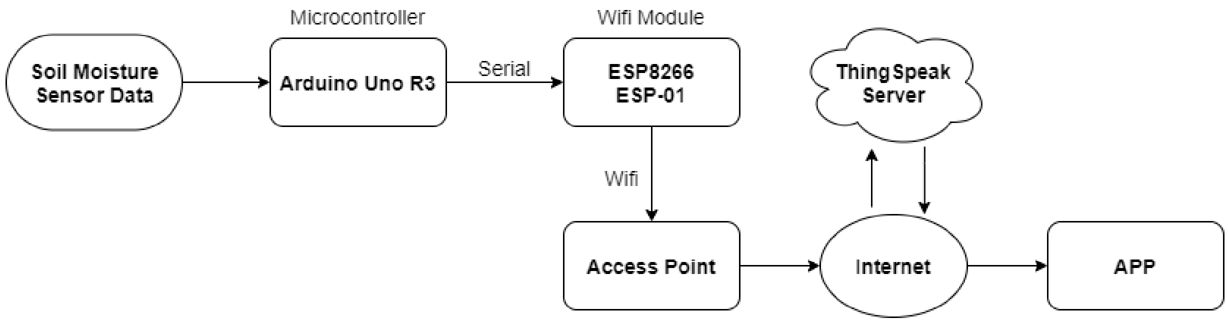

Figure 1: System architecture

with a limited lifetime. Thereby, methods for energy saving are very relevant in WSNs. The use of a WSN in order to remote monitor landslides is presented in [4], [5] and [6]. These works adoption the paradigms of Smart Cities [7] and Internet of Things [8], performing remote monitoring in real time and processing the data collected. To implement this monitoring approach a robust infrastructure is needed, once the data must be collected, transmitted, processed and presented to the users.

In this work, we consider a special type of WSN, which sensor nodes are located underground, called Wireless Underground Sensor Network (WUSN) [9]. The literature presents several works that address the remote soil monitoring based on underground sensor networks. Most of these approaches are designed for farming or general purpose activities, as shown in [10] and [11]. Despite both works are aimed for farming, they have architectural similarities with our work, such as the Wi-Fi sensor network and the cloud computing platform for storing and processing data. The works described in [12] and [13] present solutions for landslide monitoring. However, these works do not present an end to end solution, focusing in the sensor network connectivity or in the model to trigger landslides warnings.

The use of a Safety Factor (*FS*) modeling in order to define a threshold that trigger an unstable soil scenario has been addressed by the literature for decades, as discussed in [14] and [15]. This approach considers the relationship between structuring and disruptive soil forces. In addition, the finite slope model is wide used for landslides monitoring, once it assumes that a slope length, and consequently its height, is much greater than the soil layer depth. Then, most of the works use this specific modeling to apply their policies to dynamically analyze the structuring and the disruptive soil forces, and define the Safety Factor of a risk area, as described in [16] and in [17].

Despite the literature presents works for landslide monitoring, most of them address the problem partially, focusing on the sensor network dependability or in the modeling of the Safety Factor. Thus, our system differs from similar works due its holistic perspective, once it presents an end to end approach based on the IoT paradigm. Besides that, the public data visualization in real time by the citizens through an App implemented in our solution should have a major impact on the efficiency of a landslide warning, and on a successful evacuation process as well.

3 THE PROPOSED SYSTEM

The proposed system uses an Iot environment to implement a real time monitoring scheme. The solution architecture, the Safety Factor model, the cloud computing platform and its interface with the App, and a estimated cost to deploy the proposed system are presented in details in the following sections.

3.1 System Architecture

The monitoring starts with a Wireless Underground Sensor Network composed by several humidity sensors deployed in the soil of a risk slope. Then, the communication between the sensors and the access point is performed by the Wi-Fi protocol. The access point is responsible for sending the collected data to the cloud computing platform, where the data is processed and stored. The cloud computing platform also has the role of an application server running the Safety Factor model and feeding the App designed for mobile devices. Lastly, the App is responsible for data visualization and for warning messages to the users when a landslide is about to occur.

