

Internet of Things-Specific Challenges for Enterprise Architectures: A Cross-Case Comparison of Explorative Projects from the smartPORT Initiative

Full Paper

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Abstract

By implementing new technologies, enterprise architectures and their respective models are subject to change. Current changes of the enterprise architecture are often driven by the IT megatrends. In this paper, we analyze six explorative projects from a logistics company that implemented Internet of Things (IoT) technology. Our analysis focusses on a cross-case comparison of the project specific enterprise architecture (EA) models based on an integrated model. The models and its meta-model were developed in an action design research based project. The results show that in-depth insights into IoT projects and a unified way of modelling support the process of analyzing the current architecture and deriving recommendations for the to-be architecture. Furthermore, we identify and discuss five IoT-specific EA challenges for future integration and roll-out projects and provide preliminary suggestions for overcoming them.

Keywords

Enterprise Architecture, Internet of Things, Port, Implementation, Roll-out, Challenges

Introduction

Enterprises continuously adapt their strategy, processes, services and IT systems to external and internal challenges. One stream of challenges arises from the so-called IT megatrends. Beside mobile technology, cloud systems, social media and big data, the Internet of Things (IoT) – often called smart technology – is one of these IT megatrends (Gartner 2014). Today, many industries seek to adopt IoT technology for improving transparency across business processes, for enhancing the efficiency or as a basis for developing new products and services (Gubbi et al. 2013; Montreuil 2011). With the changing strategy, processes, services and IT systems, the enterprise architectures (EA) undergo a permanent and often heavy change process. This implies the need for adapting the EA models, tools and processes accordingly (Zimmermann et al. 2015). From a research perspective, major changes in practice are relevant as they might challenge established EA approaches, frameworks and meta-models. However, detailed descriptions, analyses and reflection on the impact of IoT on EA based on empirical data are scarce so far. Insights about the architectural implications of exploratory IoT projects could help to support the planning process for future roll-out activities. Based on these assumptions, we developed the following research question: Which IoT-specific architectural challenges arise for the integration and roll-out after finishing explorative IoT-projects?

To answer this question, we conducted an action research based project together with the Hamburg Port Authority (HPA). The HPA started the smartPORT initiative a few years ago. As a major part of this initiative, IoT technologies were explored regarding possible usage scenarios within the harbor of Hamburg. The paper is structured as follows: After considering related literature, we describe the context of our research and the methodological approach. In the next section, we describe six IoT projects from the smartPORT initiative and their respective EA models. Based on these descriptions, we present an integrated EA model as a starting point for a cross-case comparison, in which we identify and discuss IoT-specific architectural challenges. The paper closes with a conclusion and an outlook.

Related Research

Over the last 30 years, the modelling of enterprise architecture shifted from a niche topic to a well-researched field (Kappelman et al. 2008; Simon et al. 2013). As change in organizations today is also driven by the impact of IT innovations, EA approaches and models have to adapt to new challenges like cloud computing, mobile computing, social networks or the increasing interconnectedness with external partners and customers. Hence, the EA models and meta-models need to be modified accordingly. Meta-models play an important role, as they ensure “semantic rigor, interoperability and traceability” (Saat et al. 2010). Though existing meta-models like TOGAF (The Open Group 2011) provide a high level of abstraction, new technologies might impose the need for adapting them to new requirements (Zimmermann et al. 2015). As one of the IT megatrends, IoT technologies are expected to be one of the forces that will lead to changes of IT infrastructures, processes and business models. By using a large number of small sensors and computers, the physical world and the “information world” are getting directly interlinked. Companies from diverse industries are seeking to implement IoT devices (Bassi et al. 2013; Bitkom et al. 2016; Gartner 2015; Gubbi et al. 2013). Often, they start with identifying use cases for IoT systems that match the company’s needs. Though the implementation of a large number of new devices and the changing processes are expected to impose severe changes to the enterprise architecture, research on the relation between EA and IoT is scarce so far.

