A Systems Approach to Real-World Deployment of Industrial Internet of Things

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***Abstract*—Deployment of the Internet of Things (IoT) in real industrial scenarios is fraught with unseen challenges and planning intricacies. The inside engineering and methodologies behind a successful Industrial IoT (IIoT) setup are seldom discussed. In this paper, we describe a systems approach to identify, integrate, and deploy the different IIoT modules in a bottom-up manner. The process that go from first identifying and labelling the various assets to be monitored, to their abstraction and integration for a given industrial scenario, forms the major crux of the work presented in this paper. We deployed several sensor nodes in the Offshore Renewable Energy Catapult site, located in Blyth, UK. Each sensor node monitored a specific asset and communicated via LoRaWAN to our local *Data Hub*. A simple query interface and visualisation dashboard allowed real-time data assessment and rapid asset monitoring. To make the proposed approach easy to comprehend and applicable to other scenarios, we extracted a minimal translational bottom-up flowchart. The systems approach described here offers a robust methodology to plan out a real-world IIoT deployment.**

***Index Terms*—IIoT, Sensors, Systems, Real-world**

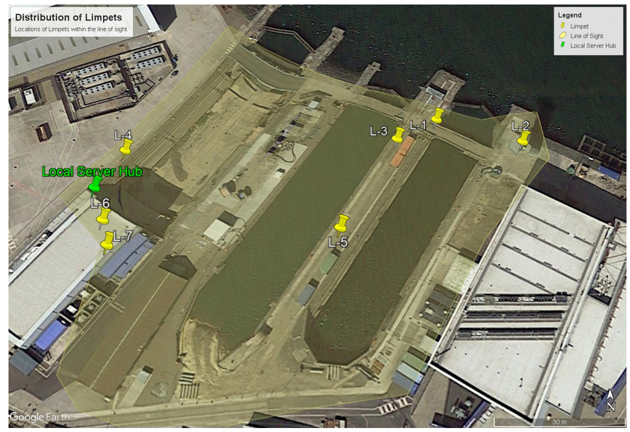

Fig. 1. Aerial view of ORE Catapult. Limpet sensor nodes (yellow pins) and local server hub (green pin) mapped on the deployment site. The yellow shaded area indicates the line of sight for LoRa from the local server hub.

I. Introduction

Offshore industries—primarily oil and gas, and the wind energy sectors—are facing a shortfall in the workforce, mainly owing to the extreme and often dangerous working conditions. To increase the safety of offshore infrastructures and render them autonomous, there has been a surge in the use of advanced technologies such as the Internet of Things (IoT), Wireless Sensor Networks (WSN), and robots [1]. Monitoring offshore assets is crucial in making economic decisions that can keep a check on the production cost. Thus, IoT and WSN systems hold significant value to such industries.

The advent of Industrial IoT (IIoT) has enabled the vision of Industry 4.0, which involves data-centric architecture for asset integrity management. For instance, by monitoring the condition of an asset and feeding the data into a prognostic model, the industries can better prepare for maintenance and reduce the downtime. This predictive planning aids in making economic decisions which can keep a rein on fluctuating oil and wind energy prices.

Since the inception of IoT, there has been a plethora of research in these domains. A substantial amount of literature has been published in the domain of IoT ranging from: introducing the new architectures [2], [3], [4], [5], computations [6], [7], [8], [9], network and communications [10], [11], [12], [13], to different applications [14]. To the best of our knowledge, however, except a few [15], it is difficult to find work where systems-based approaches to real-world deployment and challenges faced in IIoT systems, especially in offshore industrial environments, have been discussed. A recent case study by Nagy et al. [16] presents a business model for a Minimum Viable Product (MVP) that was developed and tested for KK Wind Solutions[1]. The authors integrated a system comprising a sensor node, a cloud, and a web dashboard to track shipments for KK Wind Solutions. Though they introduced the problem of monitoring wind turbines, the paper did not reports the approach to practical deployment.

In this paper, we propose a bottom-up system approach to cater to the unseen challenges faced during the deployment of an IIoT. In addition, we present a methodology to identify, integrate, and deploy the different IIoT components for a given industrial site. We also report the experiences, and results obtained from a successful test of the deployed IIoT at the Offshore Renewable Energy (ORE) Catapult located in Blyth, UK[2].