The system architecture is shown in Fig. 1. To ratify the proposed architecture, a system prototype was implemented using three Arduino Uno R3, each one attached to a humidity sensor. The Arduino uses a ESP8266 Wi-Fi module to send the collected data to the access point. Then, the access point routes the packets through the internet to a data channel previously configured in the ThingSpeak platform, which is a cloud computing environment that enables instant visualization of live data, data mining and alerts configuration, as described in [18]. An initial test was performed to analyze if the data collected by the sensors would be properly stored in the cloud computing platform and visualized in the App.

As described in [19], the WUSNs have several specific connectivity characteristics in comparison with traditional sensor networks, e.g. the communication channel, robustness. Therefore, an empirical approach was chosen for positioning the sensors in order to evaluate the connectivity and the robustness of the data collection process, instead the using simulation tools. This positioning issue refers to the distance between each sensor. If the sensor nodes are too close to each other, there may be redundant data collection, which leads to higher energy consumption due to the operation of non functional sensors. On the other hand, if the sensors are not close enough, the network can present lack of connection, leading to packet losses, and thus harming the real time monitoring process.

Each collecting point is composed by one Arduino, one humidity sensor and one Wi-Fi Module, and was deployed in a box with small amount of brown soil, as depicted in Fig. 2. The communication between each collecting point (sensor nodes) is based on the multi-hop paradigm. Thus, each sensor only can communicate with direct neighbors, and the data are sent in hops over the sensor nodes to reach the gateway, when the data is finally sent to the cloud computing platform. Each box is place apart 10m from other and buried at a depth about 0.5m, to create a real WUSN scenario. Then, three test replications were performed, in order to analyze three rain scenarios over about 40m^2 area. To this end, the boxes were filled with water using different time intervals on each scenario, performing a similar approach with the work described in [20].

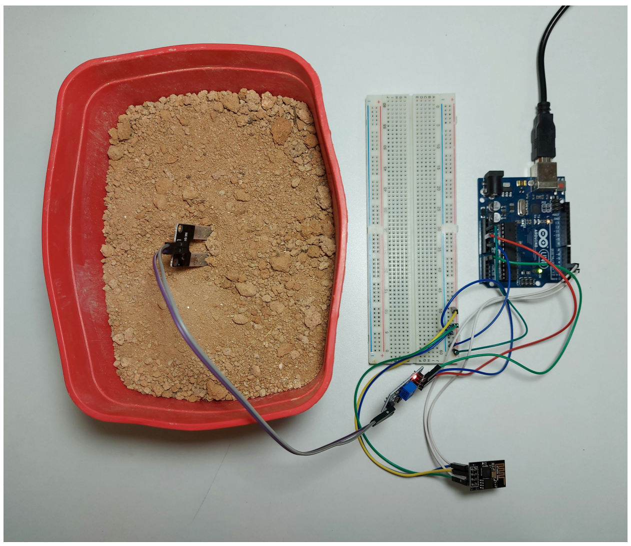

Figure 2: The Collecting Point

Every test replication is related to fill the soil box with some amount of water uses the constant value of 10 ml of water per time. The first test replication is related to a light rain scenario, and fills the soil box with 10 ml of water every 6 minutes. The second scenario maps a medium rain, and the 10 ml of water is putted in soil box the every 3 minutes. Finally, to simulate a heavy rain, the amount of 10 ml of water is placed in the soil box every 30 seconds in the last test replication.

For all the observed scenarios, the experiment was finished after 10 rounds, which means that the soil box was filled with 100 ml of water. The value of the soil moisture rate is measured by the sensors at the end of the mentioned time intervals of each scenario. In other words, on the light rain scenario the first soil moisture rate is measured at 10 minutes, just before the second round of 10 ml of water, the next measure occurs at 20 minutes, and so on. The results are presented in Fig. 3, the average value obtained from the three boxes are displayed for each scenario.

As expected, at the beginning of the experiment the highest soil moisture rate is related to the heavy rain scenario, since the measurement was performed only 10 seconds later than the first round of 10 ml of water. It is important to notice that around the seventh round of 10 ml of water (totaling 70 ml of water in the soil box) all the scenarios present a similar soil moisture rate. This point indicates the saturation of water in the soil box, once the new rounds of 10 ml of water have no relevant impact on the humidity rates collected by the sensors.

