

Building an Industrial IoT Infrastructure with open Source Software for Smart Energy.

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Abstract—Internet of Things is the cornerstone of most of the modern technological achievements and one of the biggest sources of data. The millions of Mbytes generated by telemetry sensors are already used for statistical analysis or the creation of prediction models used in various applications in the area of smart cities, smart building, smart health, smart energy, etc. From the other hand, the expansion of IoT forced the need of more standardized approaches such the ones used in industrial automation. The Industrial Internet of Things, as part of Industry 4.0 concept, promotes the cyber physical systems (CPS) as sensors and actuators that will build the modern automation world in and out of the factories. This article studies the IIoT reference architectures and the existing open source IoT platforms for proposing an integrated architecture for installing IIoT infrastructure that can collect and analyze big volume of data, easy and with low cost. The approach is evaluated in a smart building scenario.

Index Terms—IoT architecture, industrial IoT, open source software, smart energy

I. INTRODUCTION

Internet of Things (IoT) technologies provide the ability to establish complex systems that are able to sense, analyze collected information, and respond in various environments ameliorating living standards. Nowadays, more than 1600 IoT projects have been realized world-wide in various sectors such as smart cities, smart energy, smart health, etc. [1]. Exploiting the advantages of IoT technologies, the Industry 4.0 concept promotes the cyber physical systems (CPS) as the key enablers for the Industrial Internet of Things, which is extended beyond the manufacturing environments to every-day automation infrastructure paradigms like smart buildings. On the other hand, a lot of work in open source society leads to the introduction of scalable and reliable open source platforms that are able to contribute meaningfully to the installation of IoT infrastructure.

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This paper presents an approach to build an IIoT infrastructure which is based on the industrial reference architectural model of Industrial Internet Reference Architecture (IIRA). The presented use case concerns the installation of a small-scale living lab for smart energy. The scope is the creation of an innovation ecosystem where various technologies and ideas can be integrated and tested in a real environment [2] [3]. Thus, an IIoT system is installed using various networks, sensors and open source software at the premises of a research institute in Greece.

The paper is structured as follows. Section II presents the major reference architectures for the Industrial Internet of Things. Section III provides a comparison of the most commonly used IoT open source platforms, while Section IV presents the proposed solution of the installation of the living lab and the association with the reference architecture of IIRA. Finally, conclusions and future work are presented in Section V.

II. IIOT REFERENCE ARCHITECTURES

The Industrial Internet of Things is part of the general IoT evolution. In fact, the impact of the integration of IoT technologies in the manufacturing environment has led to advancements deemed as the Fourth Industrial revolution. Acknowledging the importance of this new and rapidly evolving concept, several initiatives have attempted to define reference architectures, that will standardize the architectural design of IIoT applications. The Industrie 4.0 Platform and the Industrial Internet Consortium (IIC) are two of the mainstream initiatives towards standardization of IIoT systems, supplemented by further initiatives such as Japans Society 5.0 and Made in China 2025.

The Industry 4.0 Platform is a high-tech strategy of the German Government, promoting computerization in manufacturing. It has developed the Reference Architectural Model Industry 4.0 (RAMI 4.0) [4]. It is a three-dimensional service-oriented architecture that combines all elements in a layer and life cycle model. The three dimensions are Hierarchy, Architecture and Product Life Cycle, which define the functional areas of IIoT applications from the Smart Product to the Connected World concept, the system architecture and the

aspects concerning the development and production phases of a product respectively.

