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EDGE INTELLIGENCE-BASED SELF-HEALING NETWORK FOR LARGE-SCALE LOW POWER AND LOSSY NETWORK DEVICES WITH IOC

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ABSTRACT

Techniques are presented herein that support the derivation, leveraging machine learning (ML) algorithms, of a cross correlation index of Key Performance Indicators (KPIs) – specific to wireless technologies such as, for example, Internet Protocol version 6 (IPv6) over Networks of Resource-constrained Nodes (6Lo), Wi-Fi, and Institute of Electrical and Electronics Engineers (IEEE) technical standard 802.15.4 variants – across multiple tenants within a cloud native multi-tenanted environment to proactively optimize routing performance and identify performance optimizations so that the network may be automatically self-healed. Aspects of the presented techniques provide intelligent fault management capabilities for a customer (having, for example, outdoor large-scale wireless sensor network (WSN) devices) thus reducing the difficulty and the cost of deployed device maintenance, support the generation of a working scheme for the field staff to repair faulty devices, provide a Vulnerability Scan Service (VSS) for connected mesh endpoints, and support the use of multi-tenant functionality for each vendor.

DETAILED DESCRIPTION

Connected Grid Mesh (CG-Mesh) products are being developed for many industrial customers, such as, for example, Itron, L+G, BC hydro, Duke, etc. Such a customer may have several thousand IPv6 over Low-Power Wireless Personal Area Network (6LoWPAN) nodes (or 6LNs) that are deployed over a wide area, such as, for example, streetlights in a city, fire prevention elements in a forest, and other industrial use cases. Consequently, it is difficult for most customers to maintain such large-scale WSNs in practice because many

of them lack the required networking knowledge to know which sensors may be broken and how to repair them. Typically, a customer must look for help from a networking product provider. That represents an inconvenience for the customer, as they often need a provider to remotely trace and debug problems or must send their own employees to a provider's office for professional skills training.

Many problems are easy to handle following analysis by a provider's engineers, but such analysis may be difficult for a customer. In order to solve a problem, the customer often spends a considerable amount of time communicating with a provider's engineering team, resulting in a negative experience when they are using that provider's products.

Recently, most Internet of Things (IoT) customers desire a Field Area Network (FAN) standard as a general solution for large-scale outdoor IoT wireless communication networks in a wide range of applications. Based on this, the Wireless Smart Utility Network (Wi-SUN) Alliance was founded by a number of companies including, among others, Cisco, Itron, L+G, Renesas, and ARM. Customers intend to establish WSNs with multiple vendors' Wi-SUN certificated products, resulting in additional maintenance difficulties.

In support of daily maintenance, customers essentially just want to know the following information from an outdoor WSN:

1. Where are the bad nodes? Or, which nodes are going to not work?
2. The root cause of these failures.
3. How to repair the effected nodes?
4. How to reduce the cost of maintenance?

It is difficult for a provider's customers to know the answers to the above, thus making a rapid response more challenging. Current IoT marketing typically involves some intelligent application service to provide valuable suggestions for a customer in support of rapid and highly efficient maintenance. Based on that, an IoT Operations Center may develop a new foundational service to meet the growing demand of IoT customers, such a service consisting of five components, as illustrated via Figure 1, below:

1. Edge Intelligence (EI). A cloud service which could provide some suggestions by using ML or other algorithms.
2. IoT Edge Manager (IoTEM). For example, a Field Network Director (FND).

3. Edge Application Manager. For example, fog computing elements such as an IoT application execution environment, deployment management facilities, etc.
4. Asset Vision.
5. Mesh Manager. For example, CG-Mesh products or Wi-SUN endpoints.