[1] https://www.kkwindsolutions.com/
[2] https://ore.catapult.org.uk

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II. The Real-World Scenario: Bottom-Up System Perspective and Challenges

The ORE Catapult, located in Blyth, UK was chosen as the site for the deployment. Fig. 1 shows an aerial view of the deployment site.

A. Challenges

Though the proprietary systems available in the market offer a higher level of reliability, they are seldom suited for unknown situations as found in an actual industrial site. We identified many key challenges described below:

1) The already available IIoT solutions are rigid and difficult to adapt to the different types, shapes and characteristics of assets found in an industrial site. Thus, customised components that integrate what is available on the market and suit the site to be monitored are in high demand. However, to manufacture such a tailor-made system, the first challenge is to identify the assets to be monitored.
2) Planning an optimum position for the placement of the sensor is crucial in order to allow reliable communication and targeted asset monitoring. This process is challenging as it requires the monitored asset(s) to be in the line of sight.
3) Industrial sites are prone to upgrades of their infrastructure and layout. The deployment approach should be flexible to sudden changes in the environment.
4) Network Connectivity: Industrial sites are usually equipped with large firewall systems. Integrating to their LAN infrastructure could become an arduous task.

The site, shown in Fig. 1, consists of a variety of industrial assets among which we identified those relevant to the scope of our experiment, namely: pipes, pumps, a wind tower, and shipping containers. A few of these assets were located in a building, housing large electric generators, while several others of them were distributed around the dock area. Thus, the first step in the presented approach involves recognising the assets to be monitored for the given industrial scenario.

B. Bottom-up Approach

1) High Level Abstraction: After identifying the essential assets, we categorised them in two classes -

(i) Class-1: Passive Assets (e.g., containers, stairways, and tower)
(ii) Class-2: Active Assets (e.g., water pump, flow pipes, machines)

This abstraction is necessary to make our proposed approach generic and relevant to other scenarios sharing the same general features. Class-1 assets do not produce continuous vibrations or any high-frequency movements, whereas Class-2 assets do generate them. The data collected from the sensors need to be offloaded to a hub situated in a *control room*. A control room is set up with end receivers and edge devices, which collect the data from the sensors deployed on-site. If the data packets are communicated using a low-frequency wireless medium such as LoRa (Long Range) or LoRaWAN[3], there should be at least one window for reliable reception. In addition to the class of an asset, its distance from the control room determines the mode of communication. For the assets near the vicinity of the control room, wireless modules such as Bluetooth, Zigbee, and WiFi can be selected. For assets spanning distances more than 100 metres will need long-range communication methods such as the LoRa and Long-Term Evolution (LTE). Since these assets are remotely situated, the battery life of the sensor nodes should be long (a few months). Though LoRa provides long-range and low power communication, it has bandwidth constraints, thus can not be used for high-frequency applications such as continuous vibration monitoring.

Since Class-1 assets do not produce high-frequency measurands, they are best suited for low power (and low bandwidth) communication methods such as LoRa or LoRaWAN. In the case of Class-2, however, the communication mode can be decided depending upon the specific asset. In addition, an asset can also be described based on the type of adhesion to its surface, for instance – magnetic or non-magnetic.

2) Module Selection: An IIoT is a system made of different electrical and non-electrical components or modules such as sensors, communication devices, storage drives, protective encapsulations for sensors, etc. The categorisation of assets in the previous subsection aids in selecting specific modules to be used. For instance, in contrast to the Class-1 assets, a Class-2 may require an IMU or accelerometer to monitor its vibration. Further, depending upon the sampling rate and range requirements, a suitable communication module (WiFi for a high rate and low range and LoRaWAN for a low rate and high range) is determined.

III. System Components

We describe the different layers which are integrated to form the proposed system. The modules selected (as described in Section II-B2) are segregated and added to one of the layers.

A. Sensor and Data Communication Layer

In the industrial deployment presented in this work, we used a new multi-sensing robotic platform called Limpet [17]. The Limpet has been previously used in industrial settings [18] and was developed as part of the ORCA Hub for inspection and monitoring of offshore infrastructures. It is equipped with nine different sensing modalities, which are: temperature, pressure, humidity, optical, distance, sound, magnetic field, accelerometer, and gyroscope. The Limpet system is integrated with the Robot Operating System (ROS) to allow it to interact with other robotic platforms.

