On Developing Smart IoT-Based Distributed System for Remote Detection of Slope Movements

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***Abstract*—Landslides or slope failures cause significant damage to the transportation infrastructure worldwide, resulting in billions of dollars of property damage. The initial slope movement of highway slopes, caused by environmental factors and man-made activities, must be detected early to prevent significant losses in infrastructure damages and human lives. However, traditional monitoring approaches for slope movement, such as periodic human inspection and surveying, are labor-intensive and time-consuming. With the advent of the Internet of Things (IoT) and high-speed internet, the potential to use such technologies for monitoring remote earth movement of highway embankments is becoming increasingly important. This paper presents an IoT-based distributed system for the early detection of slope movements to assist transportation authorities in immediately repairing the slope before a major failure occurs. We built a laboratory prototype embankment, equipped with various IoT sensors (e.g., tilt, moisture, and tensiometer sensors), that simulate a failure-prone slope to evaluate the effectiveness of our system. A user-friendly GUI is developed to enable users to utilize the system remotely. The collected sensory data for four months allowed us to analyze the soil hydrologic dynamics and the slope performance by detecting changes in the slope tilting both parallel (pitch) and perpendicular (roll). The experimental results showed that our system could detect negligible movement (1mm) and rotation (0.02^{o}) of slopes.**

***Index Terms*—Internet of Things (IoT); Communication; Distributed System; Remote Monitoring; Slope Movement.**

I. Introduction

Landslides or slope failures of highway embankments represent a substantial natural hazard with the potential to result in fatalities and economic losses worldwide [1], [2], [3]. Slope failures may cause serious damage to transportation infrastructures such as bridges, highway embankments, railways, etc. For instance, the Texas Department of Transportation (TxDOT) spends millions of dollars every year repairing failed embankments and performing routine maintenance [4]. The early detection of slope movement or failure, especially for failure-prone slopes can limit these losses and support the sustainability of the embankment infrastructures significantly [5]. Accordingly, an intelligent field monitoring system is critically needed to detect small-scale slope deformations or movements, which frequently precede slope failures of embankments [1].

Traditional approaches to monitoring failure-prone slopes in the field are scheduled inspections by experts and topographic surveys. However, these approaches are limited by accessibility and do not scale well regarding area coverage. Other methods that use sophisticated equipment to predict slope failure (e.g., terrestrial laser scanners [6], extensometers [7], tensiometers, and inclinometers [8]) require specific expertise and impose substantial operating costs and need recurrent field visits [9], [2].

With recent advances in the Internet of Things (IoT) capabilities [5], [10], [11], it is more possible than ever to implement remote monitoring systems that can automatically detect small slope displacements using low-cost sensors such as tilt sensors. This paper presents a cost-effective IoT-based system for real-time monitoring of slope movements and hydrologic responses. We developed a distributed system, arranged with components executing on IoT devices at the sensing slope and centralized servers on the cloud side.

We built a laboratory-scale prototype slope model using Fat Clay (CH) to simulate slope movement or deformation under controlled environmental conditions. We installed various IoT hydrologic and positional sensors into the slope model, including an MPU-6050 tilt sensor, TEROS 11 moisture sensors, and TEROS 21 water potential sensors or tensiometers. An Arduino MKR1010 WiFi-enabled board was used to collect and send aggregated sensor data to a cloud-based platform to detect potential slope movements in real time.

II. Related Work

A few works in the literature utilized IoT for remote landslide monitoring [11], [12], [13], [14]. To the best of our knowledge, no studies in the U.S. have explored integrating IoT technologies (e.g., tilt sensors) with hydrologic sensors (e.g., moisture sensors and tensiometers) to enable remote real-time slope stability monitoring and early detection of slope movements. This section reviews the existing studies that utilized a wide range of IoT sensors [5], communication protocols [1], and analytical tools [10] to capture critical hydrologic behavior of soil and corresponding responses of slope, which can be used to trigger warnings and guide preventive actions.

Paswan et al. [14] evaluated a tilt-based monitoring system for rainfall-induced landslides in Kotrupi village, India. The authors built a physical slope model to test the monitoring system in real scenarios. A rainfall generator is used to simulate rainfall over time and is equipped with a flow sensor for data recording. Various IoT sensors were utilized, including tilt and soil moisture. Unlike our research, this work mainly focuses on preventing rainfall-related landslides.

