Context-Referenced Telemetry Data for Distribution Utilities:
Quality Assurance/Quality Control by Lateral Sensors

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Abstract—**The notion of enhancing resiliency for electrical grids has become a priority for engineers and researchers within the past few years. Unforeseen natural disasters (e.g., lightning strikes, geomagnetic storms, floods, etc.) can cause devastating damage to electrical grid infrastructures. While disasters may strike with no warning, prototypical weather events can indeed be forecast. However, anticipating and quantifying the impact of weather events is a challenging task due to its stochasticity. In this paper, a weather monitoring system paradigm, as part of a lateral sensor system, is proposed. Lateral sensors for the electrical grid, such as by way of a hyper-locale set of weather sensors equipped with edge analytics and artificial intelligence, provide incredible insight, via various parameters, such as air temperature, barometric pressure, humidity, precipitation, solar radiation, and wind. These lateral sensor parameters can provide indicators regarding impending storms, which could impact power lines (e.g., via lightning strikes, downed trees, etc.) and cause communications interference. Spider radar plots concurrently reflecting both weather sensor data and grid sensor data have proven useful, as weather data can serve to provide contextual reference for the associated grid sensor telemetry data. Moreover, this involved lateral sensor utilizes a deep learning module, which is based upon a Generative Adversarial [Neural] Network (GAN). The results of this study demonstrate that the implementation of lateral sensors based upon a deep learning module can result in enhanced contextual awareness.**

Keywords—electrical grid; lateral sensor; weather monitoring system; hyper-locale sensors; 3D-printed technology; artificial intelligence; generative adversarial neural network.

I. INTRODUCTION

Resilience enhancements of electrical grids have become a priority for regulatory agencies around the world. Among other causes, extreme weather events, such as storms and lightning strikes, are considered to be some of the main causes of electrical disturbances worldwide [1]. In Indonesia, for example, the state utility company, Perusahaan Listrik Negara (PLN), has suffered major financial losses due to storms and downed trees [2]. These events are known as High-Impact Low-Probability (HILP) events, as the frequencies of occurrence are relatively low, but the impact is extremely high [3].

Over the past couple of years, critical infrastructure resilience initiatives have tended to focus upon power grid resilience efforts. Resilience, for these cases, is described as the ability of a power system to anticipate, adapt, and recover from disruption events. Resilience efforts are aimed at either preventing or mitigating the damage from outages and/or reducing outage durations.

The notion of electrical grid resilience has risen to become a critical issue for Indonesia. Millions of households (especially in remote area) suffer from unstable connections, unpredictable power surges, and frequent blackouts. To exacerbate these described problems, utilities have introduced heightened instability into the involved electrical systems by accelerating the usage of intermittent energy sources; while renewable energy does indeed create new opportunities as pertains to meeting demand, it is also accompanied by various technical challenges, as pertains to maintaining electrical grid stability. The adoption of renewable energy segues to a paradigm wherein the electrical grid network tends to become more decentralized. This complicates the “sense and respond” paradigm, as the “sensing” must now be more carefully synchronized, communicated, analyzed, and correlated.

A robust “sense and respond” paradigm is central for a reliable and stable electrical grid. First, with regards to “sensing” or monitoring, a variety of high-resolution telemetry sensor technologies play an important role in detecting, collecting, and providing that data for correlation. To complement these high resolution telemetry sensors, lateral sensors, which can ingest, process, and relay accurate information, such as key meteorological data, is of great import to electrical grid analysis.

The notion of a quality assurance/quality control function for lateral sensors to further contextualize and verify the telemetry data of high-resolution sensors at substations is proposed in this paper. Lateral sensors for the electrical grid, such as hyper-locale weather sensors, can provide incredible insight via parameters, such as air temperature, barometric pressure, humidity precipitation, solar radiation, and wind. These lateral sensor parameters can provide indicators and warnings as to impending storms, which could cause communications interference and impact power lines. Deployed lateral sensors, which include a weather monitoring system, have utilized a modified Generative Adversarial [Neural] Network (GAN) Deep Learning (DL) module. Spider radar plots reflecting both weather sensor data and grid sensor data concurrently have proven useful, as weather data can serve to provide contextual reference for the grid sensor telemetry data.