The deployment consisted of assets situated in a wide area. As a communication medium, we used LoRaWAN due to its long-range capacity and low power needs. Short-range networks such as those made of Zigbee and WiFi require a substantial amount of repeaters and routing nodes which adds

[3]https://lora-alliance.org/

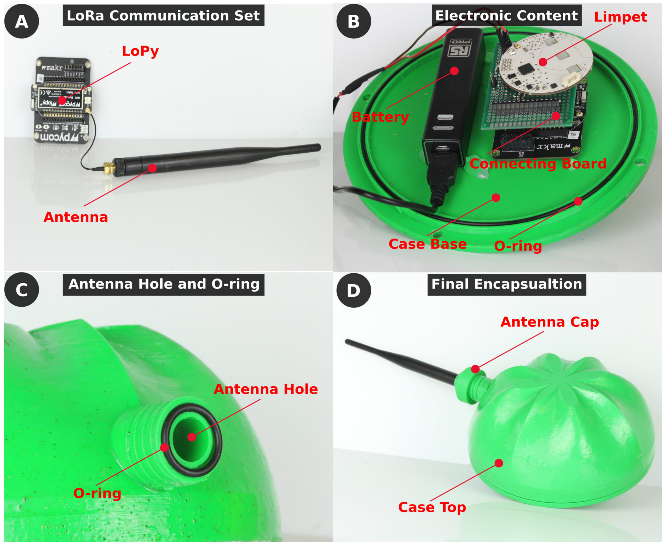

Fig. 2. Bio-inspired Limpet encapsulation.

to the system's complexity. However, depending on the area and application, these protocols are suitable for both low and high sampled monitoring. The proposed system, thus, uses a LoPy[4] hardware together with the Limpet to enable LoRaWAN communication. Since the Limpet is designed to be used on offshore platforms, where data security is essential, and internet connectivity is low, we have developed a local LoRaWAN communication network. This setup removes the dependency on internet connectivity and makes the communication secure. The local network developed uses the LoRa Server project provided by CableLabs[5]. In this communication setup, the Limpet sends the sensor data through the UART to the LoPy, which in turn sends these data packets to the data acquisition module (explained later) located in the control room using the LoRaWAN wireless protocol. A 5V lithium polymer battery powers Lopy and Limpet. We will refer to this integration of Limpet, LoPy, and a battery, as the Limpet sensor node (or L-node). Fig. 2A shows an individual LoPy with its antenna while a complete L-node is depicted in Fig. 2B.

B. Encapsulation and Adhesion Layer

A key element in the design of a device, meant to be part of an IIoT, is the protective shell. The encapsulation is necessary to shelter the electrical modules from the external, often harsh environment, and it includes a versatile and reliable adhesion method.

1) Encapsulation: The shape of the encapsulation designed and shown in Fig. 2, was inspired by a real limpet (*patella vulgata*). The shape minimises the structural stress caused by external factors, such as drag [19] caused by wind and water flow. This design is particularly important for devices meant to survive in harsh environments. We used a 3D printer to make the encapsulation of the desired shape and size. The final encapsulation is made of three main modules: antenna caps, lid (base), and main shell (body). The body and the base of the encapsulation can be attached using M6 screws. The antenna cap fits onto a threaded protuberance. We used two different methods to waterproof the 3D printed parts. The first method was the application of a filler onto the bare 3D printed parts followed by two layers of an acrylic spray paint. The second method was to apply an epoxy coating directly to the 3D printed piece. In order to prevent water from seeping inside the assembled protective housing, we tailored O-rings (Figs. 2B and 2C) to be placed around the base and the antenna cap. For the O-rings to be effective, they have to be lubricated with silicone grease. We ran permeability tests on the encapsulation, i.e., water running on it from all the directions. In both the cases, the painting, plus the O-rings, achieved the targeted waterproofing level, i.e., IP54[6]. To allow for the encapsulations to be easily located and identified by humans or robots, we chose bright, highly visible colours such as orange, blue, and green.