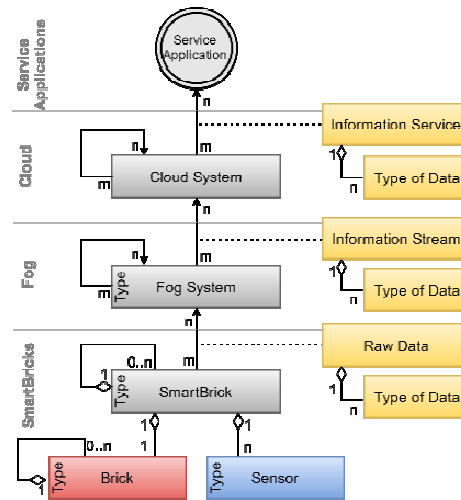


Figure 1. Extended Meta-model for the IoT-related EA at the HPA

In a previous paper, we published an extended meta-model for capturing IoT in extended EA meta-models (Schirmer et al. 2016). A fundamental concept that we use in this meta-model is called “smart brick”. This is a combined element, which consists of a brick and a sensor. A brick describes a physical element of the harbor’s infrastructure (such as streets, bridges, quay walls, etc.). As each brick is usually constituted out of a hierarchy of (sub-)bricks, a brick is made smart by adding at least one sensor to it or to one of its sub-bricks. The proposed meta-model comprises IoT specific layers with smart bricks and fog systems (each on a type level) and their relations to layers of cloud systems and service applications (each on an instance level). Fog systems (such as section controllers for induction loop sensors) aggregate and transform raw data (Dastjerdi & Buyya 2016). The meta-model classifies the related interfaces between elements of each layer in raw data, information streams and information services (see Figure 1).

Context: the Hamburg smartPORT initiative

In 2012, the Hamburg Port Authority (HPA) launched the smartPORT initiative. This initiative consists of two sub-initiatives: smartPORT Logistics (SPL) and smartPORT Energy (SPE) (HPA 2017a; HPA 2017b; HPA 2017c; IAPH 2017). While the SPE projects aim at reaching sustainability goals, the SPL projects strive for optimizing the logistic processes in the harbor mainly by adopting smart technologies. The SPL projects were carried out together with several partners from industry. Most of the projects had an innovative and pilot character. The results of these projects were presented at the IAPH 2015 (29th World Ports Conference) in Hamburg (IAPH 2017). The SPL projects strive for increasing “the efficiency of the port as an important link in the supply chain” (HPA 2017b). As the space in the harbor of Hamburg is limited, the HPA needs to manage the existing infrastructure in an efficient manner. The goals are to establish an “intelligent infrastructure” and to optimize “the flow of information to manage trade flows efficiently” (HPA 2017b). In several sub-projects, the SPL projects explore the use of smart technologies for better managing the traffic on roads (smart road, port road management system, depiction of the traffic situation, parking space management), rail and water as well as for predictive maintenance scenarios (intelligent railway point, smart maintenance for bridges) (HPA 2017b).

Our research project at the HPA started, after the results of the exploratory IoT projects were presented at the IAPH. In this phase, the HPA had to evaluate and further integrate the projects. The HPA also had to decide, which projects will be transformed to a productive mode and which partners and vendors will be chosen for this mode. Furthermore, information about the projects had to be spread within the organization. We assume that such a situation is typical for innovative and exploratory IoT projects. During the exploratory phase, the focus lay on demonstrating the feasibility of adopting a certain IoT system. A complete alignment with the existing EA might be skipped due to limited budgets and unknown outcome. Proceeding in such a way is well known in IS research and captured by the term “bricolage” (Ciborra 1994). In this paper, we look at this phase mainly from an enterprise architecture viewpoint with a focus on the challenges that arise for integration and roll-out after the explorative projects ended.

Methodological Approach

This research project was carried out as an action design research (ADR) project according to Sein et al. (2011). It started with the problem of the HPA to integrate the results of the IoT projects in its existing enterprise architecture model and tool during the consolidation phase (principle 1: practice-inspired research). We categorized this as an IT-dominant BIE (building, intervention and evaluation) type of ADR project. However, during the project we learned that the HPA wants to use the EA model and visualizations based on this model for communicative purposes with the organization as a part of the digital transformation process. This would lead to a second, organization-dominant BIE task, which will become more relevant in the future. Our research team consisted of two senior researchers and several graduate students. The research team was interested in exploring whether EA meta-models – as a fundamental type of artifacts for EA research – need to be changed and adopted if companies integrate IoT systems into their EA (principle 2: theory-ingrained artifact).