Butler et al. [12] presented a monitoring system leveraging IoT technologies to monitor landslides in Bournemouth, UK. The authors utilized the BlueFox v2.7 platform that transmits sensory data over a SigFox network to a centralized data server. The sensing platform is equipped with dielectric moisture sensors, pore pressure piezometers, strain gauges, tilt meters, geophones, rain gauges, and temperature sensors. Similar to our study, the authors developed a scalable and cost-efficient system that can remotely monitor geographical hazards in near-real-time, employing similar types of sensors such as soil moisture and tilt. However, their use of SigFox as a communication protocol differs from our approach, which utilizes a more customizable cloud-based system with broader data transmission options.

Another study presented in [11] explored using a multi-sensor framework to predict landslides using traditional sensing modules such as geophones, inclinometers, and rain gauges. The authors presented an approach focused on real-time data acquisition and Machine Learning (ML) algorithms to provide early warnings for potential landslides. Unlike our work, which focuses on measuring the soil hydrology and dynamic behavior of the slope using state-of-the-art IoT and hydrologic sensors, this approach uses an ML model to predict landslides using historical landslide patterns.

Karunarathne et al. [13] presented a three-tier IoT framework for landslide monitoring that integrates data acquisition, curation, and presentation. This study focused on collecting real-time data through low-power, wide-area networks (LPWAN), which were processed and analyzed using big data infrastructure and ML algorithms. The framework was deployed in two pilot projects in the UK and demonstrated its ability to monitor landslides in different geographical settings. While this work aligns with our approach to leveraging IoT systems for environmental monitoring, it primarily emphasizes large-scale data processing and long-term predictions using ML techniques.

In summary, the existing works focus on monitoring landslides using traditional sensing methods [9], [1] or designed for a particular scenario [15], [14], [16]. Also, none of the existing works evaluated the landslides of highway embankments in the US. Our approach, in contrast, focuses on the precision and immediate detection of minor movements in slope, providing localized and actionable insights. Also, we employed a cost-effective model in designing our remote monitoring system by using low-cost sensors and a cloud-based infrastructure that can easily be scaled across various environments. Unlike the existing studies mentioned, our approach combines advanced IoT sensors with real-time data analytics, enabling early detection of soil displacement with fine precision (e.g., 1 mm soil displacement).