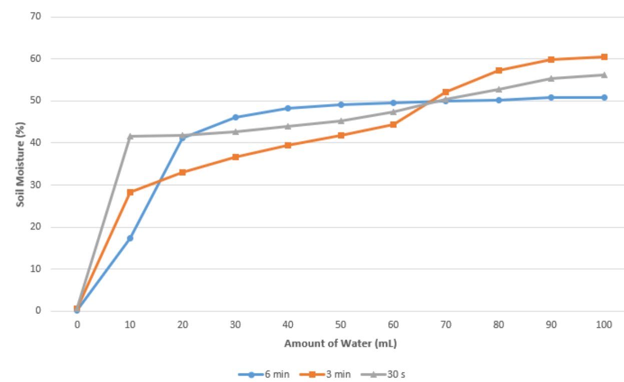

Figure 3: Results considering three rainy scenarios

Despite the experiment performed used a static time interval between each sensor reading, this approach should be dynamic in order to obtain energy savings. The soil verification time is determined according to the context. Therefore, when there is heavy rain, for example, the frequency of data collection should be dynamically increased by sensor nodes in order to perform a fine grained monitoring control. On the other hand, in sunny days, the frequency for collecting data may be decreased to provide energy saving on the sensor network. This dynamic reading of the sensor network is pointed as future work in Section 5.

It is worth mentioning that each line in the graphic depicted in Fig. 3 was generated at run time by the ThingSpeak platform. Then, all the collected data was combined into a single chart to provide a better visualization in this paper and a holistic view of the soil moisture behavior on each rainy scenario. Besides that, the platform has many data visualization options and a friendly control panel for personalized configuration according the user demand.

3.2 The Safety Factor Model

As mentioned earlier, the finite slope modeling is more suitable for landslides monitoring in hills and mountains, once these scenarios present a thin soil layer upon a big rocky layer. Since our work address landslides originated by the rain in mountainous terrains, the implemented sensor network is aimed to monitor the soil moisture, once this is the main variable to define the value of the Safety Factor (SF). It is important to notice that some characteristics that impact the value of SF are constants for each slope (vegetation type, slope degree angle, etc.).

Once the finite slope model assumes that a slope length, and consequently its height, is much greater than the soil depth, and the width is unitary, the analysis must consider only two dimensions, as depicted in Fig. 4. As shown in [21], the water penetrates the soil until reaching the rocky layer, which has a much greater density in comparison with the soil layer. Then, the water accumulates and

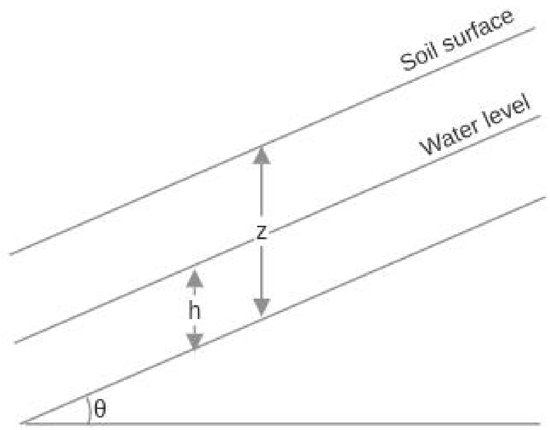

Figure 4: Finite slope model

saturates the soil in that region. The more rain, the more water is accumulated, raising the water level. This behavior of the Safety Factor is modeled by Eq. 1 as follows:

$$SF = \frac{c + (\rho_s.g.z.cos^2\theta - \rho_w.g.h.cos^2\theta).tan\phi}{\rho_s.g.z.cos\theta.sin\theta} \tag{1}$$

Where:

