Sini-Kaisu Kinnunen

MODELLING THE VALUE OF FLEET DATA IN THE ECOSYSTEMS OF ASSET MANAGEMENT

ACTA UNIVERSITATIS LAPPEENRANTAENSIS 912

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Dissertation for the degree of Doctor of Science (Technology) to be presented with due permission for public examination and criticism in the auditorium 1316 at Lappeenranta-Lahti University of Technology LUT, Lappeenranta, Finland on the 14th of August, 2020.

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Abstract

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The emergence of technologies, e.g. Internet of Things (IoT), cloud services and advanced analytics, have enabled diverse data utilization and service development based on the data. In asset management, assets, such as machinery and equipment, are equipped with sensors and abilities to be connected, which enables e.g. remote monitoring and control, and multiple other opportunities in asset management related decision-making. However, the full potential of increased data collection and availability of technologies has not been tapped, and research combining asset management, data, and value for business perspectives is scarce. To succeed in intense competition, companies need to collaborate with others in networks, and increasingly the term ecosystem is utilized to emphasize long-term collaboration and mutual aims. The objective of this thesis is to understand how data from a wide asset fleet can be turned into value in the ecosystems of asset management.

The research is conducted in close collaboration with industry as the research has a connection to the DIMECC S4Fleet research program (2015–2017). The research applies the design science approach, and the individual publications apply different research methods, including literature review, case study, framework building and modelling. The empirical data is qualitative data, including materials from seminars, meetings and other events related to the research program, but also interviews are conducted. Descriptive cases and illustrative numerical data are utilized for the testing of the developed models.

As results, a group of frameworks and observations are made and utilized as the basis for developing a model to evaluate the value of fleet data. The model is further developed into an extended model that enables the understanding and measuring of the value of fleet data in the ecosystems of asset management. It is essential to identify and define the fleet, the ecosystem around the fleet, what the decision-making situations are, and what the expected benefits and the costs of data utilization are, to create the basis for measuring the value of fleet data at ecosystem level. This thesis proposes a novel model that applies the cost-benefit approach and presents the logic of how to evaluate the value of fleet data. The proposed model can be used e.g. in developing ecosystem collaboration and data utilization, reasoning IoT investments and proving the value creation from data-based services. Development in data utilization at ecosystem level can result in increased competitive edge, improved data sharing, benefits and risks sharing, and deepened long-term collaboration e.g. in product and service development and sales. The results increase the scientific discussion on the topic, but further research is needed in measuring the value of data, defining the effects of data refining level on the value, and studying the opportunities of ecosystem level data management.

Keywords: fleet, asset management, value of data, model, benefits, costs, ecosystem decision-making, data to value, data refining, data management process

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It is time to wrap up this phase in my career. At the beginning I was just learning what it is to be a doctoral student and a junior researcher. Soon, I was taking part in a large research program, planning events and doing research at full speed with numerous research participants. I got a nice outlook what doing research can also be. I was excited. A lot has happened during these years and there are many colleagues, friends and family who I want to thank for their support.

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Sini-Kaisu Kinnunen
June 2020,
Lappeenranta, Finland

Contents

List of publications

This thesis is based on the following papers. The rights have been granted by publishers to include the papers in the dissertation.

1. Kinnunen, S-K., Ylä-Kujala, A., Marttonen-Arola, S., Kärri, T., and Baglee, D. (2018). Internet of Things in Asset Management: Insights from Industrial Professionals and Academia. *International Journal of Service Science, Management, Engineering, and Technology*, 9(2), pp. 104–119.

   Contribution: The author was the principal author and responsible for collecting and analysing data and writing the article. Co-authors participated in writing and designing the research, as well as commented on all versions of the manuscript.

2. Kinnunen, S-K., Marttonen-Arola, S., Ylä-Kujala, A., Kärri, T., Ahonen, T., Valkokari P., and Baglee, D. (2016). Decision making situations define data requirements in fleet asset management. In Koskinen, K. T., Kortelainen, H., Aaltonen, J., Uusitalo, T., Komonen, K., Mathew, J., and Laitinen, J. (Eds.), Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015), *Lecture Notes in Mechanical Engineering,* Springer, pp. 357–364.

   Contribution: The author was the principal author and responsible for writing the article. The co-authors were involved in the design of the research and commented on all versions of the manuscript.

3. Kinnunen, S-K., Happonen, A., Marttonen-Arola, S. and Kärri, T. (20XX). Traditional and extended fleets in literature and practice: Definition and untapped potential. *International Journal of Strategic Engineering Asset Management,* X(Y), pp. XX-XX. Article in press.

   Contribution: The author was the principal author and responsible for collecting and analysing data and writing the article. Co-authors participated in writing and designing the research, as well as commented on all versions of the manuscript.

4. Kinnunen, S-K., Hanski, J., Marttonen-Arola, S., and Kärri, T. (2017) A framework for creating value from fleet data at ecosystem level. *Management Systems in Production Engineering*, 25(3), pp. 163–167.

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5. Kinnunen, S-K., Marttonen-Arola, S. and Kärri, T. (2020). The value of fleet information: A cost-benefit model. *International Journal of Industrial and Systems Engineering*, 34(3), pp. 321-341.

Contribution: The author was responsible for conducting the research and writing the article. The co-authors were involved in the design of the research and commented on all versions of the manuscript.

6. Kinnunen, S-K., Marttonen-Arola, S. and Kärri, T. (20XX). The value of ecosystem collaboration: Fleet life-cycle data -based cost-benefit model, *International Journal of Industrial and Systems Engineering*, X(Y), pp. XX-XX. Article in press.

   Contribution: The author was responsible for conducting the research and writing the article. The co-authors were involved in the design of the research and commented on all versions of the manuscript.

List of abbreviations

B/C	benefit-cost
D2BK	data-to-business-knowledge
DaaS	data-as-a-service
EPC	electronic product code
EVA	economic value added
FAM	flexible asset management
IaaS	information-as-a-service
IoT	Internet of things
IP	Internet protocol
IT	information technology
KaaS	knowledge-as-a-service
LCA	life-cycle analysis
LCM	life-cycle model
NFC	near field communication
NPV	net present value
O&M	operation and maintenance
OEM	original equipment provider
R&D	research and development
RFID	radio frequency identification
ROI	return on investment
TCO	total cost of ownership
WaaS	wisdom-as-a-service
WSAN	wireless sensor and actuator networks
WPAN	wireless personal area networks
WSN	wireless sensor networks

1 INTRODUCTION

1.1 Background and motivation

The emergence of Internet of Things (IoT), cloud services and the cheapness of collecting data have increased data collection and enabled diverse data utilization and service development based on the data. In asset management, the assets, such as machinery and equipment, produce enormous amounts of data during their life cycles, which could be used more efficiently in asset management to create value, i.e. delivering maximum asset performance at minimum costs (Haarman and Delahay, 2018). Technologies and increased data collection add opportunities when managing groups of assets, i.e. fleets. Therefore, technological development makes possible to develop fleet management and fleet analysis practices, and thus develop the asset management and maintenance of fleets (Medina-Oliva et al., 2014). Recent developments in asset management and maintenance are related to the opportunities of remote monitoring and control. Assets are equipped with sensors and abilities to be connected and controlled. The increase in data availability and technologies changes asset management, and the data can be used to support decision-making in the asset maintenance context, for example it makes it possible to develop predictive models to support maintenance planning (see e.g. Brous et al., 2019; Feng et al., 2017). For its part, the emergence of technologies has caused data overload, and not all the potential of the collected data has been tapped. The utilization of asset life-cycle data has been under development recently, but there is lack of research related to the opportunities of improving data utilization and taking advantage of fleet management, i.e. the benefits of observing and managing a group of assets (see e.g. Al-Dahidi et al., 2016; Medina-Oliva et al., 2014).

The link between data utilization and business value is unclear and needs more research (Raguseo, 2018; Trieu, 2017). In order to upgrade data to business knowledge and value, links between company performance, business value and data analytics need to be understood (Ji-fan Ren et al., 2017). The impact on business value is challenging to define and verify, and models aiming to do that are lacking. In addition to the benefits and value of data utilization, the costs of data must be considered. The literature discusses multiple business cases, but the actual costs of IoT investments are rarely given. It is true that the costs of data, including all the costs of collecting, storing, processing, and analysing the data over the life cycle of the asset, are challenging to define, and it is even harder to define the benefits that should outweigh these costs (de Jonge et al., 2017).

Investments are realized with tenuous evidence and arguments, and models are needed to demonstrate, analyse, and support decision-making. The profitability aspects of IoT investments are often neglected in the literature, as the research focuses on applications and utilization opportunities. The costs and profitability of information technology (IT) investments are discussed in general in the literature (see e.g. Berghout and Tan, 2013; Kauffman et al., 2015; van der Pas and Furneaux, 2015). In order to support, analyse and optimize these decisions in the context of IoT investments in asset management, the models are needed to piece together the complex puzzle.

The efficient utilization of data requires understanding of the costs and benefits of upgrading data into business knowledge over company boundaries. To succeed in intense competition, companies need to collaborate with others in networks, and the term ecosystem is utilized increasingly to emphasize long-term collaboration and mutual aims (see e.g. Valkokari, 2015; Adner, 2017). In the context of asset management, the business models cause the fragmentation of data into multiple actors which complicates the determination of costs, benefits and profitability of data and IoT investments even more. Miragliotta et al. (2009) and Dimakopoulou et al. (2014) have studied the profitability of IoT investment in RFID (Radio Frequency Identification) technology in supply chains. Costs of data are often caused to multiple actors in the network or ecosystem (see e.g. Miragliotta et al., 2009; Uckelmann et al., 2011), when e.g. an equipment provider, its customer company and service providers may have been involved in the management of assets during their life cycles. It is challenging to define what the benefits are that should exceed the costs of refining data into usable form. While the IT investments in e.g. a data system can be internal investments within a company, these IoT investments often involve multiple companies, as the investments affect the whole operation phase of the asset's life cycle and involves e.g. maintenance service providers. The real value from technologies can be achieved only if the data is utilized in decision-making and the aim is to actually create value, i.e. the benefits exceed the costs. The players who use the data most effectively can achieve competitive edge over others in this constantly developing business environment.

1.2 Research questions

The objective of this thesis is to understand how accumulated fleet data can be turned into value in the ecosystems of asset management. Fleet management as a part of asset management need to be developed from the data utilization point of view. Especially, practices can be developed in terms of how the collected fleet data can be used in the asset management related decision-making of fleets and to create value from the fleet data that is produced over the life cycle of assets. The aim is approached with three research questions that explore and concentrate on the issue from different perspectives: defining the benefits and costs of data, evaluation of the value, and understanding the value in the ecosystem level. The research questions (RQ) of the thesis are as follows:

RQ1: What benefits and value can be derived from fleet data in asset management related decision-making?
RQ2: How can the value of fleet data be evaluated?
RQ3: What is the role of ecosystem in the process of turning fleet data into value?

Figure 1.1 illustrates how the individual publications of this thesis contribute to the research questions. The first research question aims to understand the benefits, costs and value that can be derived from fleet data in asset management related decision-making.

Publications 1, 2 and 3 respond to the first research question and focus on the opportunities of IoT in asset management, fleet management -related decision-making and understanding the benefits of utilizing fleet data. Research question 1 is emphasized because of the new and barely studied research area where the concepts and definitions which are not established or, in some cases, even defined require more exploring. This background research is required before further research on modelling the value can be conducted. Publications 5 and 6 respond to the second research question by modelling the value of fleet data as the components of costs and benefits of data. Publications 4 and 6 discuss the ecosystem perspective on value creation and address the third research question. The company view is in the core of Publications 1, 2, 3 and 5. However, the ecosystem view is always present when we discuss fleet data, but it is emphasized in Publications 4 and 6, as presented in Figure 1.1. The objective of this thesis is answered by developing a model (Publication 5) that utilizes the observations and results made in the previous publications (Publications 1, 2, 3, 4). The model is further developed and the extended model presented in Publication 6. The results and the contributions to the research questions and the objective are discussed in detail in Chapter 4.

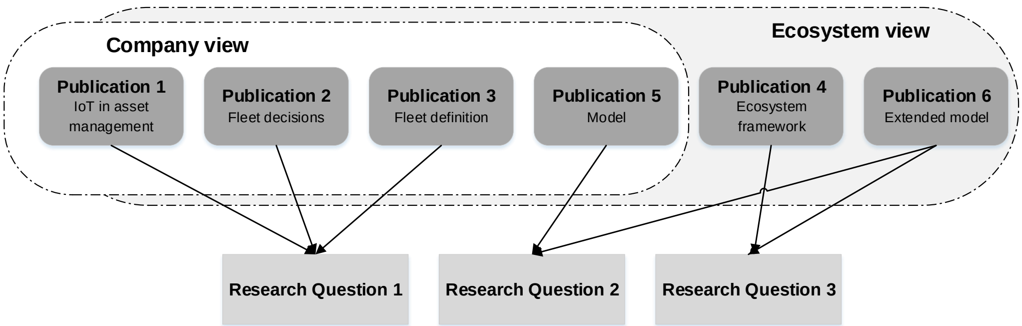


Figure 1.1: Contribution of the publications to the thesis

1.3 Positioning the research

This thesis combines the research areas of asset management, value creation, and ecosystems. The thesis focusses on fleet data utilization in ecosystems to create value that can be evaluated with the cost-benefit approach. The focus of the thesis can be defined as the intersection of three research areas as presented Figure 1.2.

In regard to asset management, the focus is on fleets of assets and mainly on physical assets (machinery and equipment, etc.) and the life-cycle data collected from these assets. From the research field of asset management, especially the different asset management related decision-making situations over the life cycle of assets are discussed. The focus is on a group of assets, i.e. fleet, and looking into the opportunities of fleet data in asset management.

This thesis discusses value creation that is defined as the trade-off between benefits and sacrifices (Zeithaml, 1988). Cost-benefit models are one way of analysing value. In these models, total costs and total benefits are expressed in monetary terms, and value is the difference or ratio between the benefits and costs. In cost-benefit analysis, a variety of measures can be used when evaluating the value for business. Finding the optimal total value is usually finding the balance between costs and benefits.

When discussing fleet data, the network and ecosystem perspective (see e.g. Valkokari, 2015; Adner, 2017) must be explored. As multiple companies are often dealing with the assets of fleet during their life cycles, fleet data is fragmented into multiple actors, and thus they are involved in the process of turning fleet data into value. The fleet data can be used in service generation (Kortelainen et al. 2016), and these services can be called data-based services (see e.g. Ahonen et al., 2019; Marttonen-Arola et al., 2019; Vaittinen and Martinsuo, 2019). Also, terms data-intensive services, data services and for example, data as a service, have been used but mainly in computer science (see e.g. Delen and Demirkan, 2013; Moshni et al., 2016). These data-based services are a way to create value from fleet data and take advantage of the opportunities of IoT technologies, data utilization and service generation in networks or ecosystems in the asset management context. In this thesis, the goal is to understand how the value of fleet data in an ecosystem can be evaluated and how the value of fleet data is formed for the actors and ecosystem around the fleet.

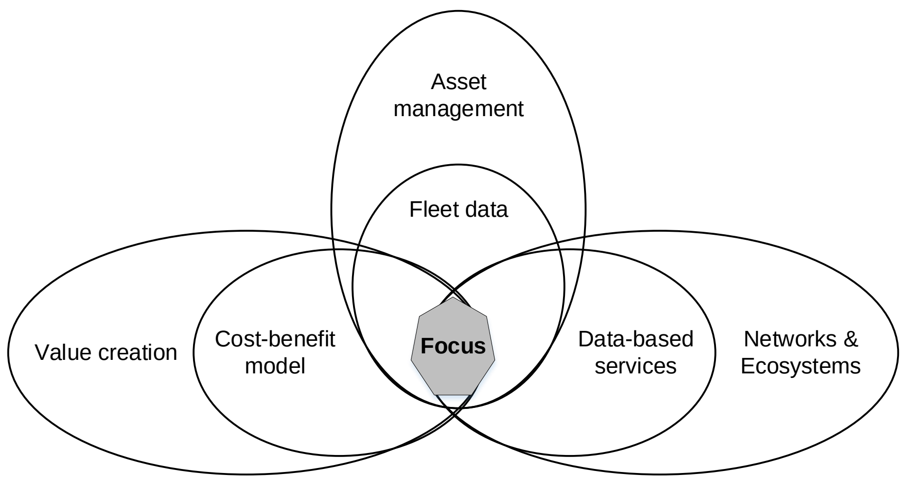


Figure 1.2: Focus of the thesis

1.4 Structure of the thesis

This thesis is composed of two parts, as shown in Figure 1.3. Part II includes the six scientific publications. Part I describes the overview of the thesis and puts together the research conducted in the individual publications. In the introduction of the first part, the motivation for research is described, the research objective is set, and the research is positioned. Then theoretical background is discussed, and methodological choices are stated. The fourth chapter reviews and concludes the results of the individual papers and the thesis, and finally chapter five presents the conclusions and implications of the research. Figure 1.3 illustrates the structure of the thesis and the outputs of each chapter.

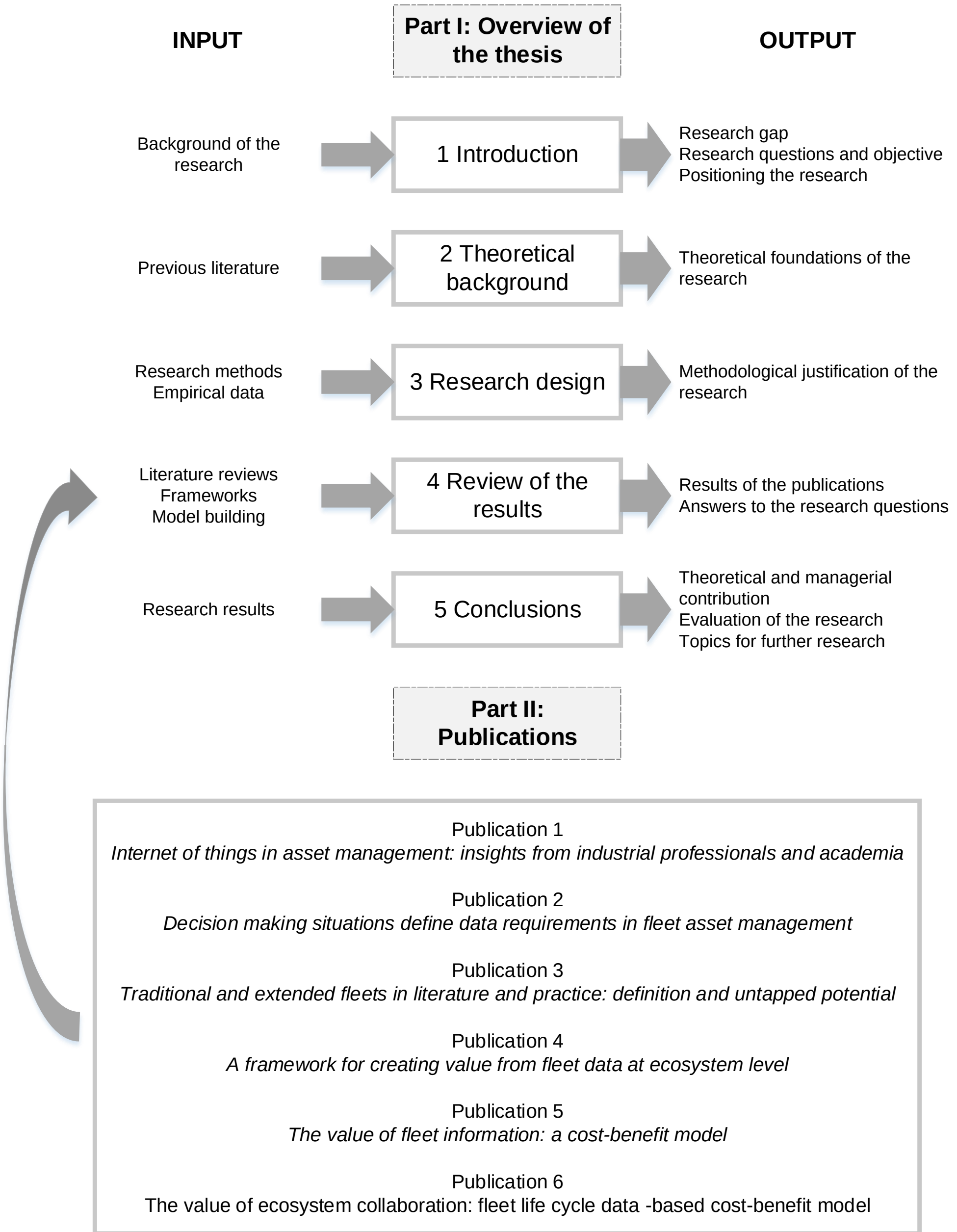


Figure 1.3: Structure of the thesis

2 THEORETICAL BACKGROUND

2.1 Asset management and fleet management

The significance of asset management is emphasized in asset-intensive industries where the assets play an essential role in business processes. Asset management can be defined as the coordinated activity of an organization to realize value from assets (ISO 55000 2014, p. 14). Asset management aims to systematically and coordinately plan and realize activities and practices to manage assets optimally and sustainably over the whole life cycle of assets (Hastings, 2015). According to the standard, asset management is balancing cost, risk and performance (ISO 55000 2014, p. 1). In asset management, several authors have studied the field (e.g. Amadi-Echendu et al., 2010; Emmanouilidis et al., 2009; Komonen et al., 2012; Kortelainen et al., 2015) and a group of researchers is specialized especially in the challenge of balancing cost, performance and risks (e.g. Crespo Márquez et al., 2012; Feng et al., 2017; Galar et al., 2017). Maintenance management is a key part of asset management and focusses on physical assets and the operating and maintenance (O&M) -phase of the asset life cycle. Maintenance management include activities such as determining maintenance requirements, strategies and responsibilities as well as implementing maintenance planning and control (SFS-EN 13306:2017, p.9). Whereas asset management considers a broader view and considers all types of assets, the whole life cycle of assets and focusses on asset systems, organizations or company networks.

The latest trends in asset management derive from the revolution of the Internet of Things (IoT), which is transforming operations and business in many industry fields (Brous et al., 2019). The emergence of technologies increases the opportunities to exploit data and data analysis tools in data-driven decision support tools. These analyses and tools enable taking maintenance planning to a more advanced level and supporting proactive decision-making (Jantunen et al., 2011). Predictive models and condition-based strategies for maintenance planning can provide benefits if they are successfully applied in suitable conditions, i.e. it is suitable if the behaviour of the deterioration process is well known and the severity of failures is relatively low (de Jonge et al., 2017). The benefits can be, for example, savings in maintenance operations, spare parts, quality costs, improved reliability, increased asset availability, diminished production losses, and improved safety (Feng et al., 2017; Gavranis and Kozanidis, 2015; Van Horenbeek and Pintelon, 2013; Yarn et al., 2001; Yongquan et al., 2016; Öhman et al., 2015).

As asset management focuses on the value that can be derived from an asset (ISO 55000, p. 3), the asset data over the life cycle plays a key role in enabling value creation. An asset can be defined as "*an item, thing or entity that has potential or actual value to an organization*" (ISO 55000 2014, p.13). Assets can be divided into physical and non-physical assets. Physical assets usually refer to machinery, equipment, inventory and properties owned by an organization, while non-physical assets refer to leases, brands, use rights, licenses, intellectual property rights, reputation or agreements. In this thesis, the physical assets are in focus.

Sometimes it is beneficial to manage assets as a group – a fleet – as discussed and defined in this thesis. A fleet can be defined as "*a population of similar entities*" (Tywoniak et al., 2008, p. 1555), or more specifically as "*a set of systems (e.g. ships), sub-systems (e.g. propulsion or electric power generation) or equipment (e.g. diesel engine, shaft)*" (Medina-Oliva et al., 2014, p. 40-41). In addition, the standard mentions that occasionally it is beneficial to manage assets as a group to gain additional benefits (ISO 55000 2014, p. 2). It is essential that the units of a fleet share some characteristics that enable grouping them together according to a specific purpose. There can be different types of fleet: 1) identical, 2) homogenous, and 3) heterogeneous (Al-Dahidi et al., 2016). The categorization depends on what kind of characteristics the assets share and what is the motivation to regard them as a group. The interest in considering a fleet of assets is often related to decision support and the gaining of economic or other benefits. Thus, it is possible to apply the interpretation of the fleet, and the fleet can be viewed in an extended way. The definition of fleet and fleet management are discussed in detail in Publication 3. In Publication 3, an extended view on fleet management is proposed, and suggested that the fleet management learnings can be utilized broadly in managing different types of asset groups and capturing the value potential of fleet level management.

