A Holistic View of the IoT Process from Sensors to the Business Value

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Abstract: Internet of things (IoT) is the focus of research, and industries are investing heavily due to potential benefits of IoT in various fields. This paper provides a holistic view of different phases in IoT covering all phases from sensor data collection to the generation of business value. In this paper, we propose to use the proven Six Sigma methodology for IoT projects. We describe each phase using a structured approach. We discuss the consequences of each phase while selecting the phase as an entry or starting point. We use predictive maintenance as a use case to demonstrate the practicability of our IoT process. Using these insights, IoT project managers can identify required activities and competencies to increase success probability. In the end, we summarise the paper findings and highlight the future work.

1 INTRODUCTION

Internet of Things (IoT), digitalization, are the terms which got popularity due to potential benefits in various fields. Daily use products or things considered useless so far from digitalization perspective are becoming valuable and are used to improve services and to generate new offerings in those areas. Some of the examples are from manufacturing industry (digital manufacturing or industry 4.0 terms are used in this context), smart city, agriculture, and livestock areas. IoT enables organisations and customers to make improved decisions based on the data gathered directly from the end devices or fields.

Due to the popularity of IoT, organisations need to innovate faster and have to digitalise their processes to take the benefit of digitalisation (Lucas Jr et al., 2013). Organisations are under a constant threat to be left behind if they do not follow or adapt the required changes or the trend. Hence it is their focus.

On the one hand, organisations are already using sensors and IoT devices in traditional products (things, machines, and equipment), to sense the environment for the overall benefits. On the other hand, such projects generate an enormous amount of data (big data) and can be used to improve the existing services or to offer entirely new services or business models.

However, management of such project is difficult due to higher complexity, heterogeneity, cost explosion, blurred boundaries between the physical and virtual world and inter-disciplinary within and outside organisations. The majority of the projects are not successful (other projects have a higher risk of failure (Lee and Lee, 2015)).

Existing approaches only touch part of the problem or specific use cases and do not provide a holistic overview of different phases required for the IoT project. So, it is necessary to have a roadmap for the IoT project with clearly defined phases and its descriptions.

In this paper, we address the issue of isolated parts, and our approach is not limited to a single case in a specific domain. We discuss why the existing data mining and organisational change management strategies are not fully transferable or applicable to the IoT projects.

We provide a complete overview of IoT process covering from the business value perspective for the organisation to the sensors. We describe each phase using a pre-defined structure naming, e.g., challenges and disciplines, and the analogy of our process phases with the six Sigma sub-methodology phases. To show the practicality of IoT process, we show how our contribution can be used in a case study scenario namely predictive maintenance which combines IoT and Industry 4.0.

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2 RELATED WORK AND DISRUPTIVE ASPECTS OF IoT

To handle an IoT project, which extends within different departments in an organisation and also across organisations, a methodology, process or framework is required to manage and coordinate throughout the IoT landscape. There are already different methodologies, frameworks, and processes discussed in the literature that are considered as a candidate for IoT projects. Few to name are 5S (Osada, 1991), Kaizen (Imai, 1986), Six Sigma methodologies (Smith, 1993), Kotter model (Kotter, 1996), SEMMA (sample, explore, modify, model, and assess) (Azevedo and Santos, 2008), CRISP-DM (cross-industry standard process for data mining) (Shearer, 2000), and KDD processes (Fayyad et al., 1996; Lodhi et al., 2008).

However, these methodologies have shortcomings, for example, methodologies and frameworks like CRISP-DM, KDD, SEMMA are more concerned with the data mining process and do not include the implication of business applications, business models and scarcely describe the effect of one phase on the other. Others, such as 5S, Kotter model, are very abstract and rather suitable with the view to workplace organisation or organisation change.

There are numerous works (Swan, 2012; Bonomi et al., 2014) who address some parts of the IoT landscape. Some of the works discuss only the IT perspective and others focus on the analytics perspective and neglect other parts. There is a considerable amount of literature which discuss IoT from the applications and future trends perspective (Curran and Curran, 2014; Khan and Turowski, 2016b; Crowley et al., 2014; Khan and Turowski, 2016a). In (Swan, 2012), the author reviews the eco-systems for IoT. It covers only a part of the whole landscape. In (Bonomi et al., 2014), authors propose a hierarchical distributed architecture and use a fog platform for analysis.