2) Adhesion Methods: Based on the continuous liaison with industries, we found steel-strap and magnetic adhesion methods to be appropriate for the assets found in ORE Catapult. The modularity of the encapsulation design makes it easy to switch from magnetic to steel-strap adhesion embedded in the base of the encapsulation. The magnetic base can have a row of 5 magnets (3mm depth, 10 mm diameter, and 1.8 Kg pull) or a circular pattern with six magnets of the same type. The steel-strap base has a slot with smoothed edges to enable the insert of the steel band. Smoothed edges are meant to ease the stress on the slot while tightening the strap.

C. Data Acquisition, Visualisation, and Querying

1) Data Acquisition: The sensors were deployed at distances varying from a few to 100s of meters from the control room. With LoRaWAN as the main mode of communication, the data acquisition system, nicknamed *Data Hub*, was set up using a Sentrius™ RG1xx series LoRa-Enabled gateway from Laird™, a NETGEAR® Nighthawk R7000 WiFi router, and an Intel® NUC kit. The components were assembled inside a laser cut box carefully designed to provide adequate airflow. Fig. 3A shows the chassis of the acquisition setup. The gateway runs a packet-forwarder software, which is responsible for forwarding the incoming packets to a network server using a User Datagram Protocol (UDP). The network server and the LoRa gateway are given IP addresses through a local Domain Name System (DNS) server.

IIoT is associated with generating continuous data, in large amount, and is in an unstructured format. Relational database technologies have been a *de facto* standard in data storage for many different applications. However, they are deemed inadequate for IoT applications due to the limited processing speed, and high storage expansion cost [20]. Thus, we selected MongoDB, a NoSQL (Not only SQL) database, to store the data received from the sensor nodes. Designing the right

[4]https://pycom.io/
[5]https://www.loraserver.io/
[6]IEC standard 60529

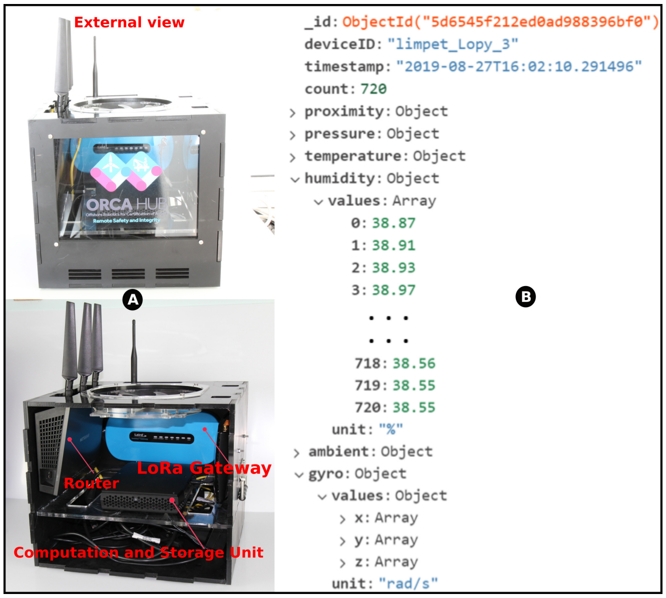

Fig. 3. (A) The data acquisition setup - *Data Hub*. (B) A data sample of an hourly time-series schema stored in the MongoDB.

schema for our deployment scenario is essential for better scalability in the future. A schema is the way the unstructured data is organised in the database. In our application, each sensor node was transmitting data every 5 seconds, which amounts to an average of 12 data packets per minute. Thus, we had various options to choose from - store a separate document every 5 seconds, every minute, or each hour or day. We decided with an hourly data schema where 720 packets are written in a single document. This schema has a considerably less number of reads than the one which writes a separate document for every data packet received. Any IoT system is associated with a massive amount of data queries. Thus, optimising the read rate is crucial, especially for high scalability. Fig. 3B shows the schema adopted in the work presented in this paper.

2) Data Query and Visualisation: Though data aggregation is essential, seamless accessing and displaying the necessary information, serves the primary purpose of the proposed system. We developed a dashboard-with-query processing engine that showed the current status of the sensors for the node selected. Since the dashboard can only present limited information, we integrated a drop-down interface to query historical data. we chose to show the data in the form f intuitive graps. The dashboard-with-query engine was created using a Python library called Dash running as a service app. The *Data Hub* hosted the app. To make the app available publicly using an URL, we used *ngrok*[7] – a quick, secured, and reliable solution. Due to the privacy concerns, we preferred collecting the data on the *Data Hub* locally.