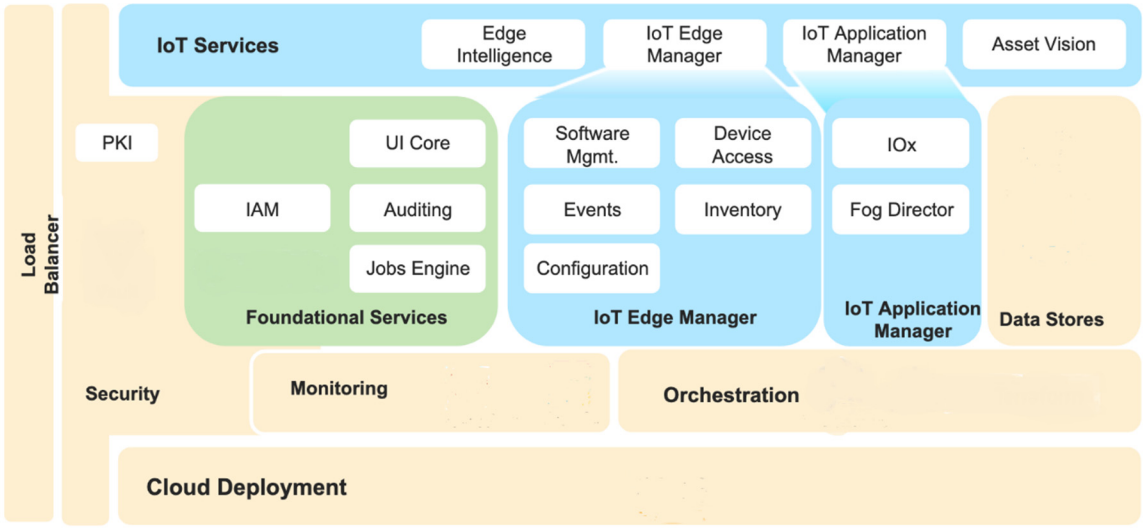

Figure 1: IoT Foundational Service Architecture

This new architecture for an IoT Foundational Service provides more resources and technology to assist customers in achieving rapid maintenance responses and leverages technologies such as, for example, machine learning, big data mining, etc.

Techniques are presented herein that support novel methods to provide better maintenance for outdoor large-scale WSN devices, something that is desired by most Industrial IoT (IIoT) customers.

If some of a deployed Field Area Network (FAN) – i.e., CG-Mesh – endpoints are out of control or experiencing an abnormal response, a customer may consider them to be broken and require a solution for repairment. There may be multiple reasons for such behavior, including:

1. Hardware problems. For example, the battery of an endpoint is exhausted or the memory which stores required configuration is broken. The customer will need to send a worker into the field to replace the battery or the entire endpoint.

2. Configuration problems. For example, the inner configurations for joining a Personal Area Network (PAN) are incorrectly configured by a FND.
3. Wireless radio interference. The radio interference may exist in a particular area, resulting in frequent re-transmission for many of the endpoints in that area. The best approach is to mask the influenced channels for all of the affected endpoints. However it is necessary to identify the specific channels and the configurable nodes using some algorithm (such as, for example, a ML algorithm).
4. Orphan endpoint(s). If one endpoint of a key path is disconnected from the network, all of its subnodes become orphan endpoints because they are no longer able to find an alternative parent node. But it is difficult for customers to know which are the broken nodes and which are the orphan nodes, because all of the nodes are out of touch with the cloud. The broken nodes need to be replaced with new devices, but the orphan nodes just need to be provided with a new possible parent node.
5. Software problems. For example, after an unsuccessful firmware upgrade an endpoint is always locked in a bootloader mode. In such a case an operation engineer will be required to upgrade the node manually in the field.

In practice, customers find it difficult to distinguish failed cases from these reasons, so they don't know how to quickly repair bad nodes. A simple and natural solution is that the customer sends some employees out to replace a node with a new device, but that brings about new problems. For example:

1. Maintaining too many backup devices increases a customer’s maintenance cost.
2. Sometimes, device replacement is not useful. For example, it does not work in a radio interference case.
3. Frequent replacement work requires many employees to go out into the field, thus increasing the customers' labor cost.

To address challenges of these types techniques are presented herein that provide intelligent fault management capabilities for a customer, which may reduce the difficulty and the cost of deployed device maintenance.