This Section I provides an overview of the paper. The remainder of this paper is organized as follows. Section II reviews state of art methods and techniques pertaining to the subject matter. Section III discusses the benefits of lateral sensor monitoring (e.g., weather monitoring) for the electrical grid. Section IV delineates the facilitating elements of a lateral sensor system. Section V presents a case study implementation and discusses the results from utilizing lateral sensors to complement the grid sensors at the terminal substation of an electrical grid. Finally, the conclusions are summarized in Section VI.

II. STATE OF ART METHODS AND TECHNIQUES

This section provides a review of different methods and techniques utilized for weather monitoring systems. Currently, Artificial Neural Network (ANN), Machine Learning (ML), and Internet of Things (IOT) are some state-of-the-art concepts as pertains to weather monitoring systems. Along this vein, Lone and Chavan proposed a design and implementation of a Wireless Smart Intelligent Network System (WSINS) utilizing Artificial Intelligence (AI) for monitoring various weather parameters [4]. They designed and implemented wind speed and directional sensors to provide real-time data; weather parameters, such as temperature, humidity, wind speed, and wind direction were monitored and visualized, via oa dashboard, which could readily pinpoint faulty nodes. In a similar vein, Mochida et al. constructed a weather monitoring system based upon Natural Language in Machine Learning (NLML) to analyze distributed meteorological data [5]. For Mochida's project, weather observation data was gathered with a 4K camera by Information Centric Networking (ICN) and utilized five weather-related parameters: temperature, wind speed, rainfall intensity, carbon dioxide concentration, and radiation dose. The experimental results demonstrated that the involved ML technique was able to classify meteorological data quite nicely, but it had difficulty in distinguishing whether the involved data had similar characteristics/features. Durrani et al. worked on a smart weather alert system for dwellers of distinct and disparate geographic areas utilizing a Non-linear Autoregressive Exogenous Neural Network (NARXNET) algorithm [6]. The solution presented was a smart weather station that not only monitored for weather-related data, but also predicted and generated instant alerts utilizing a combination of IOT and ML. The system deployed had a variety of monitoring sensors, such as temperature, humidity, rain, light intensity, pressure, wind speed, carbon monoxide, and air quality.

In addition to the aforementioned, numerous state-of-the-art techniques are presented within literature. In this paper, we present the notion of lateral sensors (that consist of 12 environmental monitoring sensors) conjoined with a deep learning module based upon a GAN so as to comprise an intelligent system. In this regard, we also leveraged 3D-printing for the production of these state-of-the-art sensors and utilized an IOT platform to collect, visualize, and analyze real-time data generated from these sensors. For this paper, we provide one such example of a lateral sensor — an intelligent weather monitoring system, which was implemented to complement the high-resolution telemetry sensor of an electric power grid system; it turns out that the intelligent weather system can provide quality assurance/quality control indicators to validate the various substation panel readings and continuous streaming telemetry data collected by the deployed grid sensors.

III. LATERAL SENSOR MONITORING FOR THE ELECTRIC POWER GRID

Automatic weather stations are commonly utilized as weather monitoring systems. The technology for manufacturing traditional automatic weather stations is very mature. Weather stations consist of various sensors to transmit an accurate stream of data related to weather variables. The automatic weather station acquires meteorological elements, such as air pressure, temperature, humidity, wind direction, wind velocity, rainfall, evaporation capacity, sunlight, radiation, and ground temperature [7]. The advantages are numerous; however, the relatively high production cost and long production period, which are the conspicuous characteristics of the traditional automatic weather station, limits the utilization of the traditional automatic weather station for the electrical grid ecosystem, particularly in developing countries. Consequently, the traditional automatic weather station may not be as ideally suited for the purposes of modern power system monitoring and analysis in many areas of the Indo-Asia Pacific [8].

The described limitations of the traditional automatic weather sensor can be overcome by a more scalable and extensible approach, such as offered, via 3D-printed weather sensors. The 3D-printed weather sensor has several advantages, such as inexpensive production costs, a size that is not too large, a relatively easy ongoing maintenance process, and the ability to update the sensor design so as to produce even better sensors as time progresses. Hence, 3D-printed sensors represent a solution set that can overcome the difficulty of providing a swarm of hyper-locale (detailed, accurate, and locally contextualized) weather sensors for an area.

