IoT Digital Enterprise Platform based on Cloud Metering and Big Data Services

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***Abstract*—The use of Internet of Things (IoT) results in more connected and smarter environments, while enabling energy consumers and providers to reduce costs thanks to advanced metering management. The demand of data traffic has recently grown as fast as the number of connected devices and smart-meters. In order to meet the explosive growth of big-data, new technologies are required to improve the existing metering infrastructure. In this paper, we propose an open IoT digital enterprise platform for smart-metering applications focused on allowing open access to big-data and cloud services. We investigate the main issues and challenges of smart-metering big-data analytics as a free business service. Referring to some major information technology architectures, we introduce our suggested architecture that can help enterprises deploy their specific big-data framework for smart objects, smart-meters, smart-homes, smart-buildings, smart-factories, smart-cities or smart-grids. This is done by adding smart-metering cloud services based on an advanced metering infrastructure.**

Keywords–Big-data; Cloud; Digital enterprise; IoT; Smart-metering.

I. Introduction

Since software is the center of technology, the industrial revolution ought to open up new horizons, dimensions, challenges, opportunities and business areas, thus freeing data and benefiting from it. Companies attempt to cut costs and make software an enabler for future success and for an industrial and digital economic revolution [1].

We are still in the early stage of realizing the vastness of customers' requirements like the infinity universe, the hugeness of data size, their deep knowledge and their streaming. We aim to broaden the data dimension as an infinite space (data from varying sources) and to ensure the data management coming from every physical signal, social media and satellite [2]. Accordingly, our new challenge is to deal with such a huge volume of knowledge available in digital platforms. The data processing is no longer enough; it is necessary to access this vast amount of data and transform the mining of information in order to create new values for companies, customers, societies, as well as the environment [3]. Therefore, connecting people, indoor and outdoor with technology in real-time helps customers conceive their business life and make sense of its impact on the economy, the society and the environment [4].

It is essential to draw customers' attention to new services they do not know and have not utilized yet and then fit them to their own objectives and requirements. For instance, controlling the energy generation according to demand is a major issue and a main objective of energy vendors [5]. The target of the offered service is to help this specific customer align an energy demand and supply it through a cloud-based IoT platform offering the opportunities of networking, processing and storing data, based on scalability, flexibility, and performance capabilities [6] [7].

Smart-meters data satisfy the basic aspects characterizing big-data as volume, variety and velocity (3'V) [8]. The big-data technology provides a real-time analysis and deals with consuming smart-meters data correlated with weather information and other readings of external behavior [9]. Using big-data capabilities, we have to manage the huge amount of data captured by smart-meters in frequent time periods. Hence, advanced analytics allows companies to extract the available information and knowledge from the massive volume of data to gain new insights reinforcing their proactivity in taking analytical actions. Smart-metering big-data management using analytical algorithms may achieve substential values needed to make decision for monitoring and prevention [10] [11]. A key to decision-making improvement is the variety of data sources.

A manufacturing company hopes to improve maintenance and ensure real-time supervision and predictive analytics for factory productivity optimization and business and operation visibility [12]. Our contribution is to propose an open IoT digital enterprise platform for smart-metering applications based on open standards to support and integrate different devices and platforms in order to help energy markets to bring solutions quickly. The advanced smart-metering systems can be integrated with an IoT platform and big-data cloud services ensuring advanced smart-meters data management and analytics. Indeed, our suggested platform can optimize the production factory capacity by predicting failures and consumption based on the correlations between historical data and real-time data.

The remainder of this paper is organized as follows. Section II discusses the background and issues of smart-metering big-data management. In Section III, we mention some leading big-data reference architectures. Our proposed IoT big-data digital enterprise platform for smart-metering applications is described in Section IV. Finally, conclusion and some future work are drawn in Section V.