In general, all of the known solutions could fall into two categories, no matter what the problems are. The two categories are:

1. Category A: Problems that may be fixed remotely.
2. Category B: Problems that require that an engineer to go to the scene.

Aspects of the techniques presented herein support a method through which the IoTEM, like a FND, periodically collects essential information from all of the reachable mesh endpoints and then forwards that information to the EI. The EI takes charge of identifying the detailed problem and the suggested solution by analyzing the data using, for example, some ML algorithms.

As mentioned above, it is difficult for customers to know the root cause of a network fault thus making more challenging their rapid response to the fault. The EI may quickly make valuable judgements and suggestions for IIoT customers in terms of either Breakdown Maintenance (BM) or Preventive Maintenance (PM). The required data collection for each endpoint may include, but is not limited to, the following subjects:

1. Routing metric unit. For example, the expected transmission count (ETX) of all neighbors.
2. Latency between a 6LoWPAN Border Router (6LBR) – such as, for example, CGR1K or IR809 – and an endpoint.
3. Geographical location information. Some devices may have a GPS module. For other devices, information may be computed using a location algorithm such as Distance Vector Hop (DVHOP).
4. The visible neighbors list.
5. Received signal strength indicator (RSSI) and Link quality indicator (SNR) information from all visible neighbors.
6. Current traffic load status. For example, average throughput (such as, as one example, 57 kbps). This parameter may be used for detecting network congestion.
7. Transmitting queue length. This parameter may also be used to detect congestion.
8. Band information. For example, a US band, or an Indian band, etc.

9. Modulation details. For example, using binary frequency shift keying (2FSK) or Orthogonal Frequency Division Multiplexing (OFDM).
10. Environment parameters. For example, temperature, humidity, etc.
11. The remaining battery power.

Under aspects of the techniques presented herein, the EI leverages supervised and semi-supervised ML algorithms (e.g., a Native Bayesian Classifier) to judge the root cause of the problem and how to fix the problem (i.e., remotely or manually) with all the above parameters. The architecture of entire process is shown in Figure 2, below.