(a) (b)

Fig. 4. Two orange coloured L-nodes each on (a) a diesel pump (Class-2) and (b) a container (Class-1).

IV. Deployment in the Real-World

Our IoT system, as such, is characterised by easy deployment. In order to achieve a neat real-world deployment, we designed a customised encapsulation, equipped with magnetic or band-it adhesion mechanisms. The choice of the adhesion mechanisms and the distribution of sensors are the result of on-site visits prior to the industrial demonstration day. There is no available off-the-shelf solution that would meet the requirement of our unique sensor node, communication system and demo site; therefore customisation and preparatory visits to the ORE Catapult were vital to confer to our demo the agility typical of IoT systems. The preparatory phase, during which we visited the demo site and reassessed the design and configuration of our network, allowed us to minimise the malfunctioning risks. Once deployed, the Limpet network works autonomously with minimal or no human intervention. After identifying the assets to be monitored and selecting the modules, we deployed the L-nodes and set up the data aggregation and visualisation layers. The map in Fig. 1 shows the location of the sensors, each of which is labelled with a unique ID, to facilitate identification.

We placed the *Data Hub* in the control room, choosing the optimum position to ensure reliable communication coverage (line-of-sight) of the assets we intended to monitor. The location of the *Data Hub* is crucial as we have chosen LoRa as the mode of communication. Albeit LoRa should have high wall permeability, in an industrial setup like ours, this was not the case. We ensured seamless communication and data acquisition with the *Data Hub* for each sensor before deployment. Once this preliminary phase was complete, a human operator deployed the sensor to its designated asset.

We deployed a total of seven L-nodes across multiple assets. Signal to Noise Ratio (SNR) is a good factor in deciding the optimum location of the sensors. In our case, LoRa SNR varied between -10 dB and +10 dB.

[7]https://ngrok.com/

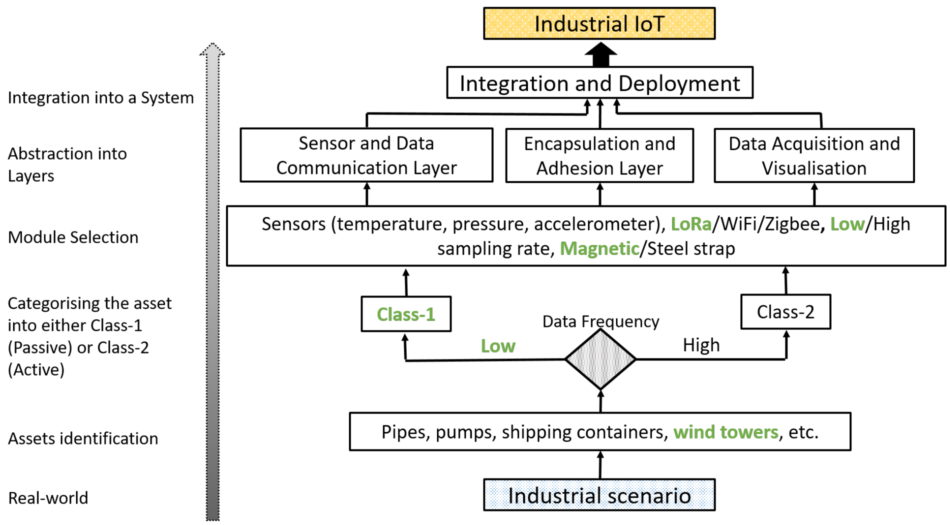

Fig. 5. A translational bottom-up representation of the proposed approach.

A high (and positive) SNR value denotes a good signal strength. Each message packet sent via LoRa carries an SNR value as a payload along with the actual data. This data format aided us in deploying the sensors at appropriate positions on the asset. Since the sensor nodes are meant to be operating for periods in the order of months, reliability is a crucial factor. Thus, testing the adhesion of the sensor node to the asset is prime, especially in the case of vibrating Class-2 assets. We ran a preliminary shock test on the L-nodes by artificially creating vibrations on to the asset and recording the sensor response, delay in transmission, and physical robustness. After the testing, we calibrated the sensors against the known standard values of the gathered data. Fig. 4(a) and 4(b) respectively shows L-nodes deployed on a pump and a container.