- c **is the cohesion level (N/m²).** Cohesion level is defined as the shear strength at zero normal pressure on the surface of failure. Based on this definition, cohesion level has a constant parameter for each soil type.
- ρ_s **is the density of wet soil (kg/m³).** Wet bulk density is the mass of soil plus liquids/volume as a whole. The dry bulk density of a soil is inversely related to the porosity of the same soil: the more pore space in a soil the lower the value for bulk density.
- g **is the gravity acceleration (m/s²).** For slope modeling scenarios, the gravity acceleration is a constant of value equal to 9.8.
- z **is the soil depth (m).** It considers the depth from the soil surface until the end of its layer, or in other words, until the beginning of the rocky layer of a slope.
- θ **is the slope degree angle (degrees).** It indicates how steep is a slope.
- ρ_w **is the water density (kg/m³).** It depends on both the air pressure and the temperature of the area. These variations in density are very slight though, so unless the analyzed slope takes place in an area with an extreme temperature/pressure, the water density may be consider as a constant of value equal to 1.
- h **is the water level height (m).** It is related with how tall is the water level underneath the soil. In other words, how much water have passed on through the soil surface when a rain scenario is observed.
- ϕ **is the internal friction angle (degrees)**. It indicates the shear strength parameter of soils, and it is used to describe the friction shear resistance.

If the value of SF is greater than or equal to 1, the soil is on a stable scenario. Otherwise, if SF presents a value lower than 1, an unstable soil scenario is detected, and a warning about landslides should be sent to the population.

As can be seen in Eq.1, the cohesion level c, the density of wet soil ρ_s, and the the internal friction angle ϕ are the variables related with the soil type of a specific location, since different soil types present different values of theses variables. To calculate the cohesion level c, usually is considered only the value of the soil cohesion (c_s). However, it is also necessary to evaluate the impact of the vegetation on the soil cohesion. As shown in [22], the vegetation has a relevant role in the Safety Factor model due its roots underneath the soil. Thus, in order to consider the vegetation impact, the value of c is specified as $c = c_s + c_r$, where c_s is the soil cohesion and c_r is the roots cohesion.

Thus, in order to observe the behavior of these four mentioned variables when different soil types are analyzed, an empiric observation was performed. This observation was aimed to verify how fast different soil types take time to get saturated (totally wet) and then to get dry. The same testbed described in the initial tests presented in Section 3.1 was used. However, instead of an unique soil type all over the test, two different types was analyzed. In this scenario, clay soil and black soil were chosen to perform the test, due their relevance over the Brazilian soil types. Thus, the experiment was designed to collect data using a soil similar to the one that will be found in a real external scenario. The results provided by this experiment enable the mapping of the variables related to the soil type in the Safety Factor modeling (Eq. 1), once different soil types were empirically analyzed.

The expected test results are that soils submitted to the same amount of water may present different results in relation to the humidity, in a determined period of time. As pointed in [23], the black soil has a higher water retention capacity than mineral particles, so this type of soil is more efficient in reducing the water effect in the friction between the mineral particles. For the clayey soil, the interaction between the mineral fraction and organic matter is higher, which results in lower availability of organic matter to interact with the water added to the soil. Consequently, clay soil retains more water. Therefore, it is possible that the humidity sensor will take a little longer to check the humidity variations close to it.

In the first experiment, it was added 10 milliliters of water for every 10 seconds in each one soil type in extremely dry conditions. After each time was observed the resultant behavior. Fig. 5 presents the result for the percentage of soil moisture in relation to the amount of water in the soil (in ml), for two distinct soils: a black and a clay soil. It can be verified that the curve for the percentage of moisture of the black soil is more accentuated. Therefore, it can be concluded that the arrival of water in the vicinity of the sensor occurs in a short period of time. The clay soil retains the water near the surface, according to expectations. After the water arrives near the sensor, the curves tend to follow constant values.

The drying time for both soils was also considered in these initial evaluations of the proposed prototype, as we can see in Fig. 6. In this experiment, the two mentioned types of soil were subjected

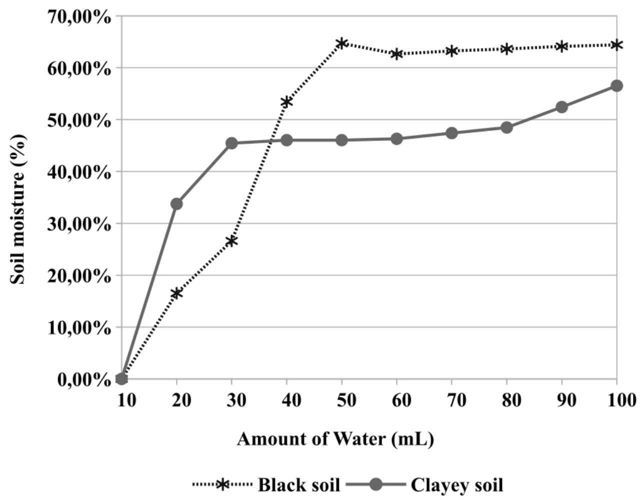

Figure 5: Soil moisture percentage in relation to the water amount in the soil (ml). For both the black and clayey soils.