II. Background And Issues of Smart Metering Big-data Management

Several IoT standards and protocols have been elaborated to construct IoT devices satisfying some requirements, such

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as batteries' power supply and limiting in-memory processing capacity where there is no continuous power supply. Major IoT systems offer private services that are exclusively allocated to particular vendors [13]–[16]. In addition, some IoT systems are unable to be extended or combined due to their limited capabilities of sensing, memory storage, or analytics functionalities [17]–[19]. The IoT protocols have to optimize these constrains and to provide an open smart space infrastructure connecting every type of vendors' devices with a free access to open data, open standards, and open cloud services [20]–[22]. Our challenge is to provide an open smart-metering big-data system with a free access to open big-data and cloud services.

In [23], a green IoT platform was developed to demonstrate the interest of open data and open Application Programming Interfaces (APIs) for a public IoT smart-city infrastructure to maximize the Swedish society benefits. A lot of business applications are based on the IoT technology. Now, the urgent requirements for enterprises are acquisition, storage management, and processing the huge amount of heterogeneous data generated by large distributed sensor networks [24] [25]. The IoT data in cloud platforms are characterized by multi-source high heterogeneity data acquired from different distributed sensors including structured, unstructured and semi-structured data types. The communication between IoT devices in a smart environment generates a massive volume of real-time and stream data. As a consequence, its multi-dimension processing in cloud needs a flexible scalability of storage, and compression schemes [26] [27]. Supported by wireless sensor networks, the IoT, cloud computing, social networks and smart engines, big-data systems can offer many benefits for business enterprises and societies by potentially acquiring, storing, analyzing a huge amount of data. Big-data can provide and implement an ecosystem of convergence and collaboration based on various services across several fields, networks and business processes and rules [28]–[31]. Cai et al. [32] proposed a functional IoT framework based on big-data storage systems in cloud computing and defined the big-data processing modules' capabilities and challenges for several industrial applications. This IoT storage system surfs cloud platforms and tracks significant information to enable any enterprise to assure inter-operation, intelligence and innovation. Ahmad et al. [33] envisioned the basic role of integrating the IoT with social networking to understand human behaviors using big-data analytics based on the Hadoop ecosystem. The authors suggested a system architecture for real-time big-data processing and analytics consisting of IoT devices, social IoT servers and applications. This social IoT system is able to improve users' behaviors by providing feedbacks sent as an alert message. The human dynamics theory describes real-time human behaviors in social areas offering an intelligent environment.

Big-data offer the possibility to find most similar users who have similar interests and tastes utilizing an item-based collaborative filtering technique that calculates the similarity between items and recommends the item which an active user previously preferred. This technique has been successfully applied in several IoT contexts to analyze IoT devices and services and to exploit the relations between users, resources and recommended tags. Mashal et al. [34] put forward a hyper-graph model for an IoT service recommendation that would facilitate the integration of IoT services that users would expect. The recommendation problem was modeled as a tripartite graph with hyper-edges among users, devices, and services. The correlations between these three parties defined the heterogeneous relationships and behaviors in the IoT service recommendation. To ensure open and secure services in IoT scenarios with lower processing load and to remotely configure fine-grained access control policies, scalability and flexibility, Simone Cirani et al. [35] suggested an IoT-Oauth-based-Authorization-Service (OAS) architecture targeting IoT applications based on HTTP and on constrained application protocol services to offer an open authorization framework integrated using the OAS.

Several companies are competing for developing advanced energy management solutions based on cloud platforms, smart-metering technologies, and advanced analytics tools. The authors in [36], provided an overview of the big-data background, components and technologies including the Hadoop framework, the data center, cloud computing and the IoT. Thus, the advanced analytics techniques will play a crucial role in the future smart-metering progress that will require efficiency in stream data analytics, integrating advanced machine-learning capabilities and the competence of decision-making techniques [37].