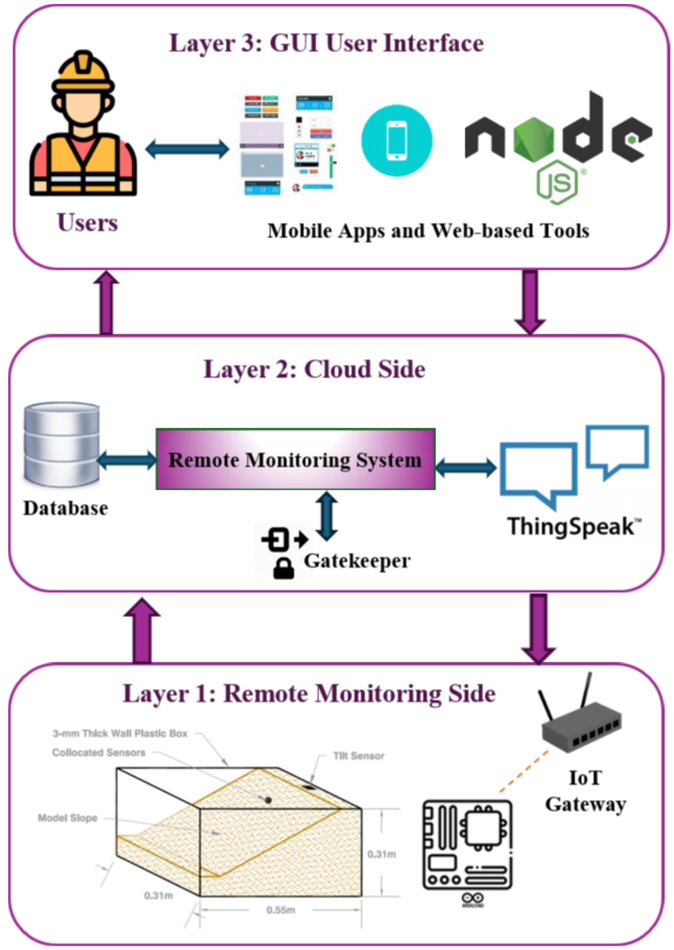


Fig. 1. System Architecture

III. System Design

A. System Architecture

Figure 1 shows the system architecture of the distributed IoT system, which is divided into three layers. Layer 1 shows the remote monitoring side, including the slope model equipped with various IoT sensors (e.g., tilt, moisture, water potential sensors) and edge computing devices (e.g., Arduino board) for data collection and communication. An IoT gateway is used to aggregate these sensing data and coordinate the connectivity of the end devices to each other and to the cloud side via WiFi technology. The gateway keeps aggregating the received sensor data until a sufficient number of them have been received to detect any interesting events such as soil shrinkage or expansion, change in slope level induced by movement, etc.

Layer 2 describes the cloud side, including the remote monitoring system utilizing a database engine and cloud-based IoT platforms (e.g., ThingSpeak and METER). A gatekeeper is used to communicate messages securely between the remote monitoring and cloud sides, where various security and encryption mechanisms are implemented. Layer 3 shows the GUI user interface, which allows end-users (e.g., transportation authorities) to use the proposed monitoring system using web-

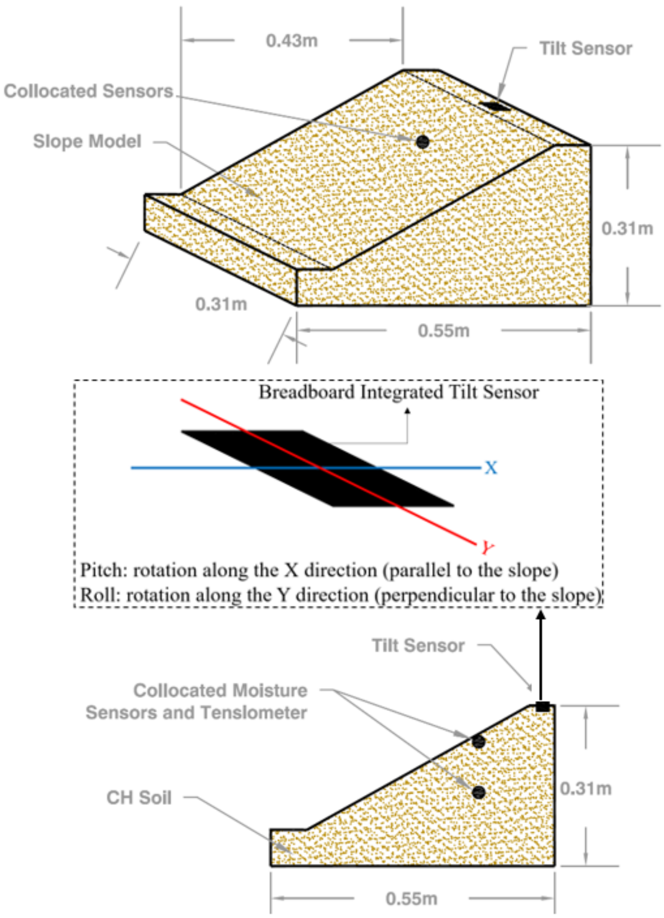


Fig. 2. Schematic Diagram of the Physical Model of the Slope

based tools and mobile apps from their computing devices, such as PCs and Smartphones.

Figure 2 depicts a schematic diagram of the small-scale physical slope model prototyped in a laboratory environment. A plastic box was used to develop the slope model, measuring 0.55 m (L) $\times$ 0.31 m (W) $\times$ 0.31 m (H), designed to replicate a failure-prone slope with a steep gradient ratio of 1V:1H. Various Sensors were strategically placed within the slope model to monitor the hydrological behavior of the soil and slope movement, including tilt, soil moisture, and tensiometer sensors.

The tilt sensors are used to detect any changes in the angle parallel and perpendicular to the slope model, recorded as pitch and roll, respectively. The collocated sensors, including moisture sensors and tensiometers, measure soil's volumetric moisture content (VMC) and soil matric suction, respectively, which are critical hydrologic indicators of the slope stability.