to 40 milliliters of water for each minute, in a total period of 300 minutes. We expect a period for the water to reach the vicinity of the sensor. This event is verified in the first minutes of the experiment, as shown in the results. Approximately 80 minutes later, the remaining water still tends to reach the vicinity of the sensor. The moisture percentage of black soil is higher than the clayey soil in the initial minutes. In addition, the black soil drying time is lower than the clay soil, as expected.

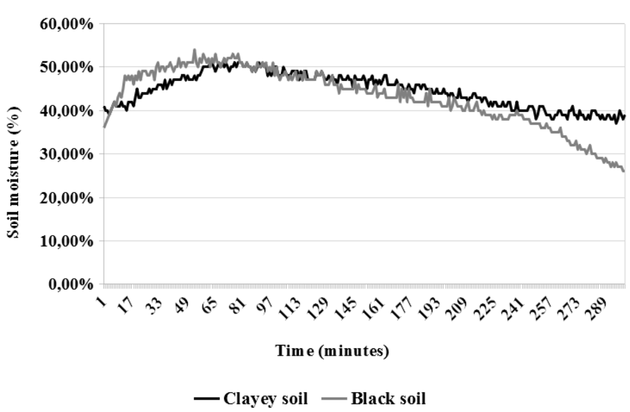

Figure 6: Drying time for brown and clay soil

Once empirically ratified that the soil type impact on the Safety Factor model, it is required to define what is the amount of water in the soil which leads to an unstable slope scenario. To this end, an analysis of the fraction h/z in Eq. 1 was carried out, since this fraction indicates how high is the water level under the soil surface. In order to highlight the significance of the h/z behavior, its value close to 1 indicates that water takes almost all place under the soil surface, leading to an unstable slope scenario.

The need is to know the value of h/z that turns the value of the Safety Factor SF equal to 1, since SF equal to 1 is the lower bound of the stable soil threshold. Thus, the definition of this mentioned value enables to know the depth that the sensor should be deployed in that location. Then, when this sensor measures a value of humidity that indicates a saturated soil (SF equal to 1), it triggers the warning of eminent landslide.

To obtain the fraction h/z, it is isolated in Eq. 1 and the value of SF is set equal to 1, leading to the relationship described below in the Eq. 2:

$$\frac{h}{z} = \frac{c}{tan\phi.\rho_w.g.z.cos^2\theta} + \frac{\rho_s}{\rho_w}.(1 - \frac{tan\theta}{tan\phi}) \tag{2}$$

When an algebraic analysis about how the values of the other variables impact on the fraction h/z, some relationships may be observed. The greater the value of c and ϕ, the greater is h/z. This is an expected behavior and was ratified by the latter experiment performed with brown and clay soil, since a soil with great cohesion level retains more water, increasing the water height under the soil surface (variable h in Eq. 1). On the other hand, θ e z are proportional inverse to the fraction h/z, so the lower the value of θ e z, the lower is h/z. This relationship is intuitive, once the higher is the soil layer, the higher is the value of z, and the height of water will have less significance for the instability in this case. In addition, the lower is the steep of a slope (θ), the lower is the impact of the gravity for leading a landslide over that area. These relationships are analyzed in a simulated scenario presented in Section 4.

3.3 The Data Server and the App

For the purpose of connecting the WUSN to a data server, the ThingSpeak platform was chosen. The main role of updating data continuously is done by Thingspeak, which has APIs for collecting data produced by sensor networks or IoT devices and APIs for running applications. Therefore, it offers real-time data collection, data processing, and also simple visualizations for its users.

Another important feature about ThingSpeak, is it allows the development of applications based on the data collected. It provides additional support for the programming languages Ruby, Python and Node.js. Thus, any user is able to implement and run his own applications on the ThingSpeak platform. In this work, a Python program was implemented for running the Safety Factor modeling presented in Eq. 1 and Eq. 2.