However, there are major issues for the smart-meters big-data management. The first issue is the storage of the huge "volume" of data. High availability is realized by ensuring data reading and data writing anywhere, avoiding joins and transactions, and tolerating redundancies, such as Hadoop Distributed File Systems (HDFS), highly distributed databases (NOSQL), and NewSQL databases. The second issue concerns "velocity" and massive data processing. As a solution, it is recommended to move processing to data using the in-memory processing standard. The third big-data issue results in the "variety" property of data collection from different sources, formats and types that can provide homogenization and data fusion. Different types of original data, such as smart-meters measurement data, weather data, geographical information data and marketing data, are collected and extracted from different sources, such as connected smart- meters, Web applications, relational back-end systems, data stream, social media and other forms of data-sets in the cloud. Data should be extracted and stored in distributed structures in memory waiting their processing. A new structure of the NoSQL database is created to manage the storage and retrieval of unstructured collected data with various format extensions. The "Spark" technology is used for "batch" and "μ-batch" processing, "storm" for streaming processing, and schema-less "NoSQL" databases as a distributed platform for massive data storage based on HDFS, using the Map-Reduce architectural pattern for parallel calculation of large data-sets, which is a programming model focusing on a simple hardware to perform complex jobs. Data processing is divided in many small activities run in different clusters and in the YARN framework for scheduling jobs and managing cluster resources [38] [39].

Due to the big-data 3'V, it is necessary to devise a new architecture for smart-meters big-data management with new technology features according to new demands. Before introducing our proposed architecture, let us investigate some big-data reference architectures developed by the major IT vendors.

III. Big-data Reference Architectures

The construction of the proposed smart-metering big-data analytics architecture is referred to various big-data reference architectures defined as consistent conceptual models. These technical references can provide an understanding of big-data structures, services and capabilities to explore our specific big-data system interoperability, extendibility, and portability. We will discuss surveyed big-data platforms, such as Microsoft, Oracle, IBM and SAP to perceive the main components of a big-data architecture.

A. IBM Big-Data Architecture

The process of big-data analytics starts with data discovery and exploration. Data are figured from different sources to incorporate and discover a new data value. The IBM big-data platform [40] [41] allows indexing, searching and navigating diverse sources of big-data represented in different formats (structured, semi-structured, or unstructured). To generate the accurate analytics applications, processing data and complex analytics models are executed both to deprive replicated data and to provide fast and multiple analytic iterations. For an effective analysis, a game-changing analytics platform provides tools for the exploration, analysis, management and storage of both structured and unstructured data. Real-time analysis can offer the opportunity of analyzing data as it is being generated insight to make decisions and actions before storing data on physical disks. The volume of the data stream depends on the dynamical variation in time. Therefore, the big-data platform should be able to manage these increasing volumes of data as well as to analyze data in motion. To consume efficiently the big-data, the accelerators as tool sets and the library of analytical packages are used to reduce the analytic cycle time acquired to discover and process data, develop and deploy models, and analyze and visualize results. The data management is focused on data integration and governance including data quality, security, life cycle management, and master data management capabilities. These big-data requirements can be managed by Hadoop (unstructured data), stream computing (real time data), and data warehouse (structured data).

B. Microsoft Big-Data Architecture

The key components of the Microsoft big-data architecture [42] are data sources, data transformation, data infrastructure, and data usage. Big-data are collected from various sources classified by the 3'V big-data characteristics. Then, independent functional blocks are implemented to ensure data transformation and pre-processing, such as the collection block to pile up data from different types and forms, the aggregation block to aggregate collected data into a larger collection, the matching block to enhance information about each object, and the data mining block for both descriptive and predictive analytics. Transformed data are stocked in metadata to be utilized by multiple data infrastructure services. Under development, the results can be provided in various data usage formats, granularity and under different security considerations.