For the case study put forth in this paper, the notion of 3D-printed weather sensors was demonstrated. The notion of a lateral sensor can be said to be very different from the prototypical weather sensor, which is currently widely used throughout the world. One of the things that distinguish the lateral sensor from the prototypical weather sensor is that the indicators captured by the lateral sensor are more complex and detailed; the concomitant technical challenge is that of processing as much of that data as possible at the edge (i.e., edge analytics) so as to minimize the amount of data being transmitted, via various Internet of Things (IOT) technologies. After all, there are limits to the amount of data that the available communications technologies can move.

Furthermore, the lateral sensor (whose further value-added proposition is that it is time synchronized) can be connected directly with other time-synchronized telemetry sensors, such as the Phasor Measurement Unit (PMU), which utilizes a Global Positioning System (GPS)-based clock to obtain real-time electrical grid data and leverages a GAN-based system for analysis. Overall, the lateral sensor has the ability to directly analyze data and send the analysis results, via a communications network, to be fused with other data, such as electrical grid data, at a reach-back concentrator located at an operations center or monitoring system center.

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IV. Facilitating Elements of Lateral Sensor System

The lateral sensor system is specialized in that it leverages GPS-based timestamping and edge analytics; in this way it sends both extra data (the timestamp) and as well as reduces the data sent (due to the processing and filtering of data at the sensor), via the involved communications network. The notion of WSN, AI (e.g., deep learning module based upon GAN technique), and IOT as a system is well exemplified by the utilization of various components, which will be described below.

A. ThingSpeak IoT Platform

ThingSpeak is an open source Internet of Things (IoT) platform and Application Programming Interface (API), which enables the collection, visualization, and analysis of real-time data from sensors or actuators utilizing the HyperText Transfer Protocol (HTTP) protocol. The data collection utilizes the Representational State Transfer (REST) API or Message Queuing Telemetry Transport (MQTT). The involved data analysis and visualization component was MATrix LABoratory (MATLAB), a multi-paradigm numerical computing environment and programming language developed by MathWorks. ThingSpeak is the open IOT platform that accompanies MATLAB. The main component of ThingSpeak is its channel, which stores data sent from various devices. The ThingSpeak channel consists of data fields, location fields, and status fields. ThingSpeak enables user to analyze and visualize retrieved data using MATLAB. Figure 1 below delineates the ThingSpeak framework.

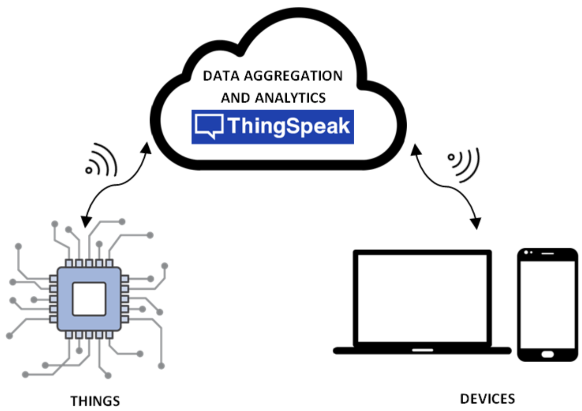

Figure 1. ThingSpeak Framework

For this particular case study, ThingSpeak was dependent upon each sensor being equipped with a cellular Subscriber Identity Module (SIM) card for the required internet connection related to the data collection piece; ideally, the sensor is connected to the internet, via wifi, but if there is no wifi in that area, then the choice of connectivity, via the sim card, is recommended.

Typically, a lateral sensor node is comprised of four basic components: (1) a sensing unit, (2) a processing unit, (3) a transceiver unit, and (4) a power unit. A lateral sensor node may also have application dependent additional constituent elements, such as location ascertainment, as in this case. Sensing units are further subdivided into two units: (1) sensors, and (2) analog to digital converters (ADCs). Similar to the entire system, of which the PMU is one constituent component, the analog signals produced by the sensors (based upon the observed phenomenon) are converted into digital signals by the ADC. For the described case of the lateral sensor, the processing unit at the sensor (i.e., edge analytics) processes the data. Data loggers, which are positioned in front of the processing unit, are electronic devices capable of recording data from sensors and constitute a major component of the telemetry system [9]. A data logger works with sensors to convert physical phenomena into electronic signals, and then convert these signals into binary data to be further analyzed by the processing unit [10].