A first analysis of the existing literature and discussions with the EA tool vendor lead to the conclusion that – regarding both problem formulations – scarce information is available in publications as well as in practice. These findings encouraged us to start a cooperative project for developing the required EA model and meta-model. During the ADR project, mixed teams (researchers and practitioners) conducted 17 informal interviews (with project managers, internal and external experts and other stakeholders within the HPA), analyzed documents about the six projects and the existing EA as well as the EA tool and the EA model. The projects were chosen along the following criteria. They belong to the sub-initiative SPL, represent important and diverse use cases and apply – and this was most important – a large variety of different, newly installed sensor and actuator types. This variety should allow us to identify a broader set of architectural challenges as well as cross-project relations. To discuss the intermediate results and for planning next steps, regular workshops were established as well as less frequent review meetings. During these meetings, researchers and practitioners evaluated the applicability, coherence and correctness of the related artifacts (models and meta-model) (principle 4: mutually influential roles).

In several iterations, the EA models for each IoT project were evaluated and refined and the EA meta-model was co-developed and evaluated (principle 3: iterative reciprocal shaping and principle 5: authentic and concurrent evaluation). Based on the insights from the interviews and the document analysis, the

project team decided which information about the IoT projects should be captured, held and managed in the EA model. The team's decisions were also driven by the goal of using concepts for the EA model that are easy to understand and to communicate while also being comprehensive and precise. The intermediate results were regularly evaluated in the above-mentioned meetings. They were also discussed at a practice-oriented conference to gain further general feedback from practitioners from different domains. Due to the cross-project comparison, we also achieved a first step of generalization from the individual projects. Additionally, we also take first steps for generalizing from the HPA case at the end of this paper (principle 7: generalized outcomes). Out of the four ADR stages, we passed through an extended and reflected problem formulation (stage 1), an ongoing intertwined BIE (stage 2) and reflection and learning (stage 3) and started with the formalization of learning (stage 4).

EA Model “Slices” of Six smartPORT Projects

In this section, we will briefly describe six projects that were part of the smartPORT initiative and present architectural models of their main elements. These models are only “slices” of a future enterprise architecture incorporating IoT. Currently, they focus - according to the projects' explorative nature - on the technical layers. In the future, they will be extended to also capture more elaborated business layers.

Project “Traffic Analysis and Forecast”

This project was launched to enhance the ability of traffic prediction and forecasts for the harbor area. Previously, the only system to analyze traffic flowing through the harbor area was a commercially available system that was developed externally but operated internally. Based on best practice, the Traffic Analysis System (TAS) utilized only pairs of inductive loops, as standardized under the German TLS, an established standard originating from governmental regulation and harmonization. The TAS's extensive standardization allowed for a considerable level of reliability regarding the accuracy of measuring traffic flow, yet it proved to be quite inflexible in terms of incorporating new types of sensors or attempting to produce traffic forecasts. The new traffic simulation system (TSS) represents an integrated approach for traffic estimation by both incorporating data gathered by a diverse yet unfinalized variety of sensors (qualitative enhancement), and by simulating actual traffic flow based on the gathered data to enable traffic forecast generation (functional enhancement). Therefore, a large number of induction loops was already deployed throughout the harbor area and connected to section controllers prior to this project.

In addition and akin to induction loops, cameras were implemented to accomplish similar tasks, such as counting the number of passing vehicles and their speed differentiated by classes of vehicles (cars, trucks and other). Yet, cameras are quite different from induction loops, as they are commonly subject to environmental factors (e.g. fog, rain) and also because they are mobile unlike an induction loop embedded into the road. Another introduced “sensor” is able to identify a small part of the passing vehicles at several positions in the harbor area, thus measuring actual travel times. This type of data, as well as the data supplied by an external provider, a large German automobile organization, is incorporated into the simulation by breaking down classical road segments into smaller segments and linking them to actual geographical positions. For various reasons, both traffic systems were coupled in such a way that the old system can be seen to act as a gateway from the new system's perspective. In this way, the old system became (without an intentional strategic choice) a hub system for gathering and storing all traffic-related data (while using only one source (induction loops) itself) and exclusively offering information services related to road traffic. The information about the current and expected traffic situation is leveraged by several service applications. Today, the information is used in external monitoring services displaying traffic guidance information. Additionally, the information enhances the functionality of an internal monitoring system and the data is used by a new complex application related to vehicle navigation and logistics chain management. Further on, the data are provided to a nationwide traffic analysis platform.