Depending on the material and shape of the asset, we could select the appropriate adhesion method, e.g., a magnetic adhesion for flat metallic surfaces. Deployment times have to take into account setting up and assembling times. Assembling seven L-nodes and setting up the local server (*Data Hub*), requires up to two hours.

V. Results

The crux of the work presented in this paper was to devise a simple methodology that could aid in the integration and deployment of different modules of an Industrial IoT. The bottom-up flowchart portrayed in Fig. 5 shows a visual condensation of the proposed approach. The figure shows a flow of the process from asset identification of a given site until the integration and deployment of different IIoT modules. As an example, the green coloured text on the figure shows the direction of flow when a wind tower is identified as an asset. As can be seen from the figure, once an asset is identified (wind tower in this case), it can be categorised into a class. Now, based on the class, the type of sensors and the mode of communication is decided. Since wind tower is a fairly passive infrastructure, it does not require a high sampling rate. In addition, usually, the wind towers are located offshore, or far from the control centre, LoRaWAN will serve as an appropriate mode of communication. The adhesion can be easily selected to be the magnetic type due to the metallic nature of the wind tower. Once all the lower-level components are selected, these can be segregated into different layers and then can be easily integrated and deployed as an IIoT.

We integrated three user-friendly interfaces for data visualisation and querying to form a dashboard-with-query app. We first developed and tested a Dashboard application, shown in Fig. 6, which allows for a quick and clear peek of the current status of the sensors. The users can easily select the radio button (shown in Fig. 6) corresponding to an asset of interest and visualise a graph of the last hour of data variations of different sensors. However, the dashboard can query only a limited amount of information. For instance, a dashboard will not suffice to visualise historical data. Thus, we developed a second interface that allows a user to query the database by feeding the desired range of date and time, along with the node ID of interest. This click-based interface is shown in Fig. 7. For the sake of clarity, we preferred to show the data graphically; however, other visualisation representations can also be chosen. It may also happen that a user needs to query the database repeatedly, which could make the use of click-based interface cumbersome. Thus, we also created a chatbot primed to understand queries intended for sensor databases. The chatbot was built using RASA[8], an open-source machine learning framework to develop contextual chat assistants. The output of the chatbot for the query, "*whats the pressure value of L-node 2 for past six months?*", is displayed in Fig. 8.

We collected the data continuously for the entire period of the industrial demonstrations. To measure the applicability of the different modules selected, we analysed the trends in the sensor values for both the classes of assets. As a sample,