We argue that there are other factors which are interrelated and have effects on other parts of the IoT project or landscape. We describe these factors and phases and elaborate the whole process with the help of a case study example.

3 AN ANALOGY OF THE IoT PROCESS MODEL

For our IoT process, we advertise that we can use Six Sigma methodology. Six Sigma methodology (Smith, 1993) was initially proposed to remove defects and improve quality in 1986 but is now often used to measure improvement in IT process execution and services (George and George, 2003; Antony, 2006). Six Sigma methodology is the best candidate to remove defects, and we can use it for IoT project problems described earlier. We propose to use Six Sigma submethodology DMAIC because of its success in other industries, and it has an analogy with the phases in our process model. The sub-methodology DMAIC is an acronym of the following steps, namely define, measure, analyse, improve, and control.

The brief description of these steps of DMAIC methodology is as follows. In the define phase, we define what is the problem; in the measure phase, we find the areas of a problem; in the analyis phase, we analyse the problem; in the improve phase, we take necessary steps to remove the problem; and in the control phases we control or check whether the problem is removed.

Our IoT process model consists of the following phases: sensors, pre-processing & analysis, business applications, and business value. The detailed description of these phases is described in Section 4.

The methodology steps of DMAIC have an analogy with the following IoT process phases.

Define: This phase has an analogy with the business value phase. In this phase, we define the scope and objective of the IoT project. General questions in the phase consider the nature of the problem or the aims we want to achieve with this project. As this phase is on the strategical level, we also identify the possible stakeholder of the project, their roles, resources, and what are the general requirements.

Measure: The sensors phase from IoT is associated with this phase of methodology. In this phase, data or measurements (raw data) are collected from the sensors. We decide what kind of sensors we need and how frequently measurement should be done.

Analyse: This phase is inline with the analysis phase in the landscape. In this phase, we perform the analyses based on the data collected in an earlier phase. We get insights from this phase which tell about the behaviour or exhibit specific patterns.

Improve and Control: This is associated with business application phase in the landscape. This phase describes the necessary steps to improve the overall situation or how we can use the outputs of other phases to improve business applications or business processes of an organisation are. In the control phase, we take measure to monitor the overall progress or performance of the cycle.

We depict our process model phases and associated DMAIC steps in Figure 1. The organisation's vision serve as an input for the IoT project, and after

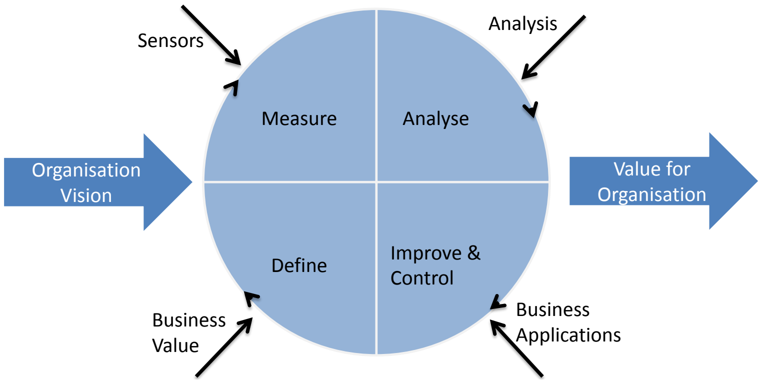

Figure 1: Analogy of IoT landscape with DMAIC process.

the successful run, the value achieved from the project is considered as an output. Due to the nature of IoT projects and the characteristics described earlier, the whole process is iterative.

4 IoT PROCESS PHASES

In this section, we elaborate the different phases of the IoT landscape. We use the following structure to describe different phases of our IoT landscape. The structure is quite simple, self-explanatory regarding the names, and consists of following parts, objectives and scope, challenges and requirements, tools and methods, disciplines, interfaces, and influences on other phases. As shown in Figure 1, it is an iterative process, so objectives and operations can be re-aligned iteratively to optimize what is needed or possible in current settings. In the following, we describe the phases of IoT process.