Our modeling captures the project's achievements in terms of smart brick types, fog and cloud systems and their connections. Three different smart brick types indicate the use of different sensors. In this case, the bricks are road segments (a logical net on top of the concrete roads), which is not used in a uniform way, but exhibits different granularity depending on different sensor types being built in. The external data source stems from another cloud system. Apparently, some smart bricks require fog systems (e.g. induction loops) while others do not, which is captured in our model. Details of the different raw data, information streams and information services are discussed in Schirmer et al. (2016).

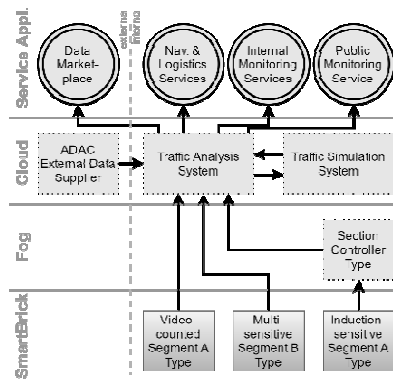


Figure 2. EA Model of the Project “Traffic Analysis and Forecast“

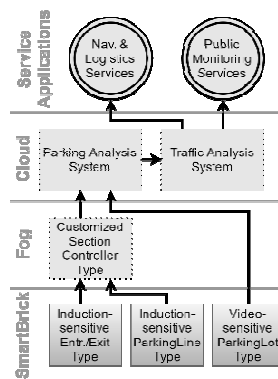


Figure 3. EA Model of the Project “Smart Area Parking”

Project “Smart Area Parking”

A significant part of the traffic within the port area is related to finding a parking lot. The smart area parking project is an explorative project to evaluate technologies for accounted parking lots. Such parking lots communicate their degree of occupancy. Given the common practice of disconnecting the trailer, for example to deposit an empty cargo container, which is either picked up later or collected by a colleague in another truck, the task of counting the amount of unoccupied space on the parking lot is more complicated than counting license plates. The resulting operational system of the smart area parking project uses therefore several strategically placed induction loops (at the parking lot’s entrance/exit as well as on parking lines) and additional video cameras that allow generating an accurate level of occupancy of the considered parking lot. Regarding our modeling we had to consider the following: Unique to this project is the fact that an often-applied type of sensor is used in a new and innovative way. Induction loops are implemented on most road intersections and usually generate data like the number of passing vehicles and their speed. However, in the smart area parking project, however, the generated raw data is interpreted in a completely different way by the attached fog system. Although a regular section controller (standardized for traffic management) was employed, the system was customized with additional, non-standard capabilities. We capture these different interpretations of raw data by (1) introducing different smart brick types being composed of the same sensor type but different (logical) location types as parking entrance/exit and parking line, thus displaying the semantic difference in the usage of sensor data, and (2) distinguishing the interpreting fog systems, which are modelled as “customized section controller type”.

Project “PrePORT Parking”

Since the space within the harbor area is confined, it is beneficial to park as many trucks as possible outside of Hamburg. This contradicts the truckers’ general preference, as they need to reach their destined terminal reliably at a fixed point of time. To circumvent delays due to congestion, truckers currently try to park as close to the terminal as possible. Building upon the “traffic analysis and forecast” project, the PrePORT Parking project introduces a new scheduling scheme. Trucks are assigned to parking spots at parking lots outside of Hamburg and notified about their ideal departure time to reach their destination in time. To give further incentive to the truckers, PrePORT Parking allows them to place reservations, reducing their time expenditure on finding a suitable parking lot. Also, PrePORT Parking is planned to be part of an integrated system for scheduling the logistical chain within the port of Hamburg. In order to perceive the current state of the parking lot, cameras are employed in two ways. Firstly, vehicles entering the parking lot are identified to either route them to their lane, if they placed a reservation, or to send them to the enrollment terminal. The other cameras are leveraged to acquire information about the parking lots occupancy. To reflect the distinct usage, the video camera sensor type is employed by two smart bricks, as depicted in Figure 4. Furthermore, each surveying camera is directly attached to an anonymizing unit to circumvent privacy issues arising from the vast number of surveying cameras. The interpretation and parking lot logic is implemented by means of the depicted Parking