The term fleet is traditionally employed in the military (Feng et al., 2017), marine (Meng & Wang, 2012; Leger & Iung, 2012), logistics (Archetti et al., 2017; Shi et al., 2014), and aviation (Zhang et al., 2015; Yan et al., 2006) industries, where a fleet is a group of ships, vehicles or aircrafts. Fleet management has been recently discussed more broadly also in industrial asset management where the fleets of machinery and equipment are considered (Al-Dahidi et al., 2016; Medina-Oliva et al., 2014; Voisin et al., 2013; Monnin et al., 2011). The interest towards fleet management in industrial asset management derived from the development in technologies that has enabled the massive data collection from assets. IoT and numerous opportunities to utilize asset data have attracted researchers and practitioners to look into the topic. Asset management is data intensive, and the asset data need to be collected, assembled, managed, analysed, and used, often in different tools to support decision-makers. The creation and utilization of these data-driven tools often increases knowledge and supports decision-making in organization. The opportunities to utilize asset data have been discussed in the literature quite broadly (Brous et al., 2019; Campos et al., 2017) but research on the value for the business point of view is scarce.

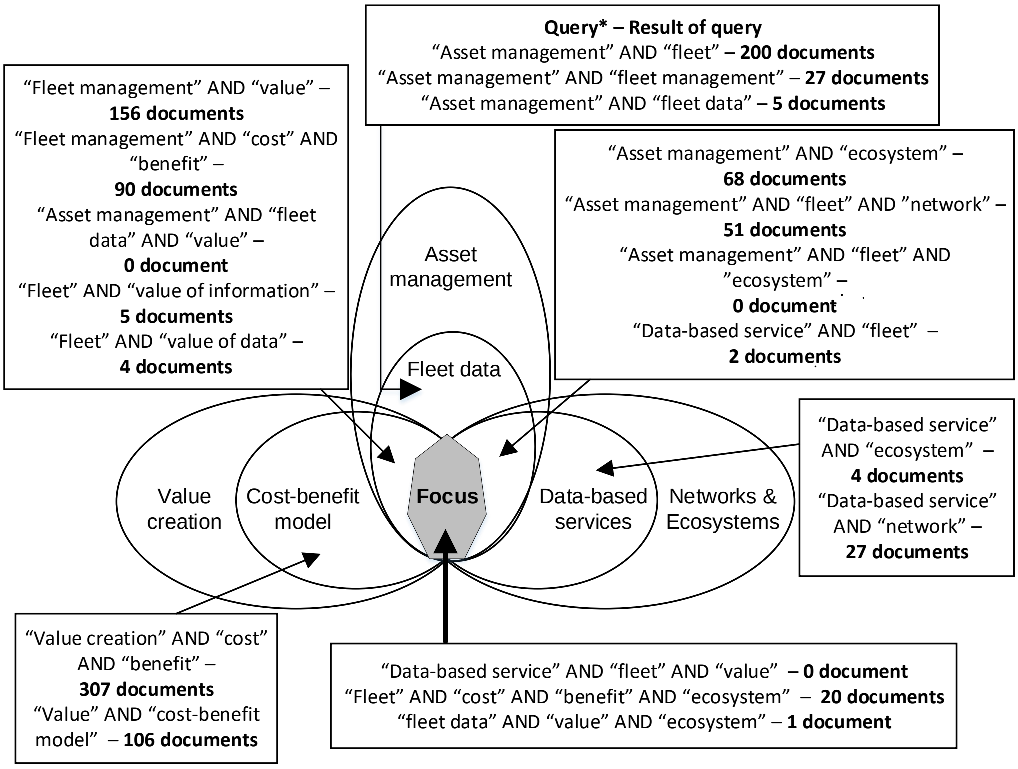
Research on systematically understanding the opportunities of fleet management is scarce (as discussed in Publication 3) but the topic has been recently discussed with a multidisciplinary approach in the DIMECC S4Fleet research program in which fleet management is discussed in terms of the transformation of service business and digitalization (see e.g. DIMECC Oy, 2017; Kortelainen et al., 2017a). There is untapped potential in taking advantage of the benefits and opportunities of fleet management. If the assets are considered as a fleet, fleet data is collected and then utilized in analyses and in asset management related decision-making, and benefits such as scale advantage can be achieved. The economies of scale in fleet management refers to the minimisation of unit costs and the maximisation of profits during the lifetime of assets (Tran and Haasis, 2015; Archetti et al., 2017). The scale advantage and pricing of the IoT-based services in the fleet environment have been discussed recently (Marttonen-Arola et al., 2019).

The value potential of fleet management needs to be studied in detail. The benefits of fleet management in the manufacturing industry have been recognized as e.g. cost savings from successful maintenance planning and resource utilization (data from the fleet can be used to optimize the preventive maintenance schedule of individual assets, see e.g. Al-Dahidi et al., 2016), as well as increased availability of assets (the failure modes and mechanisms of the fleet may provide insight into the preventive and predictive maintenance of individual assets, see e.g. Gavranis and Kozanidis, 2015). Fleet management enables additional benefits, and the advantage of fleet asset management can also be viewed as scale advantages in addition to the other purposes of fleet management (Archetti et al., 2017; Tran and Haasis, 2015). Other accrued benefits from fleet data can be e.g. risk reduction, opportunity identification and process improvement (Kortelainen et al., 2016; Wang et al., 2013). In addition, the benefits can offer advantages to multiple actors if fleet management can be carried out at network level, and thus consider fleet management as a unity larger than an in-company activity.

The literature presents these benefits mainly from the perspective of a single fleet management case. As discussed in Publication 3, a detailed literature review was conducted to understand fleet research, by reviewing fleet groups, decision-making needs and the benefits and value from fleet management, e.g. costs savings or improved availability of assets as achievements of fleet level consideration. The same trend can be noticed in newly published fleet research, and new fleet cases and decision support solutions are discussed. For example, the purchase of new buses and the rehabilitation of aging fleet (Ngo et al., 2018), the optimization of life-cycle costs and decrease of emissions in a mining fleet case (Nakousi et al., 2018), and finding the optimal replacement and shipping schedule for a machine fleet in the construction industry (Shields et al., 2019) have been recently discussed, and these are examples of individual fleet management problems and solutions.

When discussing the benefits of IoT or utilization of fleet data, there are various challenges that need to be considered as well. Disadvantages of IoT or even possible risks related to IoT are not widely discussed in literature but they can be seen related to technological, business and societal challenges (Jinbal et al., 2018; Sundmaeker et al., 2010). Technological challenges include the challenge of data quality, compatibility and accuracy of systems, security and privacy issues (e.g. data ownership and sharing), and connectivity and longevity -related challenges, such as challenges related to server load and capacity and continuous technology developments which causes the need for new investments near future (Brous et al., 2020; Jindal et al., 2018; Rose et al., 2015; Sundmaeker et al., 2010). At the same time, companies cannot stay and follow what others do and thus give the competitors competitive edge in adapting their processes, products and services along with digitalization (Maier, 2017). Business-related challenges can include the risks of over-reliance on technology or lack of risk awareness, when benefits are regarded as self-evident and the risk is relying blindly on the analyses and models (Brous et al., 2020). This may cause significant risks for business. Other challenges can be the need for new business models, new internal processes and skills, and new ecosystem-based value chains (Rose et al., 2015). These fields are not yet fully developed in order that the implementation of IoT-based systems could bring the benefits to full scale. Before the developed IoT systems and models are implemented in companies, it will take time, possibly even ten years, before the potential can be achieved. Societal challenges can include the concern of changing society and working culture which may lead to the loss of jobs in certain fields (i.e. routine repetitive tasks, harsh work environment etc.), where new intelligent solutions can bring advantages such as safer work environment and improved productivity (Maier, 2017).

Figure 2.1 demonstrates that the research, focusing and compiling the benefits and value of asset and fleet data, is lacking. A query with different combinations of search words was conducted to demonstrate the amount of research in this area. The query was conducted by utilizing SCOPUS (2020), which is the largest abstract and citation database of peer-reviewed scientific literature. Especially the value of data or value of information in asset and fleet management contexts is limited, as can be seen in Figure 2.1. In addition, if the ecosystem view and data-based services are combined with fleet and value, the research is lacking. Research on data utilization and business value have recently appeared in literature (Ji-Fan Ren et al., 2017; Raguseo, 2018; Raguseo and Vitari, 2018). However, these studies lack a strong asset management or fleet management perspective on the topic. On the other hand, the research of IoT and its opportunities in asset management decision-making have appeared lately in scientific discussion (see e.g. Brous et al., 2019). Thus, the potential of IoT and asset data have been recognized but the attempts to evaluate the value and fleet perspective on the value of data are lacking. This is the research gap to which this thesis aims to respond.



Query*TITLE-ABS-KEY ("search word 1") AND TITLE-ABS-KEY ("search word 2") AND TITLE-ABS-KEY ("search word 3")

Figure 2.1 Asset management and fleet management with value and ecosystem perspectives in scientific research (SCOPUS 2020).

2.2 Cost-benefit models defining the value

Models are tools for decision-makers to analyse and observe the results and consequences of changing variables. In asset management, models are developed for example to optimize maintenance operations, to develop pricing methods, to calculate investment costs, to evaluate the profitability of investments, and to calculate costs over the life-cycle period of an item, and e.g. to make life-cycle analysis (LCA) in order to plan and organize operations. For example, Sinkkonen (2015) has introduced a life-cycle model (LCM) in maintenance networks and emphasized the value aspect of maintenance instead of just being costs makers for organizations. Models can be developed to analyse the effects on profitability; for example, the FAM model (Flexible asset management) has been developed to improve profitability in industrial maintenance companies and networks in an asset management context (Marttonen, 2013). When purchasing intelligent/smart assets, the costs should be calculated over the life cycle instead of just considering the price, as is discussed in the development of total cost of ownership (TCO) model for the purchasing decisions of industrial robots (Landscheidt and Kans, 2016).

The models have been developed to support managerial decision-making, but increased data availability and technologies have increased the interest and the need to develop models. For example, in asset management, which is data-intensive by nature, the data-driven models are beneficial as a support for decision-making and the asset data can be effectively used in increasing the value from the assets. The need for predictive intelligence tools to optimize asset utilization in a cost-effective manner is recognized (El-Thalji and Jantunen, 2016). Models that combine the value aspect of data with the costs management approach in asset management are limited. According to Uckelmann and Scholz-Reiter (2011), the opportunities of IoT to achieve financial and non-financial benefits for companies have not been gained as quickly as expected, partly due to the missing profitability for stakeholders in the IoT business. Costs and benefits are not equally distributed among stakeholders in networks, and models are needed to understand and develop value creation. Cost-benefit sharing models have been suggested as a useful method to evaluate and improve business development around IoT technologies.

The cost-benefit approach is a useful method for economic analysis and for resource allocation decisions to identify the cases when the expected benefits to the organization exceed the expected costs (Park and Sharp-Bette, 1990). Other approaches are, for example, utility theory, risk-benefit and economic impact approaches. The cost-benefit approach is utilized in this thesis as it is commonly used in business and policy decisions and project investments to systematically evaluate the benefits and costs of actions or investments, and it is a suitable approach for the purpose of this thesis, where multiple actors are involved in the value of fleet data and the costs and benefits for each actor need to be evaluated. Cost-benefit models have also been discussed in literature (see e.g. Niyato et al., 2015). Costs and benefits have been analysed, and the aim is to express them as monetary value even though it may be a challenge in many cases. As the method of valuation, net present value (NPV) can be used, and it is also utilized in this thesis. NPV considers the life-cycle perspective and certain time periods in which the costs and benefits are realized, and thus the time effect on the monetary value is taken into account. NPV is generally used in investment appraisals (see e.g. Götze et al., 2015) and can also be used, for example, to assess the value of maintenance (Marais and Saleh, 2009). Other measures, such as ROI (return on investment), EVA (economic value added), and B/C (benefit-cost) -ratio are useful in the evaluation.

The models presented and discussed in this thesis aim to respond to the need of understanding the costs and benefits for multiple actors in IoT-related investments in a fleet context. The components of the models are discussed in detail in Publications 5 and 6, but some notes are emphasized below as well. The mathematical derivations of the models are presented in Publications 5 and 6 and summarized also in this thesis, in chapter 4. The model applies the general equations of B/C-ratio (2.1) and NPV (2.2) as presented in the following equations:

$$NPV = \sum_{n=0}^{k} \frac{R_n}{(1+i)^n} \tag{2.1}$$

$$B/_C - ratio = \frac{\sum_{n=0}^{k} \frac{B_n}{(1+i)^n}}{\sum_{n=0}^{k} \frac{C_n}{(1+i)^n}} \tag{2.2}$$

where
i = interest rate,
n = year/time,
R_n = net cash flow during single period n,
B_n = benefits during period n,
C_n = costs during period n.

In the maintenance context, the benefits can be seen as decreased maintenance costs or other costs, increased revenues or profit or other benefits that can be indirect and complex to be measured. The benefits of RFID investments have been discussed by Uckermann and Scholz-Reiter (2011). They categorize the benefits for each stakeholder, and the examples of the benefits are: reduced product shrinkage, improved information sharing and support for asset management. The benefits in asset management in a fleet context are discussed in detail in Publications 3, 5 and 6. This thesis categorizes the benefits into cost savings (e.g. reduced maintenance costs, savings in quality costs), increased revenues (e.g. increased sales) and other benefits (e.g. improved safety). The benefits can often be converted into monetary value, in one way or another. The idea is to draw comparisons to the situation before the change or potential investment in order to define the additional benefits and profits.

Costs in the case of IoT-related investments have been discussed in detail by some researchers (Uckermann and Scholz-Reiter, 2011; Berghout and Tan, 2013; Marttonen-Arola et al., 2019). Uckelmann and Scholz-Reiter (2011) discuss the costs of RFID investments that are partly similar to the costs relevant in this thesis. They also mention the costs, such as reorganizing the business processes and costs of inter-organizational communication (e.g. negotiations on data requirements and information security). Berghout and Tan (2013) categorize the costs into initial (e.g. hardware), running (e.g. software licences and maintenance), and other organizational (e.g. personnel working and training) costs. The costs have also been studied by Marttonen-Arola et al. (2019) who have developed the model for the pricing and costing of IoT-based service development in fleet environments. In this thesis, the costs related to IoT investments are divided into three main categories of costs: hardware, software and working related costs. These costs may be non-recurring (e.g. initial investment) or recurring (annual costs) by nature. In addition, e.g. working related costs include costs such as planning and preparation work of the investment project, realizing data refining process (e.g. analysis and modelling work) and training.

2.3 Data utilization in ecosystems

When discussing fleet data, the role of other organizations, the network around the assets, needs to be considered. In the field of asset management, the outsourcing of maintenance services has partly caused the fragmentation of asset life-cycle data into multiple actors (see e.g. Rong et al., 2015). There are original equipment manufacturers (OEM), their customer companies, maintenance service providers and other stakeholders that are involved in the different phases of asset life cycles. To create value from assets optimally, interplay between organizations is needed to share data and core competencies in a way that supports asset management related decision-making over the life cycles of assets.

If we observe a fleet of assets, we can identify multiple organizations involved in data generation over the life cycles of the assets (see e.g. Kortelainen et al, 2017b; Rong et al., 2015). Firstly, an equipment provider, who manufactures the assets, owns the data related to research and development (R&D), manufacturing and product specification – in other words, the asset data from the beginning of the life cycle. Secondly, the company who purchases the assets owns a lot of data from the operations phase, where the assets typically serve/operate in the processes of the customer company, i.e. process and condition data. Thirdly, the assets are often serviced by third parties, such as maintenance service providers, who maintain and overhaul the assets if faults occur or the assets break down. The data is not usually shared or sold to other actors, but the companies tend to keep their data tightly in their own hands. Thus, data is generated to multiple actors over the life cycle of the assets, but no one has access to all of the life-cycle data of the assets. To generate value from the fleet data, it is necessary to understand this challenge of fragmented fleet life-cycle data. Figure 2.2 illustrates the fragmentation of fleet data into multiple actors. The challenges are the fragmented fleet data and the problems in sharing the data, e.g. barriers are related to the ownership of data when data closely related to the business is not intended to be shared, to the data quality issues of manually entered data, and to the challenge of a common platform for sharing data which is often hard to define (Metso, 2018).

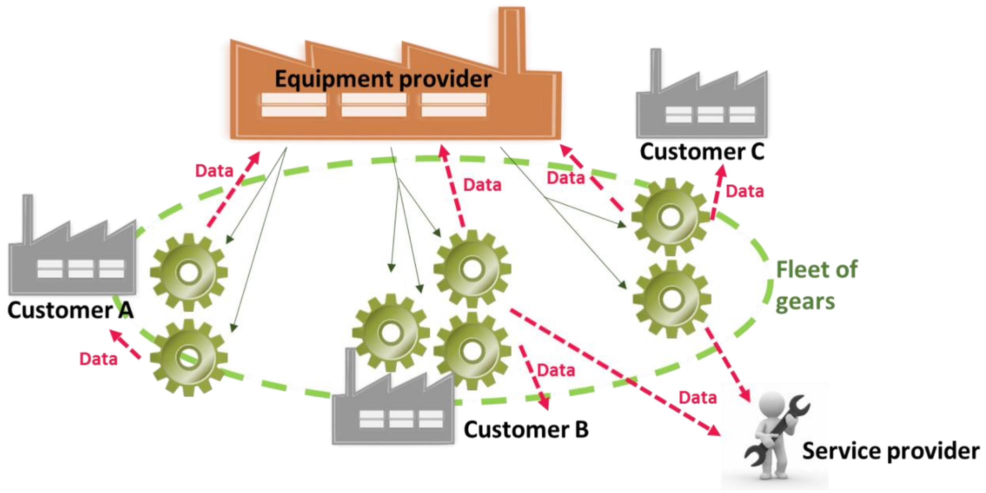


Figure 2.2 Fragmented fleet data and the actors around the fleet

The process from data to business knowledge and value has been recently discussed in literature from different aspects. From an information management perspective, the topic has been studied a lot and it focuses mainly on the technical realization from data to knowledge that is often referred to as data mining. There has also been discussion on business intelligence processes and programs. In Figure 2.3, the definition of business intelligence process is illustrated and the division into two parts can be seen: the data mining (technical) phase and the decision-making (managerial) phase (Loshin, 2012). Business intelligence is described as the tools, technologies and processes needed to turn data into plans that drive profitable business action. From a managerial point of view, research focusses on defining “data to knowledge” and “data to decision” processes and decision-making needs (Davenport and Prusak, 1998; Miller and Mork, 2013). Research programs and projects have been implemented to explore the opportunities to develop data utilization in companies, for example the DIMECC Service Solutions for Fleet Management (S4Fleet) program (2015-2017).

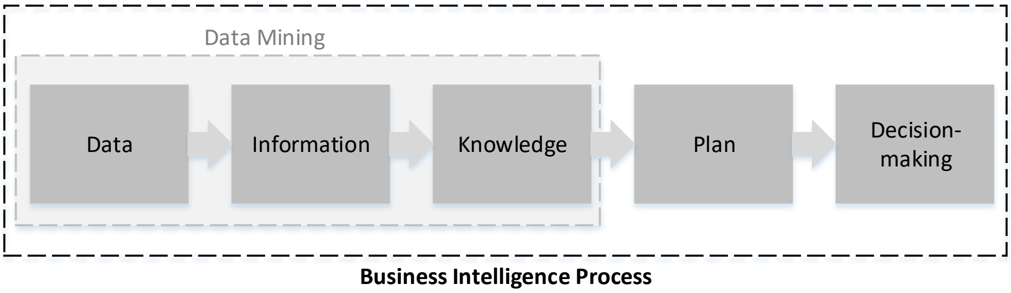


Figure 2.3 Business Intelligence Process by Loshin (2012).

In the DIMECC S4Fleet research program, the process from data to decision is applied and developed into a Data-to-Business-Knowledge (D2BK) model presented in Figure 2.4. The asset owner is the one who owns and/or operates the assets and is usually referred to as the customer company. Different levels of data-based services can be developed to support the asset owner/user to get the maximum performance from the assets. The model explores and defines the phases from data collection to data refining and business decisions. The theoretical background for the D2BK model is derived from the data, information, knowledge and wisdom (DIKW) hierarchy (Ackoff, 1989) and the knowledge pyramid (Rowley, 2007). The D2BK model discusses the levels of data-intensive services – data-as-a-service (DaaS), information-as-a-service (IaaS), and knowledge-as-a-service (KaaS). The variety of analyses, tools and models to support decision-making are discussed. The service level determines the interface and responsibility, i.e. what is delivered as a service and what is done inside the company. For example, DaaS is the basic level where the customer (asset owner) is provided with an opportunity for gathering asset data by means of specifically developed and installed technology. At DaaS level the asset owner is responsible for data analytics and data utilization, whereas at KaaS level the asset owner is provided with data analysis with e.g. interpretations of trends or needed actions. For example, manufacturing companies are increasingly offering data-based services alongside with machinery and equipment to support the core products (see e.g. Vaittinen and Martinsuo, 2019; Marttonen-Arola et al., 2019; Ahonen et al., 2019). Data-based services support the customer's decision-making, and thus deep understanding of the customer's business and what creates value for the customer is essential.

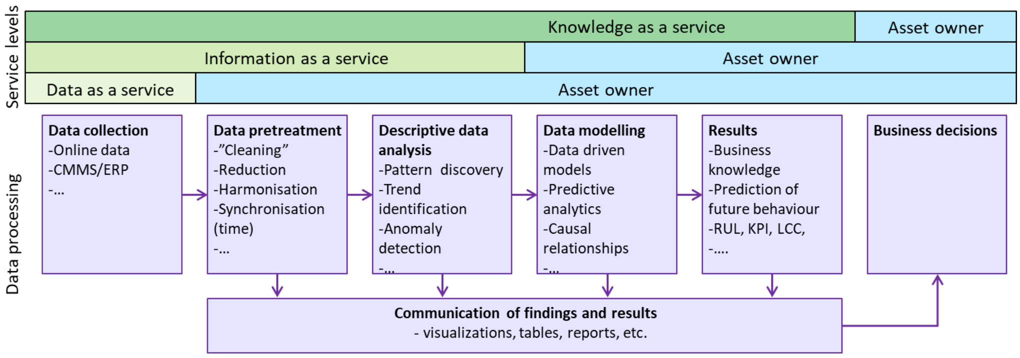


Figure 2.4 D2BK model (Kortelainen et al., 2015)

The previously introduced research program also highlighted the ecosystem view on fleet data utilization in order to exploit the data in data-based tools and services. Different organizations are involved in the data to decisions -process, but the involvement is not coordinated, and usually each organization manages their own data management processes. The networks in maintenance have been discussed in academic research, especially due to the outsourcing trend in maintenance services, where prior in-company activities have been outsourced to external operators. This has caused the need to study and develop asset management and maintenance services in networks (Ali-Marttila, 2017; Murthy et al., 2015; Persona et al., 2007; Sinkkonen et al., 2013). The literature also defines the term 'value networks' in the maintenance context to highlight the value creation aspect (Ahonen et al., 2010). Recently, the use of the term 'ecosystem' has increased to emphasize the interplay/interaction between organizations and to emphasize the intent to create value for the whole ecosystem (Valkokari, 2015; Adner, 2017). This emphasis on dynamic interaction in value generating process and the ambition to create value for the whole ecosystem can be seen as the main differences compared to networks (see e.g. Hearn and Pace, 2006; Kans and Ingwald, 2016). Different ecosystem types differ from each other in terms of their outcomes, interactions, logic of action and actor roles (Valkokari, 2015) and thus, it can be noticed that literature describes different types of ecosystems. The literature also discusses business ecosystems (Iansiti and Levien, 2004; Peltoniemi and Vuori, 2008) and recently also ecosystems around platforms, i.e. digital ecosystems (Karhu et al. 2011). An ecosystem can be viewed as a structure where value is created for each actor (Adner, 2017). In fleet management, when utilizing fleet data, the ecosystem can be formed around the fleet of assets. This structure can be defined as a "value ecosystem around a fleet" (Kortelainen et al. 2017a). It emphasizes the view of a common aim to create value from fleet data for the actors of the ecosystem and the ecosystem as a whole. The process from fleet data to decisions and eventually to value involves multiple actors, and the aim is to create value for all the actors and for the ecosystem around the fleet. The idea is to take advantage of the core competencies and the capabilities of each actor in value creation. The challenge is developing ecosystem collaboration and achieving mutual effectiveness and survival in the competition between ecosystems.

This thesis considers the actors of an ecosystem around a fleet to be the original equipment provider, its customer, the maintenance or fleet service provider, and the information service and/or platform solution provider (e.g. IBM, Wapice etc.). Figure 2.5 illustrates the ecosystem around a fleet. It is possible that an OEM also provides fleet services, and this is when the actors are limited to three actors. It is important that the fleet ecosystem and the actors are defined case specifically. However, in real life, it is possible that the actors are involved in multiple ecosystems at a time, depending on how the ecosystems are defined and from which perspective. This makes the situation complex and analysing the value of data even harder.