In parallel with Industry 4.0, the Industrial Internet Reference Architecture (IIRA) [5], another reference architecture was developed in the US by the IIC, covering a broader range of possible application sectors than plain manufacturing. Similarly, this architecture has a three-dimensional approach which uses however a different perspective, covering the Product Life Cycle, the Industrial Sectors and the Viewpoints. The Industrial Sectors represent the various sectors where IIoT applications can be implemented. The Viewpoints refer to the specific concerns and different perspectives of industry stakeholders. There are 4 viewpoints in the reference architecture, namely:

- The *Business viewpoint* which refers to business-oriented concerns such as business value, expected return on investment, cost of maintenance and product liability.
- The *Usage viewpoint* which is concerned with how an IIoT system realizes the key capabilities identified in the Business viewpoint.
- The *Functional viewpoint* which focuses on IIoT System functional components, structure and interrelation as well as the necessary interfaces and interactions, and finally.
- The *Implementation viewpoint* which is concerned with the technical representation of an IIoT system and the technologies and system components required.

Thus, the implementation viewpoint implements the activities and functions prescribed by the usage and functional viewpoints. IIoT system implementations follow certain well-established architectural patterns, such as a) Three-tier architecture pattern, b) Gateway-Mediated Edge Connectivity and Management architecture pattern and c) Layered Databus pattern.

The three-tier architecture pattern comprises the edge, platform, and enterprise tiers. These tiers play specific roles in processing the data flows and control flows involved in usage activities. They are connected by means of three networks, as shown in Fig. 1.

- The *edge tier* collects data from the edge nodes, using the proximity network. The architectural characteristics of this tier, including the breadth of distribution, location, governance scope and the nature of the proximity network, vary depending on the specific use cases.
- The *platform tier* receives, processes and forwards control commands from the enterprise tier to the edge tier. It consolidates processes and analyses data flows from the edge tier and other tiers. It provides management functions for devices and assets. It also offers non-domain specific services such as data query and analytics.
- The *enterprise tier* implements domain-specific applications, decision support systems and provides interfaces to end-users including operation specialists. The enterprise tier receives data flows from the edge and platform tier. It also issues control commands to the platform tier and edge tier.

Tiers are connected via different networks:

- The proximity network connects the sensors, actuators, devices, control systems and assets, collectively called edge nodes. It typically connects these edge nodes, as one or more clusters related to a gateway that bridges to other networks.
- The access network enables connectivity for data and control flows between the edge and the platform tiers. It may be a corporate network, or an overlay private network over the public Internet or a 4G/5G network.
- Service network enables connectivity between the services in the platform tier and the enterprise tier, and the services within each tier. It may be an overlay private network over the public Internet or the Internet itself, allowing the enterprise grade of security between end-users and various services.

III. IIoT DIGITAL PLATFORMS

A. Open Source IIoT Platforms

Production systems are progressively undertaking the digital transformation of their processes, utilizing more and more the data that has previously been impossible or unprofitable to collect or use. Even though the vision and the will for this digital transformation is a common ground among all the stakeholders, the exact definition of an IIoT platform and what it contains and offers, varies according to the context and the vendor. The IIoT platform vendor strategies continue to evolve and try to follow the evolution in areas like artificial intelligence and machine learning and simultaneously embrace innovative paradigms, like fog and edge computing. However, in general the IIoT platforms must share some common characteristics like interconnecting and managing the IIoT endpoints, collecting and processing the data, providing data visualization tools, and providing tools for IIoT application development.

The selection of the IIoT platform for a project is not a easy task. There are many surveys that compare the existed IIoT platforms [6]–[8], most of them focusing in performance issues [9], [10] and other are specialized to specific domains such as smart buildings [11] or smart health [12]. For the scope of this work, most value was given to engineering aspects like easy installation and configuration, scalability and interoperability. Taking into account these requirements, there was a selection of four most prevalent open source IIoT platforms, namely ThingsBoard¹, OpenHab², DeviceHive³, and Kaa Project⁴. We have performed a thorough comparison on the basis of several key characteristics which are important for the proper selection of a technological solution. These criteria are presented in Table I.