4.1 Sensors:

In this phase, we sense the environment and measure the surroundings. These measurements of the surrounding can be properties of technical devices, environmental situations or even human activities which are the main focus of monitoring. However, there are other types of sensors that are also used in IoT environments to receive executable commands and take actions.

Objectives & Scope: The main aim of this phase is to collect data for analysis. Such data can be collected from physical sensors in the environment, e.g., temperature, pressure, humidity in the environment or it can be a virtual data, e.g., from computing resources, e.g., disk space, rotation, memory. Physical sensors, virtual sensors, and control entities are either organized in sensor networks with a communicating link nodes, or they are able to send data on their own to data center. The form of an IoT landscape of sensors depends on a given use case and requirements.

Challenges and Requirements: The challenges and requirements in this phase are to identify what kind of data should be collected and how frequently it should be gathered. This identification depends on the scenarios and requirements, whether the data collected from the sensors should be in real time, every second, or aggregated from the sensors. The design of power-optimized micro-controllers or microcomputers in combination with sensors and network devices can follow with attention to IT security and safety issues as much as legal considerations. All devices must be part of a well-structured network to provide the desired data for a data center or storage database.

Tools and Methods: Next to standard network connections like Ethernet, Wi-Fi or GPRS there are a lot of other network technologies coming up. ZigBee, Z-Wave and LoRa are only some of them. Nevertheless, RFID and NFC are suitable for short-distance solutions. In the course of optimizing the data transfer, application layer protocols like MQTT, CoAP or XMPP are used primarily although new network technologies bring their own protocol bundles. For the same reason, these devices are becoming smaller. While Arduinos and Raspberry Pis are popular for tinkering, one can get completely operative devices by Z-Wave or LoRa, so one is not forced to think about operating systems and applications scripting. In most cases, the linkage to a data center is not made directly. All data streams that are sent by devices will be bunched on linking platforms. Depending on the size of a platform the data preprocessing or the data analysis can be realised on these IoT platforms (on-premise or cloud solutions).

Disciplines: The sensor layer is strongly characterised by the discipline of electrical engineering considering the micro controllers and sensors that are needed for IoT projects. But of no less importance is the

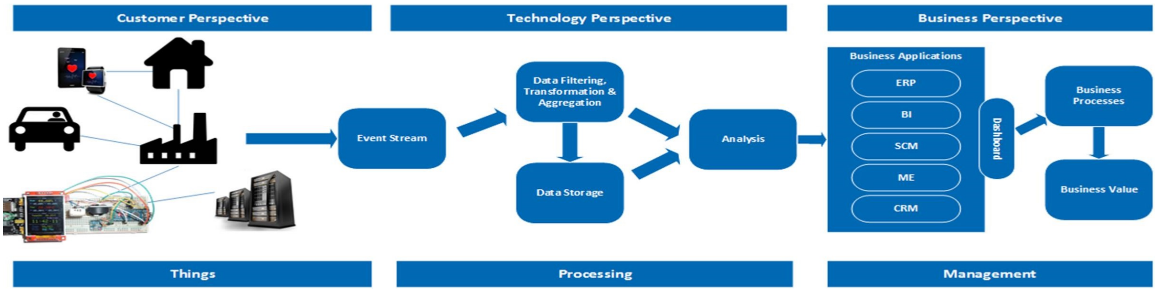

Figure 2: An overview of IoT process.

experience in computer system engineering and computer networking.

Interfaces: Business decisions can drive the construction, the extension or the improvement of a sensor network, so one sees the obvious link to the business value layer. In some scenarios, the sensors layer and the analytics layer are not clearly separable, because technical components are overlapping (e.g., SmartHomes). However, this interface is definitely visible, especially industrial, application systems.

Influences: A proper definition of required sensors, sensor networks and data streams is necessary such that one has to ensure the quality of the sensors, an efficient network and processable data. Otherwise, it would have an effect on the interfaces or the outcome. For instance, short error intervals of an observed machine or technical component will not be detected with a long sampling rate of a sensor. However, an extremely short sampling rate will produce a lot of data and could lead to system crashes in data preprocessing especially in a huge sensor network.

4.2 Preprocessing & Analysis

In this phase, we describe both the preprocessing and analysis phase of the IoT project, because preprocessing is a necessary step for the analysis. In preprocessing, we prepare the data for anlysis purpose.