B. Sensor Calibration

The tilt sensor (MPU 6050) provides time-series accelerometer readings, indicating the tilt variation in the x, y, and z dimensions that represent the device's acceleration along each axis. Using trigonometric functions, we converted these accelerometer values into angular measurements (i.e., pitch and roll angles). In particular, we used the `atan2` function to compute the arctangent ratio of the two accelerometer readings, providing a robust way to calculate the tilt angles while accounting for the direction of rotation and quadrant of the angle.

The MPU 6050 module has a configuration of 16-bit resolution, ranging from -2g to +2g, where 1g is a gravitational unit equal to 9.8m/s^2. Therefore, the scale factor of 1g can be calculated as 16,384 Least Significant Bits (LSB). We used the following equations to convert the raw acceleration data to a gravitational unit.

$$a_x = \frac{\text{accel\_x}}{LSB} \;\; ; \;\; a_y = \frac{\text{accel\_y}}{LSB} \;\; ; \;\; a_z = \frac{\text{accel\_z}}{LSB} \tag{1}$$

where LSB = 16,384, a_x, a_y, a_z are the acceleration values in the x, y, and z dimensions measured in gravitational units, respectively.

The title pitch and roll values can be calculated using a_x, a_y, a_z, as follows:

$$\text{pitch} = \arctan\left(\frac{a_x}{\sqrt{a_y^2 + a_z^2}}\right) \times \frac{180.0}{\pi} \tag{2}$$

where arctan is an Arc Tangent Function implemented using $atan2(y, x)$ that returns the angle between the positive x-axis and point (x, y). It considers the signs of both arguments to determine the correct quadrant of the computed angle. a_x represents the acceleration along the X-axis. The denominator $(\sqrt{a_y^2 + a_z^2})$ represents the magnitude of the projection of the acceleration vector onto the YZ plane, which helps in isolating the X-axis tilt by comparing it against the combination of Y and Z axes. The production of $\frac{180.0}{\pi}$ is used to convert the output result from radians to degrees.

$$\text{roll} = \arctan\left(\frac{a_y}{\sqrt{a_x^2 + a_z^2}}\right) \times \frac{180.0}{\pi} \tag{3}$$

where a_y represents the acceleration along the Y-axis. The denominator $(\sqrt{a_x^2 + a_z^2})$ represents the magnitude of the projection of the acceleration vector onto the XZ plane, which helps in isolating the Y-axis tilt by comparing it against the combination of X and Z axes.

The TEROS 11 sensor measures the soil's VMC at the remote monitoring side. It utilizes an electromagnetic field to determine the dielectric permittivity of the surrounding soil medium. This raw dielectric permittivity value, denoted as ρ, is then converted to VMC (θ) using the following factory-calibrated equation:

$$\theta\,(\text{m}^3/\text{m}^3) = 3.879 \times 10^{-4} \times \rho - 0.6956 \tag{4}$$

where θ is the VMC in cubic meters per cubic meter (m^3/m^3), and ρ represents the raw dielectric permittivity value obtained from the sensor.

The TEROS 11 sensor operates at a frequency of 70MHz for dielectric measurements, providing a resolution of 0.001 m^3/m^3 and an accuracy of 0.03 m^3/m^3 for VWC. Additionally, the TEROS 11 can measure soil temperature with an accuracy of 0.5^{o}C and a resolution of 0.1^{o}C. It has a measurement range from -40^{o}C to +60^{o}C. The sensor contains three needles, where the center needle employs a thermistor to report temperature readings. Before installation in the physical slope model, the TEROS 11 sensors were calibrated in the laboratory to ensure accurate measurements.

IV. Implementation

A. Physical Implementation

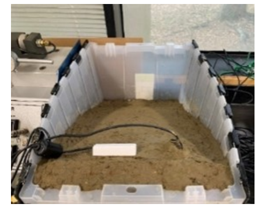
The soil used for creating the physical slope model was high-plastic clay collected from Sugar Land, Texas. The soil obtained exhibited little presence of roots and ferrous nodules. Therefore, the soil was processed before building the slope. Initially, the ferrous nodules and roots were isolated from the soil. Then the soil underwent air-drying and later was pulverized for adequately compact the soil in the model. Based on the laboratory characterization, the soil was classified as Fat Clay (CH) according to the Unified Soil Classification System (USCS). The required volume and weight of soil were calculated based on the geometric dimensions of the model. An adequate amount of water was added to the soil to achieve the target Optimum Moisture Content (OMC). As shown in Figure 3, the soil was then placed into a 3-mm thick plastic box in layers and compacted using a manual compactor to achieve 95% of the maximum dry density.