The App was implemented for Android mobile devices, and is presented in Fig. 7 with the GUI in Portuguese, since this project is initially addressed for people who live in Brazil. The users are able to visualize the current average rates of soil moisture and rainfall, and a twelve hours historic of both metrics. These main screens enable the real time monitoring from a specific location. In addiction, a screen designed for landslides warning is also presented.

As mentioned earlier, the soil moisture is obtained directly from the humidity sensors. The works described in [24] and [25] show the soil moisture and the pluviometric rate have a direct relationship, and the latter could be calculated by analytic models. However, there are several public weather API available on the internet, such as Open Weather Map [26] and Free Weather API [27], which

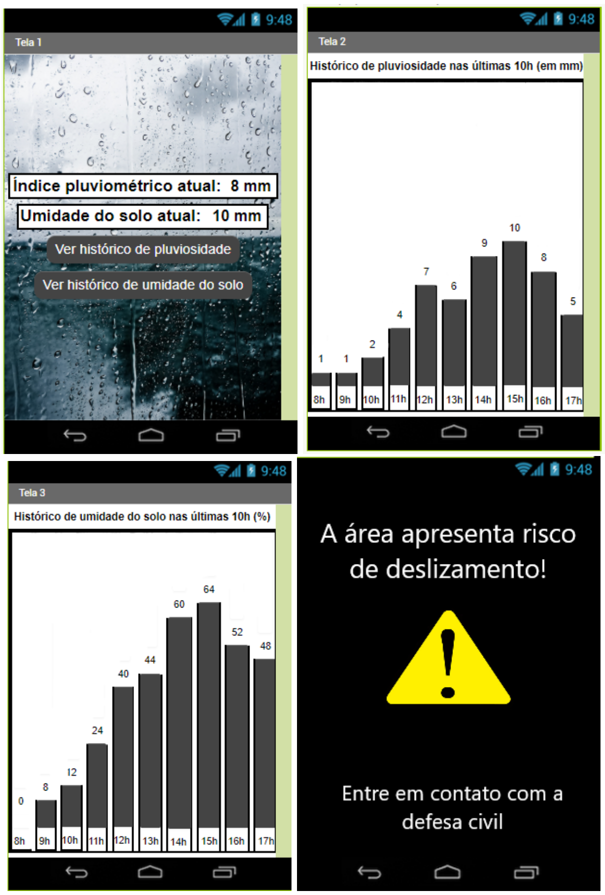

Figure 7: The main App's screens

provide pluviometric rate and other relevant weather data from a specific location with a suitable accuracy. Therefore, in order to provide a low cost solution, the App gets the estimated pluviometric rate from a specific location through a HTTP request to the Open Weather Map API. The use of the mentioned API enables a significant reduction of the solution cost, once the data collected by several pluviometric sensors attached to Arduino controllers with Wi-Fi modules are replace by the data obtained from the API.

However, it is important to notice that even without an App to provide data visualization, the ThingSpeak platform is able to make feasible the real time monitoring of the soil moisture rates collected by the sensor network. This feature was the main reason that justify the cloud computing platform chosen for this project, since the authorities related with civil defense activities could remote monitor selected areas only using the cloud computing interface.

3.4 Estimated System Cost

As mentioned before, one of the main characteristics of the proposed solution in this work is its low cost. This is achieved due the system architecture is composed by simple devices, which are easily found in most of electronic stores around the cities. Therefore, even when large areas should be monitored, the system cost is suitable to the budget of the cities.

In order to deploy the whole system to perform a real time monitoring of a risk area, enabling also real time visualization through an App, the devices listed bellow is required:

- **Collecting point:** Its prototype is depicted in Fig. 2 and is responsible for collection data from the target slope. It is composed by 01 Arduino Uno R3, 01 Humidity Sensor, 01 9V Battery, 01 Wi-Fi Esp 8266 module, 01 CD4050 integrated circuit to supply 5V output for the Wi-Fi module, 01 Protoboard and a set of cables and jumpers;
- **Gateway Wi-Fi:** Composed by a router aimed to send the data collected by the sensor network to the internet;
- **Data Server:** Responsible for storing and processing the collected data, and for feeding the information displayed on the App;
- **App:** Aimed to data visualization by the local population, government agents, or any person interested in.