C. SAP Big-Data Architecture

The SAP big-data reference architecture includes ingestion, storage & processing, and consume components. Additional components are also added to manage the data life cycle, the infrastructure, security and data governance [43]. The SAP High-speed Analytical Appliance (SAP HANA) platform provides several advantages, such as serving big-data features to the business customers in order to improve their applications. The ingestion key component of the SAP HANA platform permits the acquisition of various data types (structured, semi-structured, and unstructured data) from different sources (sensors, relational back-end systems, data stream, social media, etc.). For data processing and storage functions, the SAP big-data platform investigates the potential between transactional and analytical processing abolishing the computing time latency by using in-memory computing and an engine for real-time simulation and planning cycles. Other components, such as graph engine and spatial or location data processing are also integrated in the SAP big-data architecture. An integrated Hadoop platform supports the treated data through a distributed file system. The Hadoop real-time platform offers to users efficient data processing and storage as benefits of real-time processing. The consume component supports the analytics functions, such as dashboards, reports, exploration, charting and visualization, and applications including machine learning and predictive and native HANA applications & services. Within the SAP HANA platform, the infrastructure management provides the security and life cycle management of a data object using common services for data security and governance.

D. Oracle Big-Data Architecture

The Oracle big-data reference architecture proposes an incorporated big-data platform based on Hadoop and Oracle NoSQL database technologies to acquire, process, and analyze big-data using decision-making techniques. As an infrastructure service component, the Oracle big-data architecture suggests hardware, a network, connectivity, an operating system, virtualization, storage, security, and management. Data sources support the data streams, the NoSQL /Tag-values and the relational and unstructured databases. The information-provisioning component provides big-data processing including information discovery, data conversion and massive unstructured data and stream processing. The data warehouse and the operational database are used to store processing data. The information analysis component recovers the analytics applications as descriptive (reporting / dashboards) and predictive analytics (statistical analysis, semantic analysis, data mining, text mining, in-DB Map/Reduce and spatial) [44].

E. Discussion

Through the review of big-data architectures and the descriptive Table I, several components can identify big-data system. As a result, we can consider three common ones. The first one is the big-data management and storage component which investigates (i) structured, semi-structured and unstructured data, (ii) volume, variety, velocity and variability, and (iii) SQL and NoSQL and distributed file systems. The second one is the big-data analytics and application interfaces studying descriptive, predictive, spatial, real-time, interactive and batch analytics, besides reporting and dashboards. The third component is the big-data infrastructure as well as in-memory data grids, operational databases, analytic databases, relational databases, flat files, content management systems and horizontal scalable architectures. Other components can support these three main components, namely the user usage, landscape management, the modeling & life cycle management, and the data governance as security, compliance, etc.

Our architecture is in fact based on these three components. In addition to what is existing in big-data platforms, we have integrated the cloud-based IoT big-data platform and the smart-metering cloud services.

IV. Proposed IoT Big-data Digital Enterprise Platform

Our integrated architecture is built to involve data management and help IT organization to develop applications that support digital transformations with analytic capabilities. It helps to free IT data and to spend the majority of data sources for more consumed operations. The proposed IoT big-data digital enterprise platform, represented by Figure 1, allows the access to a leverage data in many ways, such as digital data management, flexible data management or incorporated integration.