We installed two Teros 11 moisture sensors to monitor VMC, two Teros 21 tensiometers to monitor soil matric suction, and an MPU 6050 tilt sensor to monitor the pitch and roll value variations. We collocated the moisture sensors and tensiometers at two monitoring depths. One sensor was placed on the soil surface, while the other was positioned 0.15 meters below the surface. The moisture sensors were carefully inserted until the needles were entirely inside the soil to ensure accurate readings (See Figure 3(a)).

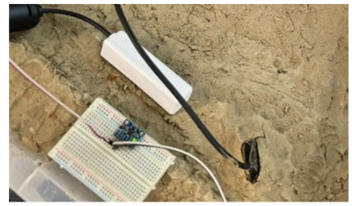
For the tensiometers, small holes were drilled at the collocated depths, and the soil around the sensors was moisturized to ensure good contact between the sensor and the soil. After installing the sensors, we backfilled the holes to maintain the in-situ soil density and the sensor's functionality in the soil (see Figure 3(b)). As shown in Figure 3(c), the tilt sensor was inserted at the top edge of the soil model to monitor the slope's rotational movement. It was aligned with the slope's x-axis and y-axis to measure pitch and roll, respectively.

After placing the sensors in the slope model, the tilt sensor was connected to an Arduino MKR WiFi 1010, which provided wireless connectivity via a WiFi network. The Arduino board transmitted real-time data from the tilt sensor to ThingSpeak [17], a cloud-based platform, to be meticulously analyzed to discern patterns and anomalies that could indicate impending slope movement. For the Teros 11 and Teros 21 sensors, a ZL6 data logger was utilized to collect and log the data. The data logger transmits the collected sensory data to ZENTRA Cloud [18] for storage and visualization.

(a) Sensor Installation



(b) A View of the Model Surface



(c) Tilt Sensor Position

Fig. 3. Construction of the Laboratory Prototype Embankment

B. GUI User Interface

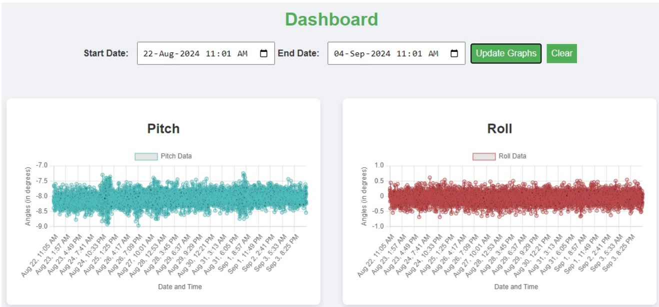
The Graphical User Interface (GUI) user interface was developed as a web-based application to facilitate real-time monitoring and analysis of slope movements. This GUI was designed to visualize the pitch and roll values collected by the tilt sensor installed on the slope model. We built the web application using Chart.js, HTML5, CSS3, JavaScript, and JSON. The web application is designed to be device-agnostic to ensure the interface is user-friendly and adaptable to different devices and screen sizes.

We developed a JavaScript module to coordinate the communication between the web application and ThingSpeak via a REST API using date-time parameters. It also handles user interactions, facilitates asynchronous data retrieval from the fetch API of ThingSpeak, and updates the pitch and roll graphs dynamically. It ensures that the GUI remains responsive even when fetching large datasets from the cloud storage.

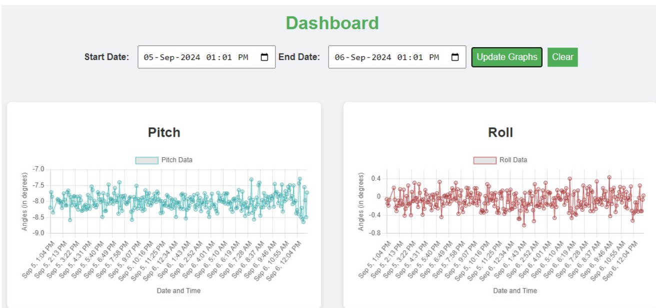
The Chart.js was used to create interactive visualization line charts, rendering the pitch and roll data collected from the tilt sensor. It provides a clear visual representation of soil deformation over time. Figure 4 shows the homepage of the web application, which allows users to select a date/time range using from/to date-time picker controls. Upon clicking the `Update Graphs` button, the JavaScript module fetches data from ThingSpeak using the REST API as a JSON response corresponding to the selected date/time range.