Lateral sensors may have slighting more complex building components, but 3D printed lateral sensors are lighter and easier to assemble. One example of 3D printed lateral sensors, which have just been assembled, can be seen in Figure 2.

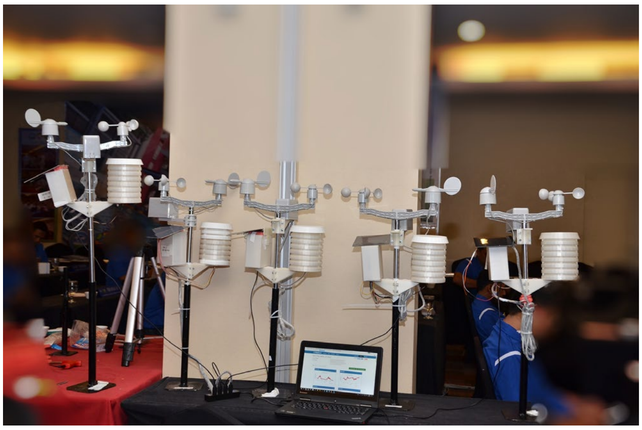

Figure 2. The 3D-Printed Lateral Sensor

The lateral sensor is capable of more robust sensor capture, and the resulting data is more accurate and precise. The overall system consists of a variety of sensors for weather monitoring as pertains to complementing grid monitoring sensors (see Table I).

TABLE I
Representative Sensors of a Lateral Sensor System

No.	Sensor	Description
1	Ozone sensor	O^3 detector that measures ozone concentration
2	Carbon Monoxide sensor	Detects the presence of CO gas
3	Hydrogen Sulfide sensor	Gas sensor for the measurement of H_2S
4	Volatile Organic Compounds sensor	Electrochemical sensor to monitor exhaust gases
5	Particulate Matter sensor	Monitors PM10 (particulate matter that has a diameter of less than 10 micrometers) and PM2.5 (particulate

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No.	Sensor	Description
		matter that has a diameter of less than 2.5 micrometers) concentrations
6	Meteorological sensor	Measures climate and weather
7	Nitrogen Oxide sensor	NO_x sensor for smog and acid rain detection
8	Carbon Dioxide sensor	Measures CO_2 gas
9	Sulfur Dioxide sensor	Measure SO_2 gas
10	Non-Methane Hydrocarbons Compounds Gas Series Sensor	Measures NMHC GSS
11	Noise sensor	Sound sensor to analyze the surrounding ambient sounds within the audible frequency
12	Air Pressure sensor	Measures air pressure

B. Wireless Sensor Network (WSN)

The advantages of a Wireless Sensor Network (WS are that it is easy to maintain, utilizes less energy, and has high transmission distances [11]. The major elements of WSN are the sensor nodes and the base stations. Sensor nodes represent the sensing layer of a WSN and generate information (e.g., parameters) in the form of electrical signals. These signals are sent through the involved network system to base stations, which are the central processing and controlling units within the WSN [12].

Most of the sensor network routing techniques and sensing tasks require knowledge of location with high accuracy. It is common that a sensor node has a location ascertainment system [13].

C. Deep learning module

In this paper, the weather monitoring system of the lateral sensor utilized a deep learning module based upon a modified GAN technique. Deep learning techniques are well suited for handling large amounts of data and computationally intensive processes [14]. The word "deep" refers to the large number of hidden layers that comprise the neural network. One of deep learning techniques is GAN. GAN involves an unsupervised learning task in deep learning that automatically discovers and learns the patterns of input data. GAN frames the problem with two sub-models: the generator model $G(z)$ that creates random synthetic outputs and the discriminator model $D(x)$ that tries to determine whether information is true (generated from the domain) or false (generated). In other words, GAN learns to choose samples from a special distribution (i.e., "generative") by setting up a competition (i.e., "adversarial").

Formally, GAN is a structured probabilistic model with latent variables z and observed variables x. The generator $G(z)$ takes an input z from probability distribution $p(z)$, and the generated data is then fed back into the discriminator network $D(x)$. The discriminator network takes input from either the real data or from the generator's generated data and tries to predict whether the input is real or generated. It takes an input x from real data distribution $P_{data}(x)$ and then solves a binary classification problem giving an output in the scalar range 0 to 1 [15]. The function of the discriminator is optimized so as to assign the correct labels to both the training data as well as the data produced by the generator while the generator itself is trained to minimize and segue to the correct assignment of the discriminator [16]. For training, both generator and discriminator networks utilize the cost function. An exemplar GAN framework is shown in Figure 3 below, and the formulation of GAN is expressed in Equation (1) below.

$$min_G max_D V[D,G] = E_{x\sim P_{data}(x)}[\log D(x)] + E_{x\sim P_z(z)}[\log(1 - D(G(z))] \quad (1)$$

where x is the training data, z is the generated sample, p_{data} is the probability distribution of the training sample, and p_z is the probability distribution of generated sample.