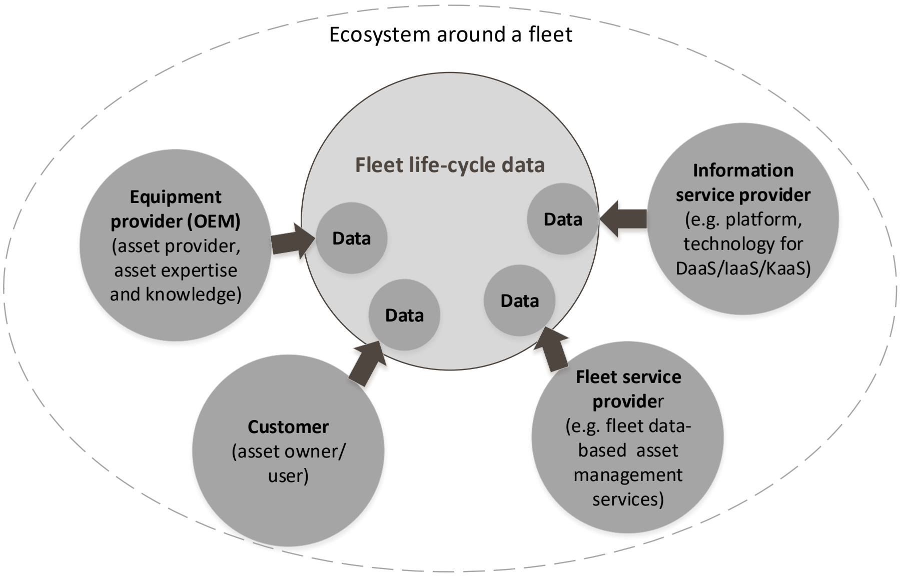


Figure 2.5 Actors of ecosystem around a fleet

3 RESEARCH DESIGN

3.1 Research approach

Research design works as a guide to how to approach the studied phenomena. This research design section presents the methodological foundations for building constructions, e.g. frameworks and models, in management research. First, the research approach and philosophical assumptions are discussed including ontological and epistemological considerations. Then, methodological choices are discussed and the utilized research methods and data collection techniques in individual publications are described.

The research paradigm determines how to approach the studied phenomena. The research paradigm defines the nature of research questions, used research methods and the pursued research outcomes (van Aken, 2004). The paradigm describes how to understand reality, how to gain knowledge, how to investigate reality and how to confirm that the knowledge is valid. In other words, the research paradigm includes the ontological, epistemological, and methodological considerations. There are different classifications for research paradigms (Bryman and Bell, 2011; Järvensivu and Törnroos, 2010; Peters et al., 2013). In management research, the generally appearing paradigms are positivism, realism, and constructivism. This thesis applies the constructivist paradigm.

Constructivism is not as widely utilized as e.g. critical realism, but several researchers have emphasized the potential of constructivism in business and management research (Peters et al., 2013; Järvensivu and Törnroos, 2010; Mir and Watson, 2000). The constructive research approach is also applied in management accounting research and operations research (Kasanen et al., 1993). Design science is considered to share some of the same features as constructivism, but design science is considered more a research approach or methodology than a paradigm (Johannesson and Perjons, 2014). The strengths of constructivism are, for example: contribution of results to contextual insights, applicability, highlighting the importance of the community in knowledge creation, and the active role of the researcher in shaping a theoretical perspective (Järvensivu and Törnroos, 2010; Mir and Watson, 2000).

The paradigms are classified based on their presumptions about reality and knowledge. Epistemology describes the essence of knowledge. The constructivist approach considers that there is the possibility of multiple community (e.g. researchers) formed knowledge bases rather than only one universal truth (Järvensivu and Törnroos, 2010). Thus, there is no universal definition of valid knowledge but there can be multiple valid approaches, which help in gaining a better understanding of the world. Constructivism is generally considered to be the theory-driven approach where researchers interact with the phenomena to create a model of reality which we call knowledge (Mir and Watson, 2000).

Ontology describes how reality is understood. In terms of ontological considerations, in constructivism the research should proceed towards finding local, community-bounded, interacting forms of truth. The truth is created and validated through dialogue, critique, and consensus in different communities of usable knowledge and empirical evidence. Constructivists believe that theory and practice are fundamentally interlinked (Mir and Watson, 2000). Constructivism is closely related to the critical realism paradigm, and these paradigms differ mainly in regard to ontology. Constructivism can apply a subjective approach to reality while critical realism trusts more in objectivity. Critical realism and constructivism might also share the same ontological and epistemological concerns. (Järvensivu and Törnroos, 2010)

Constructivism is applied by this thesis as a research approach to study the phenomenon and aiming to find the solution as a result to the practical problems recognized in the industry. The purpose is to provide mostly theory-based solutions for managerial purposes in the industry environment. The research is conducted as part of a large research program, and it is therefore influenced by the researchers and companies involved in the research program. It can be assumed that subjectivity is present to some extent. The research program participants are involved in the research process and their interests have partly affected the research, but the feedback from other researchers outside the research program has been requested during the research process to reduce researcher bias and increase the objectivity of the study. This thesis is based on the constructivist paradigm because constructivism makes it possible to assess prior theories and generate new knowledge through dialogue between theoretical conceptualization and empirical investigation. The issue can be studied in a real-life context and the phenomenon can be evaluated in relation to previous findings while developing novel ideas based on empirical discovery. Approaching research with constructivism enables the conduct of innovative research with practical relevance (Järvensivu and Törnroos, 2010). In management and business research, constructivism is applied e.g. in management accounting (Kasanen et al., 1993), business network research (Peters et al., 2013; Järvensivu and Törnroos, 2010) and strategic management (Mir and Watson, 2000) research. Thus, constructivism is the appropriate approach to research this topic as the research combines theories from the fields of management accounting, knowledge management and ecosystem research. This research is interdisciplinary by nature, and it aims to combine theories to create novel and innovative solutions for the studied phenomenon.

3.2 Methodology

Methodological choices provide the basis for the selection of suitable research methods. Methodology provides a frame for how the research can be conducted, how the research questions can be shaped, how to approach them and what kind of research methods can be utilized. Van Aken (2004) distinguish three categories of scientific disciplines: formal, explanatory and design sciences. The formal science is applied e.g. in mathematics. Explanatory science aims to describe, explain and possibly predict observable phenomena. The explanatory science is applied e.g. in social sciences, economics and sociology. The design science aims to describe, explain and propose a solution to the researched phenomenon, and it is applied e.g. in engineering and medicine (van Aken and Romme, 2009). Design science can be seen as prescription-driven research and it is used in management theory, while the explanatory science is rather considered a description-driven research approach and is usually used in organization theories. Design science can be defined as follows:

"The mission of a design science is to develop knowledge for the design and realization of artefacts, i.e. to solve construction problems, or to be used in the improvement of the performance of existing entities, i.e. to solve improvement problems" (van Aken, 2004).

"Design science aims to change the world, to improve it, and to create new worlds. Design research does this by developing artefacts that can help people fulfil their needs, overcome their problems, and grasp new opportunities. In this endeavour, design research not only creates novel artefacts but also knowledge about them, their use, and their environment." (Johannesson and Perjons, 2014)

Thus, in the design science approach, it is essential to develop scientific knowledge that can be used in designing solutions to management problems (van Aken, 2004). The design science aims at developing a construction, a model or a method in order to solve a problem. The typical phases of design science are (1) identification of the problem, (2) development of the solution, i.e. design, (3) demonstration of the solution, and (4) validation (Johannesson and Perjons, 2014). The phases are illustrated in Figure 3.1.

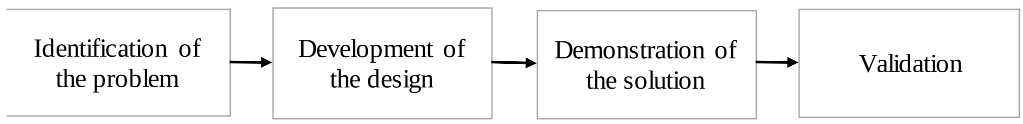


Figure 3.1 The phases of design science research process

The design science approach is used in this thesis because the aim is to solve managerial problems related to the researched topic (fleet management). There is also the strong influence of company needs and involvement. In this thesis, the empirical observations and researchers' perceptions of knowledge are combined in knowledge creation with the empirical observations. Therefore, the voices of previous theories, researcher community and companies are present. The research results are based on existing theory, but the empirical observations have a significant influence as well. The logic has been to create a construct or a framework based on literature or theories, and then the theoretical frameworks has been tested with empirical data and complemented with the empirical results. The study has progressed in an abductive manner where the theory and empirical observations have influenced one after another. In the constructivist approach, research can be abductive, i.e. theory generating and testing. Thus, constructivism often occupies the middle ground between induction and deduction (Järvensivu & Törnroos 2010). The results are both theoretical and empirical, and the outcome is a construction representing a phenomenon or a suggestion how the phenomenon can be modelled and solved.

In this thesis, when developing the constructions, different methods, such as analytical modelling and case study, are utilized. In management and operations research, it is acceptable and quite common to apply methodological pluralism or mixed methods regardless of the challenge of incommensurable viewpoints (Midgley et al., 2017). From philosophy of science perspective, it has sometimes been regarded as a problem to apply different methodological stances because other approaches may not accept other methods as valid (see e.g. Jackson, 2006; Midgley et al., 2017). However, some researchers have proposed that the methodological pluralism may bring benefits (Midgley et al., 2017). Management and operation research usually studies research problems close to managerial practical problems and often it has been acknowledged that different research methods, including also both qualitative and quantitative methods, enrich and give added value to these research problems (Jackson, 1999). In this thesis, methods such as analytical modelling and case study are utilized which are representing quantitative and qualitative research. The different approaches are not questioning each other's, but they enable to create understanding by utilizing different insights and enriching the results.

The phases of design science appear in the individual publications as shown in Table 3.1. Publications 1–4 focus on identifying and describing the problem, Publications 2 and 4 also develop ideas that can be further developed in the next publications. Two publications (5 and 6) focus on model development and the demonstration of the model. Preliminary validation is done with descriptive cases in Publications 5 and 6. The actual validation, the last phase of the design science process, needs to be done as further research, due to the lack of real case data, as discussed in section 5. Regardless of the incomplete validation of the developed models, the utilized descriptive data and testing gives satisfactory results and foundations for theoretical and managerial implications. The overview of the roles of individual publications are presented in Table 3.1. Research methods and data collection are discussed in detail in the following sections.

Table 3.1 Overview of the methodological choices and empirical data employed in the individual publications.

	Research methods	Empirical data	Purpose of paper	The phase of design science approach
Publication 1	Literature review, Industrial professional and academic expert panels	Insights from industrial professionals and academic experts, six industrial professionals, twelve academic experts	Background paper: Literature matrix IoT technologies in asset management	Identification of problem
Publication 2	Literature review, Framework building based on literature and insights from industry practitioners	Insights of companies involved in the DIMECC S4Fleet research program, in total 10 companies, qualitative data from seminars, presentations & other material	Supports model building: Fleet Decisions Identification tool (fleet decision-making and benefits perspectives)	Identification of problem & Development of design
Publication 3	Literature review, Case study, empirical examples	Interview data from companies: Six cases: three cases from Finland and three cases from Norway In total 19 interviews in six cases, in total 10 companies involved	Supports model building, Fleet definition and Summary table (fleet management, benefit perspective),	Identification of problem
Publication 4	Framework building based on literature and insights from industry practitioners	Insights from research program participants in seminars and other project materials	Supports model building Framework of the roles of actors in the ecosystem (ecosystem perspective, costs and benefits)	Identification of problem & Development of design
Publication 5	Model building	Built model is tested with descriptive case: Illustrative data with sensitivity analysis, numerical data	Building the model, cost-benefit approach Model (company level)	Development of design & Demonstration
Publication 6	Model building	Developed model is tested with illustrative data: Illustrative data with sensitivity analysis, numerical data	Developing the model, value at ecosystem level Extended model (ecosystem level)	Development of design & Demonstration

3.3 Research methods

This thesis applies methods such as literature review, framework and model building and case study. The research methods of the individual publications are presented in Table 3.1. Overall, Publications 1–4 identify the research problem and support model development by building conceptual frameworks about specific areas of the aimed models. Then, Publications 5 and 6 focus on model development and testing it with descriptive cases.

Literature review

Literature reviews are utilized to map the previous literature and to specify the research problem. Literature concerning IoT technologies in asset management, fleet management and ecosystems are reviewed. Literature has been scanned with large scientific research databases, mainly with SCOPUS and Google Scholar, which are extensive databases of peer-reviewed scientific literature. Queries with different combinations of search words have been conducted to gain a wide and comprehensive view on the current state of scientific research in this relatively new research area. Literature reviews have been summarized in the individual publications, for example as a literature matrix (Publication 1) and summary table (Publication 3). Literature reviews formed the basis for the framework and model building.

Framework and model building

The frameworks are built based on previous literature and tested and improved with empirical data and cases. In Publications 2 and 4, the frameworks were tested in an industrial environment and presented in seminars to gain feedback from industrial professionals and academic experts to ensure the validity of the research. Creating frameworks is a useful research method for illustrating the research problem and proposing a structure and logic of the studied phenomenon. These kinds of frameworks are one form of constructs design science aims to produce – a proposition to describe and model the phenomenon (van Aken and Romme, 2009). In this thesis, the difference between framework and model building is that frameworks are conceptual frameworks and the models aim at conceptualization but also at mathematical derivation. Figure 3.2 summarizes how the developed frameworks and models are connected to each other in this thesis and how the developed frameworks form the basis for further model building in the last two publications.

Publications 5 and 6 apply model building as a major research method. The modelling in these publications has the characteristics of analytical modelling. Analytical modelling aims to depict constructs or processes with deductive logic (Demski, 2007). Analytical modelling is considered a suitable method in management research to perceive phenomena and to observe the effects of variables. Modelling is considered a useful tool for decision-making in many research areas related to management research (Gorry and Morton, 1989; Mun, 2008). Models are tools for decision-makers to analyse and observe the results and consequences of changing variables. Models can be used to analyse, compare and optimize decisions, and therefore they support decision-making. The advantage of modelling is its transparency, which promotes the internal validity of constructs. The developed models in Publications 5 and 6 are demonstrated with descriptive cases.

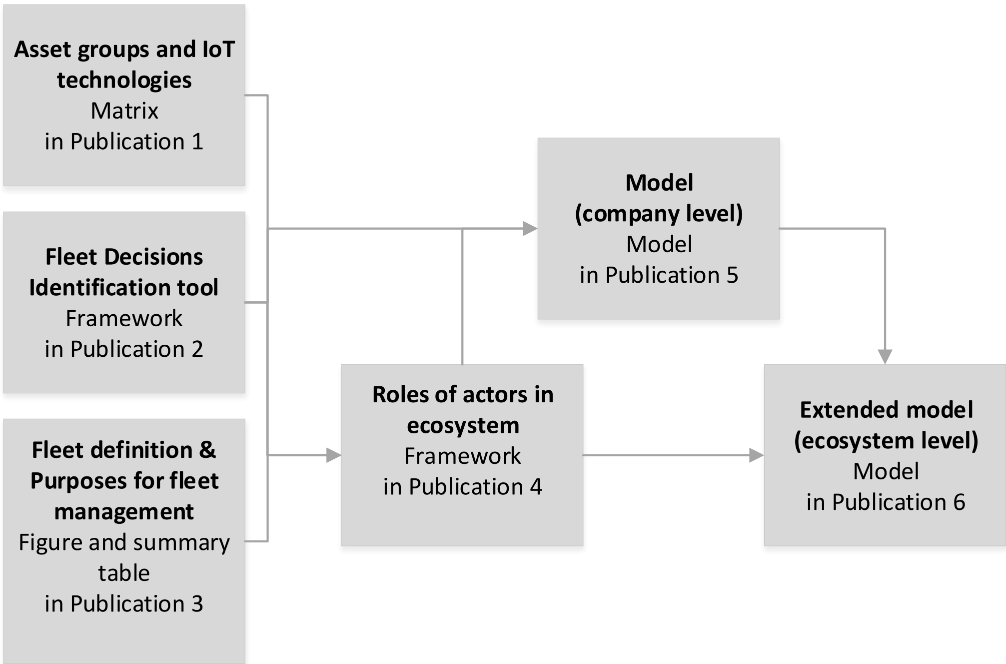


Figure 3.2 The development of frameworks into models.

Case study

In this thesis, case study is utilized in Publication 3 and descriptive cases are used in Publications 5 and 6. Case study is defined as an empirical research that uses contextually rich data from real-world settings to investigate a focused phenomenon within a bounded system (Barratt et al., 2011; Creswell, 2013). A bounded system refers to a case where the boundaries, such as time, place, and phenomenon, are defined. Case studies can be used to provide description, test theory or build theory (Eisenhardt, 1989; Ketokivi and Choi, 2014). Case study enables the research of a phenomenon in detail by exploring and giving a rich description of the issue. Case study is suitable for operations management research where the aim is often to build and extend theories (Eisenhardt, 1989) and to explore and widen the understanding of the phenomena or issues in their real-world settings. Case study is considered suitable for industrial engineering and management research where the context and experiences of actors are critical, especially the experiences of managers are valuable in many research areas. Case studies are utilized broadly in e.g. business-to-business marketing research (Borghini et al., 2010; Piekkari et al., 2010), industrial network research (Halinen and Törnroos, 2005; Dubois and Gadde, 2002), and purchasing and supply management research (Dubois and Salmi, 2016).

Case study is utilized in this thesis because it enables the study of the issue in detail in a specific context and provides a detailed description of the case. Secondly, the research is conducted in collaboration with the industry, and several companies are involved in the research program within which this research is conducted. The case study is a suitable method for the research because the aim is to deepen the understanding of a relatively novel topic, and therefore it is a suitable method to deepen the understanding and provide practical managerial insights from the field. Deep and detailed descriptions about the phenomenon are beneficial when developing the concept and model, and especially when testing the model with cases to validate the construct (see Hevner et al., 2004). In addition, it is beneficial to interview company representatives, mainly managers, to get valuable insights from their points of view. In this way, relevant and practical ideas can be gained to improve the ideas and the final result. For example, in Publication 3, multiple cases are used to test whether the hypothesis based on literature is true. In other words, whether the reality of literature applies to the real-world settings or whether there is further knowledge in the field. The cases are used to deepen understanding and to provide more detailed information about the studied issue than the theory could provide. The utilization of wide statistical data would have not given any added value for this research, as only few organizations in a large sample have advanced their fleet management practices or data management practices at ecosystem level.

3.4 Data collection

This thesis utilizes empiric data that are primary collected from companies involved in the DIMECC S4Fleet research program (DIMECC S4Fleet, 2015–2017). Companies are highly interested in taking advantage of utilizing IoT technologies and applications in their business to develop service solutions for fleet management. Companies represent a group of different sized companies, with differed resources, in different roles in the ecosystems and they were in different phases in developing IoT applications, i.e. others already had their first applications ready, others just considered if they were going to start the development. Thus, the companies represented a balanced sample of companies taking advantage of digitalization in developing service solutions for fleet management. Qualitative data are gathered through interviews and group sessions, such as meetings, workshops and seminars. In addition, three Norwegian companies outside the research program were interviewed to support the international fleet management views from the traditional fleet management perspective. Next, data collection is discussed in detail in regard to the individual publications.

Publication 1

In Publication 1, an enquiry, where the potential of IoT technologies was evaluated on a 5-point Likert scale and through open comments, was implemented to collect empirical data. Empirical data have been gathered via an industrial professional panel that is comprised of industrial asset management and industrial maintenance specialists from five companies, representing original equipment manufacturers (OEMs) and their customer companies from the mining and energy industries. The mining and energy industries are traditionally asset and capital-intensive industries where IoT technologies and automation create significant potential. In total, six professionals from these companies participated in the panel. The panel was duplicated with a group of Finnish researchers in the fields of performance, cost and asset management. In total, twelve researchers participated in the researcher panel. The researchers who participated in the panel have knowledge of asset management, and they consider the topic from an industrial management perspective, specializing in performance and cost management.

Publication 2

In Publication 2, the empiric data were collected from case companies who participated in the kick-off seminar of project 3 in the S4Fleet research program. Companies were asked to provide presentations, and certain questions were required to be answered in their presentations. The used empirical data is qualitative data based on the presentations and presentation material provided by the companies. The presentation materials have been archived, and notes from the presentations have been made and archived. In total, data from 10 companies were utilized in this publication. Empiric data was used to complement the framework created as a result of the synergy of theory and empirical observations. The companies had basic knowledge and interest towards the topic as they are involved in the same research project. The companies were large and medium-sized companies representing e.g. original equipment manufacturers and service providers from the mining, forest, logistics and information technology industries.

Publication 3

Publication 3 applies multiple case studies. Qualitative interview data were collected from six cases: three cases in which the companies operated in Finland and were involved in the DIMECC S4Fleet research program, and three cases in which the companies operated in Norway. In total 19 interviews in ten companies were conducted during 2015–2016. In addition, public materials provided by the companies were utilized. Interviews were semi-structural and the interview sessions have been recorded. The Finnish companies are equipment manufacturer companies and service providers representing the mining, forest and logistics industries. The Norwegian companies represent different stakeholders in the oil and gas industry, including a shipping company, an exploration and production company, and an equipment manufacturer. The cases were selected to respond to the results of literature in order to find real-world cases to verify the results found in literature in practice. The purpose is to present cases that represent traditional and extended fleets. Data collection is described in detail in Publication 3.

Publication 4

The framework in Publication 4 is based on the multiform data collected during the research program. The data were collected from the companies involved in the ecosystem data -focused part of the program structure, and includes materials from seminars, meetings and other events, such as workshops. Prior research, the research work during the research program and the collaboration with companies within the program formed the basis for the development of the framework.

Publications 5 and 6

Publications 5 and 6 utilize numerical illustrative data, which describe a descriptive case. The descriptive case is based on a real case, utilizing secondary data from previous research (Sinkkonen et al., 2013), and these are added with some complementary illustrative data. The cost structure is real and based on the real case. However, as the case is not defined for this research and not all data were available, some additions have been made. Therefore, the cases in Publications 5 and 6 have been complemented with illustrative data regarding e.g. the costs of IoT technologies and data refining processes as well as the estimations of benefits and costs for the actors of the ecosystem (in Publication 6). The validity of this kind of data has been ensured by conducting a sensitivity analysis to demonstrate the variation of used data. Sensitivity analysis enables the examination of the effects of variables and decreasing the possibility of biased interpretations and conclusions. In addition, the main point in these publications has not been the actual results of calculations, but rather testing the logic of models and how the models suit numerical cases.

4 REVIEW OF THE RESULTS

4.1 Summary of the publications

Publication 1

The objective of Publication 1 was to recognize the relevant IoT technologies for asset management from both theoretical and practical perspectives. A literature review was conducted to identify the asset groups and IoT technologies in an industrial context. Literature was scanned to understand how the IoT technologies (RFID, WSN, WSAN, WPAN, NFC, naming and location-based technologies) were utilized in the management of different physical asset groups (machinery and equipment, buildings, vehicles, inventories and spare parts). RFID (radio frequency identification) uses radio waves to identify items with RFID tags and readers. WSN (wireless sensor networks) utilizes sensors to collect data about the targeted phenomenon and transmits the data to base stations that can be connected to the Internet. WSAN (wireless sensor and actuator networks) combines sensor technologies with actuating possibilities. NFC (near field communication) refers to short-range high frequency wireless communication technology. Naming technologies can be used to identify objects, and they refer to barcodes, 2D barcodes, EPC (electronic product code) and IP (internet protocol) addresses. Localization technologies include satellite, mobile network and local area network -based technologies to locate objects. Examples of technology applications include the WSN technology in monitoring applications, naming technologies in storing e.g. maintenance history and product information, and location-based technologies in locating the machinery and equipment to be repaired within a factory area.

In the empirical part of the research, industrial professionals and academic experts were asked to evaluate the potential of different IoT technologies in the management of different asset groups (see Publication 1 for the potential evaluation). As a result, the potential was identified as remarkable in industrial environments but there is still a lot to do before the technologies can be exploited fully in collecting data and then utilizing the data in asset management related decision-making. Table 4.1 collects the asset management related applications or decision-making situations where the IoT technologies can be utilized, both from literature and insights from industrial professionals and academic experts. The original literature matrix is presented in Publication 1, and here the matrix is adapted, summarizing both theoretical and practical perspectives.

Publication 1 works as an introduction to the opportunities of increasingly collected data in supporting decision-making in the asset management of asset groups. Publication 1 partly answers to RQ1 of this thesis by recognizing the application opportunities and decision-making purposes where data collected with IoT technologies could be utilized. Publication 1 also starts the categorization of different asset groups and works as a starting point for understanding the different asset fleets in the asset management of the smart factories of the future.

Table 4.1 Opportunities to apply IoT technologies in the management of asset groups, the matrix adapted from Publication 1 and added with insight from empirical findings.