The fetched data is then processed and plotted on two separate line charts representing the pitch and roll angles. For instance, Figure 4(a) depicts the pitch and roll data over two weeks. This view offers a broader perspective on the stability and behavior of the monitored slope. The pitch data fluctuates within a specific range, while the roll data remains comparatively stable, reflecting minor angular variations. This granularity is ideal for tracking long-term trends in slope movements and detecting slow but significant changes.

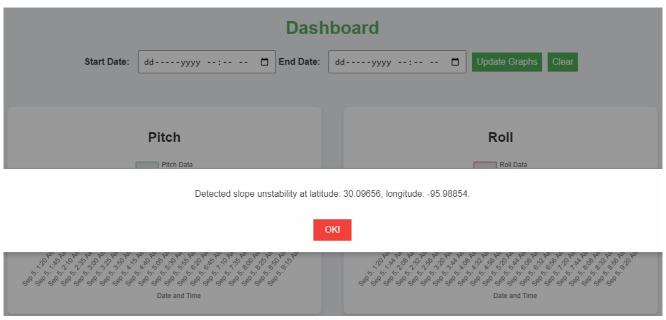
Figure 4(b) shows the pitch and roll data over a single



(a) The Pitch and Roll charts using two weeks of data



(b) The Pitch and Roll charts using one day of data



(c) Triggering an alert message when detecting a significant slope movement

Fig. 4. Screenshots of the Web-based GUI

day, providing a more focused and fine-granularity view of the slope soil behavior. This view allows users to perform a detailed analysis of short-term fluctuations, which can be crucial for identifying rapid changes or unusual behavior in the slope's condition. The shorter time frame highlights more immediate shifts in pitch and roll angles, giving insight into potential real-time risks or instabilities.

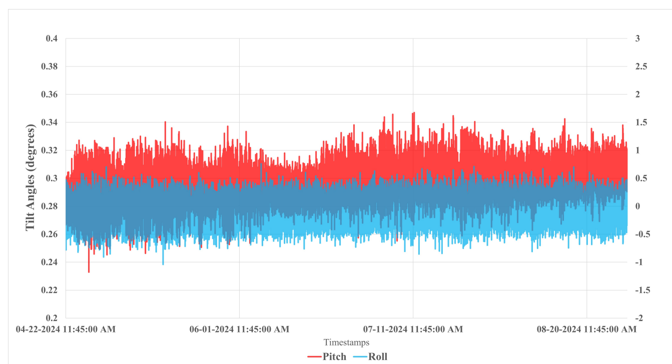
We developed an alert mechanism that monitors any significant changes in the soil deformation or slope movement that exceed predefined thresholds. When the application detects such an event, a modal alert is triggered with the geolocation coordinates (i.e., longitude and latitude) of the detected slope movement, informing the user to take necessary precautions. Figure 4(c) shows an example of an alert message triggered when detecting a significant event of slope movement or soil deformation. This alert mechanism could be helpful for safety and operational decision-making, allowing for immediate action based on real-time data.

The `Clear` button defaults the charts to display the most recent eight hours of data, providing a quick snapshot of the latest slope conditions. Also, the web application refreshes every two minutes, ensuring that the latest sensor data is constantly updated on the dashboard to provide near-real-time tracking of slope behavior.

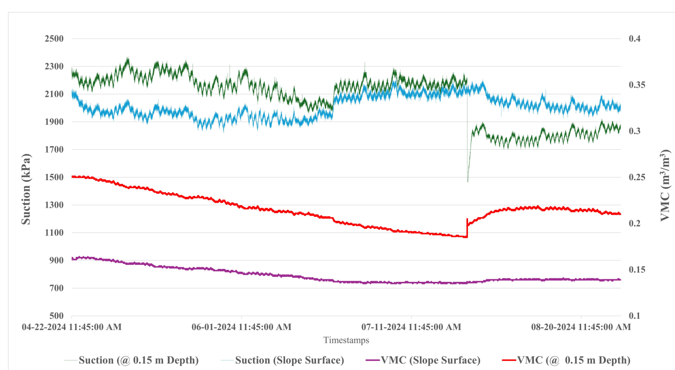
For the TEROS 11 and TEROS 21 sensors, users need to access data visualization through the ZENTRA Cloud platform [18]. This platform provides detailed insights into soil moisture content and matric suction. By logging into ZENTRA Cloud, users can view TEROS sensors reading in real-time, analyze trends, and export data for further evaluation if needed. The ZENTRA Cloud interface allows users to monitor the critical hydrological metrics necessary for understanding slope stability, complementing the tilt sensor data displayed via the web GUI. Additionally, we are developing a more efficient and customized web page that will be integrated into our current web GUI system in the future, enabling users to view all sensor data, including TEROS sensors, directly through our streamlined web GUI.