Objectives & Scope: The main objective of this phase is to obtain a data model or prediction model for knowledge generation or decision making by data analysis. Before performing data analysis, data preparation is necessary to increase the effectiveness and efficiency of the analysis. The preparation of data spread over data selection, where one identifies available and required data and provides it in a utilisable way, and a data cleansing, where one handles missing data, noise and outliers and also verify data reliability. After data quality is checked one continues with data transformation, that includes data transformation and data dimension reduction. The separation between important and less important data also involves algorithms for clustering, classification or component analysis, so one sees intersections with data analysis methods. The final part of this process step is data analysis. The prepared data will be the input of the descriptive statistical analysis or the machine learning algorithm to obtain prediction models and prescriptive statements.

Challenges and Requirements: A definition of processable data sets and output variables is not required, but a postulation could simplify the data analysis. In consequence of the assumption that data collection is error-prone and 40% of collected data is "dirty" (Fayyad et al., 1996), a solution is crucial, especially in real-time IoT cases. Due to needed context information, human interactions are sometimes necessary but should be minimized as much as possible to avoid additional error sources. The main challenge at all is the choice of the best algorithm or method for specific problems. It is not just that one is interested to gain knowledge out of data, one is encouraged to find a suitable trade-off between complexity and resource consumption or between accuracy and comprehensibility. That does not only refer to data analysis methods, handling huge amounts of data also requires suitable strategies that regard data management and data processing, e.g., store raw or aggregated data, efficient storage, and parallelization.

Tools and Methods: There is a considerable amount of tools and methods, that could be used for analytics. Therefore, we can differentiate between the tools required for data processing and data analysis purpose. On the one hand Apache Storm, Samza, SAP Smart Data Streaming are used for data processing and preprocessing, and on the other hand, Apache Spark Mlib, R, SAP PAL are used for data analysis purpose. The choice of certain tools depends on the chosen system landscape. However, the methods are mostly similar. Data integration, feature filters, wrappers, clustering, pattern recognition, principal component analysis, descriptive and predictive statistics are rough terms that one will use in the analytics phase.

Disciplines: The mass of machine learning methods and statistical methods require expertise in mathematical statistics, algorithmics, and data science. At the latest, when one is compelled to adjust and require development of methods for individual use cases. However, data management is fundamental to handle data streams and storage.

Interfaces: This phase has interfaces on the adjacent phases. Data streams are obviously the connection to sensor networks and furthermore the processed and analysed data will be provided for business applications.

Influences: This phase has an influence on business applications and business value. Although, a useful outcome of data analysis is not guaranteed. A suitable data preprocessing can affect the task of data analysis. However, to ensure a reliable and valuable result, one has to verify them with appropriate testing procedures. Misleading statements as an input for business applications are certainly undesired.

4.3 Business Applications

Information systems are used to support business. An information system (IS) "consists of people and machines that generates and/or uses information and which are interconnected by communications. An information system in the narrow sense is an application system or application software for performing operational tasks" (Gabriel, 2012). In general information systems can be classified based on different criteria. One possible classification for IoT applications can be made by means of the business intelligence concept because Business Intelligence solutions play an important role in the area of planning, analysis and help in decision making. Gabriel defines the business intelligence system as: "Applications based on data warehousing, OLAP and data mining concepts, as well as a modern reporting and portal system with which a diverse and powerful IS can be used in various application areas" (Gabriel, 2012).

Objectives & Scope: The objective of an IoT application is to improve the decision quality, optimise the business processes, and support the user in their daily operations. This objective is achieved by utilising the outcomes of the project and using them for analysis and reporting.

Challenges and Requirements: IoT applications are highly complex and interconnected as described in (Vermesan, 2014). The single truth of information is missing because of information silos, and correct decisions can not be made on such data. Another challenge is an exponential growth of data in data silos which lead to inconsistent and redundant data. The key requirements in this phase are a high informative value (usability of information, e.g., within a business process), availability (important reports receive more resources and available when required), and stability (low failure rate). Another challenge in the data warehouse architecture is to link data that historically grew into separate data silos.