IoT technologies	**ASSETS**				
	Machinery and equipment	**Buildings**	**Vehicles**	**Inventories**	**Spare parts**
RFID	Remote condition monitoring, Failure follow-up notifications, Embedded health history with the asset, Device management, Maintenance information sharing, Collecting real-time production information	Access control system	Electric vehicle batteries	Storage levels of parts, Real-time information about products on assembly line, Inventory tracking and control, Resource management	Spare part tracking and inventory level, Spare parts supply chain management
WSN	Condition-based maintenance, Condition monitoring, Fault diagnostics, Collecting running parameters, Monitoring the conditions of environment	Energy monitoring, Behavioural monitoring, Space monitoring, Energy management, Power consumption monitoring, Condition monitoring	Traffic estimation, Traffic control, Condition monitoring	Online inventory management System inventory management, Monitoring the conditions of inventory environment	Condition monitoring data from equipment to support the spare part ordering decisions
WSAN	Gas detection and immediate isolation of gas leak source, Process control applications, Improve safety with automation	Energy saving, Adjust the conditions in work and process environment, Power management, Building automation	Unmanned ground vehicle		
WPAN (Bluetooth, Zigbee)	Collecting running parameters	Bluetooth, Zigbee, Wifi: communication of smart living space	Communication between vehicles, Bluetooth headset and voice-activated features	Inventory tracking with Zigbee	
NFC	Context-aware mobile support system, Recurring maintenance processes: central process control and maintenance event documentation	Classroom access control, Access keys for offices and houses	Maintenance event documentation	Availability and stock information of products, Inventory control	
Naming technologies, (barcodes, EPC, IP address)	Maintenance event documentation and information sharing, Remote monitoring and remote control	Building automation, Remote monitoring and remote control, Access to documentation	Tracking of individual vehicles, Remote monitoring and remote control	2D barcodes: product information, mobile product verification	Barcodes in spare parts management, Spare part history of an asset
Location based technologies (satellite, mobile networks, local area networks)	Tool tracking and localization with RF signals	NFC smartphone indoor interactive navigation system	Asset localization/tracking, GPS: location of vehicles	Indoor locating with RF signals	

Publication 2

The objective of Publication 2 was to identify decision-making situations in fleet asset management. The publication categorizes decision-making situations and proposes a framework that can be used in identifying fleet decision-making situations through the life cycle of asset fleets.

Publication 2 discusses the different asset management decision-making situations during the life cycle of assets and combines the idea with the frequency of decision-making needs, i.e. in which time span the decision needs to be made. Literature often categorizes the decisions into operational, tactical and strategic level decisions. However, this study emphasizes the opportunities to make different types of data-based decisions enabled by IoT and increasingly gathered data. Decisions can be made more on an ad-hoc basis and in real time, but complex models can be developed to support decision-making, as well. Thus, the decisions were categorized into reactive, real-time, proactive and strategic decisions – in which the time available for decision-making defines the requirements for data availability and quality or nature of data.

The main result of Publication 2 is the Fleet Decision Identification framework (Figure 4.1) that identifies and illustrates the wide range of decision-making situations in fleet asset management during the life cycle of an asset. The framework is based on a literature review but the insights of industry practitioners were involved in the development of the framework as well.

The results of Publication 2 contribute to RQ1 of this thesis by identifying the fleet decision-making situations. It also introduces the link to analysis requirements and decision-making needs as well as introduces the preliminary ideas of benefits in fleet asset management.

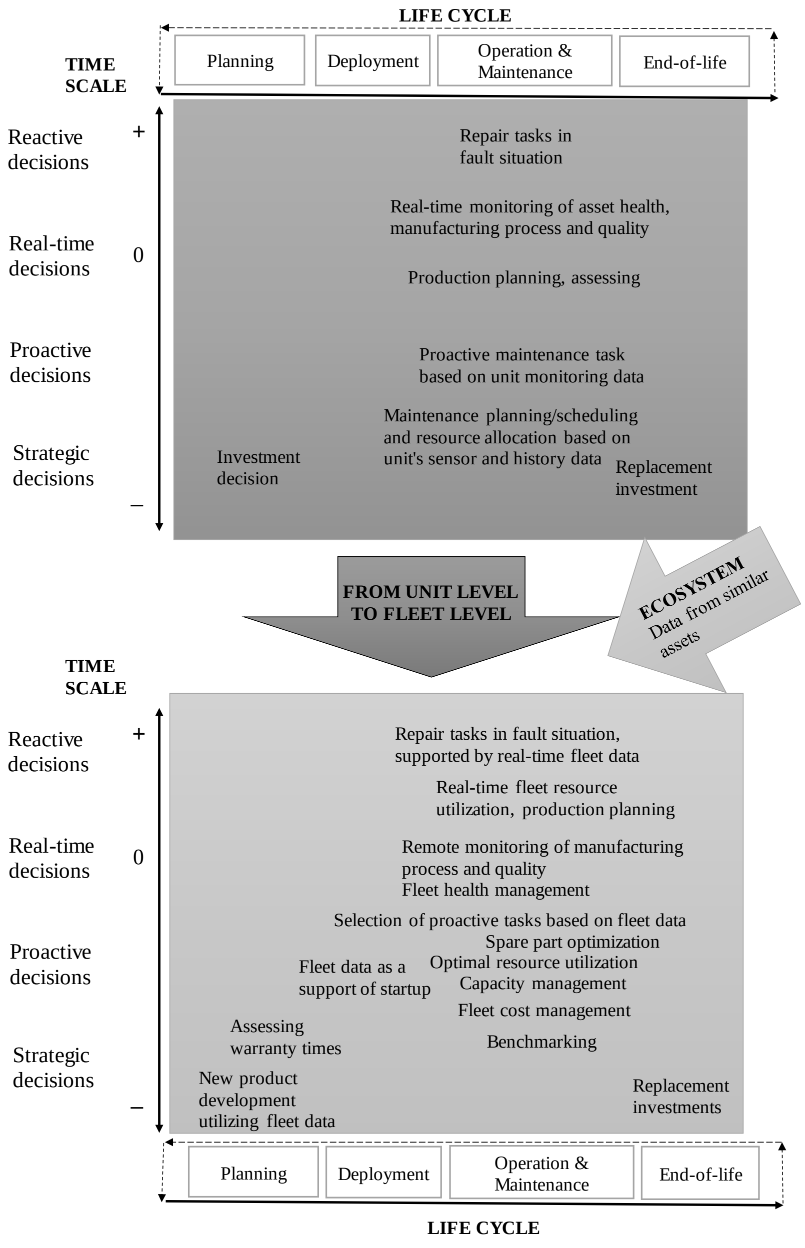


Figure 4.1 Fleet Decision Identification framework (Publication 2)

Publication 3

Publication 3 deepens the understanding of fleet management, including the concept of fleet, fleet management purposes and fleet decision-making situations. The purpose of the publication was to understand the concept of fleet, analyse and upgrade the definition and consider whether the concept can be applied to different extended contexts (see Figure 4.2). The publication discusses the value of traditional fleet (i.e. ships, aircrafts, vehicles, machinery and equipment) management practices in new contexts by analysing the definitions in prior research and comparing findings from the literature to empirical findings. The presented cases represent examples of different fleets (traditional and extended fleets). The cases discuss what are considered as fleets in the contexts and how fleet level management could be applied in the case fleets. The empirical findings are compared to the findings from literature, and the technologies and application opportunities are recognized to some extent but they are not yet exploited fully in practice in industrial environments. Table 4.2 summarizes the results of Publication 3 and presents the fleet management purposes in the literature and based on the empirical findings.

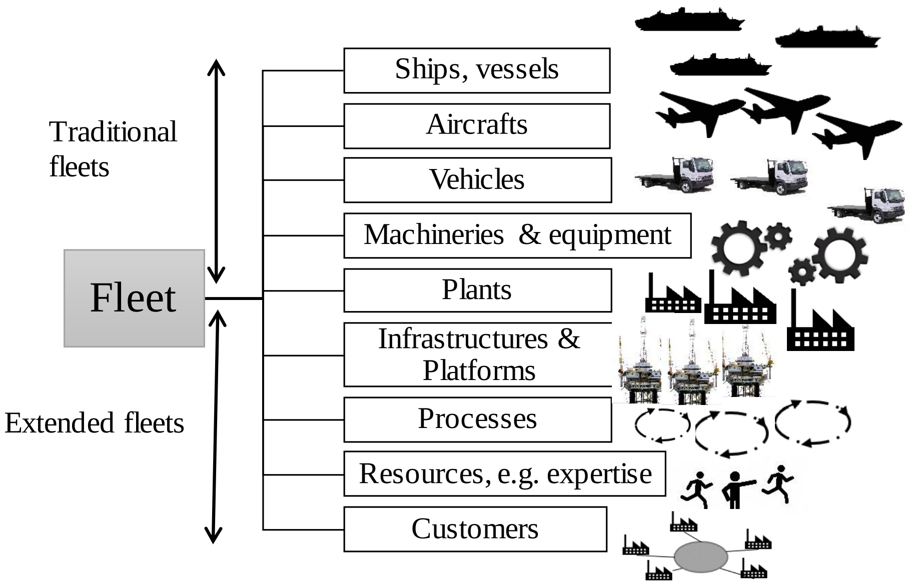


Figure 4.2 Traditional and extended fleets (Publication 3)

Based on the empirical results, there is untapped potential in utilizing fleet data both in traditional fleets and in unusual, extended fleets. In traditional fleets, where the ownership of the assets is complex, the fleet data is often fragmented and the different motives of asset owners for data utilization may hinder the optimal exploitation of fleet management opportunities. To benefit fully from fleet data in fleet management decisions, collaboration between the companies in the networks or ecosystems is usually needed. In extended fleets, such as infrastructures, platforms, processes, resources (e.g. expertise) or customers (e.g. customer sites: see Publication 3, case 3), it is possible that the fleets are not yet recognized and therefore there is untapped potential to benefit from fleet management. The benefits of fleet management can be achieved in operations and maintenance management as well as in strategic asset management. The benefits were recognized as e.g. the learnings from fleet data, applying the learnings to the whole fleet and the optimization of resource utilization, including optimal spare part utilization.

Publication 3 provides answers to RQ1 by introducing the fleet definitions, purposes and benefits of fleet management and by presenting wide practical descriptions of applying fleet management in different environments based on empirical results. The empirical results of Publication 3 deepen the understanding of the benefits of fleet management, including different cost savings and multiplied benefits because of fleet level management.

Table 4.2 Purpose of fleet management from the perspective of literature and practice in traditional and extended fleets (Publication 3)

Fleet	**Purpose of fleet management Theory/Literature**	**Purpose of fleet management Practice/Empirical results**
Traditional fleet - Aircrafts - Military - Vessels/ships - Vehicles - Machinery - Equipment	**O&M management** - Asset performance - Fuel consumption - Health management - Life-cycle analysis, remaining useful life estimation - Maintenance planning and optimization - Monitoring and proactive maintenance actions - Routing and scheduling problems - Resource management and allocation - Safety - Spare part management **Strategic management** - Investment and replacement decisions - Management strategy evaluation - Organizational performance - Risk management	**O&M management** - Automatized recommendations based on fleet data - Customer satisfaction - Fault detection and localizing - Increased availability - Life-cycle analysis - Maintenance planning - Monitoring - Optimization of fuel efficiency, including performance of a ship, fuel consumption, pollution and environmental costs - Performance analysis - Predictive models – proactive operations - Remote support and decision support (operational, tactical and strategic decisions) - Resource management - Safety, accident prevention - Spare part management **Strategic management** - Benchmarking - Investment decisions - Risk management
Other fleets – Extended fleets - Customers - Infrastructures (e.g. harbours) - Platforms - Plants - Processes - Resources (e.g. expertise of workforce)	**O&M management** - Asset performance **Strategic management** - Organizational performance - Benchmarking	**O&M management** - Best practices - Customer profiling - Increasing safety - Maintenance planning - Monitoring, corrective actions in time - Performance analysis - Predictions of future behaviour - Resource management, including human resources, system resources etc. - Unified spare part management **Strategic management** - Benchmarking - Investment decisions

Publication 4

The objective of Publication 4 was to understand the role of the ecosystem in creating value from fleet life-cycle data. This was realized by developing a framework (see Fig. 4.3) that illustrates the process from fleet data to decision-making and how the actors of an ecosystem can be involved in the data refining process. The starting point was to understand how the ecosystem is defined in the fleet context. The value ecosystem around a fleet was defined to include actors such as equipment provider, its customer company and service provider, and the asset fleet and fleet data were in the centre of the ecosystem, i.e. the ecosystem is founded on the fleet data of asset fleets. Service providers can be IT service providers and/or fleet service providers, depending on the case.

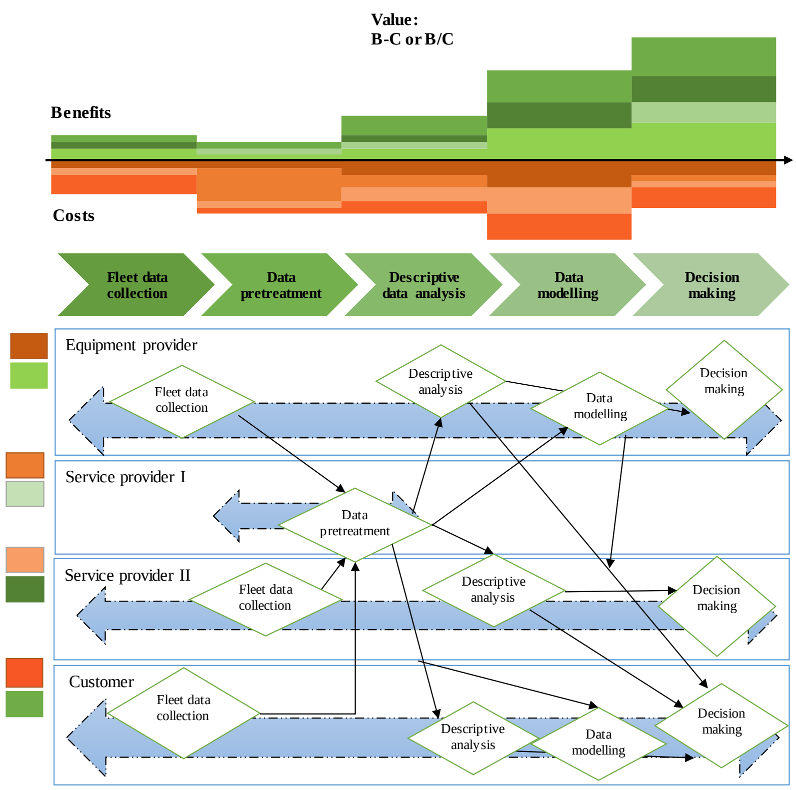


Figure 4.3 Framework for exploiting fleet data at ecosystem level (Publication 4)

The actors can be responsible for different phases of the data refining process and they can benefit from their core competencies. For example, data pre-treatment and the technical realization of analyses and models can be managed in a centralized manner by the IT service provider, and the equipment provider can provide their expertise and knowledge in developing the ideas and logics behind the analyses and models. On the other hand, fleet data can be generated by multiple actors, and each actor may utilize the refined data to support their own decision-making and gain benefits. Thus, the framework proposes that the costs and benefits from the data to decision-making process can be realized by different actors and the value of fleet data should be defined based on the costs and benefits. It is highly important that these costs and benefits are measured even though they are hard to define and measure as they contain parameters that are challenging to define objectively and precisely. This measuring makes it possible to discuss and develop the collaboration between the actors and to aim at ecosystem level collaboration and value creation.

Publication 4 contributes to RQ3 by defining the ecosystem around a fleet and discussing the roles of actors in the ecosystem in the fleet data to decision-making process. In addition, it links the roles of actors to the generation of costs and benefits for each actor, and eventually to the value of fleet data. The framework can be utilized as a tool to develop fleet data utilization in ecosystems, and the logic was further developed in the models of Publications 5 and 6.

Publication 5

Publication 5 focuses on creating the logic of how the value of fleet data can be evaluated from a company perspective with the cost-benefit approach. The objective was to create a model that can evaluate the value of fleet data and its cost and benefit components, when the fleet data is utilized to support decision-making in the asset management context. The model applies the cost-benefit approach, and as the method of valuation the net present value (NPV) is utilized. The structure of the model is presented in Fig. 4.4. The model applies the equation on NPV and the applied equations (4.1) are presented below. The model is discussed in detail in Publication 5 and only outlined in this section.

$$NPV = \sum_{n=0}^{k} \frac{B_{total_n}}{(1+i)^n} - \sum_{n=0}^{k} \frac{C_{total_n}}{(1+i)^n} \tag{4.1}$$

where

i = interest rate

n = year/time

k = length of an inspection period

B_{total_n} = total benefits in certain year

C_{total_n} = total costs in certain year

Publication 5 describes the total benefits of fleet data utilization in asset management related decision-making and categorizes the benefits into savings in maintenance costs, savings in quality costs and other benefits (see equations 4.2). The model also presents the logic of how the benefits and costs of data refining are cumulated with a certain data refining level. The data refining level includes phases such data collection, data pre-treatment, descriptive analysis, models and visualization, and the level of data refining refers to the amount of investments in these data processing phases. For example, the input to data pre-treatment usually reflects a higher data quality and advanced models can lead to the right decisions. The level of data refining, i.e. how advanced the phases of data processing are, affect the costs of data refining but also increase the benefits as better decisions can be made with detailed analyses and decision support. The size of the fleet affects the benefits in two ways: 1) the larger the fleet, the more accurate analyses can be made, and 2) benefits are multiplied if the decisions are made with all assets of the fleet in mind.

$$B_{total} = B_1 + B_2 + B_3 \tag{4.2}$$

where
B_1 = savings in maintenance costs in certain year
B_2 = savings in quality costs in certain year
B_3 = other benefits in certain year

The savings in maintenance costs (B_1) can be evaluated with a failure model that represents the typical maintenance costs of the fleet during the life-cycle of the assets. For example in Publication 5, the Weibull function, i.e. bathtub curve, is utilized to represent the maintenance costs of the fleet. With refined data as support for asset management decision-making, which can be illustrated as the data refining level, a certain maintenance cost level can be lowered, i.e. the maintenance costs of a certain year are reduced by a factor when compared to not utilizing the data as support for decision-making. These are the cost savings that can be referred as (B_1). The savings in quality costs (B_2) use the same logic that a certain cost level can be lowered with the data refining level. Other benefits (B_3) can also be savings in costs (e.g. in emissions) or they can be increases in revenues (higher profit from better quality products etc.).

The costs of fleet data utilization are generated from the process of upgrading fleet data into usable form to support fleet-level decisions. Costs can be divided into hardware, software and working costs (see equation 4.3). Costs can be initial investments or annual (recurring) by nature. For example, hardware costs are often realized once but software licences are annual costs. The level of data refining affects working related costs in particular because often the phases from data to analyses and models require a lot of working hours if the data and analysis quality are something that should be invested in.

$$C_{total} = C_1 + C_2 + C_3 \tag{4.3}$$

where
C_1 = hardware costs in certain year
C_2 = software costs in certain year
C_3 = working-related costs in certain year

The model as a main result of Publication 5 is unique and it responds to the need of understanding the value of data utilization for businesses. The results emphasize the importance of data utilization in decision-making in order to gain benefits and to create value from data. The model is multidisciplinary by nature, integrating theories from the areas of investment appraisal, maintenance management and information management. It contributes to RQ2 by introducing the logic of evaluating the value of fleet information as the difference between the discounted total benefits and total costs and connects the significance of data refining level to the value as well as the benefit of fleet level consideration.

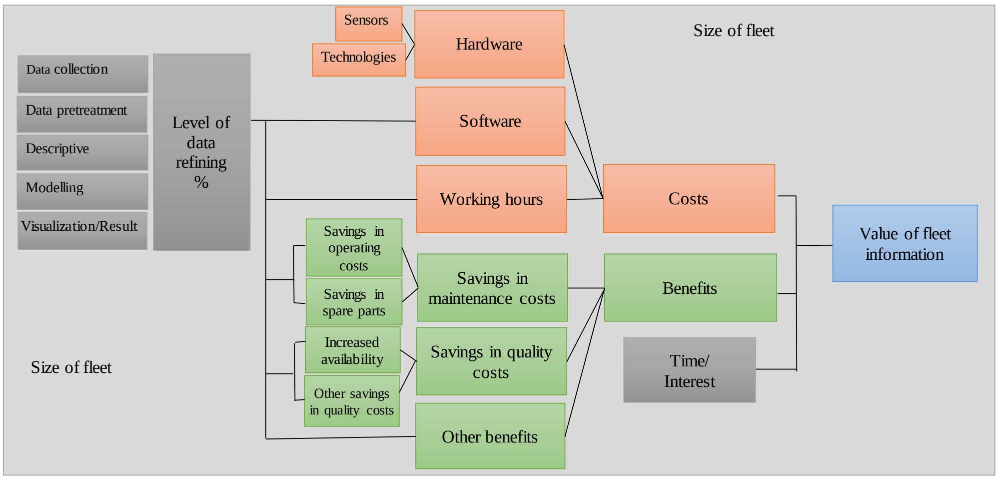


Figure 4.4 The structure of the model in publication 5

Publication 6

Due to the nature of fragmented fleet data, it is important to discuss value creation at ecosystem level. The objective of Publication 6 was to extend the previous model to comprise the value of fleet data utilization for each actor in a fleet ecosystem, including the costs and benefits of fleet data utilization for each actor.

In Publication 6, the costs and benefits for each actor were categorized and the structure of the extended model was presented (see Fig. 4.5). Analytical modelling was used to express how the value of fleet data can be evaluated for each actor and for the whole ecosystem with net present values and benefit-cost ratios. The model was demonstrated with descriptive data, which gives the results of a certain fleet ecosystem, and with sensitivity analysis the results were further analysed. The benefit of considering the value of fleet data from the ecosystem perspective makes it possible to divide the costs of data collection and other data processing between the actors of the ecosystem, which then could influence the profitability of the investment in data processing. The extended model applies the equation of net present value (4.1), and it is first calculated for each actor separately and then for the whole ecosystem. The extended model also considers the benefit-cost (B/C) ratios for each actor and for the ecosystem. The extended model applies the equation 4.4, and the ratios for each actor and for the ecosystem are calculated separately. The components of the benefits and costs for each actor are discussed in detail in Publication 6 and they are not repeated in this section. However, the structure of the extended model (Figure 4.5) illustrates the components.

$$^{B}/_{C} - ratio = \frac{\sum_{n=0}^{k}\left(\frac{B_{total_n}}{(1+i)^n}\right)}{\sum_{n=0}^{k}\left(\frac{C_{total_n}}{(1+i)^n}\right)} \tag{4.4}$$

where

i	= interest rate,
n	= year/time,
k	= length of an inspection period,
B_{total_n}	= total benefits in certain year
C_{total_n}	= total costs in certain year

The results indicate that creating value from fleet life-cycle data at ecosystem level requires the actors to collaborate. The actors may conduct different phases of the data refining process and provide fleet data -based analyses and services for the other actors. The pricing policies between actors can play an important role in the value formation for actors while often the customer is the one who gains the benefits from more efficient asset management. There should be measures that indicate the developments in the collaboration within the ecosystem and in the more efficient utilization of fleet information. An interesting point of discussion is to consider which measures should be optimized as value should be created to each actor and to the whole ecosystem. Another interesting point of discussion is the risks that might be related to the developed fleet analysis and decisions made based on those analyses. If a customer is provided with fleet analysis services and the customer makes decisions based on them but then something happens, e.g. unexpected fault occurs, who is responsible for the consequences? Is the customer responsible for their decisions or should the risks have been considered in the pricing policies of fleet services or how should the risks be shared?

Publication 6 contributes to RQ2 and RQ3 by continuing the discussion on the logic of evaluating the costs and benefits, and thus the value of fleet data, and extending the logic to the ecosystem level. In this publication, the importance and complexity of utilizing fleet data in an ecosystem is emphasized as well as the need of companies to collaborate and develop data management practices at ecosystem level.