V. Experimental Results

Data collection started on April 22, 2024, and is still ongoing. The data analysis and visualization presented in this section focus on the initial four months of data (from April 22, 2024, to August 29, 2024) to capture early observations.



(a) Pitch and Roll Metrics



(b) VMC and Matric Suction Metrics

Fig. 5. Measured tilting angles parallel (pitch) and perpendicular (roll) and hydrologic variables to the slope from the developed IoT-based system.

Figure 5(a) illustrates the changes in pitch and roll angles during the monitoring period. The red plot corresponds to the pitch angle (i.e., tilting parallel to the slope), and the blue plot represents the roll angle (i.e., tilting perpendicular to the slope). Both tilt angles remained mostly between -1.5 and +1.5 degrees. However, there were slight fluctuations, with the pitch reaching a maximum of around 1.2 degrees and a minimum of -1.3 degrees. Similarly, the roll values showed more stability, remaining close to zero, with minimal deviation beyond -1 degrees and 1 degrees. Regardless of the direction of movement, the system could detect as low as 0.02 degrees of rotation demonstrating the high sensitivity of the system to detect slope movement.

Figure 5(b) presents the monitored hydrologic data, including VMC and matric suction at two different depths where the sensors were placed. The green and blue plots show the suction measurements at the slope surface and a depth of 0.15 meters, respectively. Both suction profiles exhibit an almost flat propagation over the monitored period, except for a sudden reduction in suction from around 2300 kPa to 1500 kPa at 0.15 meters depth on July 24, 2024. This sudden decline occurred during the model maintenance.

The soil VMC also followed a predictable trend, with some degree of fluctuations. The slope surface VMC remained consistently low, between 0.135 to $0.15 m^3/m^3$, while the deeper VMC measurements fluctuated between 0.26 and $0.19 m^3/m^3$. The changes (increase from 0.185 to $0.2^3/m^3$) in the VMC at 0.15 meters depth on July 24, 2024, are attributable to the decline in suction due to slope maintenance. These trends signify that the slope soil is at the drying condition and suggest that no significant external hydrological influences.

The collected data indicates a stable slope with minor movements with no major hydrological influences. The minor slope movement or the soil deformation identified by the tilt sensor (pitch and roll) data indicates the shrinkage cracks developed in the model. This initial monitoring phase is crucial for understanding the baseline behavior of the soil system. We plan to use a rainfall simulator and temperature control system to assess the effect of significant climatic events on slope stability.

VI. Conclusions

This paper presented a remote monitoring system leveraging low-cost IoT and hydrologic sensors for detecting slope movement. The developed distributed system, with components running on IoT sensors at the slope model and centralized servers in the cloud, created an opportunity for transportation authorities to monitor and detect slope instabilities using various granularities efficiently. The preliminary results of the collected sensory data for four months indicated that our system could detect slight slope movement of 1mm and rotation of 0.02 degrees. We built a user-friendly GUI interface that allows users to monitor the slope movement in real-time and receive timely alerts when a significant slope movement or rotation is detected.

In ongoing work, we are looking into opportunities to generalize our approach to utilize Machine Learning (ML), including Random Forest, Support Vector Regressors, and Artificial Neural Networks (ANN), to model slope movement patterns and predict imminent failures, as shown effective in geotechnical studies [10]. We will also incorporate statistical methods to ensure sensor data robustness, expand comparisons with existing IoT systems, and address environmental noise and power management challenges.

Acknowledgments

This research work is supported by the National Center for Infrastructure Transformation (NCIT), grant number: 01-08-PVAMU.

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