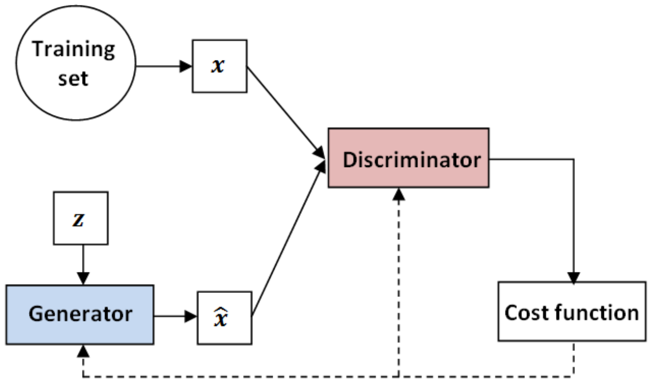
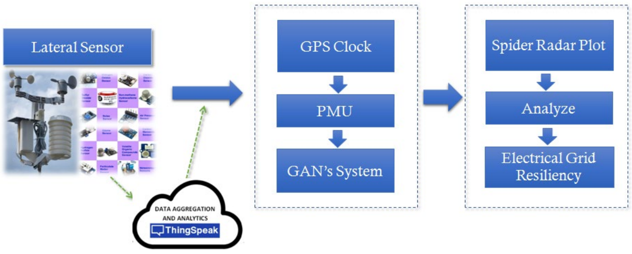


Figure 3. Generative Adversarial Network (GAN) Framework

V. WEATHER MONITORING SYSTEM BASED UPON A UNIQUE LATERAL SENSOR ARCHITECTURE

The discussed PMU real-time monitoring system was instantiated to help provide early warning to power engineers when a fault in the electrical grid is detected. The proposed system utilizes lateral sensors, which leverage a WSN architecture, GPS-based timestamping, ThingSpeak, a GAN deep learning system, and spider radar plots for data visualization analytics. The WSN is responsible for sending tsensor readings to the ThingSpeak cloud platform, via an IOT gateway, for real-time monitoring and analysis purposes. The parameters monitored include air temperature, barometric pressure, humidity precipitation, solar radiation, and wind. The lateral sensor connected directly to PMU and its GPS-based receiver for synchronized timestamping. In turn, the GAN system discerned pattern of the timestamped data so as to perform event correlation. The ensuing analysis was visualized, via Spider Radar Plots reflecting both weather sensor data and grid sensor data concurrently. This was invaluable, as weather data nicely serves to provide context reference for the grid sensor telemetry data. This is reflected in Figure 4 below.



VI. IMPLEMENTATION OF LATERAL SENSORS

This study discusses the implementation of a lateral sensor predicated upon a weather monitoring system that utilizes a deep learning module, which is a modified GANN technique. The weather monitoring stations were installed at five distinct and disparate points within a sports complex, which supports international sporting events. The described lateral sensor utilized 3D-printing technology for the production of certain components of the overall sensor suite.

The 3D-printed lateral sensor was connected directly to a Global Positioning System (GPS)-based receiver so as to produce timestamps that could be correlated with the involved Phasor Measurement Unit (PMU) grid sensor that was utilized to detect disturbances within the electrical grid. The lateral sensor was equipped with a communications suite consisting of wifi and cellular capabilities.

The lateral sensor was found to exhibit a significant increase in performance over the sensor it replaced. The previous sensor was categorized as a "Automatic Waterlogger Telemetry" sensor. Basically, the sensor measured three main items: temperature, groundwater lever, and rainfall. Unlike the lateral sensor, the previous sensor system utilized telephone lines to collect the sensor data. Consequently, if the land-based communications network were interrupted, data could not be collected optimally. The other weakness of the previous sensor was the inability to find underlying data patterns within the data it collected and organized (please refer to Figure 5). This is caused by the absence of an interval that is set automatically according to the category (please refer to Figure 6).