[8]https://rasa.com/

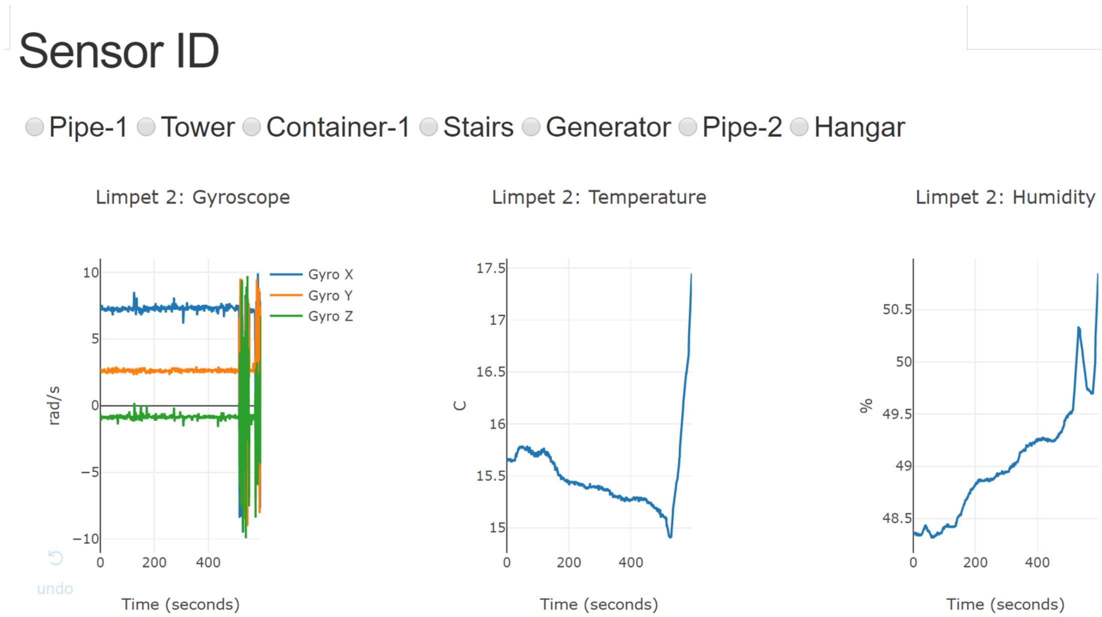

Fig. 6. The dashboard displaying the current status of the L-node placed on the tower.

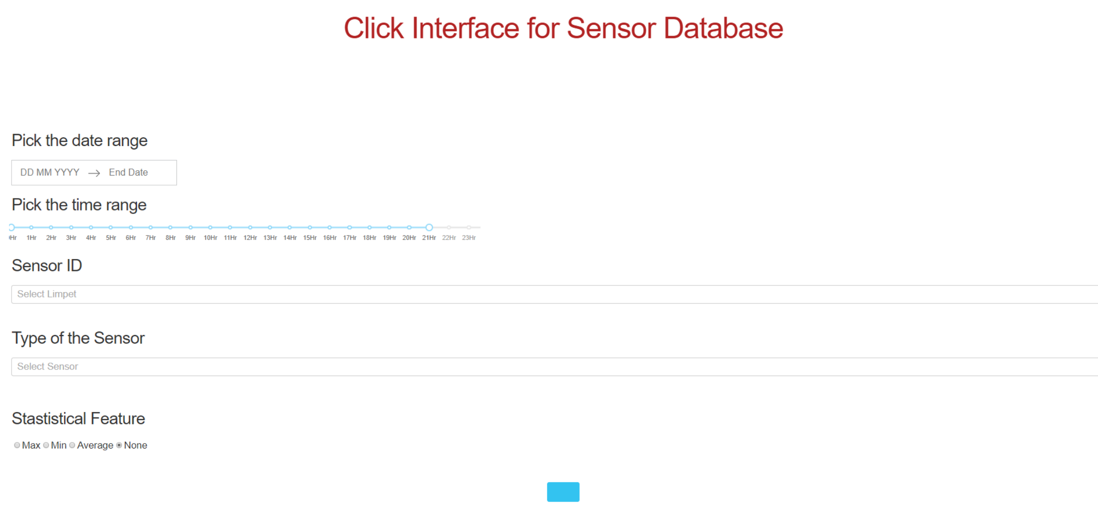

Fig. 7. The click-based interface with the dropdown menus to select the date and time range, sensor ID, type of the sensor, and statistical feature.

Figs. 9 show the variations in the temperature for Class-1 assets. As can be seen from the figures, an hourly schema with this class of assets (Fig. 3B) outlines a clear change in the behaviour of the asset. Vibration monitoring finds promising applications in industrial scenarios. Fig. 10 presents vibrations detected during the functioning of a Class-2 asset (a pump). In industrial environments, data is prone to display a noisy signal; therefore, we used a moving average filter with a 10 seconds window to smooth the sensory data.

A. *Key Issues in Industrial IoT Deployment*

1) Accessibility: Industrial sites are prone to safety risks. Finding personnel who could aid during the deployment of sensors is a managerial challenge.
2) Line-of-sight: Low frequency long-range wireless communication strength degrades under a dense infrastructure. Thus, it is crucial to locate a control room that can be in line-of-sight to the area where the sensors are deployed.
3) Adhesion: Though the two types of adhesion methods (steel-strap and magnetic) used in this work are suitable for a wide variety of assets, they may still not suffice. For instance, a non-magnetic cuboid-shaped asset can pose a challenge to place a sensor on it reliably.
4) Operating Time: Such sites also carry out other internal activities, and thus the time provided for a third-party to test their systems is limited.