Tools and Methods: There are various tools and methodologies available for this phase. From the integration of applications perspective, integration tools and platforms are available, e.g., SAP Process Integration, integration services to integrate the data. Change management and configuration management methodologies can be used to manage the change and configure the system.

Disciplines: In this phase, following disciplines from business economics, and roles are determining factors in the implementation and development of such IoT applications. For example the domain expert provides the technical input for the business application, the business analyst covers the business perspective, and the IT consultant provides the necessary link between business and IT. The IT consultant also provides systematically and formally presents the requirements for the IT system so that they can be implemented in design and implementation.

Interfaces: The information generated in the application can serve then as input for other applications or further analysis (Vermesan, 2014). Although an interface or integration is required to access or provide the results to other applications.Ideally, the output of the application is a standardized format, which can be used in other applications and systems.

Influences: The application has a direct influence on the business value. A well-designed application can clearly visualize the measured or analyzed data for the end user. A well-designed application is an application which has a good usability, availability or actuality.

4.4 Business Value

The concept of business models and generating business value is the focus of management in the research literature (DaSilva and Trkman, 2014; Fielt, 2014; Petrikina et al., 2014). Here we provide two definitions of business models. A business model is defined as "A business model describes the rationale of how an organisation creates, delivers, and captures value" (Osterwalder and Pigneur, 2010). In (Teece, 2010), it is defined as "The essence of a business model is in defining the manner by which the enterprise delivers value to customers, entices customers to pay for value, and converts those payments to profit". As in the case of IoT projects, where customers or different organisations are involved, business value can be defined from the project's and participant's perspective. This outcome can be a new business model or improve the existing business processes, offering new services to the customers.

Objective and Scope: From the organisational perspective, it is the important phase of the IoT project. In this phase, organisations define the objective of the IoT project. The objectives of the project can generate new business models to be offer in a new market, improving an existing process, understanding customer needs and requirements where the product is in operation, solving existing problems or offering completely new business models. The scope of the project not only defines items included or targets of the iteration, but also the business value that a project brings to the organisation as well as the problems the aims of an organisation.

Challenges and Requirements: For the IoT project in this phase, higher management commitment played an important role and is mentioned as a challenge in literature (Sundmaeker et al., 2010; Khan and Turowski, 2016b). IoT projects involve other departments of an organisation, without a clear directive from higher management, departments or individuals may not be interested in participating in the project. Similarly, the decision maker's vision is also important to prepare the organisation for the future. **Tools and Methods:** There are various tools and methodologies available for business value. From a methodological perspective, following methods are commonly used e.g., business canvas, design thinking workshops, and strategic information management techniques.

Disciplines: The involved disciplines are business economics and project management. The overall understanding of business and project management experience is vital for a successful completion of a project. From a role perspective, project managers and an overall understanding of the whole process is a requirement.

Interfaces: The outcome of the project can be used in business applications, offering new services, or business models to generate revenue directly from the customers. In the case of business applications, overall business processes are improved, e.g., in CRM, Sales. New offerings are made to the customer to generate the revenue for the organisation.

Influences: This phase influences different phases of the process. Depending on the objectives, requirements in other field are decided, e.g., what kind of data we have to measure using the sensors, business processes or applications which we can improve, or the whole process.

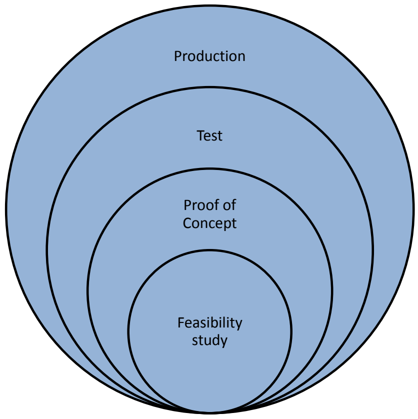

Figure 3: A cycle of an IoT project.

5 DISCUSSION

For an IoT project, an entry point can be any of the shown five phases although, the considerations are different for each entry point. Generally, requirements for different phases come from a business perspective. Then the business case is defined, and requirements for each phase are decomposed. We show an example in our case study for such entry point. Although, in the ideal case, it is suggested to start from the business value phase. However, in practice, some of the organisational settings, devices already recorded data (historical) in different locations, e.g., pressure, temperature. Organisations start from the existing data and then enhance the scenarios or combine the existing data with other data. An organisation may take sensors as a starting point for business value or better business decisions.