Guidance Platform, which is locally deployed at the PrePORT parking lot. The coupling with other HPA systems is yet quite loose, as it only requires a connection to traffic forecasts and publishes the number of available parking lots to the HPA's main traffic analysis system. Instead, the offered services are directly using the parking guidance platform, namely controlling video boards (public monitoring), offering enrollment and services necessary to operate the parking lot (internal management services, operator analytic services).

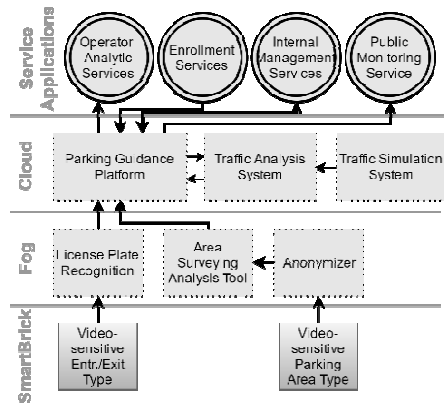


Figure 4. EA Model of the Project “PrePORT Parking”

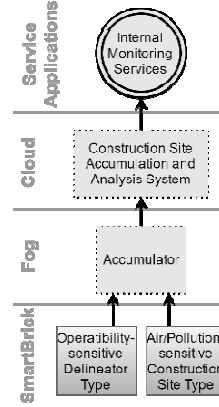


Figure 5. EA Model of the Project “Smart Tag”

Project “Smart Tag”

As an effort to reduce preventive maintenance, the smart tag project was launched, which is strongly related to construction site delineators. Delineators are used to guide traffic in road construction sites and are required to have a shining (operative) light on top of them. Within the project, an integrated sensor for these delineators was developed, allowing traffic operators to view the battery status of the delineator’s lighting as well as their position and whether the delineator was tipped or otherwise disturbed. The delineators’ data is accumulated per construction site level, forwarded through wireless mobile networks and displayed in an internal monitoring system. Unique to this project is the utilization of composite sensors. A composite sensor is an integrated sensor, which combines multiple sensors without making each sensor’s raw data stream externally accessible. Instead, an aggregated information stream is published. Considering the cost of long-range data transmission, both hardware costs as well as energy cost for the battery, the smart delineator sends its data to a local gathering unit (accumulator), which then forwards the aggregated data to the dedicated cloud system. Furthermore, this project introduces movable smart bricks. The composite sensors are attached to delineators which will later be used at different construction sites. This fact is captured in a brick attribute. The project contributes also to the strategic energy area in sensing pollution at the construction sites. Overall, the system is not used operatively yet and its data is only displayed in an internal monitoring service.

Project “Smart Road”

The smart road project was introduced to implement and evaluate several innovative IoT technologies related to smart infrastructure. Following the overall goal of reducing maintenance expenditures by making maintenance more predictable, several sensors were attached to a movable bridge. Whenever a ship passes the observed bridge, the roadway has to be lifted vertically, introducing a certain amount of stress to the affected bridge elements. The impact of bridge movement as well as the weather’s impact are measured by gauging the material strain and tilt angle of essential bridge parts. However, the wide-spread distribution of the involved sensors led to the decision to collect and merge their data wirelessly over an IP-based, meshed wireless network. As depicted in Figure 6, the meshed network has an entry-node (gateway) and an exit-node (root), while the number of involved relaying access points varies. Since the gateway accepts only IP-based traffic, most sensors (vibration, strain and tilt) require an additional fog system to transform the continuous raw data stream into IP packets and to decrease the amount of data sent, as the introduced wireless network offers only limited resources shared between all participants

(shared medium). Another aspect of the smart road project was to reduce energy consumption by controlling the road illumination in an on-demand fashion. To accomplish this, each lighting post hosts an infrared camera and is separately switchable by the closely located section lighting controller. The switching logic was sourced in a separate controller to allow for tracking mechanisms, e.g. turning on one or more lights in the pathway of a cyclist while saving energy by turning off the lights in the opposite direction. The switchable lamppost was modelled as a smart brick, though it uses an actuator instead of a sensor. The proposed smart brick logic copes well with this issue. The systems of the smart road project are not used operatively so far. The data is accumulated and visualized in a dedicated internal monitoring system.