B. Comparison results

All four platforms examined cover the basic specifications of a digital platform that would support an industrial internet

¹<https://thingsboard.io>

²<https://www.openhab.org>

³<https://devicehive.com>

⁴<https://www.kaaproject.org>

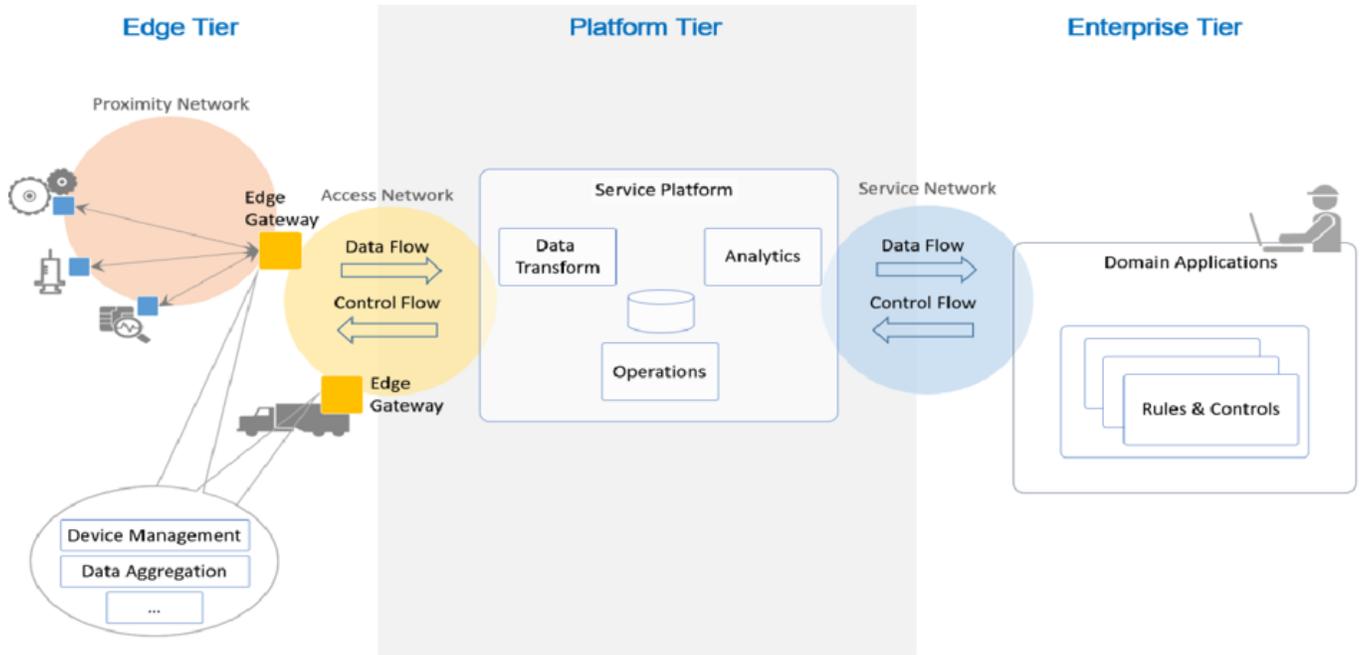


Fig. 1. Three-Tier IIoT System Architecture for IIRA.

TABLE I
IIoT PLATFORMS COMPARISON CHARACTERISTICS

Characteristic	Explanation
Technical Characteristics	HW requirements, programming language, OS, installation method monolithic, microservices etc.
Architecture	monolithic, microservices etc.
Services	device management, data visualization, remote command execution etc.
Documentation	user manual, developer manual, API reference etc.
Supported Protocols	MQTT, CoAP, HTTP, REST API, OPCUA etc.
Device Management	firmware update, role support, device control etc.
Security	HTTP/SSL support, device authentication etc.
Data persistence technologies	SQL, noSQL, Postgress, Cassandra DB etc.
Data Pre-Processing	support of aggregation functions, filtering, pipeline etc.
Data Visualization	widgets, Tables etc.
Data Analytics	connection with data analytics platforms and tools
Scalability	API or SDK for the integration or communication with and other system

of things infrastructure. Each one of them can interconnect IoT devices and gather data from them. Furthermore, both relational and NoSQL databases are supported to store the collected data from the devices. All platforms under consideration are JAVA-developed and provided under licenses that allow their free use without limitations in various applications. They also all support microservices architecture, allowing its

use in fog architectures. Nonetheless, the offerings of each platform varies regarding each criterion, so depending on the needs of each application one may be more or less appropriate.