Different perspectives also play an important role for the selection of an entry point. In (Khan and Turowski, 2016a), the authors discuss two inside-out and outside-in perspectives.

There are numerous challenges which cross cut the phases in IoT landscape. One of the challenges is the security. The security of sensors means that sensors are generating and providing real data and it is not breached or corrupted. Another aspect concerns the ownership of the data. Regarding this, it is important to know who is responsible- the organisation that collects the data or the one that generates the data? In Figure 3, we show the lifecycle of an IoT project. The project usually starts with a feasibility study. Afterwards, proof of concept is made to show the practicality of the project. After an initial test, the actual project will be rolled out in the real production environment.

6 PREDICTIVE MAINTENANCE

We use predictive maintenance as a use case to show the importance and implication of the IoT landscape process. This example also shows how a change in one phase will have an impact on the whole landscape. Generally, requirements come from a business strategy or business level. Then these requirements are further analysed or classified in each phase accordingly. All phases contribute in reaching the objective of the project.

First of all, we describe the associated IoT landscape process with this case.

For predictive or preventive monitoring, data is collected from numerous kind of sensors, e.g., from pressure, temperature, humidity, and motion sensors. These data are then processed for further analysis. It results in solution where the company can avoid failures and avoid cases where break down occurs in the organisation. Using sensors in the machine or at location helps to sense the situation early, and actions can be performed rapidly or reported at a higher level in real time. Such data is further analysed to diagnose potential threats, and necessary actions can be taken before equipment breakdown or inefficiency occurs. Services processes can be constructed in such a way that error-prone parts can be replaced before they actually break.

We also discuss a few challenges and future scenarios in this use case. In some systems, machine condition data is stored in summarized form in row-oriented database systems. Such summarization can hide vital information regarding the machine state. Analysing raw data over time or correlation of such data with other attributes (like temperature, vibration, quality of operation performed on material) will help to find new insight information on machine conditions in which they are operated and will increase the reliability of a machine while predictive maintenance can be performed. In future, a huge amount of data can be stored without summarization and such data can be analysed for future scenarios.

Predictive maintenance can lead to savings in maintenance costs (up to 30%) and up to 75% fewer failures, inducing an increase in productivity of up to 25% (Smith, 2008) (relevance proved by a study of the US energy department). Now we discuss the various entry points of our phases for this scenario.

Business value: Costs of machinery downtime can be very severe to a business' performance (e.g., loss of reputation, costs for additional taff, replacement machines, additional stock capacities, opportunity costs) . In order to optimize cost-effectiveness of e.g., production processes, predictive maintenance initiative may be introduced by the management.

Business Applications: A predictive maintenance initiative may also be started from an application point of view. An example could be the improvement of supplier relations management in order to minimize replacement time for equipment. In addition, the success control for a predictive maintenance initiative would be done on an application level (cost-benefit analysis). Thus, an identified need for further improvements in existing predictive maintenance contexts states another entry point. Also optimisation attempts for existing processes may lead to a PM initiative.

Preprocessing and Analysis: An already performed analysis can serve as an entry point, too. Besides an existing, but maybe not very effective predictive maintenance analysis (e.g., alarms could be too late, root cause analysis does not lead to improvements), also other analyses that utilize sensor data from equipment can be used in the predictive maintenance context.

Sensors: The equipment already in use may provide information about maintenance-relevant statistics that are not used in a predictive maintenance context. From this starting point, processing opportunities may be discussed. Another entry point could be the availability of some sensors for an existing predictive maintenance initiative and the planned introduction of new sensors to improve its quality.

7 SUMMARY AND OUTLOOK

This paper deals with the IoT process. We provide a holistic view of different phases in IoT projects covering from sensor perspective of data collection to the generation of business value for an organisation. We emphasise to use proven Six Sigma methodology for IoT projects. We discuss the consequences of each phase while selecting the phase as an entry or starting point. We use predictive maintenance as a use case to demonstrate the practicability of our IoT process. Using these insights, IoT project managers can identify required activities and competencies to increase success probability. In the end, we summarise the paper findings and highlight the future work.

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