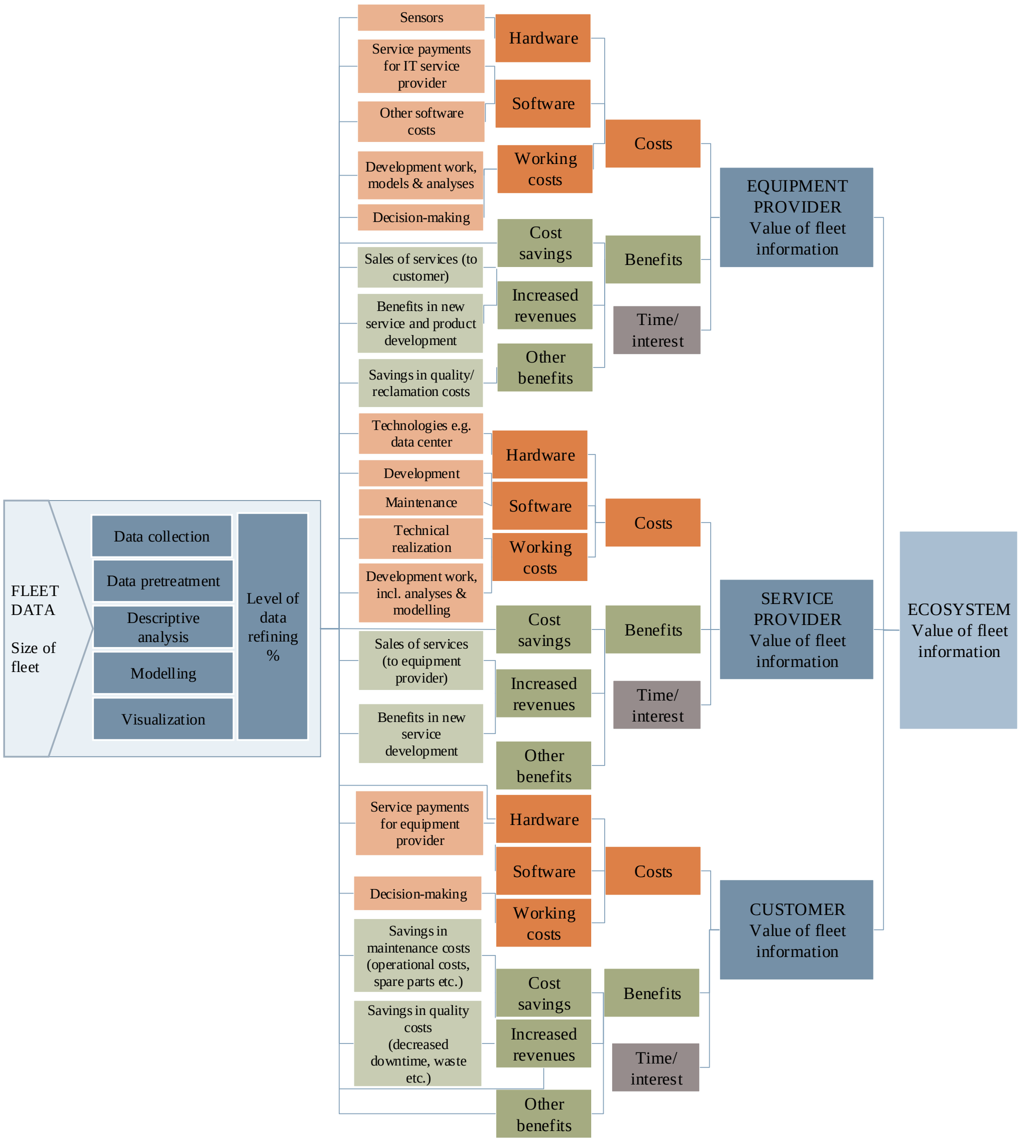


Figure 4.5 The extended model to evaluate the value of fleet information at ecosystem level (publication 6)

4.2 Summary of the results and contribution to the research questions

A summary of the publications, the results of individual publications and the link to the research questions are presented in Table 4.3 at the end of this section. The objective of the thesis is achieved by answering the research questions of the thesis. Next, the contribution of the publications to each research question are summarized.

The answer to RQ1 (*What benefits and value can be derived from fleet data in asset management related decision-making?*) can be concluded from the results of Publications 1–3. These publications present the definition of fleet, describe fleet decision-making situations and discuss what the expected benefits from fleet level decision-making are. The results of these publications can be condensed to Figure 4.6 which illustrates the main ideas from the publications and emphasizes the importance of identifying the fleet and fleet decision-making needs or purposes as the basis for generating benefits and value from fleet data. Figure 4.6 answers RQ1 and suggests that

- There is a variety of decision-making situations during the life cycle of an asset fleet where the fleet data-based analyses can be utilized to make better decisions. The key is identifying the fleet and the decision-making situations.
- Different level fleet analyses (reports, descriptive analyses, models etc.) can be utilized to support decision-making at different decision-making levels and situations.
- The expected benefits of fleet data utilization can be categorized into cost savings, increased revenues and other benefits.

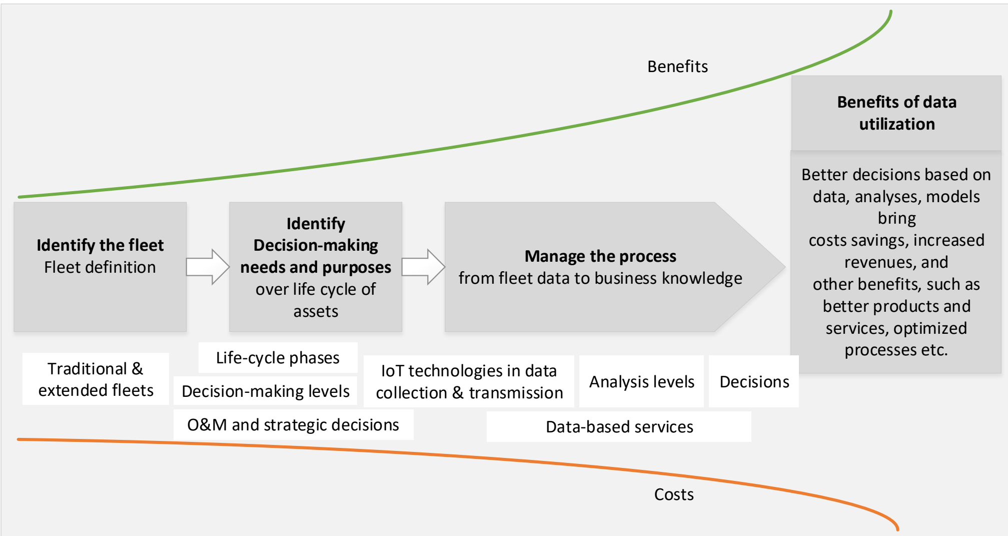


Figure 4.6 Summary of the contribution to RQ1

RQ2 (*How can the value of fleet data be evaluated?*) is answered by applying the cost-benefit approach in the first model and the extended model. First, the idea of understanding the value of fleet data by utilizing the cost-benefit approach was suggested in Publication 5, in which the first version of the model was built from a company perspective. Then the idea was further developed to the extended model in Publication 6, which deepens the idea of utilizing the cost-benefit approach in defining the value of fleet data and extends the perspective to the ecosystem level. Consequently, the answers to RQ2 can be stated as follows:

- Value can be defined as the difference of discounted total benefits and costs.
- The cost side consist of the costs from the fleet data refining process, including hardware, software and work-related costs.
- Benefits can be evaluated as achieved cost savings, increased revenues or other benefits that can be gained due to better decision support at fleet level decision-making.
- The value and profitability of IoT investments in fleet data utilization can be evaluated with the measures of net present value and B/C ratio.

RQ3 (*What is the role of ecosystem in the process of turning fleet data into value?*) discusses how the significance of ecosystem is emphasized when exploiting the value potential of fleet data. The roles of the actors are reflected in the accumulating costs but also in the gaining of benefits when the actors utilize fleet information in their decision-making. The costs and benefits are divided into multiple actors but usually those are not equally shared. Thus, firstly the actors of the ecosystem are needed to exploit the fleet data efficiently by taking advantage of the data and competencies that each actor has. Secondly, collaboration is needed to share the costs and benefits more equally between actors but also to optimize the value for the whole ecosystem. Publication 4 and Publication 6 discuss the role of the ecosystem in terms of the costs and benefits of fleet data. The results can be summarized as follows:

- The actors of fleet ecosystems have different roles in the process from fleet data into decision-making.
- Creating value from fleet data requires that the actors of the ecosystem collaborate in order to increase data availability and to exploit the core competencies of each actor in creating maximum value and support for the decision-making needs of all actors.
- The benefits for the ecosystem when utilizing fleet data are the division of costs between multiple actors (also scale advantage), service generation (better or new services) and improved data quality which enables better decisions based on data.
- Ecosystem collaboration makes it possible to develop a competitive and effective ecosystem that can achieve competitive edge.

The answers to RQ1, RQ2 and RQ3 together fulfil the objective of the thesis, and the extended model to evaluate the value of fleet data in the ecosystems of asset management is proposed. Figure 4.7 illustrates the connection between the research questions and the main contributions of the publications to the research questions. As a result, the components are needed when using the extended model and understanding the value at ecosystem level. All the parts, including IoT in asset management (Table 4.1), Fleet Decision Identification framework (Figure 4.1), fleet definitions (e.g. Figure 4.2) and fleet management purposes (Table 4.2), the framework of the roles of actors in the ecosystem (Figure 4.3), the company level model (Figure 4.4) and the extended model (Figure 4.5), are needed to create a complete understanding of how fleet data can be turned into value in the ecosystems of asset management. In each case, it is important to define the fleet, the ecosystem around the fleet, what decision-making situations can be supported with data analysis and models, what fleet services are developed, what the costs and expected benefits are, and how these are shared in the ecosystem, and finally, what is the value. The frameworks and models can be used when the fleet data utilization is supposed to be improved, and it requires all the phases from fleet identification to the measurement of value.

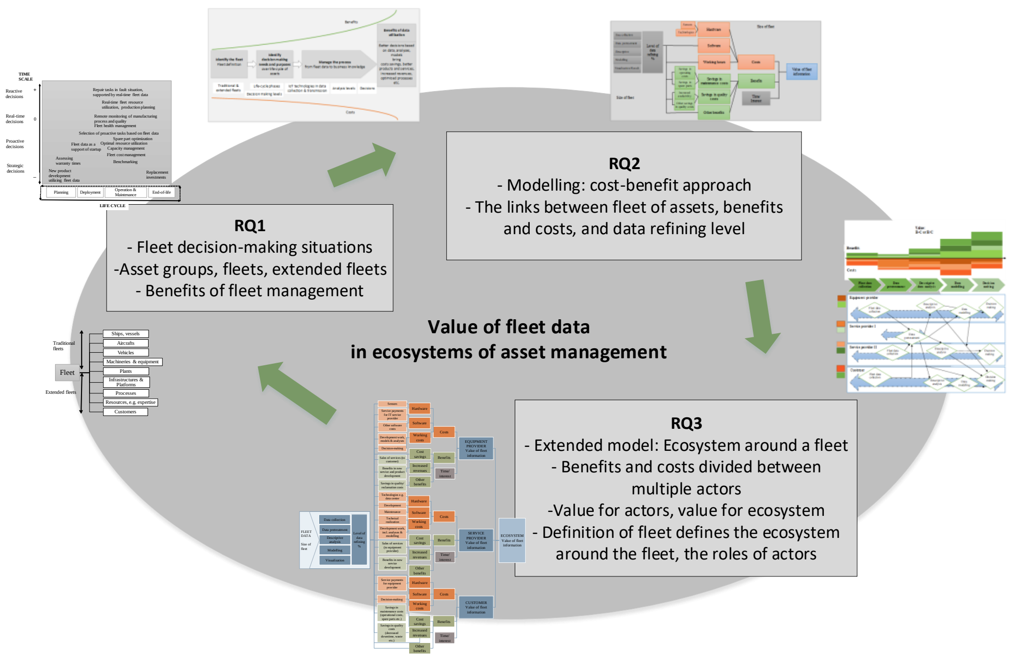


Figure 4.7 The connection between research questions and results, the path from frameworks to the model and extended model, to evaluate the value of fleet data in the ecosystems of asset management

Table 4.3: Summary of the publications and the results

	Objective of publication	Theoretical background	Main findings	Contribution to dissertation
Publication 1	Identify the potential IoT technologies in the management of asset groups	IoT technologies, Asset management, definition of assets groups	**F1:** Literature matrix presents the application opportunities to apply IoT technologies in the management of different asset groups **F2:** Empirical results emphasize untapped potential related to IoT technologies to be applied widely in industrial environments	**RQ1:** Decision-making situations and application purposes for data utilization in the management of asset groups
Publication 2	Identify and categorize fleet decision-making situations in asset management	Fleet management Decision-making situations	**F1:** Fleet Decision Identification framework helps to identify fleet decision-making situations through the whole life cycle of assets **F2:** Decision-making situations define what kind of data and analysis are needed	**RQ1:** Fleet decision-making situations through asset life cycle
Publication 3	Understand, analyse and upgrade the definition of fleet	Fleet definitions Fleet management purposes	**F1:** Identification of traditional and extended fleets **F2:** Fleet decision-making situations **F3:** There is untapped potential to apply fleet management practices and learnings from traditional fleet management to extended fleets	**RQ1:** Purpose of fleet asset management: usage examples and benefits
Publication 4	Identify the significance of the ecosystem when creating value from fleet data and illustrate the process from fleet data to decisions in an ecosystem	Ecosystems Data to decision process	**F1:** The roles of actors in an ecosystem in the process from fleet data to decision-making **F2:** The data utilization of an ecosystem can be developed by analysing the process with the framework	**RQ3:** Process from fleet data to decisions and the roles (incl. costs and benefits) in the process
Publication 5	Develop a model to illustrate the logic of value creation from fleet data in asset management related decision-making	Costs and benefits in fleet asset management Costs of data processing (IoT investment)	**F1:** A model to evaluate the value of fleet information **F2:** Value is created if the benefits of data utilization in decision-making exceed the costs of data refining	**RQ2:** A logic to evaluate the value as the difference between the discounted total benefits and total costs
Publication 6	Develop a model to illustrate value creation from fleet data in a fleet ecosystem	Cost-benefit analysis Costs of data processing (IoT investment)	**F1:** A model to evaluate the value of fleet information in an ecosystem **F2:** Creating value from fleet data requires that the actors of the ecosystem collaborate	**RQ2, RQ3:** A logic to evaluate the value of fleet information in a fleet ecosystem

5 CONCLUSIONS

5.1 Contribution to theory

This thesis contributes to the existing theoretical discussion by responding to the research gap related to understanding the potential of fleet data in value creation in the ecosystems of asset management. The contribution to theory can be divided into four distinct contributions.

Extending the understanding of the opportunities of fleet management in an asset management context. There is discussion on individual fleet management situations and on the benefits of certain fleet management situations for which the models are developed to support those individual situations. However, the theoretical discussion lacks a systematic and deeper approach to this topic. This thesis provides a literature review on gathering fleet decision-making situations, categorizes the decision-making situations over the life cycle of assets and creates a link between the nature of decision-making situations and the data-based analysis levels (i.e. reactive, real-time, proactive, strategic) that can support decision-makers.

The benefit-cost model(s): These are developed to demonstrate the logic of how value can be created from data in an asset management context. The models (the company level model and the extended model) highlight the profitability perspective on the value of data and IoT investments, and the need to measure the value of data. These kinds of models pursuing to model the value of data have not been widely presented in literature. The developed models are novel in terms of perceiving the data refining level and its effects on both the benefit and cost sides of the model. The models also emphasize the special characteristics of fleet management, such as scale advantage and the benefit of observing a large group of assets and e.g. learn the behaviour of assets. Acknowledging the fleet perspective is important because often IoT investments are made, for example, concerning a group of assets, when sensors are invested in and measuring features and services are developed based on the collected data to create value for the actors. IoT-related investments are increasingly implemented, thus the profitability of these investments needs to be studied and intentionally aim at creating value from these investments. Increasingly produced data and continuously developing (IoT) technologies induce the need to understand the value of these investments in technologies and data processes. Occasionally, data is considered an asset or a factor of production in the literature, but the existing investment and cost models have not kept pace with the needs of technology developments. The value of data needs to be considered differently compared to conventional cost objects, which makes the evaluation of the value of data a highly interesting research object.

The link between data refining level and its effect on benefits and costs. This is an essential part of the first version of the model and the extended model, but a linkage like this has not been previously formed in the literature. The theory discusses in detail the data management process, i.e. the process from data to business knowledge or decisions. In addition, it is acknowledged that data processing into forms, such as analyses and models, that can be utilized in decision-making increases the value for the business. Also, the costs of data management are discussed to some extent. Data quality has been discussed in the field of information management, and the importance of data quality for decision-makers is acknowledged. The measures to evaluate data quality have been presented and, for example, maturity models to evaluate data quality have been discussed (see e.g. Ryu et al, 2006). These models have some similar viewpoints, such as data accuracy and data availability, with the data refining level discussed in this thesis. However, these impressions remain relatively separate views, and attempts have not been made to analyse or develop a logic to evaluate how this relation (between data refining level, costs of data processing and value of data) functions. In this thesis, the data refining level has not been studied in-depth, and the need for further research is recognized.

Ecosystem perspective of the extended model. The extended model suggests that collaboration is needed in order to optimally and effectively exploit the potential of data utilization. The involvement of different actors is presented as the roles in upgrading data into value, and each actor has their inputs and outputs. In fleet data utilization and value creation, the core competencies can be taken advantage of more effectively. The data refining process can be divided to be managed and operated by different actors, i.e. one actor could be responsible for data pre-treatment, another for specializing asset management services etc. The extended model works as a tool to develop ecosystem collaboration over organizational boundaries. The fleet data is fragmented to multiple organizations, and the effective utilization of the data requires collaboration and coordinated activities to optimally exploit each other's capabilities to create value for each actor and for the ecosystem as a whole.

5.2 Managerial implications

As a managerial implication, this thesis provides a group of frameworks and models that can be utilized as tools to identify fleets and fleet decision-making situations, to understand the ecosystem around the fleet, and to evaluate the value of fleet data with the benefit-cost models, i.e. the model for the company and the extended model for the ecosystem level. The extended model in particular can be used as a managerial tool when planning and analysing IoT-based investments and data-based services in the fleet management context. The following benefits can be achieved:

Reasoning IoT investments: The extended model enables the exploring of the profitability aspects of IoT investments. It emphasizes that IoT investments are not made just to increase data collection but to improve data utilization in decision-making within organizations. The model forces managers to ponder the purposes data management or IoT investments have been developed for and what is the value potential of those investments. The investments do not necessarily pay back instantly, but the payback period needs to be relatively short, e.g. 3–5 years, as technologies are developing constantly and new investments may be needed to fare in the competition. It is important that these models consider the costs of IoT investments critically and consider how to overcome the challenges related to IoT investments and what the costs of solving the challenges, e.g. technical realization, including the data quality, compatibility and security aspects are. Modelling the costs and benefits of IoT technologies offers valuable knowledge for supporting decision-making about IoT investments but also other decision-making situations in strategic maintenance management.

Managing value creation from data (utilization). The model(s) increases understanding of how the benefits and eventually the value are formed. It helps in understanding what benefits, such as cost savings, increased revenues or other benefits, can be achieved if decision-making is supported with data-based analyses and models. The models also remind that the cost side is always present; developing these advanced analyses and models cause costs, and it is important to consider the benefit-cost ratios. The model(s) provides a structure that enables companies to explore how the changes in the variables affect the value. The model encourages managers to concentrate on purposefully utilizing data in decision-making and to improve business performance.

Understanding the benefits and value of data-based services. If the model is observed at ecosystem level (extended model), it makes it possible to analyse the relations between the actors and what are their roles in creating value from data and to whom. Different actors, such as maintenance service providers or equipment providers, can plan and develop data-based services, i.e. different kinds of analyses (KPIs), models and decision alternatives/options. It is important for them to understand the customer's needs and operations and have insight into future business trends. Data-based service providers need to understand what the value their data-based services offer is for the customer. In addition, understanding the benefits of the services for the customer makes it easier to develop a reasonable pricing policy. Thus, service agreements and pricing policies are essential, but the vital starting point is to understand the costs and benefits of each actor. The extended model can be used as a tool to test different pricing scenarios and service agreements to maximise the value of collaboration. Evaluation at ecosystem level leads to the opportunity to manage data utilization and value creation from fleet data effectively for each actor and for the ecosystem as a whole.

Improving ecosystem collaboration: Companies can achieve added value from new types of network models, and the extended model presented in this thesis emphasizes the need to improve data and knowledge sharing to create value. The usage of the extended model enables the analysis of collaboration between actors and the taking of actions that lead to the development of ecosystem collaboration and create competitive edge for the actors of the ecosystem. The ecosystem could be managed in a sustainable way, meaning that the position of each actor is profitable and secured. This is an advantage for the whole ecosystem, enabling continuous and fruitful collaboration. This type of ecosystem collaboration, which takes advantage of each actor's core competencies, is collaboration at its best, and it can lead to results and total value better than what the actors could achieve on their own if they were operating without the support of the ecosystem.

Examples include the fleet services for customers that are developed and further improved with the aid of the extensive fleet data and knowledge that the equipment providers have. The benefits for the equipment provider or fleet service provider are based on long-term collaboration and long-term service sales that is a profitable form of business, enabling persevering collaboration in product and service development.

5.3 Limitations and evaluation of research

The limitations of this study are testing the models with descriptive data and the simplifications made to the models, such as only three actors in the extended model and the rough estimation of the data refining level. Next, the limitations are discussed in detail and the evaluation of the research is considered in terms of *credibility*, *transferability*, *dependability* and *conformability* (Eriksson and Kovalainen, 2008)

The main limitation of this study is the lack of proper validation of developed models. The models are tested with descriptive data due to the lack of real case data. However, the main point has been testing the logic of the models, not the actual profitability of IoT investment. Therefore, the utilized descriptive data, testing and sensitivity analysis give satisfactory results and foundations for theoretical and managerial implications. Testing the models with descriptive data gives certain results, and the variables can be changed and the effects on the results can be analysed. On the other hand, this testing with descriptive data is beneficial when we can choose different variables and analyse the results. However, it would be interesting and fruitful to use data from real cases. However, this kind of data from an ecosystem of multiple actors is challenging to get because usually this kind of data is sensitive and not intended for sharing; in addition, real ecosystems are rare and challenging to find. Collecting real case data means that, in addition to the technological developments, the business models and cultures of companies and ecosystems need to be developed. At this point these are not developed to a level that allows conducting this study with real case data. Thus, research is needed on developing ecosystems but also on improving collaboration in the existing ecosystems.

The extended model has been limited to three actors, which eases the demonstration of the different roles in the fleet ecosystem. They represent the typical actors in this kind of an ecosystem around a fleet. This thesis considers the actors of an ecosystem around a fleet to be an original equipment provider, its customer, a maintenance or fleet service provider and an information service and/or platform solution provider. The division into three actors emphasizes the three perspectives on the process from data to value. In a real case, there can be more actors or their roles can be a little bit different compared to the model. For example, the roles can vary in terms of who is providing fleet services, i.e. the OEM or separate fleet service provider, or how the information technology services are provided. In addition, in real life, it is possible that the actors are involved in multiple ecosystems at a time, depending on how the ecosystems are defined and from which perspective. However, the developed frameworks and models can be applied to different fleets and ecosystems. Then the fleet and ecosystem, the roles of actors, and their benefits and costs need to be defined case specifically.

Another limitation of this study is the rough estimation of the data refining level that is based on subjective expert judgement. Regardless of the roughness, the data refining level illustrates the different phases from data to decisions and the possibility to invest in different phases in the data refining process. The estimation is sufficient enough as it is made by an expert or a panel of experts who have adequate understanding and ability to make an estimation/educated guess.

Regardless of the limitations of this study, the quality of research can be assured in terms of credibility, transferability, dependability and conformability. *Credibility* can be viewed as internal validity, and it is assured with the data collected from academic experts and industrial professionals (Publications 1 and 3). Some of the academic experts and industrial professionals were involved in the research program that dealt with this specific topic (Publications 2 and 4). The descriptive data utilized in Publications 5 and 6 have been appropriate as discussed earlier, and the validation is compensated with a sensitivity analysis. The frameworks and models developed in this thesis have received feedback form research participants and experts familiar with the topic. In addition, extensive literature reviews have been conducted as the basis for research and the development of frameworks and models. *Transferability*, also referred to as external validity or generalizability, is assured with in-depth definitions and descriptions in order for the results to be applied to different fleet contexts. In addition, the frameworks and models are generalized to be utilized in different fleet contexts. *Dependability* (i.e. reliability) refers to the transparency of the data and research methods, i.e. how the research is conducted. The data and research methods have been discussed in the individual publications and this thesis (section 3), and the utilized data is documented throughout the research process. The documentation of the research process also strengthens the *conformability* (objectivity) of the research and indicates that the research is not just the opinions of the researchers. As in the different phases of the research process, for example research program participants have been somehow involved in the process and provided feedback, which confirms the results and decreases the probability of a subjective bias.

5.4 Suggestions for further research

The topic of this thesis is highly interesting and relevant for both academia and industrial professionals, and developments in the area of data utilization as a value creator and the role of ecosystem collaboration will be vital elements in future research as well.

To develop data utilization in organizations in the asset management context, organizations could consider more systematically what kinds of decision-making situations could be supported by data-based analyses, models and services. The key is recognizing the business potential, i.e. the value for business, and the basis for this is recognizing the decision-making situations to which the data-based analyses and models can bring advantage. In addition, an understanding of how the data is transformed into value is essential in order to follow up and manage the realization of value from IoT technology investments. Research collaboration between researchers and companies would be beneficial in developing this subject area.

Measuring the value of data needs further research. Models and other attempts to measure the value of data is scarce. Measuring and follow up form the basis for developments in the area. There are several ways to gain benefits and business value from data and, in other words, to create business from data. These benefits and values could be modelled. The modelling could also include the risk perspective, as the expected benefits are not always realized as planned.