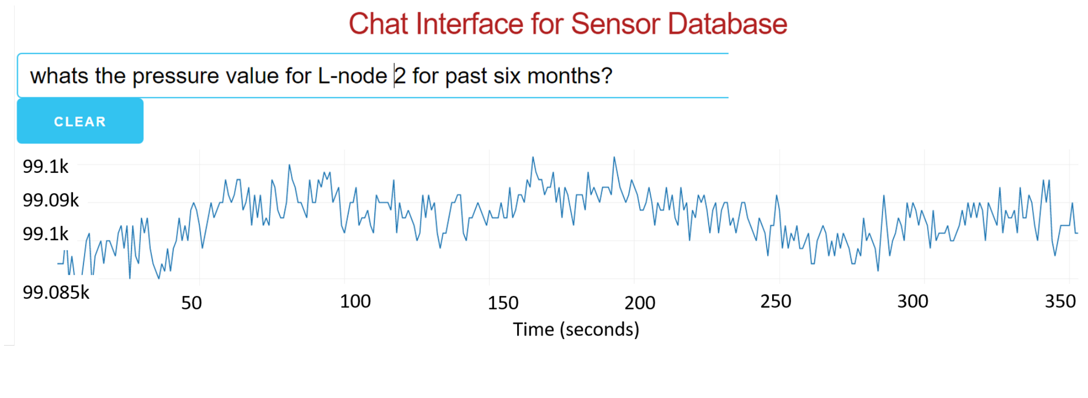

Fig. 8. The output of chatbot to the query entered in English language.

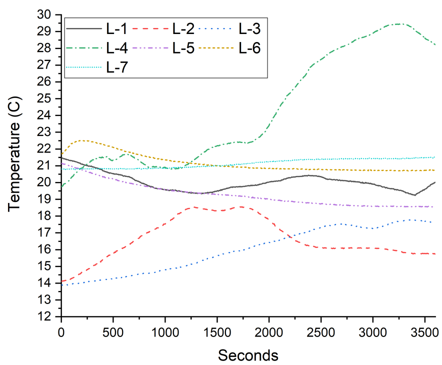

Fig. 9. Hourly temperature variations reported by all seven L-nodes.

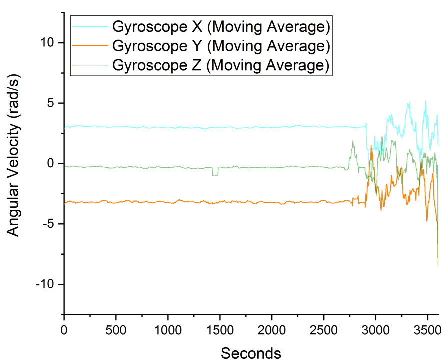

Fig. 10. An example of high frequency vibrations data filtered using a moving average.

B. Solutions

A few solutions which helped us in tackling the above challenges faced are briefly discussed below:

1) Accessibility: Working closely with the responsible staff and planning in advance can reduce this issue.
2) Line-of-sight: We can solve this either as stated by locating the optimal line-of-site location or through the use of repeaters.
3) Adhesion: More permanent method of adhesion can be considered, e.g., drilling, glue, welding. Novel methods could employ bio-inspired adhesives.
4) Network Connectivity: Not relying on propriety infrastructure and using our own deployed network as much as possible.
5) Operating Time: Advanced preparation and planning can mitigate this challenge.

VI. Conclusions

In this paper, we presented a systems approach to deploy an Industrial IoT (IIoT) in a real-world scenario. We offer our experience and challenges faced in deploying an IIoT system in an industrial set up. We implemented a bottom-up approach to tackle these challenges. First, we studied the site and identified the assets to monitor. We then classified the assets into two classes - active and passive. Depending on the class of a device, we selected the appropriate sensing modality, sampling rate, and adhesion method (steel-strap or magnetic) to best perform the monitoring. Next, we segregated the modules into different layers - communication, encapsulation, and visualisation. Finally, we deployed the system and monitored the assets in real-time. The integration of the described steps constitutes our bottom-up approach to the deployment of an IIoT. This abstraction allows for a general translational model, which could be ported to other scenarios. To ease the comprehension, the results presented a minimal flow diagram (Fig. 5) extracted from the detailed methodology presented in this paper. The experience and the results obtained at the ORE Catapult during the ORCA Hub industrial demo will aid in the future development of better, efficient, and more robust IIoT systems.

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