To provide an estimated budget for a risk slope with a size of a soccer field (8,250 m^2), considering the same rate of sensor per m^2 used in the initial tests presented in Sec. 3.1, the estimated cost to deploy the system is described in Table 1.

Device	Unitary cost (USD)	Amount
Collection Point	38	200
Gateway	55	1
Data Server	948	12 months
App	6k	1
Total cost (USD):	**14.6k**	

Table 1: A budget to monitor a soccer field size slope

The unitary cost was calculated using the value of each device available in [28]. Ten certified sellers by these mentioned e-commerce platforms were analyzed in order to obtain the average devices price. To define the data server cost, instead of evaluate the server price for buying and configuring it, the cost of a cloud computing platform (ThingSpeak) annual plan is shown.

To analyze if the system budget effectively address a low cost solution, we performed a comparison with the most recent slope containment plan made by the city of Petrópolis in Brazil and described in [29]. The mentioned plan indicates the need of intervention in 25 risk areas spread over the city. The whole project was budgeted in 26 million USD, which means an average cost of 1.04 million USD per risk location. Thus, consider the system budget for one risk location presented in Table 1, the system cost is about 1.4% of a slope containment intervention cost in one mapped risk area.

However, it is worth mentioning that the slope containment intervention and the proposed monitoring system are complementary approaches. The interventions specified in the slope plan are required for preventing a landslide. On the other hand, the proposed solution in this work has the role of monitoring the risk of eminent landslide in real time, and is aimed for general information and to send warnings for the local population.

It is important to notice that the total cost mentioned in Table I is composed only by activities directly related with the system, such as devices, cloud computing plan's fee, software development (App), etc. Therefore, there are indirectly costs not listed in Table I.

Scenario	ρ (kg/m³)	c_s (N/m²)	c_r (N/m²)	ϕ (°)	θ (°)	z (m)
1	1,488	14,613	4,292	28	30	5
2	1,569	2,224	6,718	46	48	6
3	1,779	6,704	9,323	32	28	14
4	1,673	17,011	18,077	10	32	6
5	2,052	419	14,765	24	27	13

Table 2: The parameters used for each scenario

These costs are may be related to previous geological analysis of the risk area, skilled labor, hiring of machinery and other equipment required for the deployment stage, among others.

Besides that, the system consider the multi-hop architecture for the sensor network communication, where the data collected is sent to the internet through a single gateway. This was the architecture chosen for the system and ratified through the initial tests described in Section 3.1. However, the sensor network literature offers several approaches for the communication architecture and topology, as discussed in Section 2 and 3.1. As the ones that highlight the most, it is worth to mention the clustered network communication, mesh, star or hybrid networks, among other. Despite several architectures may be suitable for the proposed system, they present similar concerns to the trade-off between power consumption and communication performance. Thus, the great difference between them should be the number of gateways deployed over the sensor network. Table I shows the unitary cost of a gateway is about 0.3% of the total costs, and different sensor networks communication approaches will not present a relevant impact on the system budget.

4 SAFETY FACTOR EVALUATION

This evaluation is aimed to analyze if the Safety Factor is able to define the depth of the collecting points accurately, according to the characteristics of the slope to be monitored. As the performing of real tests to evaluate the proposed Safety Factor is practically infeasible, due to the several restrictions to reproduce a real slope considering all its natural elements presented in Eq. 1, a simulated evaluation was chosen.

The information about the sensors depth to trigger the warnings consistently should be obtained according to the following steps: (*i*) observing the slope characteristics to define the values of the parameters described in Eq. 1; (*ii*) assuming the value 1 to the Safety Factor (lower bound of a stable slope scenario); (*iii*) finally, using the Eq. 2 to define the fraction h/z, and consequently the value of z, once the value of h is previous knew (height of the soil layer) for a specific location. To this end, random values for the variables described in Eq. 2 were generated, in order to have several slope scenarios, e.g. a steep slope with great soil cohesion but few vegetation, a slope not too steep but with low soil cohesion and large vegetation. As mentioned earlier, g and ρ_w are constants, and equal to $9,81m/s^2$ and $1000kg/m^3$, respectively. The remain values which are randomly generated are depicted in Table 2.