Project “Smart Switch”

This project is also devoted to preventive maintenance, here regarding rail traffic. Railway switches are naturally subject to attrition, mainly adhesive wear. They need to be greased regularly, because a failing switch might not be bypassed on other rails, thus impacting many other railway sections and trains. To reduce the expenditure on excess greasing while still reducing the risk of switch failure, the Smart Switch project introduces a system to estimate the condition of a railway switch. Several switches were chosen to pilot the technology and allow an evaluation of the employed technology. Generally, the condition is estimated by gauging the force needed to slide the switch into the opposite position, which is specifically achieved by both a dynamometer and an ampere meter at the electromotor. This allows maintenance staff to service switches on demand and to schedule switch maintenance to a convenient time, when there is no or very few traffic at the worn-out switch. As shown in the model, the data of multiple sensors is gathered per switch at the associated signal box. The received data is then analyzed, enriched and transcoded in order to be transmitted to an internal monitoring system operated by the HPA.

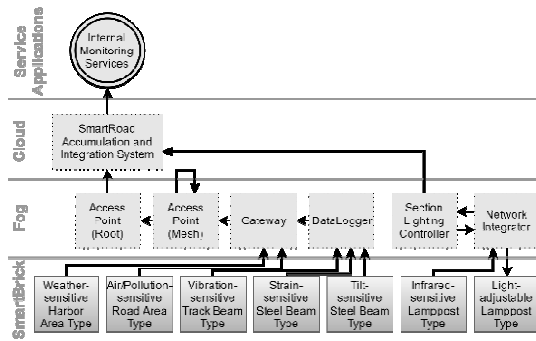


Figure 6. EA Model of the Project “Smart Road”

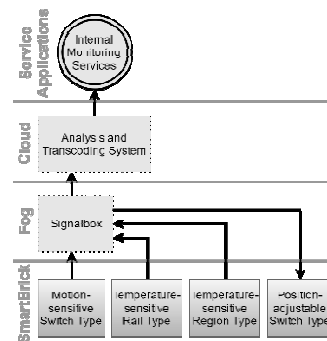


Figure 7. EA Model of the Project “Smart Switch”

Results: IoT-specific Challenges based on a Cross-case Comparison

Building the Integrated EA Model

The individual project-scoped EA models presented above were developed after the explorative projects at the HPA were finished. They contribute to the different tasks of the consolidation phase, which typically follows innovative projects and underlines the role of enterprise architecture. Since these models were developed using the same co-developed IoT-specific meta-model they are similarly structured following a recurring pattern. Each project typically employs one or more smart brick types, mostly sending raw data to fog system types for accumulating raw data and applying simple transformations feasible for resource-limited systems. The resulting semantically enriched information streams flow towards purpose-specific accumulating cloud systems, which leverage these information streams to develop purposeful information services. Hence, the models support comparing across projects and building of an integrated model.

Thus, we assembled the models into an integrated EA model (see Figure 8) following guiding rules: (1) Due to the underlying meta model, we kept the layered structure in the integrated model. (2) We composed the integrated model from the individual project EA-models as building blocks/“slices” while depicting their interrelationships in the upper layers (cloud and services). (3) We positioned these “slices”

according to a staged concept of “closeness”. If projects exhibit existing interrelationships – e.g. sharing the use of the same cloud system – the project EA slices are positioned close to each other. If projects are planned to be integrated in the future, they are positioned nearby. Furthermore, we used areas (traffic, maintenance, energy) and domains as general ordering principles (e.g. traffic on road, on railway). (4) We separated internal from external data sources or services. This distinction leads to a general research questions how to integrate IoT external sources or services into an extended or business ecosystems EA (Drews & Schirmer 2014).