The Thingsboard [13] platform is the latest open source effort with a good presence and support in the open source community. It can be considered as the most complete platform, since in its free version it incorporates the most features, such as device management, collection, pre-processing, editing and graphical presentation of the data. It can be installed easily and it is easy to interconnect a new device since it is accompanied by a gateway that allows the two-way connection of devices with different communication protocols and message structure. Furthermore, it supports industrial protocols like the OPC-UA and Modbus. Finally, it provides a complete graphical environment with a decision engine that allows user and device feedback according to rules on data values.

The openHab [14] platform is the most mature work in the field of building automation using the Internet of Things. It is supported by a large community, which also helps in the development of plugins for interfacing with various commercial devices. Moreover, it fully supports all the basic data collection, processing and presentation functions. It lags behind others in installing and customizing complex files and providing a friendly graphical environment. A multiplicity of communication protocols are supported via the existing plugins, yet industrial protocols are not supported. From a security standpoint, it does not support device authentication and graded access.

The DeviceHive [15] platform is a satisfactory attempt from the open source community. Its special feature is the provision of an SDK in several languages which enables the further

extension of its functions. It does not support graphical data representation and data analysis for which a third application is required. The interconnection of a new device may pose serious difficulties due to the lack of built-in support of many known device interface protocols.

The KAA [16] platform is a platform supported by a large group of developers but not updated recently. The platform supports specific data collection and storage functions. Data processing and graphical visualization are only supported by the commercial version.

Each platform has its positives and negatives aspects according to which it can be considered satisfactory depending on the specifications in each case. In the context of an industrial environment, in which it is necessary to integrate various heterogeneous industrial network devices of things, and where there is also a need for bidirectional communication with the devices, the platforms must support many protocols and interact with the devices in an untroubled manner. In addition, the degree of support by the community is a decisive factor that must be taken into account. From this perspective, the ThingsBoard and openHab platforms seem to be one step ahead from the rest of the competition.

IV. DATA ANALYTIC PLATFORMS

A. Overview of modern data analytics

The industrial IoT is characterised strongly by the hallmark 3Vs of Big Data, as described in the classical definition of Big Data by [17]: Volume, Variety and Velocity. Labrinidis and Javadish [18] define the process of managing big data as consistent of two distinct levels, namely Data Management (where data is acquired and subsequently pre-processed, e.g. for the purposes of cleaning, transforming, integrating, aggregating etc., and Analytics (where data is modelled and analysed, leading to interpretations and knowledge). As explained by Tsai et al. [19], the process of data analysis (or data analytics) utilizes the outputs of the data management process as input, in order to find hidden patterns, rules and information from the data. For this purpose, a range of statistical techniques is often used to mine data, though more recently, other analytics methods such as supervised and unsupervised machine learning techniques, have begun to rapidly gain ground, used either exclusively, or in conjunction with statistical processing techniques. Big Data analytics are typically classified as Descriptive, Predictive and Prescriptive analytics [20]. In the context of the IoT, analytics can also be applied in real-time (i.e. upon the incoming stream of data), or off-line (on stored data).