It is important to notice that even the same slope may present heterogeneous scenarios, once at some point the slope may be steep, but at others it tends to be flat. Therefore, sensors from a same WUSN may be deployed in different depths, leading to a complex heterogeneity that should be detailed analyzed in the design stage.

The values of the variables and the depths of the corresponding sensors for each scenario are presented in Table 3.

Scenario	h/z [%]	Sensor Depth [m]
1	83.9	0.8
2	21.4	4.72
3	50.5	6.93
4	44.7	3.32
5	4.1	12.47

Table 3: Sensor depth for each scenario

A dataset that implement a double ramp similar to the shape of the letter "M" was used in this simulated evaluation. The dataset provides readings of soil moisture, collected by humidity sensors, and was obtained in [30]. The double ramp with "M" shape means the value of the soil moisture increases fastly in the beginning, until reach the upper bound. Then, it starts to decrease to a medium value, when it starts to increase again achieving the upper bound for a second time. Thus, the selected dataset models a scenario with heavy rain, turning into medium rain until the beginning of a new window of heavy rain. The sensor of the mentioned dataset reads the soil moisture in a values range of 0 to 1023, and related a saturated soil with the reading value equal to or greater than 1015.

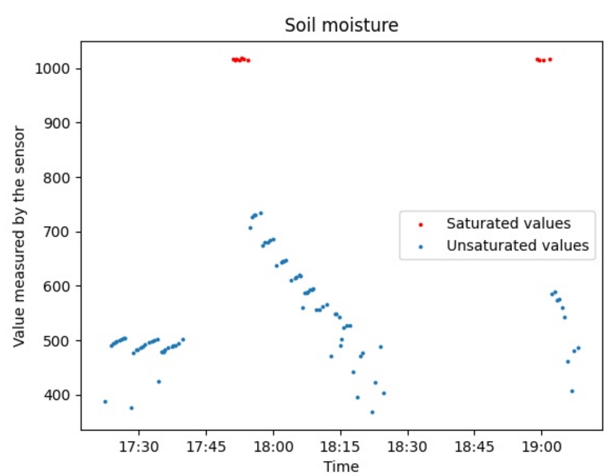

Figure 8: Soil moisture measurements from the dataset

The Fig. 8 depicts when landslides warnings should be sent if the proposed Safety Factor modeling was used. These warnings occurs in two time windows, the first is between 17:45 and 18:00, and the latter is about 19:00, as indicated by the red dots in the graphic.

5 CONCLUSION AND FUTURE WORK

This work presented an IoT-based system for remote monitoring slopes mapped as risk areas for landslides. A prototype was implemented and evaluated through real tests, which was aimed to simulate the system behavior for several rainy scenarios. The results ratified the model architecture to measure the soil moisture rates with a suitable accuracy. The cloud computing platform chosen for the system implementation enabled data processing in real time, in addition to provide a reliable and robust storage for the data collected by the sensor network. Moreover, it had been able to feed an App consistently, in order to achieve real time data visualization by the user through a friendly interface.

In addition, a model to calculate the Safety Factor of a slope was also described. This model is aimed to trigger landslides warnings for the local population, based on the soil moisture rates collected by the Wireless Underground Sensor Network. Using a simulated scenario, the proposed model was able to indicate the effective depth of each sensor of the WUSN, considering several parameters related the monitored slope, such as soil type, slope angle, depth of the soil layer, among others. The results show the Safety Factor modeling consistently trigger warnings when the collected data indicates a saturated soil moisture rate.

As future work, we intend to expand the WUSN in order to implement a heterogeneous network, running different communications protocols, such as Bluetooth, LoRa and ZigBee. The objective is to analyze relevant issues related to each protocol, such as power consumption of the wireless modules attached to the Arduino, distance between the sensors, network dependability, among others. More to the point, we will also analyze the efficiency of a hybrid wireless sensor network (underground and surface), adding rainfall sensors to the system architecture. This hybrid sensor network can be an interesting alternative to the use of the public weather API mentioned in Section 3.3, since the data collected from the rainfall sensors is more accurate than the provided by the weather API. The authors would like to acknowledge the financial support of FAPERJ and CEFET/RJ for this work.

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