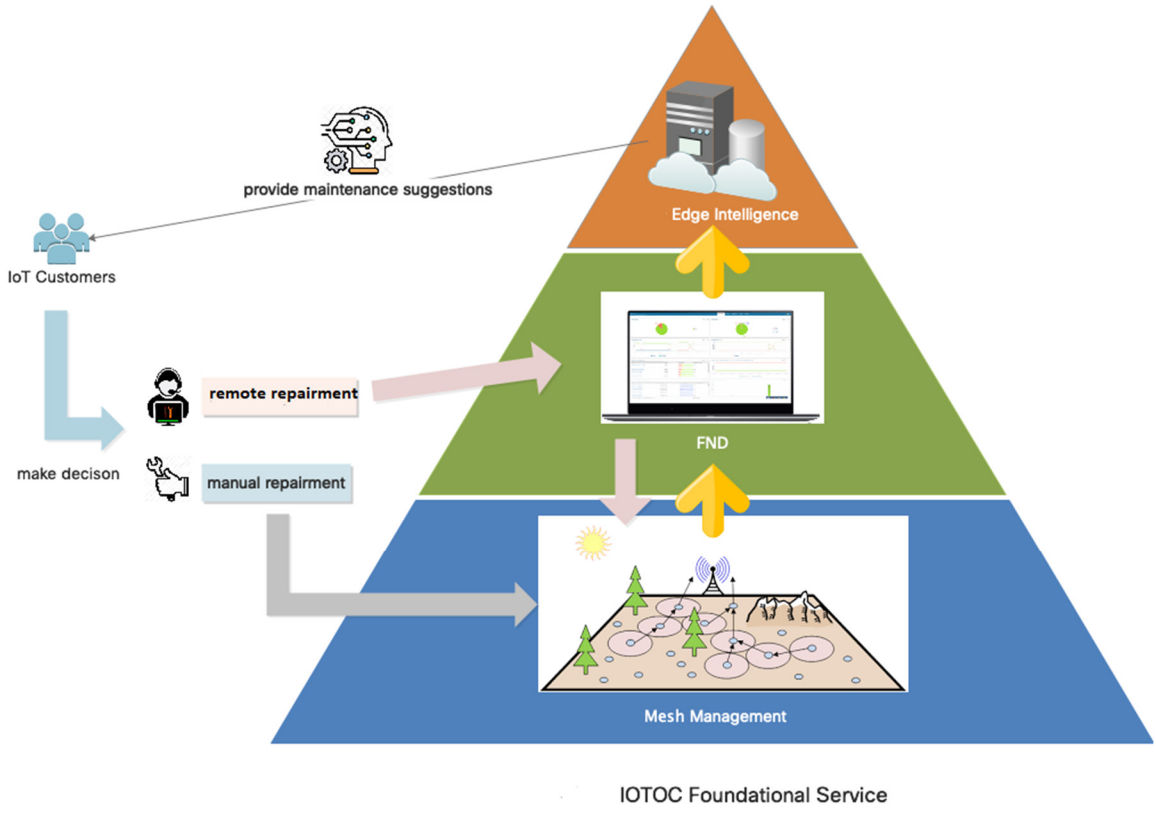

Figure 2: Intelligent Troubleshooting Assistance System Architecture

As long as a customer receive the suggestions from the EI they can make decisions regarding taking action for repairing faulty devices. If the problems could be solved remotely, the customers could confirm the solution with a FND, and then a FND may configure mesh endpoints automatically. Otherwise, the customer may consider sending field staff to the scene for manual repairment.

Further aspects of the techniques presented herein support the generation of a working scheme for the field staff to repair faulty devices when they go to the scene. For example, if a customer elects to perform manual repairment by sending a worker to the scene, a working scheme will be required in advance. Such a scheme may contain, at a minimum, the following subjects:

1. Who is the selected field staff? And is he/she available at the planned time?
2. The detailed work items, such as which endpoints need to receive a new battery, which endpoints need to be replaced with new devices, which endpoints need to be deployed with range-extender devices, etc.
3. The repairment roadmap. Because the mesh network is deployed in a wide area, the worker will likely spend a significant amount of time on the way to the broken nodes. For the field staff to avoid taking a longer route than needed, the EI provides a detailed work sequence that indicates which one is the first bad node and how to get there, and so on for the remaining nodes.
4. The repairment roadmap may be adjusted in real time according to a worker's GPS position, similar to a navigational aid. The EI may push updated information to the smartphone of the field staff while they are moving.

It is important to note that for multiple subtenants that are associated with different customers within a cloud native multi-tenanted environment, cross correlation statistical analysis via ML may be applied to identify the correlation patterns of problems within 6LNs across customer instances (subtenants). Based on the correlation threshold it is possible to identify the severity of the problem in 6LNs of a CG-Mesh across subtenants so that the network may be automatically self-healed.

Further aspects of the techniques presented herein support an IoTEM (like a FND) providing a VSS for connected mesh endpoints. It is well known that, rather than preventive maintenance, it is more expensive to repair endpoints after they are out of control. As noted previously, an IoTEM may periodically collect key status information from all of the connected endpoints so that it may check and predict the health of those endpoints.

For mesh endpoints four kinds of status may be identified, including:

1. Unhealthy and significant endpoints. Such endpoints are required to be fixed with high priority, as soon as possible.
2. Unhealthy and insignificant endpoints. Such endpoints are low priority devices for repairing.
3. Unhealthy but workable endpoints. Such endpoints could be workable although something may be wrong with them (e.g., their firmware version may be old). The repairment may be postponed as needed by a customer.
4. Healthy endpoints. Such endpoints are good devices.

A customer may, if they wish, see the results of the above on the screen with an IoTEM (e.g., a FND) and the maintenance working schedule could be generated based on the results of a VSS.