Although data analytics can be applied for a wide range of purposes, Gandomi and Halder [21] outline some of the most common uses for multimodal data analytics. In text analytics, typical uses are information extraction (structured data and relationships from unstructured texts), summarization (from single documents or collections), question answering (responses to questions posed in natural language) and sentiment analysis. Another type of use case is audio analytics, either applied to sounds or speech, in order to extract structured

information (e.g. audio features to help recognise and classify sound, or extract semantics and sentiment from speech). Video analytics refers to the extraction of information from static images or video streams (e.g. image classification and content description, detection of presence). Social network analytics includes several techniques found in text and multimedia analytics (content-based analytics), but also focuses on the relationships between users and entities, since social networks are typically represented as graph structures (e.g. community detection, social influence and link prediction). Finally, predictive analytics is a modern trend that attempts to provide predictions on the future values of certain data, by generating data models trained on historical data. Common examples of these could be predicting a users interest in particular products, forecasting the electricity demands of a region, or inferring the likely remaining time-to-failure of a hardware component.

B. Open Source Big Data Platforms

To address the challenges of Big Data in the IoT, the concept of scalability is fundamental. In this respect, there are two major approaches, namely to horizontally scale a system (i.e. add more servers to increase storage capacity and distribute computational loads), or to vertically scale a system (i.e. add more hardware resources to existing servers, such as more RAM, processors or GPUs).

Whether one chooses horizontal or vertical scalability, in the open-source world there are few product offerings that combine all the necessary components for Big Data analytics (storage, pre-processing, analysis) in one single package. Instead, most solutions based on opensource software, depend on a range of base components that manage data storage, querying and program execution, upon which further components for data analytics can be installed and executed. This allows system developers to adopt a mix-and-match approach, depending on their needs and available expertise. In the next section, we present the most well-known such components.

C. Base components

The most well-known Big Data platform is Apache Hadoop [22]. This consists of a distributed file system (HDFS) for storage across a large number of nodes, and a resource management layer (YARN) which schedules jobs across the node cluster. The MapReduce programming model allows parallel execution of data queries, which can be simplified by using other components such as Apache Hive or Apache Pig, which offer SQL-like capabilities to programmers.

Finally, we report two horizontally scalable database platforms, which offer NoSQL database storage and querying components. The most well-known examples are MongoDB and Apache Cassandra, both of which offer rapid performance in querying and fault tolerance through distributed database storage.

D. Data analytics components

Most of the open-source solutions in data analytics offer bolt-on compatibility with base components such as Hadoop,

and are typically offered alongside a more feature-rich paid version. Many implementations refer to data analytics in the context of visualizing data and generating reports. While these techniques offer valuable services, we focus on those implementations which include machine-learning algorithm integrations, aligning with the data analytics definition in [21]. For the purpose of this work, we selected three machine learning supporting open-source platforms for Big Data analytics. These offerings are the Knowage⁵, the H2O⁶ and KNIME⁷. A summary of the features found in each offering is shown in Table II.

TABLE II
IOT PLATFORMS COMPARISON CHARACTERISTICS

Software Platform	Base support	Feature set	Data processing	ML algorithms
Knowage	Spark	Limited	Yes	Yes
H2O	Hadoop, Spark	Full	No	Yes
KNIME	Hadoop, Spark	Full	Yes	Yes

Further from the above, data analytics solutions developers may base their solutions on popular programming languages (such as R, Python) which include many pre-compiled libraries for statistical and machine learning processing. These also include libraries for connecting to popular base components such as Spark and Hadoop, making data integration easy. Software libraries for common programming languages (e.g. Weka for the Java language) can also be employed to this end.

E. Complete platforms

The open-source products reported here offer complete platforms that integrate storage, processing, querying and analysis tools. Apache Spark [23] is considered the next step up from Hadoop and it also provides a scheduler, query optimizer and execution engine, which can run either standalone, or on top of an existing Hadoop installation (replacing Hadoops YARN). One advantage of Spark is that it comes not just with data query capabilities, but a full machine-learning library, which contains classification, regression, clustering and other ML algorithms, optimized to run under Sparks parallel execution environment. Finally, HPCC is a complete big data storage and analysis platform, similar to Spark, offering a suite of tools for data pre-processing (Thor), data querying (Roxie), job scheduling and automation and finally processing via distributed execution machine learning algorithms, over commodity computing clusters. HPCC claims superior performance compared to Spark and Hadoop, since it supports three types of parallelism: Data (division and processing), Pipeline (two operations on the same dataset simultaneously), and System (parallel execution of independent operations).