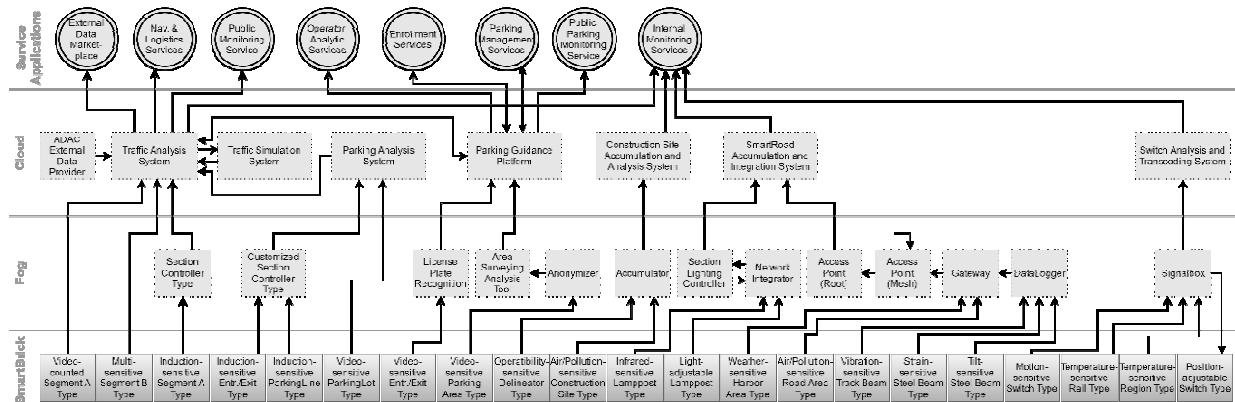


Figure 8. Integrated EA model

Challenge 1: Increasing Integration Demands for Integrated Analysis

The scope of the projects was straightforward as each project served a single purpose and was developed together with different hard- and software vendors. Hence, after the explorative phase, the projects are mostly unintegrated. Each of the projects uses several newly installed smart brick types for delivering data to certain information services being unique to each of the projects. However, by successively building up the smartPORT in several roll-outs, we see indications that integration demands will increase. To fully exploit the potentials of the installed smart bricks and to overcome existing limitations of some projects, a deeper integration is necessary. In some cases, if the introduced smart bricks can serve more than a single purpose, full usage would require: (1) The introduction of more advanced or possibly different data accumulation systems by using data sources from the same smart brick types for different IoT services (e.g. smart tag systems could also provide data about pollution over time), or (2) the need for advanced data accumulation systems together with a tighter integration of the systems for additionally evaluating and accumulating data sources from other smart brick types for existing, yet higher quality IoT services (e.g. smart tags are planned to inform traffic analysis about daily road works). To support this kind of integration analysis, the EA model should be extended by including “IoT potentials”, information and attributes about not yet realized but possible data and system extensions at the smart brick, fog or cloud layer. On this basis, IoT-specific analysis patterns for extracting these potentials could inform decisions about the future development stages and enhance a better exploitation of existing sensor data.

Challenge 2: Managing New Forms of IoT-specific Heterogeneity in EA

The integrated EA exhibits a large range of different smart brick types. They differ in purpose and regarding their brick and sensor type components. Thus, and due to vendor specifics and missing standards, they contribute to a new form of heterogeneity in enterprise architectures. To reduce this “new” heterogeneity, the as-is EA can be analyzed according to the following aspects: (1) Different sensor types may serve the same purpose, i.e. their distinct data may be interpreted in ways that yield similar information. E.g. cars passing a certain location can be “sensed” by leveraging induction loop data as well as evaluating a camera’s video output. Analysis should lead to decisions whether the use of different sensor types is intended or which sensor types should be more widely deployed. (2) The same sensor type may serve different purposes. For example, video cameras may be leveraged to sense passing cars, recognize license plates or to measure the amount of free space on a parking lot. Hence, standardized uses

of sensor types across different smart brick types proved to be a good decision so far. (3) Same sensor types might be applied from different vendors. This kind of heterogeneity should also be reduced.