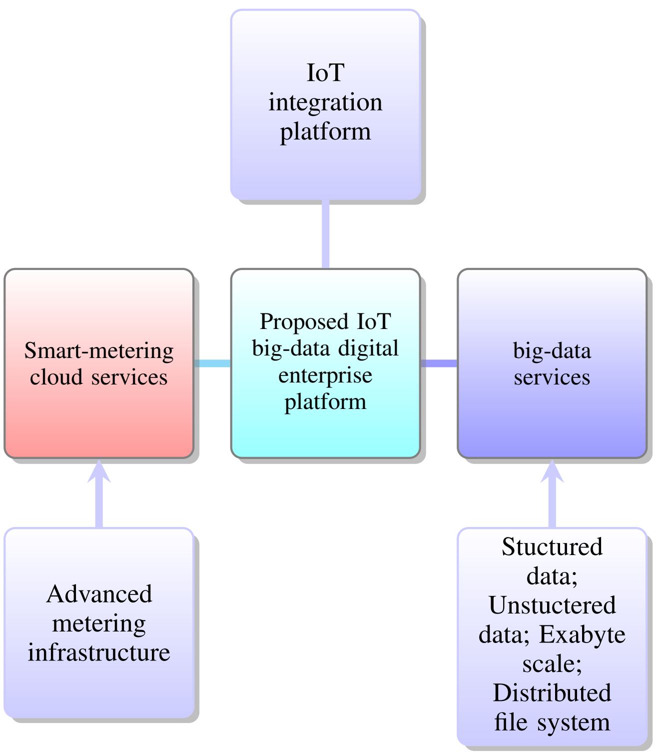

Figure 1. Proposed IoT big-data digital enterprise platform for smart-metering applications

Indeed, our suggested platform permits data processing and access to handle the huge amount of data collected by widely deployed sensors, as well as a solution for the advanced smart-meters to interact with the platform. For real-time data, such as weather data, data from sensors and smart-meters, production and consumption data, we propose to use external data storage in an effort to measure energy consumption. With our solution, we can increasingly manage the data from a variety of sources that can be real-time data from databases which contain user details, user energy consumption data, user equipment, weather API or collected data from social media. The big challenge is to take control of the data stream and to use it in more efficient ways. This can be realized through connectivity up in the space with big-data.

In our architecture, we can filter and extract the data in which we need in other tasks, like machine learning, and to train and test our intelligent system. Also, we analyze the collected data and clearly present it to facilitate understanding our data content in charts and graphics formats in order to support rapid and confident decisions. Our integrated IoT big-data platform imports multi-store tables, which enables new partition tables in memory or file systems. It is possible to move across the stores using big queries or in-memory processing capabilities. The solution allows providers or customers easy access to applications. The different cloud services offered by our integrated platform are shown and described in Figure 2 . This integrated platform consists of IoT

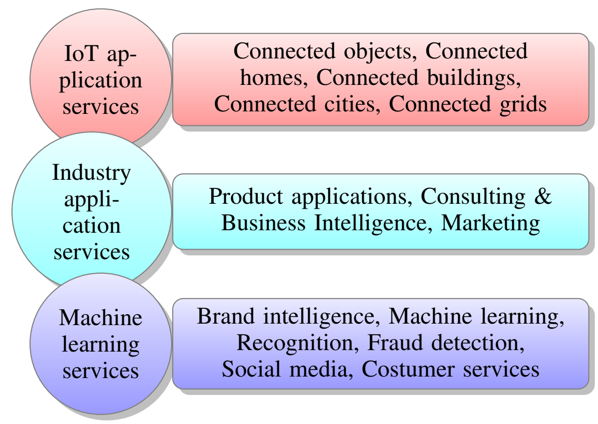

Figure 2. Cloud-based IoT big-data platform services

applications services for connected objects, homes, buildings, cities and grids in order to ensure industry application services like product applications, consulting and business intelligence, and marketing. The advanced analytics of these services is done by integrating machine learning services, such as brand intelligence, machine learning, recognition, fraud detection, social media and customer services, so as to attribute new values to big-data.

Figure 3 illustrates in detail our proposed IoT big-data digital enterprise platform that ensures many functionalities:

- Smart devices and gateways: To substantiate and manage several connected devices and smart-meters based on different communication protocols. The Advanced Metering Infrastructure (AMI) uses various networking models to manage and control the communication with the smart-meters in the field. The AMI head end system involves software applications and databases for smart-meters data acquisition and storage. It promises real-time monitoring of the AMI network of smart-meters. Furthermore, the AMI head end system enables utilities to take advantage of the accurate measurement devices available in the market in order to measure customers' energy consumption, configure smart-meter parameters, and check these smart devices via firmwares.
- IoT integration platform: To apply analytics at the edge and to enable low-latency decision making.