⁵<https://www.knowage-suite.com>

⁶<https://www.h2o.ai>

⁷<https://www.knime.com/>

V. A LIVING LAB FOR ENERGY EFFICIENCY

A well-known source of energy inefficiency in a building reality is the human behaviour. For example, while opening a window for one minute can be seen as a decision of negligible impact from the building user point of view, the actual impact of a simple action like this depending on the external environmental conditions could be drastic in terms of thermal dispersion and thus energy costs. It is then clear that any expression of the simplest user freedom in a building can impact considerably on the overall building energy consumption.

Following the concept of living labs, an IIoT infrastructure has been installed at the Industrial Systems Institutes (ISI) premises in order to examine new approaches to the energy efficiency based on automation and human factor. The open source platform Thingsboard has been chosen as the central IIoT platform that implements an IIRA driven architecture.

A. IoT Devices and Networking

ISI occupies three different independent offices at the building of Patra Science Park. The only constrain for the installation was the inability to install smart energy meters at the central energy infrastructure, thus only smart plugs and power switches have been used.

Both commercial solutions and hardware open source custom projects are used as IoT sensors. For the smart plugs, the products of the MEAZON SA⁸, a Greek company with an open telemetry protocol and Sonoff⁹, a series of products from the Chinese company ITEAD with open source firmware, were used. For monitoring the environmental parameters (temperature, sensitivity, light, etc.) and room occupation (motion detection), a custom multi-sensor based on Arduino board was used.

For the networking of IoT sensors and the aggregation of the telemetry, the existing WiFi and Ethernet network infrastructure was enabled. Furthermore, in each room a ZigBee gateway was installed, creating a proximity network for the MEAZON smart plugs to eventually communicate with the central IIoT platform. **Furthermore, two depth cameras....**

B. IoT Architecture

The proposed architecture follows the three-tier model suggested by IIRA. Thingsboard platforms services were used for the implementation of both platform and business layer. Fig. 2 shows the functional components that are used for installing the proposed living lab.

In the edge layer, the IoT devices are communicating through the WiFi, Ethernet and ZigBee networks to a central server where the ThingsBoard Platform is used. The devices are communicating using both MQTT protocol. In the central server, two MQTT brokers are installed, the one is used by the Thingsboard platform as the endpoint of input and output of data and the second is an Eclipse Mosquito broker