In addition, Wi-SUN is an open-standard for all members, thus multiple vendors may co-exist in the same customer campus. For example, a utility company may establish a network with thousands of nodes, 50% of which may be provided by Cisco, 30% may be provided by Itron, and the rest may be from L+G. Although all of the vendors' products follow the Wi-SUN protocol, both the hardware and the software are different from each vendor.

Therefore, in order to distinguish such differences among vendors, aspects of the techniques presented herein support the use of multi-tenant functionality for each vendor. More specifically, each vendor may be an independent tenant where they may see their products and the collected data from their endpoints respectively. But the customer (e.g., the utility company) may see all of the endpoints with their account, and get the desired analysis report for all of the devices.

For the techniques that are presented herein, of particular interest and note are, for example:

1. Cross tenanted correlation data analysis between tenants running on the same cloud native multi-tenanted instance is possible in order to perform data analysis and identify the rank positions in an Routing Protocol for Low power and Lossy Networks (RPL) tree for 6LoWPAN, which is an important problem that is solved.

For example, Customer-A is in Tenant-A and Customer-B in Tenant-B. All of the generic wireless network metrics may be analyzed in a cross-domain manner, with 6LoWPAN-based metric derivation and usage as possible examples.

2. The approach is to make the multi-tenant and multi-customer cloud approach overlay as generic as possible so that it could be applied to any other wireless radio technology and not just specifically to CG-Mesh (e.g., a FAN) or 6Lo.
3. Various 6LoWPAN-based routing inefficiencies may be considered if the decision is taken from a local view as opposed to the decision taken from a cloud-based centralized view for forwarding the traffic and packets in terms of using EI . Consider how this workflow may look in terms of the KPIs for a cloud based multi tenanted solution. For example, in 6LoWPAN we can derive a routing latency metric from one Personal Area Network Identifier (PAN ID) in a RPL tree for a customer (mapped to, for example, Tenant-A) and then use the derived metric by a cloud native multi-tenanted EI to compare the 6LoWPAN's performance with another customer's tenant (e.g., Tenant B with a different RPL ID) to identify what must be changed in an optimum manner in Tenant-B to derive better performance. As well, how that metric can be adaptively changed, proactively, by a comparison approach to other customer cloud tenant instances as well. Such an EI-based workflow becomes very important.
4. Under 6Lo mobility the migration of 6LoWPAN across customer instances with zero downtime is important. For example, in a cloud native multi-tenanted environment Cloud Tenant Instance A is a customer in one region and Cloud Tenant Instance B is the customer in a different region. The customer wishes to seamlessly migrate the 6LoWPAN network across PAN IDs in a seamless manner across multiple connected grids. Aspects of the techniques presented herein may be employed and improve the customer user experience, including, for example:
    a. The seamless migration of the 6LoWPAN network.
    b. An in-service software upgrade capability.

c. Zero down time for customers.
d. Operations and maintenance (OAM) of the 6LoWPAN network becomes easier, a benefit that many customers would find desirable.

5. Aspects of the above may be positioned as an IoT as a service (IaaS) option for customers with a cloud native multi-tenanted environment.

In summary, techniques have been presented that support the derivation, leveraging ML algorithms, of a cross correlation index of KPIs – specific to wireless technologies such as, for example, 6Lo, Wi-Fi, and IEEE technical standard 802.15.4 variants – across multiple tenants within a cloud native multi-tenanted environment to proactively optimize routing performance and identify performance optimizations so that the network may be automatically self-healed. Aspects of the presented techniques provide intelligent fault management capabilities for a customer (having, for example, outdoor large-scale WSN devices) thus reducing the difficulty and the cost of deployed device maintenance, support the generation of a working scheme for the field staff to repair faulty devices, provide a VSS for connected mesh endpoints, and support the use of multi-tenant functionality for each vendor. Under aspects of the techniques presented herein essential information may be periodically collected from all of the reachable mesh endpoints and then forwarded to the EI where the root cause of a problem and a repair approach for the problem may be identified through, possibly among other things, the use of supervised and semi-supervised ML algorithms (such as, for example, a Native Bayesian Classifier).