TABLE I. BIG-DATA REFERENCE ARCHITECTURES

	Big-data management and storage components	Big-data analytics and application interface components	Big-data infrastructure components	Supporting components
IBM architecture	**** Data Integration and Governance:*** Data integration, Data quality, Life cycle management, Master data management; **** Accelerators***; **** Hadoop***; **** Stream computing***; **** Data warehouse***.	**** IBM big-ata platform:*** - Visualization and discovery: Indexing, Searching, Navigation; - Application development; **** Analytics applications:*** - Business Intelligence /Reporting; - Exploration/ Visualization; - Industry applications; - Functional applications; - Content analytics - Predictive analytics.	**** IBM big-data platform:*** - Systems management	**** Data Integration and Governance:*** - Security
Microsoft architecture	**** Data Sources:*** - Data Objects; Variety; Velocity; Volume; **** Data transformation:*** - Collection; Aggregation; Matching.	- Data Minning: Descriptive / Predictive.	**** Data infrastructure:*** - Conditioning - Storage & Retrieval; *** Security**; **** Management***	****Data Usage:*** - Network Operators / Telecom; - Industries/Businesses; - Government: Health & Fin. Institution; - Academia.
SAP architecture	**** SAP HANA in-memory:*** - Transactional; Analytical; Graph; Spatial; Text & Social media processing; Extended storage; Planning and simulation; **** Hadoop Platform:*** Processing & storage; **** Modeling & Life cycle management***.	**** Analytics:*** Exploration, Dashboards, Reports, Charting, Visualization; **** Applications:*** - Machine learning & predictive; - Native HANA applications & services; *** Modeling & Life cycle management**.	**** SAP HANA platform:*** - Data objects management; - Data objects security.	- Landscape management; - Modeling & Life cycle management - Data governance: Security; Compliance; Audits.
Oracle architecture	**** Information provisioning:*** - Data processing and discovery: Information discovery; Conversion data; Processing of massive unstructured and streaming data; - Operational database and data warehouse; **** Data sources:*** Distributed file system; Data streams; NoSQL/Tag-value; Relational; Faceted unstructured; Spatial/relational.	**** Information analytics:*** - Descriptive analytics: Reporting; Dashboards; - Predictive analytics: Statistical analysis; Data minning; In-DB Map-Reduce; Semantic analysis; Text mining; Spatial	**** Infrastructure services:*** Hardware; Operating System; Storage; Security; Network; Connectivity; Virtualization; Management.	

- Big-data management, advanced analytics & machine learning: To enable deep business insights and business intelligence by integrating IoT big-data processing and advanced analytics utilizing machine learning and business rules for decision making.
- Big-data enterprise applications: To permit the integration with enterprise and IoT big-data analytics applications in order to ensure the development and deployment of enterprise applications with low complexity, authorization, data security and data governance.

Our proposed architecture is based on open standards to support and integrate different devices and platforms in order to help energy markets to bring solutions quickly. Every enterprise can freely select its IoT technology protocols. The advanced smart-metering systems can be integrated with IoT platform and big-data cloud services ensuring advanced smart-meters data management and predictive analytics. The big-data analytics can facilitate the integration and deployment of various utility applications.

V. CONCLUSION AND FUTURE WORK

Big-data will be more and more a complex distributed data environment with dynamic acquisition necessitating a strong orchestration of the inter-process and its dependencies. Software enablement for enterprises will make a sense of big-data orchestration by providing not only an available storage system but also to integrate the big-data analytics in their concerning business framework. In this paper, we have proposed an open IoT enterprise platform for smart-metering applications focused on allowing an open access to big-data and cloud services. This platform seems to be a digital enterprise platform offering both specific services deployed in the cloud and external open services offered by big-data to improve and satisfy the customers' requirements. Furthermore, several issues, such as scalability, flexibility, interoperability and availability should be considered in this digital enterprise platform. As a future work, we will study some aspects of our proposed architecture, such as multi-vendor interoperability, low cost, low power consumption and security, which require considerable attention from energy communities.