Insights from analyzing the smart brick layer might also inform roll-out strategies and IoT extensions. Smart brick types make structured roll-out “walkthroughs” possible by type-wise analyzing the existing status of the corresponding smart bricks. E.g. determining the actual degree of smartness of a certain brick type, or determining the percentage of already realized smart brick instances of a certain type. Based on this analysis, future roll-out stages can be designed by using a set of roll-out criteria. These criteria might address different brick properties, future usage scenarios, environmental dimensions, available energy or network coverage. The type-wise applied criteria should be documented in the EA model.

Challenge 3: Non-uniform Architecture on the Fog and Transmission Layer

On the fog layer, the integrated EA shows a non-uniform architecture, i.e. some of the smart bricks do not use fog systems, but most of them do. Fog systems usually aggregate raw data from sensors close by and transmit them to cloud systems. At present, the existing fog systems exhibit a large variation in functionality, from mere gateways transmitting nearly unfiltered incoming data, over vendor specific closed systems dedicated to certain sensor types, to general-purpose systems providing standardized operating systems on top of which aggregating systems for different raw data streams can be installed and combined. Future development and further analysis should lead to guidelines which fog system types should be the preferred ones and which type of exceptions for which sensor types might be allowed. Still, the actual transmission type is mostly cable-based and not yet wireless-based. For future roll-outs, this layer also needs careful selection of fog systems as well as transmission kinds. New tests on wireless technologies (WLAN, LoRa, LTE, 5G, UMTS, Bluetooth, MFC, etc.) will lead to guidelines for special harbor areas and might influence future contracts with external partners.

Challenge 4: The Need for Overcoming Vendor-specific Cloud Heterogeneity

On the cloud layer, the integrated EA model reveals that currently only three of the explorative projects are exchanging information. Yet, with further IoT extensions their number will increase. Already in the as-is EA, two aspects were identified which we assess as typical for connected cloud systems. First, systems use redundant data (partly from same sensors) for their accumulation, while applying local lists for resolving sensor positions (a second type of redundancy). Second, one system serves as a hub for gathering and storing data from different smart brick types. Based on this analysis, we argued in a previous publication for a standardized to-be architecture of the cloud layer that should incorporate three different components: a common data acquisition and conversion component (for all accumulation systems), a data fusion and calculation component with different accumulation systems and a common information-provisioning component (Schirmer et al. 2016). These components substitute vendor-specific built-in acquisition and provision components. Furthermore, the data acquisition and conversion component resolves identifiers of divers sensors by using a unique smart brick identity resolution management component (Schirmer et al. 2016).

Challenge 5: Cross-layer Analysis for Tracing Origins of Service Failure

The service application layer shows several special purpose services as well as common monitoring services. These can be distinguished in external ones and an integrated internal one allowing to merge multiple sources of information. With a focus on services at the top layer, the interconnections across the layers get to the foreground together with “typical” EA queries. For several reasons, e.g. to inform future user about IoT-services or in case of malfunction of sensors, it is important to easily identify the origin of data used by a certain service. E.g. which smart brick type contributes to which information services. Currently, our modeling does not support this tracing since it does not capture this level of granularity. Different information streams are used in cloud systems to provide several information services, hence modeling more detailed cloud components would be needed instead. Also, dealing with more complex application systems is still under discussion. A revision of the meta model should capture these requirements.

Conclusion and Outlook

In this paper, we analyzed six projects from an IoT initiative in a port by using simplified EA models. Our paper contributes to the fields of enterprise architecture and IoT research in three ways: First, we identified five IoT-specific challenges for the enterprise architecture that arose after the explorative projects ended. These challenges might also arise in other enterprises that explore IoT and think about the forthcoming integration and roll-out activities. Second, we developed some preliminary recommendations to overcome these challenges. Third, we provided case descriptions that help to better understand the suggested meta-model extensions (smart bricks, fog layer) we developed in the project. Our research is limited by the focus on a low number of projects. However, it took a long time to gather the data from the empirical context at a level of detail that is sufficient for building the appropriate models and to discuss the models with the people at HPA. The results are also limited due to the focus on only one sector (port / infrastructure / logistics). A cross-industry analysis could provide richer insights into architectural implications of IoT projects. For future research, we see the need of generating more case studies and EA models from other enterprises and industries. This will allow comparing the challenges and requirements of capturing IoT in EA frameworks (like TOGAF), meta-models and models. In addition, privacy and security aspects will require special attention in IoT-related EA meta-models and models.

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