The data refining level and its effect on the value of data need further research. There are some resemblances to data quality measurements, where for example maturity models have been developed to understand the effects of data quality on decision-making. However, the measurement of the data refining level requires that the links between the data refining levels (e.g. analysis, models, visualizations etc.) and their effects on decision-making, benefits and costs are taken into consideration. On the other hand, the level has some resemblance to the capacity utilisation rate, and it would be interesting to define the data refining level and its effects further (see, e.g., McNair and Vangermeersch, 1998). Thus, more research is needed to define the effects of data refining on the amount of costs and benefits.

The benefits of ecosystem collaboration when upgrading data into value need further research. There is still potential to study how fleet data could be used in ecosystems over the boundaries of companies. Competitive edge can be achieved if the ecosystem can effectively use and refine data into value for all the actors of the ecosystem and to the ecosystem as a whole. The value that can be achieved by working as an ecosystem is greater than the value that the actors could separately achieve without the support of the ecosystem. For example, if one company needs to survive with the data they own and only utilize only their own competencies and then purchases services from external third actors without any deeper collaboration, the total value for this company is presumably less than if there was persistent collaboration with the service provider. Future competition is between networks or ecosystems that manage to share competencies in the right places and to aim at higher value creation. The value of ecosystem collaboration, especially the sharing of benefits and risks in ecosystems, is an interesting topic to be further researched.

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Internet of Things in Asset Management:

Insights from Industrial Professionals and Academia

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ABSTRACT

The emerging Internet of Things (IoT) technologies could rationalize data processes from acquisition to decision making if future research is focused on the exact needs of industry. This article contributes to this field by examining and categorizing the applications available through IoT technologies in the management of industrial asset groups. Previous literature and a number of industrial professionals and academic experts are used to identify the feasibility of IoT technologies in asset management. This article describes a preliminary study, which highlights the research potential of specific IoT technologies, for further research related to smart factories of the future. Based on the results of literature review and empirical panels IoT technologies have significant potential to be applied widely in the management of different asset groups. For example, RFID (Radio Frequency Identification) technologies are recognized to be potential in the management of inventories, sensor technologies in the management of machinery, equipment and buildings, and the naming technologies are potential in the management of spare parts.

KEYWORDS

Asset Management, Data Acquisition, Internet of Things, IoT, Smart Factory, Technologies and Applications

1. INTRODUCTION

As a result of the rapid and world-wide globalization in the industry today, companies and other organizations are networking, whether intentionally or unintentionally, at an increasing pace. Complex interdependencies in the organizational interface set entirely new requirements for data acquisition and data transmission as well as for generating usable decision-making information from the data. Based upon the above-mentioned need to manage and control inter-organizational environments, academia is producing a growing number of decision-making models and tools designed for industrial asset management. The authors of this paper have previously developed a number of models to support asset management decision making, including “Life-Cycle Model for Maintenance Service Management”, created for inter-organizational operation and maintenance planning and decision making of a production asset (Kivimäki et al., 2013; Sinkkonen et al., 2014), and the “Flexible Asset

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Management Model" or "FAM-model", targeted for optimizing a network's asset quantities and balance sheet -positioning in a strategic level (Marttonen et al., 2013).

The amount of data in companies and the numerous information systems are constantly growing, which has created a number of problems in separating relevant data from irrelevant data. Therefore, it has proven very difficult to generate accurate, adequate and timely data for industrial asset management models and tools, such as the "Life-Cycle Model" or the "FAM-model". One viable solution to improved data acquisition and transmission are the Internet of Things (IoT) technologies that will automate asset-related data processes in smart factories of the future through embedded communication within the existing internet infrastructure (Vermesan & Friess, 2013). IoT does not however intrinsically solve any difficulties in data utilization, i.e. turning data to business information, where suitable data penetration and analytics software or techniques, so-called middleware is highlighted instead (Wang et al., 2008). There is a trend to generate more value from an array of ubiquitous sensors utilizing the IoT which will have the ability to monitor and measure the assets, the operators, the business and the environment in which they work (Baglee and Knowles, 2010). As IoT technologies are altogether a novel approach, the field remains somewhat unclear, which creates a need to carry out research especially from an industrial asset management perspective. Therefore, research is needed to clarify industrial applications in order to improve data exploitation and data-based decision making in an industrial environment. The objective of this paper is to collect, correlate and study the Internet of Things technologies which are relevant for asset management systems by connecting an industrial asset group to an IoT technology both in theoretical and at a practical level. The remaining sections of this paper are structured to support the following research questions:

1. What are the essential IoT technologies to be employed in the data acquisition and data transmission of various physical industrial assets in smart factories of the future?
2. How do the industrial professionals and industrial engineering and management academic experts foresee the industrial asset management potential of IoT technologies?

2. METHODOLOGY

This research is qualitative research by nature. Qualitative research aims to understand and interpret the phenomena and highlight the viewpoints of research participants (Bryman & Bell, 2011). Our research employs two methods. Firstly, current knowledge on existing IoT technologies and their potential applications are studied by conducting a comprehensive literature review in order to achieve a theoretical overall view and to determine the research gap. Theoretical framework is formed based on previous literature to create a basis for empirical research. Secondly, the empirical evidence is mapped via an industrial professional panel and an academic expert panel. Qualitative data is gathered through these panels to complement the perception based on the literature review and to get valuable insights and rich description about the potential of IoT technologies in industrial environment. An industrial professional panel is comprised of industrial asset management and industrial maintenance professionals representing internationally distinguished companies in Finland and Sweden. An academic expert panel consists of industrial engineering and management researchers in the fields of cost, performance, and asset management. The empirical evidence is gathered through these panels separately and they are compared and analyzed in order to get the perception in which ways the views of industrial professionals and academic experts encounter.

3. THEORETICAL FRAMEWORK

In this section the foundations for theoretical framework are explored. The terminology and definitions related to IoT technologies and asset management are presented. Section 3.1 discusses the IoT technologies and section 3.2 presents the definitions for asset management and asset groups. Section 3.3 combines the IoT and asset management perspectives into matrix framework. The literature matrix sums up the current state of literature concerning the essential IoT technologies to be employed in asset management. The purpose is to present the theoretical framework which acts as a basis for the empirical research.

3.1. IoT Technologies

IoT comprises of a network of smart objects that are connected to the Internet. In the context of industry, the term of Industrial Internet and Industry 4.0 are often used alongside IoT. Applications utilizing IoT technologies are increasing as enabling technologies are developing and becoming less expensive. IoT is transforming businesses and it has been stated to be an industry revolution taking place right now (Porter & Heppelmann, 2014). Companies are developing new applications and innovative uses for IoT technologies. IoT technologies have been applied to numerous environments, such as logistics, manufacturing, security, and healthcare. Hence, the applications vary from inventory control to e-Health applications. The possibilities of IoT enabling technologies and applications have received attention in the literature (Atzori et al., 2010; Miorandi et al., 2012; Gubbi et al., 2013; Li et al., 2014). The categorization of IoT technologies is not uniform and different technologies are often applied together. Commonly discussed technologies are: RFID (Radio Frequency Identification), WSN (Wireless Sensor Networks), WSAN (Wireless Sensor and Actuator Networks), WPAN (Wireless Personal Area Networks), NFC (Near Field Communication), as well as naming and localization technologies which are mainly used for identification, sensing and communication purposes.

RFID technology uses radio waves to identify and is primarily used for identification purposes but it enables also storing limited data in RFID tags (Jantunen et al., 2010). RFID technology consists of electronic tags (RFID tags) and RFID readers. RFID tag stores the unique code of the attached object and RFID reader can act as a gateway to the Internet by transmitting the object identity, read-time and the object location which therefore enables real-time tracking (Kopetz, 2011). RFID technology enables automating the process of object identification and eliminating the human link. Researchers, for example, Zhu et al. (2012a) have reviewed applications based on RFID technology in different industries. RFID technology enables preventing stock outs and excess stocks, improving data accuracy, and increasing information visibility in the supply chain. RFID technology is applied, for example, to inventory control, product tracking, building access control and real-time location system in complex manufacturing processes (Zhu et al., 2012a).

WSN technology refers to a group of sensors that can monitor and record the physical conditions of the environment. WSN technology utilizes sensors to collect data about the targeted phenomenon and transmits the data to base stations that can be connected to the Internet (Kopetz, 2011). There are many different types of sensors and they are able to monitor a wide variety of physical conditions, including temperature, humidity, vehicular movement, pressure, noise levels and mechanical stress levels on attached objects (Akyildiz et al., 2002). WSN technology can be applied to great variety of different applications, for instance, to machinery condition monitoring, traffic estimation, and power consumption monitoring (Jacquemod et al., 2014; Jantunen et al., 2010; Tubaishat et al., 2009).

WSAN technology combines sensing technologies with actuating possibilities. Sensors gather information about the physical world, while actuators take decisions and then perform appropriate actions upon the environment. This allows remote and automated interaction with environment. (Akyildiz & Kasimoglu, 2004) WSAN technology provides innovative application possibilities and it is applied to a variety of building automation applications, for example to temperature control, to air conditioning system which reacts to the presence of people, and to other applications that can provide energy savings in buildings (Jung et al., 2012; De Paola et al., 2012; Fortino et al., 2012).

WPAN enables the energy efficient wireless access and data transfer to smart objects over a short distance (1 m–100 m). Examples of WPANs are Bluetooth and ZigBee. Bluetooth defines a complete WPAN architecture, including a security layer. However, the main disadvantage of the Bluetooth is its relatively high energy consumption. Therefore, Bluetooth is not usually used by sensors that are powered by a battery. ZigBee is developed to be corresponding technology but simpler and less expensive than Bluetooth. Additionally, ZigBee has low power consumption and is more energy efficient. (Wang et al., 2014b; Kopetz, 2011)

NFC refers to short-range high frequency wireless communication technology which enables the exchange of data between devices over a distance of less than 20 cm. NFC technology is compatible with existing smartcards and readers but also with other NFC devices and it is suitable for use in mobile phones (Kopetz, 2011). NFC technology can be utilized in public transportation, proximity payment and access keys for offices and houses, for example. NFC utilized in mobile phones enables peer-to-peer communication between two NFC devices and, for instance, business cards and other information can be exchanged (Conskun et al., 2013; Kopetz, 2011).

In order to be able to communicate via the Internet, smart objects need appropriate naming technologies. Smart objects need to be identified and the access path to the object needs to be established. Examples of naming schemes are barcodes, 2D (two-dimensional) barcodes, EPC (Electronic Product Code) and IP (Internet Protocol) address. Naming technologies make it possible to identify items with appropriate accuracy. Then, sometimes it is adequate to identify items at item group level and sometimes an item specific identification is needed. Item specific identification is needed especially when particular object or device needs to be accessed, for example when tracking vehicle (Rajkumar et al., 2013) or controlling particular appliance in building automation (Jung et al., 2012). Then EPC or IP address would be more appropriate choice.

Localization technologies can be categorized into three groups based on the infrastructure of the technology: satellite based, mobile networks based and local area networks based technologies. Satellite positioning technology utilizes distance measurement to satellites to determine three-dimensional location. An example of satellite positioning systems is GPS (Global Positioning System). A satellite positioning system is intended to be used outdoors and it is not suitable for indoors. Network based positioning technology is based on mobile networks that maintain the location data, whereas local area networks can utilize technologies, such as RF (Radio Frequency) signals or local positioning properties of Bluetooth (Motamedi et al., 2013).

By applying and combining these IoT technologies, there is a potential to develop enormous amount of new IoT based applications in different environments. When considering supporting technologies, such as mobiles, social media (Wahi et al., 2014) and memory capabilities of cloud computing (Tiwari & Joshi, 2015; Patra et al., 2016; Guerfel et al., 2017), the IoT based application possibilities increase. These IoT applications produce increasing amount of data which is known as big data. Big data is often semi-structured or unstructured by nature and collected data is useful only if it is analyzed (Chen et al., 2014a). The challenge is how to effectively exploit the collected data and therefore turn data into business information (Wahi et al., 2015). For companies to actually start gathering, analyzing and using the data, the decision-making value and potential end use of data must be transparent for them.

3.2. Definitions of Assets and Asset Management

An asset is generally defined by the ISO 55000 standard as "an item, thing or entity that has potential or actual value to an organization". The value will vary between different organizations and their stakeholders, and can be tangible or intangible, financial or non-financial. Tangible or physical assets usually refer to equipment, inventory and properties owned by the organization. Physical assets are the opposite of intangible assets, which are non-physical assets such as leases, brands, digital assets, use rights, licenses, intellectual property rights, reputation or agreements. (ISO 55000, 2014, p. 13)

In the context of this research the assets are considered as physical items in a factory environment. Physical industrial assets include various assets with different management decisions and data needs. To include the special features of these various assets we have divided physical assets into the following five categories: machinery and equipment, buildings, vehicles, inventories, and spare parts. As the research is limited to explore physical industrial assets in factory environment, the category of vehicles includes all mobile vehicles at the factory area, such as motor vehicles and trucks. Vehicles can be considered assets as long as they are transporting the property of the company to other destination, although the vehicle leaves the factory area. Therefore, e.g. the company's own railway wagons and trucks can be counted among assets in this research.

The asset group of inventories comprises four types of inventories: 1) finished goods, 2) work-in-process, 3) raw materials, and 4) maintenance and operating items, such as spare parts. Spare parts have been separated from inventories to a category of their own. Spare parts are replacement items that are required to keep assets operating in a plant and they prevent excessive down-time in case of a breakdown (Gulati, 2009). The category of buildings at factory area includes factory buildings and other buildings, such as warehouses and office buildings. Machinery and equipment are the physical assets that are required in factory-specific processes. In addition to process-related machinery, this category includes also other equipment such as tools and computers.

Asset management is defined to be broader perception than the term of maintenance gives to understand. Asset management is considered as a set of activities associated with 1) identifying what assets are needed, 2) identifying funding requirements, 3) acquiring assets, 4) providing logistic and maintenance support systems for assets, and 5) disposing or renewing assets. Therefore, asset management aims to manage assets optimally and sustainably over the whole life cycle of assets. (Hastings, 2010)

3.3. Matrix Framework

In the context of this research, a matrix framework (Table 1) combines the aspects of IoT technologies and asset management has been generated. A detailed literature review has been conducted to identify IoT based technologies and if they have been applied to the different asset groups and asset management. These findings have been included into the matrix framework (Table 1). Academic articles, in which IoT technologies have been researched or applied to a specific asset group, are referred to in the matrix.

According to the literature matrix, it can be stated that IoT technologies have been applied to a range of asset groups. RFID and WSN technologies have been researched widely and several applications have been identified. WSAN applications have not been studied widely but recently this technology has got more attention in literature. WSAN technology has not been applied to inventories or this just does not appear in literature. This might be because of the possibilities to benefit from sensing and actuating features in the management of for example equipment (turn off and on are practical possibilities) whereas with stock there are not such possibilities or they are not seen equally tempting. WPAN communication technologies have been applied in different contexts and especially the potential of ZigBee has been acknowledged in literature. Also, NFC technology has been studied in literature and there are several applications. Barcodes have been in use for many years but 2D barcodes and their ability to store data and the potential of IP address to identify a certain object have become useful in the management of different asset groups. Localization technologies have also been applied to different asset groups and particularly in smart factory context the indoor localization applications stand out in literature. When examining asset groups, it can be noticed that machinery and equipment, buildings and inventories have most applications while vehicles and earlier mentioned spare parts do not have as many applications or they just do not appear in academic publications.

Based on the matrix framework, it can be concluded that 1) RFID technology has been widely researched and applied, 2) WSN technology appears to be easily varied in different contexts, 3) WSAN has interesting applications and there might be untapped potential as automation can be employed more widely in the management of different asset groups e.g. in machinery and equipment, where automation can be used to prevent failures, or in vehicles, 4) NFC technology might have potential to be applied more widely in different contexts, such as in simplifying documentation during maintenance tasks and access control in various contexts, and 5) there are various applications for communication, naming, and localization technologies.

Table 1. Literature matrix: IoT technologies applied to the management of asset groups

	ASSETS				
	Machinery and equipment	**Buildings**	**Vehicles**	**Inventories**	**Spare parts**
RFID	Remote condition monitoring, failure follow-up notifications, embedded health history with the asset (Haider & Koronios 2010), device management, equipment monitoring (Wang et al. 2014a), maintenance information sharing platform (Lin et al. 2014), collecting real-time production information (Liu et al. 2015)	Access control system (Qiu et al. 2012; Zhu et al. 2012b)	Electric vehicle batteries (Wang et al. 2013)	Storage levels of parts, real-time information about products on assembly line (Chen et al. 2014b), inventory control (Chang et al. 2012; Liu & Chen 2009), resource management system (Liu et al. 2006)	Spare part tracking in assembly lines (Giannoccaro et al. 2014), spare parts supply chain management (Cheng and Prabhu 2012; Chen et al. 2013)
WSN	Condition-based maintenance (Jantunen et al. 2010; Tiwari et al. 2004), fault diagnostics (Lu & Gungor 2009), collecting running parameters (Hsu 2010)	Energy monitoring, behavioral monitoring, space monitoring (Fortino et al. 2012), energy management, power consumption monitoring (Jacquemod et al. 2014)	Traffic estimation, traffic control (Tubaishat et al. 2009)	Online inventory management system (Vellingiri et al. 2013), inventory management (Mason et al. 2010)	Condition monitoring data from equipment to support the spare part ordering decisions (Godoy et al. 2013)
WSAN	Gas detection and immediate isolation of gas leak source (Somov et al. 2014), process control applications (Lu et al. 2016)	Energy saving, maximization of the comfort in the building (Fortino et al. 2012), temperature control in a work environment (De Paola et al. 2012), power management (Survadevara et al. 2014), building automation (Jung et al. 2012)	Unmanned ground vehicle (Li & Selmic 2015)		
WPAN (Bluetooth, Zigbee)	Collecting running parameters (Hsu 2010)	Bluetooth, Zigbee, Wifi: communication of smart living space (Bai & Huang 2012)	Bluetooth-enabled headset and voice-activated features (Mahmud & Shanker 2006)	Inventory tracking with Zigbee (Yang & Yang 2009)	
NFC	Context-aware mobile support system (Papathanasiou et al. 2014), recurring maintenance processes: central process control and documentation (Karpischek et al. 2009b)	Classroom access control (Palma et al. 2014), access keys for offices and houses (Conskun et al. 2013)		Availability and stock information of products (Karpischek et al. 2009a), inventory control (Iqbal et al. 2014)	
Naming technologies, (barcodes, EPC, IP address)	Maintenance information sharing platform (Lin et al. 2014)	IP address: building automation (Jung et al. 2012)	IP address: tracking of individual vehicles (Rajkumar et al. 2013)	2D barcodes: product information, mobile product verification (Gao et al. 2007)	Barcodes in spare parts management (Gan et al. 2013)
Location based technologies (satellite, mobile networks, local area networks)	Tool tracking and localization with RF signals (Goodrum et al. 2006)	NFC smartphone indoor interactive navigation system (Choo et al. 2014)	Asset localization (Motamedi et al. 2013), GPS: location of vehicles (Rajkumar et al. 2013)	Indoor locating with RF signals (Chang et al. 2012)	

4. EMPIRICAL RESULTS

This section discusses the empirical results of industrial professional and academic expert panels. Firstly, the results of each panel are presented separately and then the results of both panels are compared. The section 4.3 compares and discusses differences and similarities between the insights of industrial professional and academic expert panels.

4.1. Industrial Professional Panel

Empirical data have been gathered via an industrial professional panel that is comprised of industrial asset management and industrial maintenance specialists from five companies, representing original equipment manufacturers and their customer companies from mining and energy industries. Mining and energy industries are traditionally asset and capital-intensive industries where IoT technologies and automation create significant potential. In total, six professionals from these companies participated in the panel.

Industrial professionals were asked to evaluate the potential of IoT technologies in the management of different asset groups. The scale was 0–5, where 0 is “cannot say”, 1 “no potential”, 2 “some potential”, 3 “potential”, 4 “quite high potential”, and 5 “high potential”. The first matrix (Table 2) sums up the views of professionals, as an average number given by the six professionals. In addition to numbers, the potential is also illustrated by the shades of grey, darker grey representing higher potential and lighter grey representing less potential. White areas mean that potential is unclear or a large proportion of respondents, i.e. over half of the respondents could not say if there is potential, and therefore the average value could be distorted. In addition, the average value of each asset group and the average value of each technology category have been calculated.

By observing Table 2 from the asset management point of view each asset group and the potential of IoT technologies in the management of each group can be reviewed. The asset group of vehicles has highest average value (3.8) and the technologies such as WSN, localization technologies, RFID, and WPAN have highest potential in the data acquisition and transmission from vehicles. The asset group of machinery and equipment has quite high potential (average value 3.6) and especially the technologies such as WPAN, WSN, and WSAN have highest potential in the data acquisition from machinery and equipment. The potential related to the buildings is 3.4 and the highest potential is

Table 2. Potential of IoT technologies in the management of asset groups evaluated by industrial professionals

	ASSETS					
IOT TECHNOLOGIES	Machinery and equipment	Buildings	Vehicles	Inventories	Spare parts	Average value
RFID	3,0	3,7	4,0	3,7	3,0	3,5
WSN	4,4	4,0	4,7	2,7	2,0	3,5
WSAN	3,8	4,8	3,3	2,7	1,5	3,2
WPAN	4,8	4,0	4,0	2,7	2,8	3,6
NFC	3,5	2,3	3,5	2,5	3,0	3,0
Naming technologies	3,2	2,5	3,0	3,7	4,5	3,4
Localization technologies	2,8	2,7	4,2	4,5	2,0	3,2
Average value	3,6	3,4	3,8	3,2	2,7	**3,3**

related to WSAN, WSN, and WPAN technologies. The potential related to the inventories is 3.2 and the highest potential is related to RFID, naming technologies, and localization technologies but the value of localization technologies might be distorted as half of the respondents could not say the potential. The asset group of spare parts has the lowest potential but on the other hand the potential of naming technologies stands out in the data acquisition from spare parts and the naming technologies have high potential in the management of spare parts.

By observing the IoT technology point of view the results of industrial professional panel (Table 2) indicate that 1) RFID technology is seen as a potential technology (average value of 3.5) to be applied to different asset groups, 2) there is potential to utilize WSN in the management of machinery and equipment, buildings, and vehicles, 3) WSAN technology has potential to be applied especially to management of buildings, but to machinery and equipment and vehicles as well, 4) potential of WPAN has also been recognized (average value of 3.6), 5) NFC technology could be potential in the management of machinery and equipment, 5) naming technologies might be useful to important spare parts, inventories, and machinery and equipment, 7) localization technologies have been identified as potential technologies especially when tracking vehicles.

In addition to the summary matrix, professionals have provided comments and usage examples of IoT technologies. For example, related to RFDI technology the professional from the original equipment manufacturer company in mining industry has said that: "…RFID technology could be applied to the control of raw material and spare part inventories…" and "…RFID technology could benefit condition-based maintenance calculation when operating hours can be targeted at each component…"

Regarding NFC technology, the professional representing an energy company has said that: "…NFC can be utilized to access control and signing for working orders…", "…NFC applications are handy in mobiles and tablets, and therefore other separate devices are not needed…", and "…NFC could work better in some contexts where RFID applications are inflexible to use…"

Regarding naming technologies, the professionals from mining and energy industries have said as follows: "While doing maintenance work, the equipment could be identified and then the information and conducted operations could be entered into the follow-up system…", "The most important spare parts should be named and this allows monitoring the spare part consumption of whole installed base…", and "…2D barcode could enable the access to the documentation…"

Although the potential of localization technologies in the management of machinery and equipment is not high, the professional from the OEM in mining industry highlighted that: "Sometimes it would be practical if maintenance worker could localize accurately the equipment that needs to be overhauled…"

In addition, apart from the benefits and potential that were mentioned above, the threats of IoT technologies have also been recognized especially by the professional representing energy company: "If it is possible to control important assets, such as machinery, via IP address, information security challenges must be acknowledged…"

4.2. Academic Expert Panel

The panel was duplicated with a group of Finnish researchers in the fields of performance, cost and asset management. In total, twelve researchers participated to the researcher panel. The researchers who participated in the panel have knowledge of asset management and they consider the topic from industrial management perspective, specialized in performance and cost management. The matrix (Table 3) sums up the views of researchers in the field of performance, cost and asset management, as an average number given by twelve experts. The same scale (0–5) was utilized and the shades of grey are illustrating the potential. In addition, the average value of each asset group and the average value of each technology category have been calculated.