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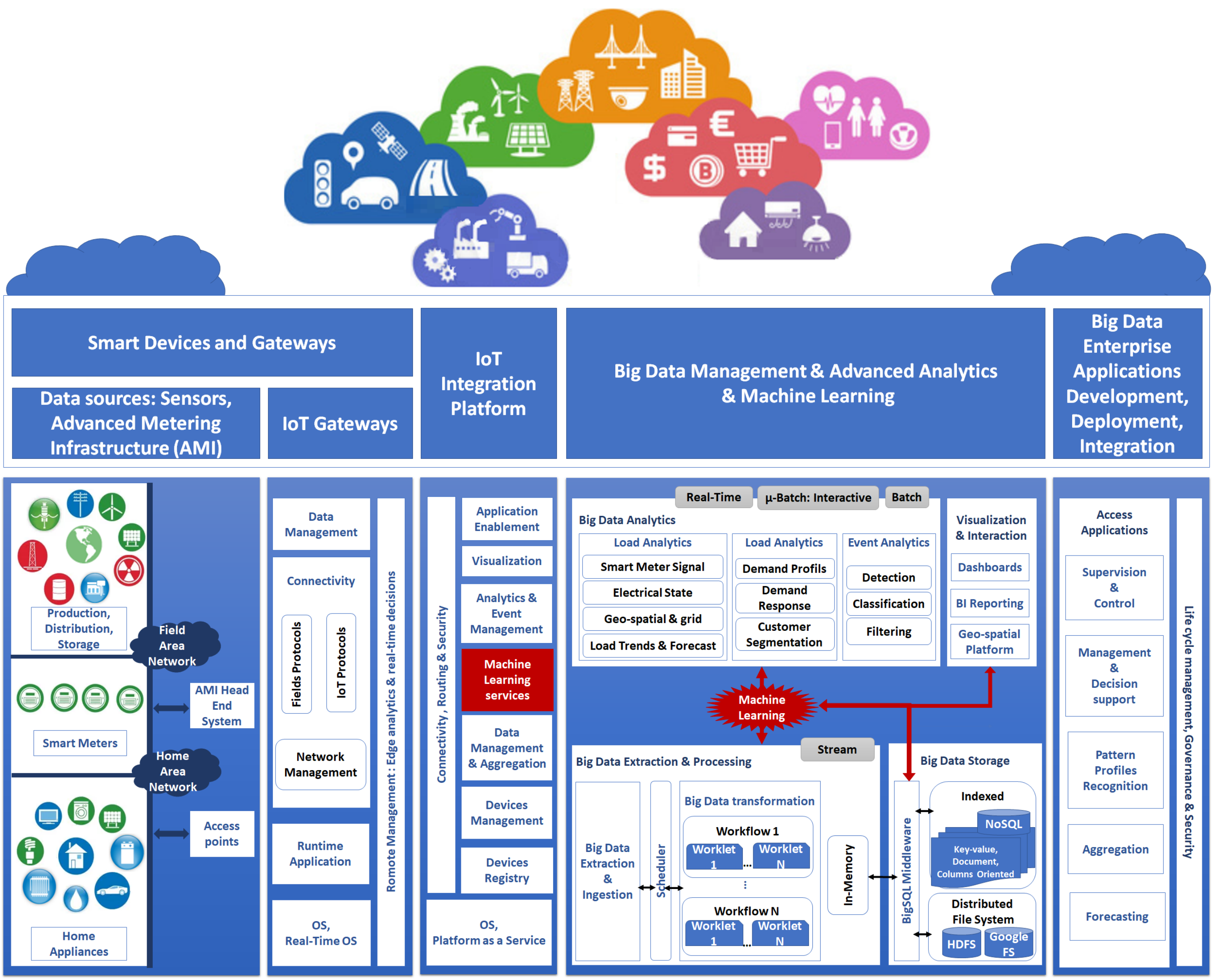

Figure 3. Detailed description of the suggested IoT big-data digital enterprise architecture based on smart-metering services

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