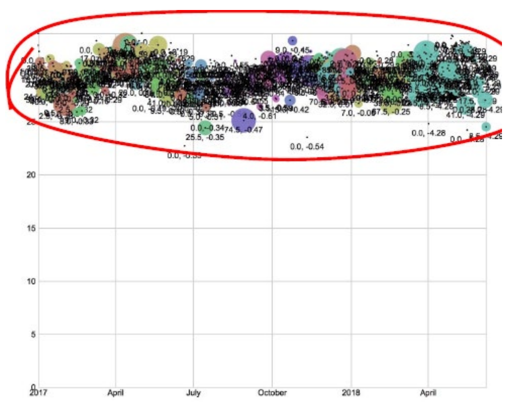


Figure 5. No Pattern is Ascertained from the Previous Sensor

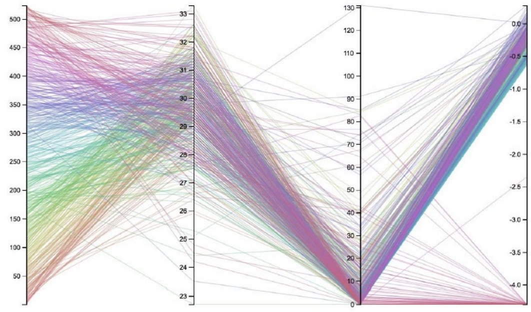


Figure 6. Parallel Coordinate System of Previous Sensor

After the installation of the lateral sensor, the data that was ultimately ingested, processed, analyzed, and correlated was much more accurate and had well-defined intervals as well as a deep learning module, which could readily analyze the data automatically and ascertain a specific pattern for each component (please refer to Figure 7). Overall, the lateral sensor detected more clusters than the previous sensor (please refer to Figure 8).

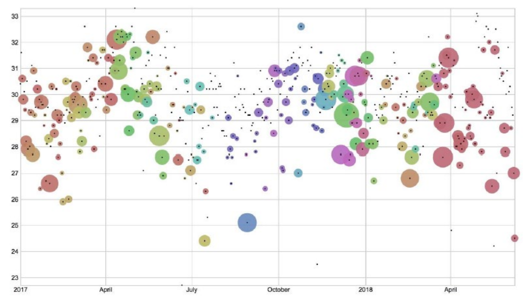


Figure 7. Data Analysis from the Deep Learning Module

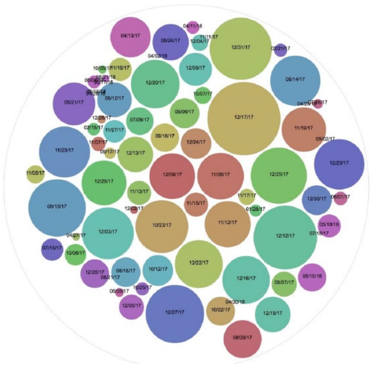


Figure 8. Data Analysis from the Deep Learning Module

VII. CONCLUSIONS AND FUTURE WORK

The results of this study demonstrated that the implementation of lateral sensors based upon a deep learning module, predicated upon a GAN, can be more robust in terms of leveraging operational data than previous monitoring paradigms. The deep learning module was able to discern underlying patterns within the ingested data as to indicators of an impending storm, which could cause communications interference, power surges, and power outages. Moreover, the deep learning module-based

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intelligent system was able to glean quite interesting trends for the particular locale where each particular sensor was located. It should be noted that the paucity of sensors in some areas and the far distances among the sensors posed some issues.

A number of future works are being planned to increase the application and suitability of this study. For the future works, we will examine techniques to facilitate the fine-tuning of lower resolution data. There is a wealth of algorithms for processing, among other things, remote sensing imagery. This can nicely complement and be correlated with the data from the lateral sensors described herein. In addition, to improve system performance, we can conduct a more comprehensive benchmarking of hybridizing techniques for processing IOT data and evaluate more advanced edge analytic paradigms for the lateral sensors. Moreover, Low Power Wide Area Network (LPWAN) technologies, such as ZigBee, Long Range Wide Area Network (LoRaWAN), and Narrow Band-Internet of Things (NB-IOT) can be utilized by the involved weather monitoring systems for a more robust communications network.

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