By observing Table 3 from the asset management point of view each asset group and the potential of IoT technologies evaluated by academic experts can be reviewed. According to the academic

Table 3. Potential of IoT technologies in the management of asset groups evaluated by academic experts

	ASSETS					
IOT TECHNOLOGIES	Machinery and equipment	Buildings	Vehicles	Inventories	Spare parts	Average value
RFID	3,7	2,3	4,0	4,7	4,6	3,9
WSN	4,5	4,9	4,3	3,0	2,4	3,8
WSAN	4,1	4,9	4,2	3,4	2,4	3,8
WPAN	4,7	3,6	3,7	4,0	3,3	3,9
NFC	4,0	3,4	3,6	3,3	3,3	3,5
Naming technologies	4,0	2,6	3,6	4,2	4,5	3,8
Localization technologies	3,5	2,6	4,9	3,6	3,5	3,6
Average value	4,1	3,5	4,0	3,8	3,4	**3,8**

experts the asset group of machinery and equipment has highest potential (average value 4.1). In the data acquisition and transmission technologies such as WPAN and WSN have highest potential but the other technologies have significant potential as well. As regards the asset group of vehicles the average potential is 4.0 and the highest potential is related to localization technologies (4.9) but the other technologies such as WSN, WSAN, and RFID have also significant potential related to the data acquisition from vehicles. The asset group of inventories has the average value of 3.8 and RFID technology stands out with the potential of 4.7. Naming technologies and WPAN have quite high potential as well in the data acquisition and transmission related to the management of inventories. Regarding the buildings WSN and WSAN technologies are highlighted with the average potential of 4.9. The asset group of spare parts has the lowest average potential (3.4) but the usability of RFID and naming technologies stand out with high potential (4.6 and 4.5) whereas sensing technologies (WSN and WSAN) do not seem to have significant potential.

By observing from IoT technology point of view, the results of researcher panel (Table 3) indicate that 1) RFID has high potential in the management of inventories and spare parts, 2) WSN have high potential related to machinery and equipment and buildings, 3) WSAN have high potential in the management of buildings but quite high potential in the management of machinery, equipment and vehicles as well, 4) The potential of WPAN is high in the management of machinery and equipment and also the potential to apply WPAN to the inventories has been recognized, 5) There is potential related to NFC but only the group of machinery and equipment has quite high potential, others have the value below 4, 6) Naming technologies have quite high potential related to the inventories, spare parts and Machinery and equipment, and 7) The vehicles are emphasized when considering localization technologies.

Academic experts also provided some comments and usage examples of IoT technologies. For example, RFID was mentioned to be usable technology for several kind of tracking purposes, e.g. inventory and spare parts inventory. WSN was mentioned to be usable in the management of each asset groups what comes to condition and health monitoring. WSAN in the management of machinery and equipment were mentioned to have “high potential”. WSAN in the management of buildings were mentioned to have “high potential” as well, especially in factory environment where “…the external circumstances of process environment need to be at certain level…” Thus, WSAN enable e.g. to maintain the required and favorable temperature level. The role of naming technologies was identified to be important in the management of different asset groups. Remote monitoring and control were mentioned to be possible because of naming technologies. Naming technologies were also named to be "…a key to view the spare part history of certain machine or equipment and help to select right spare parts…"

4.3. Comparison and Analysis

Here the views of industrial professionals and academic experts about the industrial asset management potential of IoT technologies are compared and some highlights are discussed. In general, academic experts have evaluated the potential higher than the industrial professionals, which can be noticed by comparing the average values in Table 2 and Table 3. Based on the views of industrial professionals the overall average potential of IoT technologies in asset management is 3.3 while the overall average potential of IoT technologies by academic experts is 3.8. One reason can be that the academics are very development oriented and they are also interested in applications for a variety of industries whereas companies usually tend to see things mostly from the perspective of their own business. Academics consider the topic broadly but the industrial professionals have deeper knowledge of their own specific business and they can provide the ideas of practical applications for the specific industry.

The fact that the industrial professionals have expressed more practical applications might be because the industrial professionals have more operative perspective to asset management whereas the academics often to focus on strategic rather than operational asset management. This might be a result of not working with a specific industry but the academics usually have a wider perspective and ideas of several industries. An example about this situation is the potential of NFC technology. Academic experts did not highlight the potential of NFC technologies but the industrial professionals emphasized the practical potential of NFC technologies in the management of machinery and equipment while performing e.g. maintenance tasks and entering the tasks with mobile phones and tablets.

Table 2 and Table 3 show that it can be concluded there is the potential to utilize sensor technologies in the management of machinery and equipment, buildings and vehicles, according to both panels. Sensor technologies have been evaluated to have significant potential in sensing the physical conditions of these asset groups. However, the potential of actuating possibilities that WSAN technology is providing did not have as high potential as the WSN technology. There was high potential related to WSAN technologies merely in the management of buildings i.e. the highest potential to exploit automation is related to buildings. However, the academic experts evaluated that the WSAN technology has quite high potential in the management of machinery, equipment and vehicles while the industrial professionals did not value the potential of WSAN equally high.

Both the industrial professionals and the academic experts emphasized the usability of naming technologies in the management of spare parts. Both panels agree that there is significant potential (average value 4.5 in both panels), and they also provided examples of practical applications related to the utilization of naming technologies in the management of spare parts. Monitoring the spare part consumption of at the level of asset fleets, viewing the spare part history of certain machine or equipment and helping to select right spare parts were mentioned as the examples. In literature, Gan et al. (2013) have also mentioned the potential of barcodes in the management of spare parts. However, the literature related to spare parts seems to be quite limited and perhaps not all the potential related to utilization of IoT technologies in the spare part management has been utilized.

5. DISCUSSION AND CONCLUSION

IoT technologies and applications have been studied in detail. However, this paper has shown that there is a lack of academic and peer reviewed literature which discusses in detail IoT technologies and applications in asset management. In addition, the results highlighted within this paper have described an understanding of applying IoT technologies in the asset management of the smart factories of the future and the understanding of utilizing the technologies to rationalize data acquisition and transmission in industrial applications. The research acts as a kick for interest to apply IoT technologies more in industry. The research also helps to identify the potential of IoT technologies for data processes and recognizes themes for further research.

The literature matrix and empirical matrixes present the results from the respondents to both research questions. According to the literature review, IoT technologies can be applied widely in the management of different asset groups. Also, industrial professionals and academic experts see the potential to exploit technologies in a number of business environments and in the management of different asset groups.

If the literature matrix is compared to the views of industrial professional and academic expert panels the main difference is related to spare parts. While research is limited, the industrial professionals and the academic experts see potential for a number of technologies, especially for naming technologies. A reason for this might be the fact that research has not focused on spare part inventories while asset management practitioners and academic experts in the field of industrial engineering and management are more interested in spare parts in particular. Another difference is that, based upon the literature, there are fewer IoT applications for vehicles than the views of industrial professionals and academic experts indicate. In both panels vehicles have been valued one of the most potential asset groups regarding IoT applications. This could be because the research is only just increasing or IoT innovations related to vehicles might be carefully protected by companies from publicity but on the other hand the possibility to utilize technologies in the management of vehicles is acknowledged. Thus, there could be a lack of academic discussion compared to for example, machine or inventory-related applications. Comparison between the views of industrial professionals and academic experts indicates that the academics evaluate the potential of IoT technologies higher than industrial professionals. This might be because of the wider perspective of academics compared to industrial professionals who are focusing on their own business environment. Another reason could be that the expectations of industrial professionals are not as high as the expectations of academics, related to e.g. WSAN technologies, since there are still lots of work to be done before even the less developed technologies (sensors, naming technologies) are implemented widely in industrial environments.

IoT technologies have a huge potential but more needs to be done before applications can be exploited more widely in real industrial environments. The emerging IoT infrastructure is now being designed to support a range of systems, i.e. assets, people and the environment. Until as recent as 2010 this was deemed unnecessary, technically challenging and cost prohibitive. The recent introduction of intelligent predictive analytics is used to support the use of IoT technologies to intelligently process the large amount of data, often called Big Data. Such tools and techniques are still in their infancy, although the data and internet revolution is moving at a pace often difficult to follow. An important issue is how the collected data can be effectively turned into business information. The IoT will undoubtedly affect different industrial sectors at a rate of change that may be difficult to foresee. It is estimated that 20% of manufacturers within the world are using or planning to introduce Internet of Things technologies. By 2030 this figure could be over 85%.

The main limitation of this research is the small size of the industrial professional and academic expert panels, and therefore more comprehensive empiric research needs to be conducted. Further research could concern more comprehensive empirical research regarding the potential to apply IoT technologies in different business environments. The future research could also focus on examining the limited amount of research in the field of spare parts. Naming technologies in the management of spare parts were highlighted by both panels while the literature concerning IoT applications in spare part management are quite limited. It needs to be researched if there is untapped potential related to e.g. automation possibilities in spare part management. The next step is also to study how all the collected data could be used effectively in applications and decision making.

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Publication 2

Kinnunen, S.-K., Marttonen-Arola, S., Ylä-Kujala, A., Kärri, T., Ahonen, T., Valkokari P., and Baglee, D.

Decision making situations define data requirements in fleet asset management

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Decision Making Situations Define Data Requirements in Fleet Asset Management

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Abstract: Large amounts of data are increasingly gathered in order to support decision making processes in asset management. The challenge is how best to utilise the large amounts of fragmented and unorganised data sets to benefit decision making, also at fleet level. It is therefore important to be able to utilize and combine all the relevant data, both technical and economic, to create new business knowledge to support effective decision making especially within diverse situations. It is also important to acknowledge that different types of data are required in different decision making context. A review of the literature has shown that decision making situations are usually categorized according to the decision making levels, namely strategic, tactical and operational. In addition, they can be classified according to the amount of time used in decision making. For example, two situations can be compared: 1) optimization decision where a large amount of time and consideration is used to determine an optimum solution, and 2) decisions that need to be made instantly. Fleet management of industrial assets suffers from a lack of asset management strategies in order to ensure the correct data is collected, analysed and used to inform critical business decisions with regard to fleet management. In this paper

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we categorize the decision making process within certain situation and propose a new framework to identify fleet decision making situations.

1 Introduction

Automated decision making is increasing due to large and often detailed amounts of available data. This is not just an issue within manufacturing organisations; recently this problem has been identified within asset management. New technologies including advanced sensor arrays, advanced analytics and cloud computing enable the development of new approaches to collect, analyse and utilize data to improve decision making within fleet asset management. The term fleet can be described as "a population of similar entities" (Tywoniak et al. 2008). Often the term fleet refers to equipment provider's installed base of units in customer sites around the world, including machinery and equipment, such as cranes, trucks, and paper machines. It is important to identify which use of the term fleet is appropriate for each research. Therefore we suggest that the concept of 'fleet' can be broadened on demand to describe different kind of fleet. In this paper we regard the fleet as "*a population of similar physical assets"* (machinery, equipment, vehicles and spare parts). Fleet may include even thousands of assets and they generate valuable data that could be utilized to fleet management.

Fleet management is an important area of research and several authors including (Mishra et al. 2013; Hounsell et al. 2012) discuss this topic in detail. Furthermore little consideration is given to the whole-life management, and the data required to manage and maintain a fleet of vehicles (Knowles and Baglee 2015). The trend in asset management has changed due to introduction of advanced technologies including eMaintenance and condition based maintenance (CBM), both of which have been discussed in the academic literature. Due to the large amounts of data available it can be argued that the required data has not fully been captured and data from historic systems is often challenging to obtain, therefore the necessary data should be identified and collected in order to be utilized more effectively in the decision making process. More effective use of data in decision making makes possible the management of asset fleets. Fleet asset management has still not been sufficiently researched and increasing understanding of fleet management and different fleet decision making situations is highly important.

The objective of this study is to increase an understanding of fleet asset management, fleet decision making situations and to identify the key data required in order to make accurate decisions. The main research question of this paper is: *What kind of decision making situations are related to enhancing fleet asset management?* This question is supported by two sub questions: 1) how are various fleet decision making situations categorized in literature? 2) what decision making situations are identified by industrial practitioners?

In this paper, we utilize design science approach as we aim at building a theoretical framework for practical managerial purposes. The design science approach aims at developing a construction, a model or a method in order to solve a problem (van Aken 2004). In design science research process, the following steps are included: identification of the problem, development of the solution (design), demonstration of the solution and validation. In this paper, we deal with the first phases of design science process, as we identify the problem and the need for a solution; in addition, we propose a framework based upon a literature review and supportive insights from industry practitioners. Insights from industry practitioners are collected in workshop organized by a research program dealing with the service solutions for fleet management. Insights are gathered from representatives of ten companies. Further testing and development of proposed framework are executed later in future research.

2 Literature Review

Fleet management techniques have been studied in the literature with regards to vehicle fleet management (Mishra et al. 2013; Hounsell et al. 2012) and fleet-wide asset health management (Voisin et al. 2013). The literature has presented a number of different fleet management systems, tools, and models which have been developed for a number of different decision-making situations. For example, Antuñano and Dessureault (2011) have developed a real-time fleet cost tool and Andersen et al. (2009) present an optimization model that improves the integration of vehicle management and service network design. Knowles and Baglee (2015) have proposed an asset management strategy for vehicle fleets based upon the use of pre-installed vehicle telematics systems which offer an opportunity for operators to continuously monitor the performance and effectiveness of their vehicles.

Optimal fleet management requires all relevant fleet data is available between stakeholders in industrial network which may consist of a large number of players, including equipment providers, customers, and service providers. This is now possible with Internet of Things (IoT) enabling advanced technologies, which help to gather and share large amounts of new data more easily between business partners. These new possibilities bring the concept of the 'industrial ecosystem' into discussion. We define the industrial ecosystem as an industrial network combined with IoT, where the ecosystem consists of companies, their assets and data which all are connected by the Internet. Availability of data gathered in ecosystem needs to be uncomplicated in order to get all the relevant data to decision making in order to enhance fleet management. To better understand the problem related to fleet decision making, the current academic literature has been reviewed to gain an insight as to how decision making situations have been categorized and what fleet decision making situations have been already designed, developed and implemented. It can be argued that there is no comprehensive framework which allow categorizing decisions making situations and takes into consideration multiple dimensions at time, such as fleet perspective. One commonly used approach is to divide decision making situations based on the level at which they are made, i.e. operational, tactical, and strategic levels. This will allow the user to separate everyday routine decisions from decisions with longer-term effects on the whole organization. Thus, the division into short and long-term decisions have also been addressed in literature. In addition, decision making situations have been categorized based on the level of uncertainty and risk. Due to the development of a number of innovative technologies the division into human and machine decision making is covered extensively within the literature (Porter and Heppelmann 2014; Davenport and Harris 2005). In asset management, Sun et al. (2008) present the classification of decision making situations using relevant time scale as criteria. They separate decisions with time scale varying from several years to the decisions that need to be done when an event occurs. Consequently, there are several ways and perspectives to observe the categorization of decision making situations but none of them takes into consideration the perspectives of fleet decision making.

Classifying fleet decision making situations is not widely discussed in literature and framework to analyse or structure fleet decision making are at best limited. As table 1 shows, fleet management is somewhat discussed in latest academic research and there is a need to better understand the subject. When reviewing the literature, it can be noticed that fleet management problems presented in literature can be separated into four groups of decision making situations: reactive, real-time, proactive, and strategic decisions. This categorization is a conclusion from literature concerning asset management decisions and fleet management.

Table 1 Categorizing fleet decision making situations, literature review.

Category of decision making situation	Decision making situation
Reactive decisions • Decisions after the event occurs • Detailed technical data and cost analysis usually cannot be conducted	Corrective maintenance, fault diagnosis and corrective actions based on data from multiple similar assets (Sardar et al. 2006)
Real-time decisions • Fast reaction, aiming to act real time • Technical, real-time data	Real-time accident handling (Ngai et al. 2012), Real-time bus fleet management (Hounsell et al. 2012), Dynamic fleet management problem (Shi et al. 2014)
Proactive decisions • Developing predictions and plans: actions before something happens • History and life-cycle data, including technical and economic data	Fleet-wide diagnostic and prognostic assessment, proactive monitoring (Voisin et al. 2013), Optimized resource utilization (Andersen et al. 2012; Mishra et al. 2013), Optimizing reliability, availability and maintainability of fleet, Fleet cost management (Antuñano and Dessureault 2011)
Strategic decisions • Long-term strategic decisions • Plenty of time and consideration can be used • History and life-cycle data, emphasis on economic data	Replacement investments and strategy (Richardson et al. 2013)

Therefore, we can identify two extremes in the categorization of fleet decision making situations based on the time scale in which the decisions are done. The available time essentially affects to the nature of data and information that can be used in decision making situations. In other words, in reactive decisions which need to be made after an event occurs, detailed technical data and cost analysis usually cannot be conducted (Sun et al. 2008). Due to advanced technologies the trend is moving toward real-time decisions, where the available time is limited but the constantly monitored real-time technical data enable to make decisions even in real time. External forces and uncertainty, for example customer demand (Shi et al. 2014), are typical for real-time decisions but also for proactive decisions. The opposite is strategic decisions where plenty of time can be used and history and life-cycle data, both technical and economic data, are usually needed. Decision making situations can also vary according to the life cycle phase of the assets they are related to. It can also be noticed that maintenance-related decisions, representing the operation and maintenance phase decisions, and replace investment decisions, representing the end-of-life phase decisions, may take place for different levels of the system hierarchy.

3 Fleet Decision Identification Framework

Based on the observations from literature review and supportive insights from industry practitioners, a framework for helping to identify fleet decision making situations is proposed. The framework utilizes the categorisation of fleet decision making situations made based on literature in table 1. The main observations related to Fleet Decision Identification framework (figure 1) are that usage of time varies between different types of decisions, which also affect data requirements. Secondly, there are different fleet decision making situations in every phase of asset life-cycle. Therefore, the framework aims to bring multiple dimension together when categorizing fleet decision making situations. These dimensions are life-cycle perspective, time scale, and asset hierarchy (from unit level to fleet level). Fleet level also include the ecosystem aspect to the decision making as data sources from different parties of ecosystem are needed in fleet based decision making.

In figure 1, the first box illustrates decision making situations at unit level trough the life cycle of asset. The second box represents the decision making situations at fleet level where data from the ecosystem and other units can be used. The decision making situations are quite similar both at unit and fleet level, but there is more data available for fleet decision making situations. This is expected to enable more accurate predictions and optimizing models as supporting data is collected from other similar assets and it can be used to make fleet level decisions. Fleet level makes possible, for example, to develop resource and capacity utilization as performance data of all assets in the fleet can be analysed. Consequently, fleet data can be utilized in diverse optimizing decision making situations in order to improve asset management.

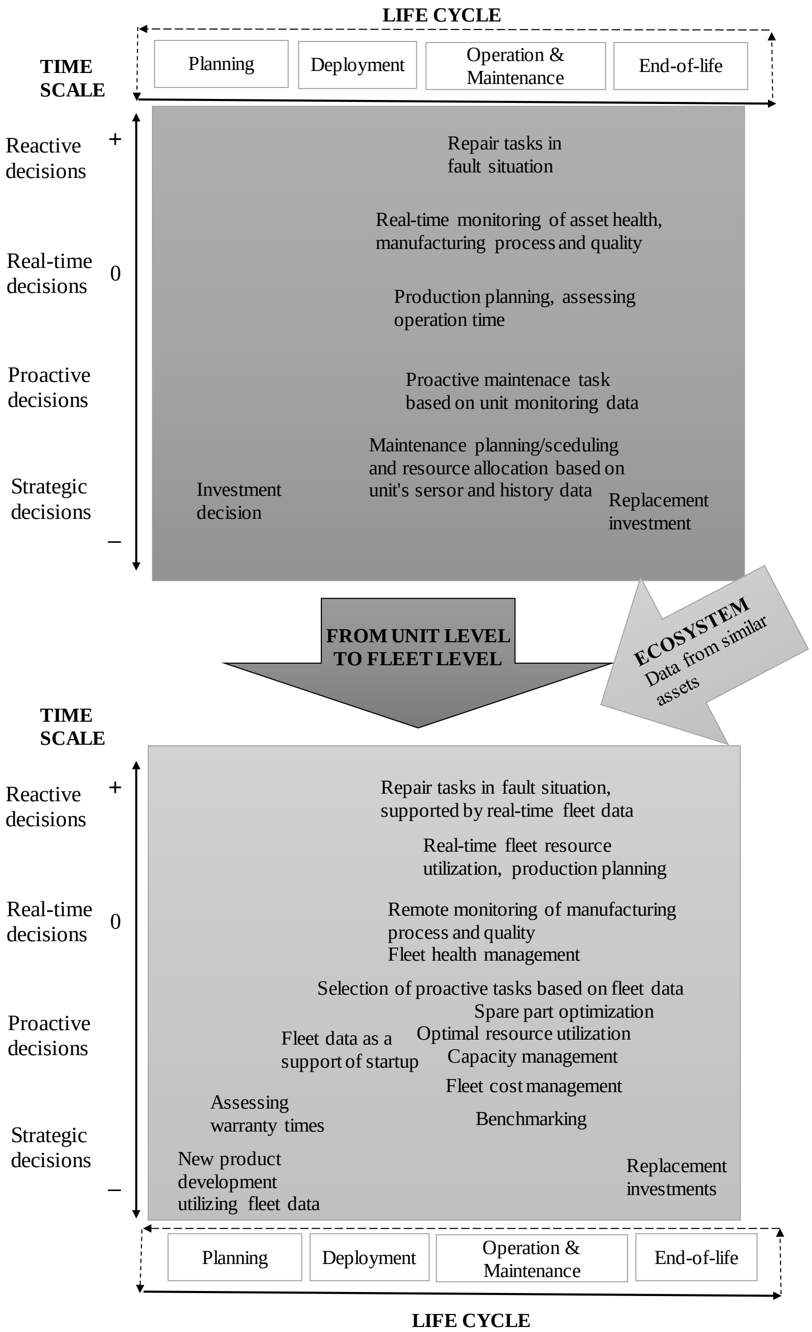

Figure 1 Fleet Decision Identification framework.

4 Conclusion

Researching fleet management is becoming relevant as business practitioners are facing continuous pressure to manage their assets more efficiently. The results of this research extend current understanding of different fleet decision making situations and work as a basis for better fleet management. The Fleet Decision Identification framework helps researcher and practitioners to identify various fleet decision making situations through the whole life-cycle of assets and therefore helps to understand the significance of ecosystem behind the fleet decisions as the data needs to be gathered from different sources in ecosystem. A benefit is a replacement investment which occurs only once in a unit's life-cycle, but these replacement investment decisions become significant if those decisions can be made perceiving the whole fleet. In addition, increasingly gathered data, technologies, and analytics enable to take advantage of the data in decision making, compared to previously when it was hard to utilize both technical and economic data in decision making. If the amount of automated decisions is pursued to increase, fleet data might enable scale advantage and mass tailoring of fleet services in future. This research acts as a basis for further research which will highlight the problem of how fleet based life-cycle data can be turned into business knowledge in fleet decision making situations. The proposed Fleet Decision Identification framework will be developed further and future research will focus on evaluating information network more precisely in certain fleet decision making context.

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Publication 3

Kinnunen, S-K., Happonen, A., Marttonen-Arola, S. and Kärri, T.

Traditional and extended fleets in literature and practice: definition and untapped potential

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Traditional and extended fleets in literature and practice: definition and untapped potential

Abstract: The concept of fleet is traditionally discussed in certain industries, such as military, marine, logistics, and aviation industries, where leadership- and asset management -related decisions concerning a fleet of assets are made. Recently, the term fleet has also been utilized in the asset management context, where the fleet can consist of machineries or equipment. To achieve the benefits of managing large groups of assets, it would be beneficial to exploit the learnings from the traditional fleet management fields in other environments, where fleets can be considered in an extended manner. E.g. digitalization generates massive amounts of data which can be exploited more efficiently for fleet management purposes. Data is increasingly gathered not only of physical assets but of other assets, such as business processes and humans, as well. The literature lacks a comprehensive review of existing fleet research. The aim of this paper is to identify fleets appearing in the literature and to find out whether we should make extended fleet definitions to which the fleet management practices from traditional and well-studied fleets can be applied. The research has been conducted by reviewing the literature and describing empirical examples of different fleets. The empirical part is based on interviews made in six cases with 19 interviews in ten companies. The results indicate that traditional fleets have been studied widely, but e.g. the more complex fleets in the manufacturing industry context could be studied more deeply. In addition, fleet management learnings can be applied widely to different types of asset groups, in other words to extended fleets. There is potential to apply fleet management e.g. to improving business processes, managing complex systems as a fleet, and categorizing fleets at multiple levels.

Keywords: fleet, asset management, fleet management, physical asset, extended fleet, fleet literature, fleet decisions, case study

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1 INTRODUCTION

The significance of asset management has become manifest as companies are required to make the most out of their assets during the whole life cycle of the assets. Asset management has been studied in detail by several authors (e.g. Emmanouilidis et al. 2009; Amadi-Echendu et al. 2010; Crespo Márquez et al. 2012; Komonen et al. 2012; Kortelainen et al. 2015). Standard ISO 55000 (2014) series have also been published recently, providing principles, terminology and expected benefits of adopting asset management (Hodkiewicz 2015).