⁸<https://meazon.com/>

⁹<https://sonoff.ithead.cc/en/>

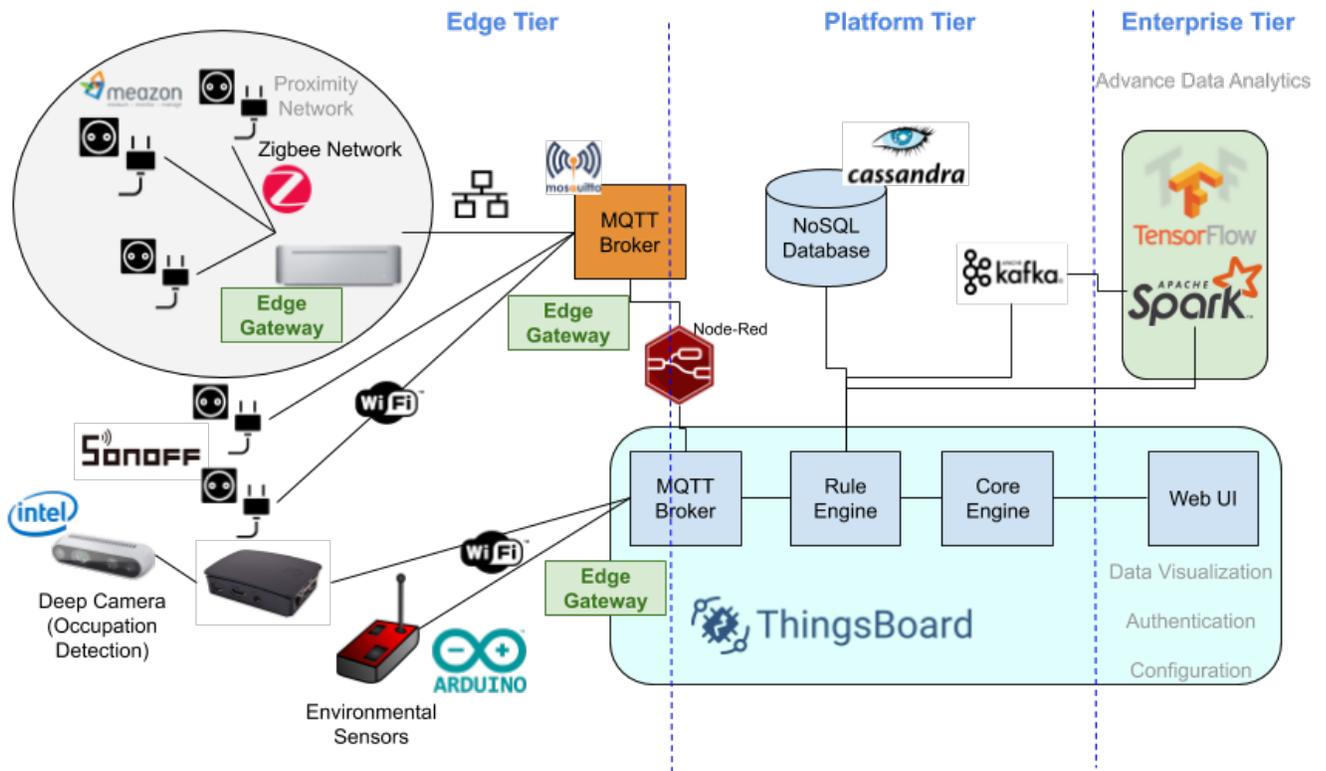


Fig. 2. IIRA driven Three-Tier IIoT System Architecture.

which is used for communicating with devices that are not supporting the message content defined by the IoT Platform. For IoT devices where there is access to their firmware, we implemented the exchange of data with platforms native MQTT. This data contains messages for sending telemetry as well as receiving commands from the platform (i.e. turn off a plug). For the rest of the devices that follow their own message structure, the Node-RED data transformation pipeline management software is used for acting as gateway that translates the from and to the devices messages to Thingboards messages structure. The platform layer consists of the modules of Thingsboard platform. Platforms Rule Engine is used as the Data Transformation and Analytics modules where the incoming and outgoing data filtered or transformed following a rule-based logic. The transformed data is forwarded to the ThingsBoard core module for storage to the local database. A Cassandra No SQL database is used for storing the telemetry and device configuration data. Additionally, Thingboards core module provides assets management and user authorization and authentication services as part of the operations capability defined by IIRA.

Finally, at the Enterprise Layer, a web interface allows the creation of dashboards with visualization of the telemetry data in interactive charts. An example is depicted in Fig. 3.



Fig. 3. Screenshot of the overall dashboard with Living Labs power metrics.

C. Big Data Analytics

We have to write something about the data that is send to a VM Spark cluster in the cloud and works with tensorflow as depicted in figure of architecture

VI. CONCLUSIONS AND FUTURE WORK

The proposed work presents a practical paradigm for applying an IIoT reference architecture in our case the IIRA utilising open source software in combination with industrial products that can be found in the market. As a use case, small scale Living Lab was installed at the premises of Industrial Systems Institute. As future work, an extension of

this Living Lab is scheduled, mainly in the Enterprise Layer where an additional platform for big data analytics including Apache Spark and Tensor Flow will be installed in a cloud computing infrastructure. This platform will enable the users to proceed with complex data analysis tasks and use the results to create new rules which will feed the IoT platforms rule engine.

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