The latest trends in asset management derive from the revolution of the Internet of Things (IoT), which is transforming operations and business in many industry fields. There has been discussion on numerous possibilities to improve asset management as well (Emmanouilidis et al. 2009). In asset management, smart assets and automation have become more common and produce enormous amounts of data to be processed. Especially the developments in data gathering, transmission and warehousing enable massive utilization of data concerning assets. There is still a lot to do to make the most of the data and to support decision making in companies. For example, added systematics in analysis would offer better gains for companies in decision making. The increased amount of data enhances e.g. statistical trend analysis of asset behavior. When multiple similar kind of assets data is gathered simultaneously, we get asset fleet data. This brings the term fleet management into discussion. The term is traditionally employed in the military (Feng et al. 2017; Zhang et al. 2015), marine (Meng & Wang 2012; Leger & Iung 2012), logistics (Archetti et al. 2017; Shi et al. 2014), and aviation (Zhang et al. 2015; Yan et al. 2006) industries, where a fleet is a group of ships, vehicles or aircrafts. The term fleet has been utilized recently more broadly in asset management as well, by some researchers talking about a fleet of equipment in maintenance management (Al-Dahidi et al. 2016; Medina-Oliva et al. 2014; Voisin et al. 2013; Monnin et al. 2011). Benefits of fleet management in the manufacturing industry have been recognized to be e.g. cost savings from successful maintenance planning and resource utilization, as well as increased availability of assets.

Although the term fleet is in a sense established in certain industries, and some efforts for defining it exist (e.g. Medina-Oliva et al. 2014; Al-Dahidi et al. 2016), an explicit definition for fleet is still lacking. Owing to the lack of a proper definition, and therefore a lack of understanding the benefits of fleet-level analysis, there may be untapped potential related to the management of different fleets. For example, learnings from schedule planning of aircraft maintenance or truck routing problems can be applied in the manufacturing context e.g. to plan a maintenance schedule for machineries and equipment or efficient utilization of workforce expertise in different process lines. Analysis of increasingly gathered data and understanding of different kinds of fleets may have significant business potential in many areas. The purpose of this paper is to understand the concept of fleet, to analyze and upgrade the definition of fleet, and to consider whether the concept can be applied to different contexts. The research questions are the following:

1) *Is the definition of fleet in the literature in line with the different asset groups found in empirical evidence?*
2) *What kind of learnings from traditional fleet management practices can be applied to extended fleets?*

The research questions are answered by conducting a literature review and presenting empirical cases of different fleets. The aim of the literature review in section 2 is to find out how a fleet is examined in the academic literature and what kind of exact definitions are given to explain a fleet. Firstly, the literature is reviewed by analyzing fleet-related articles regarding how a fleet is defined or what kind of fleets are discussed in different business contexts. Secondly, the purposes of fleet-level considerations and decision support purposes are analyzed in relation to the categorization of different fleets. Then, the findings from the literature are compared to empirical evidence. The empirical examples of fleets are presented with 6 cases: three cases in which the companies operate in Finland and are involved in the DIMECC S4Fleet (Service solutions for fleet management) research program, and three cases in which the companies operate in Norway. These companies were selected to represent a group of companies that have special interest in fleet management. In the DIMECC S4Fleet research program (size 29.5 M€), a large consortium has been collected of 23 companies and six research institutes who are highly interested in the opportunities of fleet management. The members of the consortium operate in Finland, but also international collaboration partners are involved. The three Finnish cases were selected from this group of organizations, and the three Norwegian companies were named by an international collaboration partner to offer a point of comparison from the traditional fleet management perspective with sound knowledge of data-based asset management. Qualitative interview data from these cases was utilized to gain rich descriptions and deep understanding about the topic (Eisenhardt 1989). Semi-structured interviews were the main data collection method. Section 3 presents the empirical results, with data collection described in detail in section 3.1 and the results in comparison with findings from the literature discussed in section 3.3. Section 4 concludes the paper and proposes ideas for further research.

2 LITERATURE REVIEW

2.1 Different fleets in the literature

In order to gain understanding of how the concept of fleet is considered in academic research, the literature was reviewed in detail. **Table 1** illustrates how a fleet is understood in academic research and what kind of a group of assets is called a fleet. The term fleet appears in several contexts where it is used to represent a group of assets varying from military aircrafts and vessels to equipment in factories. Already since the 19th century, articles of vessel fleets have been published e.g. in the Royal United Services Institution journal. The traditional usage of fleet is associated to the military (Feng et al. 2017, Zhang et al. 2015), marine (Wang et al. 2013; Meng & Wang 2012; Leger & Iung 2012) and aviation (Zhang et al. 2015; Yan et al. 2006) industries. In these contexts, it seems that the term fleet does not need a comprehensive definition, as the term is established to represent e.g. a group of ships or aircrafts. In addition, the term fleet has established its place in the management of vehicle fleets (e.g. Archetti et al. 2017; Shi et al. 2014; Ngai et al. 2012) where a fleet consists of a group of trucks, busses, etc. Research related to traditional fleets, i.e. ships, aircraft and vehicles, does not challenge the usage of the term nor pay attention to definitions, as the concept of fleet is established to represent a certain group of assets.

However, the concept of fleet has recently taken a place more broadly in the field of industrial asset management. The divergent interpretations of a fleet have brought about the need to discuss and define the fleet properly so that it can be utilized in contexts differing from the traditional usages in marine, aviation and transportation. Several researchers (e.g. Al-Dahidi et al. 2016; Medina-Oliva et al. 2014; Voisin et al. 2013; Monnin et al. 2011; Tywoniak et al. 2008) have brought into discussion the possibility to use the term of fleet more widely in other contexts as well. They suggest that the concept of fleet can be utilized more broadly in the management of machinery and equipment. Thus, these researchers have extended the definition of a fleet. For example, according to Tywoniak et al. (2008, p. 1555) a fleet can be defined as ”*a population of similar entities*”. Medina-Oliva et al. (2014, p. 40–41) have continued the efforts to formulate more a comprehensive definition for fleet, and they define the fleet with the following descriptions:

"A fleet shall be viewed as a set of systems (e.g. ships), sub-systems (e.g. propulsion or electric power generation) or equipment (e.g. diesel engine, shaft..)."

"Fleet's units must share some characteristics that enable to group them together according to a specific purpose."

On the basis of these descriptions it can be understood that Medina-Oliva et al. (2014) state that there are fleets at different levels (systems, sub-systems and equipment). They define broadly that the units of a fleet need to share some characteristics to be viewed as a fleet. In addition, Medina-Oliva et al. (ibid.) identify that there can be three different types of fleets, where the fleet can consist of units which are identical, similar or heterogeneous. This also gives more looseness into the definition. Although the definition is loose and enables interpretation, the research leads the reader to understand that the units should be considered as physical assets. Medina-Oliva et al. (ibid.) do not consider whether the units could be something else than physical assets, as e.g. bots in the Internet or human beings in real life.

Al-Dahidi et al. (2016) support the categorization into three different types of fleet: 1) identical fleet – a fleet of assets with identical technical features and usage in the same operating conditions, 2) homogenous feet – a fleet of assets with some same technical features working in similar operating conditions but may have some differences in some features or in their usage, 3) heterogeneous fleet – a fleet of assets with different and/or similar technical features but with varying usage and operating conditions. This definition into three different fleets is really close to the definition suggested by Medina-Oliva et al. (2014).

In conclusion, there are different kinds of fleets, depending on how many similarities the assets in the fleet share. Assets are divided into fleets for specific purposes of use. For example, Kortelainen et al. (2017) continue the discussion on the definition of fleet and suggest that there needs to be an interest to consider a group of assets as a fleet. The interest is often related to decision support and the gaining of economic or other benefits. Monnin et al. (2011) also define a fleet as an abstraction point of view to consider a group of assets for a specific purpose, e.g. to observe the behavior of the fleet, to detect faults or to plan the usage of assets. The purpose of use often defines the fleet and other factors that limit the composition of the fleet, such as the age of the fleet, the operating conditions or the time period. Sometimes it is reasonable to observe assets of the same age or a group of assets operating in similar conditions. The time period can be a limiting factor when observing assets with the same malfunction, and the features before breakdown need to be analyzed in a specific fleet. Thus, the criteria for defining fleet can vary a lot, and a fleet does not automatically mean a group of aircrafts with the same marque and model, or the whole vehicle fleet of a company.

Based on the literature review, it can be stated that the definition of fleet has been already extended from the traditional use to a more general use in asset management, to concern the management of machinery and equipment as well. It can be seen in **Table 1** that the researchers focus mainly on certain types of fleets. Some authors are specialized in marine fleets while some focus on vehicle fleets. There are not many researchers who consider that there could be different fleets or even define that the fleet could represent something else than the traditional ships or vehicles. However, the discussion about an even broader usage of the fleet has been raised by a few researchers. On the basis of **Table 1** it can be concluded that Tyvoniak et al. (2008) and Medina-Oliva et al. (2014) define the fleet the most widely. They have discussed the definition of fleet broadly, and have also suggested that the fleet can be used to represent a group of even more complex systems, such as paper machines, power plants and infrastructures, e.g. harbors. Thus, more complex systems have not been studied yet as fleets, but some researchers have acknowledged the possibility.

Table 1. Different fleets in literature

		Fleets						
References	**Year**	**Military**	**Marine**	**Aviation**	**Vehicles**	**Machinery &Equipment**	**Other fleets**	**Purpose of fleet management**
Tywoniak et al.	2008		x	x	x	x	x	Asset and organizational performance
Mardiasmo et al.	2008				x			Asset and organizational performance, fleet services
Galletti et al.	2010				x			Benchmarking, cost control and management
Shi et al.	2014				x			Dynamic fleet management problem
Ngai et al.	2012				x			Dynamic fleet management
Ninikas et al.	2009				x			Dynamic vehicle routing
Sherali et al.	2006			x				Fleet assignment problem
Meng & Wang	2012		x					Fleet deployment problem
Lun & Browne	2009		x					Fleet mix and performance
Koc et al.	2014				x			Fleet size and mixed pollution-routing problem
Dong & Song	2009		x					Fleet size and routing problem
Newnam & Watson	2011				x			Improving safety
Kelly et al.	2014				x			Investment decisions, asset portfolio
Feng et al.	2017	x						Maintenance planning problem
Johnson	2014					x		Maintenance planning, condition monitoring
Zhang et al.	2015	x		x				Maintenance planning, health management
Kortelainen et al.	2016		x	x	x	x		Maintenance services, fleet level
Pascoe et al.	2013		x					Management strategy evaluation
Yongquan et al.	2016			x				Ordering decisions on spare parts
Hounsell et al.	2012				x			Performance monitoring
da Costa Albuquerque et al.	2013				x			Proactive monitoring
Leger & Iung	2012	x	x					Prognostics and health management
Medina-Oliva et al.	2014		x	x	x	x	x	Prognostics and health management
Monnin et al.	2011		x	x	x	x		Prognostics and health management
Voisin et al.	2013					x		Prognostics and health management
Al-Dahidi et al.	2016				x	x		Estimation of remaining useful life
Sokri	2011	x						Replacement investment
Richardson et al.	2013					x		Replacement investment
Stasko & Oliver Gao	2012				x			Replacement problem
Tierney et al.	2015		x					Repositioning problem
Mishra et al.	2013				x			Resource allocation
Wang et al.	2013		x					Risk management, uncertain demand
Fagerholt	2004		x					Routing and scheduling
Yan & Tseng	2002			x				Routing and scheduling
Christiansen et al.	2004		x					Routing and scheduling, fleet size and mix
Yan et al.	2006			x				Routing and timetable setting
Archetti et al.	2007				x			Routing problem

Vidal et al.	2014				x			Routing problem
Archetti et al.	2017				x			Routing problem, profits vs. costs vs. capacity
Attanasio et al.	2007				x			Routing problem, real-time
Andersen et al.	2009				x			Service network design, fleet coordination
Shaheen et al.	2016				x			Shared mobility services, carsharing
Zhao et al.	2013		x	x	x			Technical condition management, Fleet management center
Aljaafreh et al.	2011				x			Tracking, maintenance planning, remote diagnosing, driver and vehicle status reporting
Van Putten et al.	2012		x					Understanding behavioral drivers

2.2 The purpose of fleet-level considerations

Fleet management aims at purposefully finding ways to manage a group of assets more efficiently. Asset management in general focuses on making right decisions concerning an asset during its life-cycle and does not necessarily focus on groups of assets, whereas fleet management aims at finding ways to make right decisions concerning all the assets of the fleet to maximize profit with minimal cost. In fleet management, the target may be pursuing the economies of scale or economies of scope, and many times the focus is on considering fleets from a sort of top down managerial point of view. As the term of fleet has been established in certain industries, several applications for fleet data have been introduced in these industries. It has been noticed that when analyzing the data concerning the whole fleet, benefits like increased availability and reduced fuel consumption can be achieved. It could be possible to apply the same management practices into new contexts. For example, in the case of a “human fleet”, savings in work time, or in the case of a “virtual bot fleet”, savings in calculation resources can be achieved. Thus, management situations related to traditional fleets (ships, aircrafts, and vehicles) could benefit management situations related to other fleet groups as well. In this chapter, we present some utilization purposes or applications of fleet-level considerations identified in the literature (see **Table 1**).

Fleet management is often related to the aim of profitability, in one way or another. For example, studies of improving efficient use of a fleet are numerous (e.g. Yan & Tseng 2002; Shaheen et al. 2016; Archetti et al. 2017). According to Christiansen et al. (2004), the objective of fleet management in industrial shipping is to offer the required transportation services at minimum costs, which is achieved by taking advantage of the economies of scale. Ship fleet management problems have been reviewed by Christiansen et al. (ibid.), and fleet decision making problems, such as fleet size and mix, deployment, system design, resource management, and scheduling-related decisions have been recognized. Also objectives, such as minimum costs, maximum profit, minimum fleet size, customer satisfaction, and evaluation of alternative solutions have been identified. The same kind of fleet management situations are confronted in the management of vehicle fleets. Fleet-level considerations for vehicle fleets are usually related to resource usage and routing problems (e.g. Hounsell et al. 2012; Vidal et al. 2014; Archetti et al. 2017). In the management of ship and vehicle fleets, fuel consumption and savings in fuel have been under discussion (Koc et al. 2014).

Fleet management is often associated with logistical problems, but maintenance- and asset management -related decisions have also been under discussion in the literature. The benefits of fleet-level consideration in maintenance are e.g. wider knowledge concerning equipment behavior (Al-Dahidi et al. 2016), fault detection and diagnosis (Sardar et al. 2006; Monnin et al. 2011), health and condition monitoring (Voisin et al. 2013; Johnson 2014; Medina-Oliva et al. 2014), spare part management (Yongquan et al. 2016), and remaining useful life estimations (Al-Dahidi et al. 2016). According to Monnin et al. (2011), fleet management in maintenance aims at making decisions that affect asset life extension and performance, operational costs and future planning. Considering assets as a fleet provides managers and engineers with a comprehensive view on the status and health of the assets in the fleet (Monnin et al. 2011). Fleets can also be monitored and managed from a control room, which Zhao et al. (2013) call a Fleet management center. In the maintenance literature, fleet management focuses on industrial assets, i.e. machinery and equipment, but these fleet-level maintenance decisions can also be applied to different fleets, such as aircrafts (Feng et al. 2017; Yongquan et al. 2016: Sokri 2011), ships (Leger & Iung 2012), and vehicles (Aljaafreh et al. 2011).

Other purposes that are not dependent on fleet type or a certain industry are strategic-type decisions, for example replacement investments and benchmarking purposes. Replacement investments for fleets in mining industry equipment (Richardson et al. 2013), replacement of military aircraft fleet (Sokri 2011) and vehicle fleets (Stasko & Oliver Gao 2012; Kelly et al. 2014) are discussed in the literature. Benchmarking is also mentioned as an advantage of fleet management (Galletti et al. 2010), where benchmarking procedures are developed for fleet cost control and management, and management strategy evaluation at fleet level has been mentioned as a valuable method as well (Pascoe et al. 2013).

In general, the purpose for fleet-level considerations is to support different types of decision making. These fleet decision levels can be categorized as presented in **Figure 1**, where the main division is made into operating and maintenance (O&M) and strategic decisions. The decisions in strategy asset management may include e.g. risk management- and product development -related decisions. Naturally, the decisions concerning a fleet can be made at all the different levels from operational to tactical and strategic levels. When considering from the life-cycle perspective the division into acquisition, operating and maintenance, and disposal phases can be made and different kind of decisions are related to these phases. The categorization of fleet decisions has also been discussed by Kinnunen et al. (2016). Despite the fleet type or application business area, the decisions supported by fleet-level analysis or applications can vary from reactive decisions based on real-time data (Ngai et al. 2012; Wang et al. 2013) and proactive decisions (Monnin et al. 2011; da Costa Albuquerque et al. 2013; Johnson 2014) to optimizations (Lun &

Browne 2009; Yongquan et al. 2016) and strategic decisions (Sokri 2011; Pascoe et al. 2013; Richardson et al. 2013). Monnin et al. (2011, p. 3) conclude that "*fleet management aims at maximizing adaptability, availability and mission success while minimizing costs and resource usage*". This concludes the issue incisively, and these characteristics can be seen in multiple studies (e.g. Galletti et al. 2010; Stasko & Gao 2012; Archetti et al. 2017; Feng et al. 2017). It can be concluded that the same kinds of fleet decisions or purposes for fleet-level considerations are confronted in the literature despite the industry or a certain asset category.

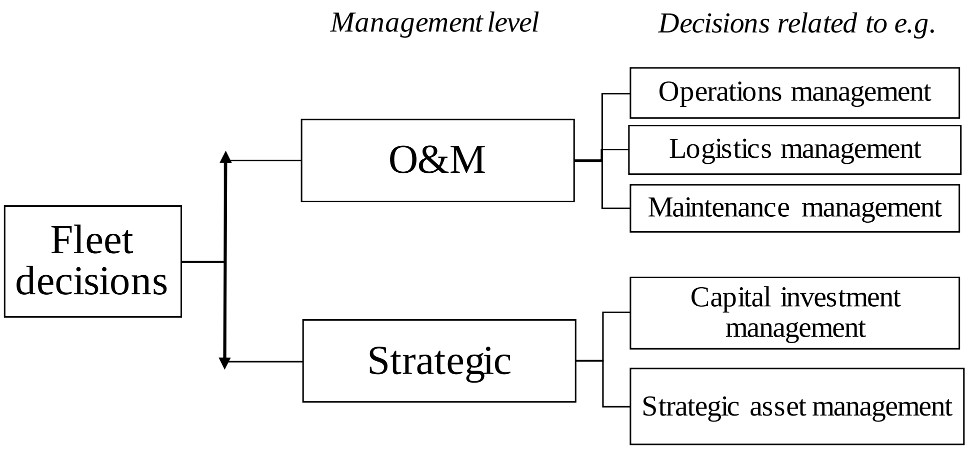

Figure 1. Categorization of fleet decisions

3 EMPIRICAL RESULTS

3.1 Data collection

In this study, the views on fleet management were examined in six cases, where in total 19 interviews in 10 companies were made during 2015–2016. Each case was formed around a fleet. For example, in Case 1, the fleet was the assets provided by Company A, and the customers utilized the assets of the fleet. The interviewed companies elaborated on how they understood a fleet, what the fleet was for them, and for what kind of purposes fleet-level considerations could be used. The companies' current fleet management status was explained and future potential was discussed for developing fleet management further, as today the increasingly gathered data enable improved analyses and models to support decision making.

The companies in Cases 1, 2 and 3 operated in Finland, and the companies in Cases 4, 5 and 6 operated in Norway. The cases were selected so that the interviewed companies represented companies with special interest in or knowledge of fleet management. The companies in Cases 1, 2 and 3 participated in a research program which studied service solutions for fleet management. The companies in Cases 4, 5 and 6, were selected by a Norwegian university that participated in the same research program. Cases 1, 2 and 5 were formed around fleets provided by equipment providers specialized in asset management. In Case 3, Company C was a logistics service provider; in Case 4, Company D was a shipping company; and in Case 6, Company F was an exploration and production company. Thus, the companies had both traditional and novel views on fleet management.

The empirical data were collected with semi-structured interviews, and the data concerning the companies involved in the research program were collected from project meetings as well. The data collection is described in detail in **Table 2**. To ensure transparency, notes were made in project meetings, and the interviews were recorded and documented. The interviewees worked in managerial positions, and examples of titles are Section Manager, Research and Development Director, Development Manager, Sales Manager, and Service Product Manager. The interview questions regarding the research topic of this paper are presented in **Appendix 1**.

Table 2. Data collection

Case	Data collection	Number of interviewees
Case 1: Fleet A - Company A: Equipment provider ○ Division A1 ○ Division A2 ○ Division A3 ○ Division A4 ○ Division A5 - 3 customer companies	- Project meetings - In total 9 interviews ○ 1 semi-structured interview with each of the 5 divisions ○ 4 customer interviews	- 3 company representatives in project meetings - In total 11 interviewees from the equipment provider (Company A) - In total 6 interviewees from the customer companies
Case 2: Fleet B - Company B: Equipment provider & Maintenance service provider - 1 customer company	- Project meetings - 1 semi-structured interview with the customer company	- 1-2 company representative(s) in project meetings - 1 customer company representative in a customer interview
Case 3: Fleet C - Company C: Logistics service operator	- Project meetings - 6 semi-structured interviews	- 1 representative in project meetings - In total 8 interviewees
Case 4: Fleet D - Company D: Shipping company	- 1 semi-structured interview	- 1 interviewee
Case 5: Fleet E - Company E: Equipment provider & Maintenance service provider	- 1 semi-structured interview	- 1 interviewee
Case 6: Fleet F - Company F: Exploration and production company	- 1 semi-structured interview	- 2 interviewees

3.2 Different fleets in practice

The interviewed companies had different views on a fleet, depending on their area of business. Companies operating in the shipping industry naturally consider ships as a fleet, whereas companies operating in an industrial environment often consider machinery and equipment as a fleet, and in logistics, vehicles usually form a fleet. The interviewed companies, their views on the fleet, and usage examples of fleet management are summed up in **Table 3**.

Starting from the traditional point of view, in Case 4, Company D represents one of the most traditional views on fleet management. For Company D, the fleet consists of the ships that they provide and operate. However, inside their business, they can observe the fleet at different levels: (1) all the ships as a fleet, (2) a fleet operated from a certain location, (3) fleets divided by different segments (shuttle tankers, floating storage units etc.), and (4) geographical fleets. The representative of Company D stated that fleets and fleet management are essential and commonly used in this field of business. For example, there are even positions like fleet managers who are responsible for the management of their fleet. Fleet managers need to handle multiple matters from maintenance to customer service.

Case 1 represents a good example of fleet management from the equipment provider's perspective, where Company A is an equipment provider and considers their products as a fleet. Also Company E in Case 5 is an equipment provider and provides their own products to customers, but in addition to that they also offer comprehensive asset management service for customers. Therefore, Company E can consider the provided equipment as a fleet, but on the other hand, they consider the customer's whole platforms and their equipment as a fleet. In a similar way, Company B, an equipment provider, considers their products as a fleet, but they can consider the customer's machinery as a fleet as well, because they provide maintenance service to the whole set of paper machines owned by the customer. Thus, Company B can identify behavior patterns and optimize maintenance which then can be applied to all the paper machines they serve worldwide. It can be concluded that Companies B and E have quite a traditional view on a fleet, but as service providers they consider fleet management from a wider perspective.

In Cases 3 and 6, Companies C and F are operators by nature, and their interpretation of a fleet is more unconventional. Company F operates closely with traditional fleets and thus considers ships as natural units of a fleet. However, Company F can also consider the platforms that they operate as a fleet, but as the platforms are highly complex systems, there are challenges in managing them as a fleet. Although Company C operates in logistics, they have a novel viewpoint to fleet management, and in addition to their own equipment and vehicles, they consider their customer sites and logistics processes as units of a fleet.

Table 3. Fleets and fleet management in the cases

Case	What is the fleet in the case?	Purpose of fleet management
Case 1: Company A - Equipment provider Customers 1) Electricity distributor 2) Engineering and service company 3) Forest industry company	Fleet: Machinery and equipment - Equipment sold to customers	- Fault detection and localizing - Fault prediction - Life-cycle analysis - Maintenance planning - Optimal usage of assets (performance vs. energy/fuel consumption) - Optimizing investment decisions - Remote support and decision support (operative, tactical, strategic decisions)
Case 2: Company B - Equipment provider - Maintenance service provider Customer - Forest industry company	Fleet: Machinery and Equipment - Different fleet levels - Equipment sold to customers - Customer's machinery (paper machines)	- Estimating and extending the lifetime of equipment - Maintenance planning, optimized maintenance - Minimizing wear-out - Predictive models
Case 3: Company C - Logistics service operator	Fleet: Other, Vehicles - Logistics processes - Customer sites - Own equipment or vehicles (e.g. forklift trucks)	- Benchmarking - Best practices - Monitoring, taking corrective actions in time - Maintenance planning e.g. for forklift trucks - Process optimization - Resource utilization, including human resources
Case 4: Company D - Shipping company	Fleet: Ships - Own vessels/ships - Different fleet levels	- Fault detection and prediction - Increasing safety, preventing accidents - Maintenance planning - Monitoring and automatized recommendations based on fleet data - Optimization of fuel efficiency, including performance of a ship, fuel consumption, pollution, and environmental costs - Resource management and planning
Case 5: Company E - Equipment provider - Maintenance service provider	Fleet: Machinery and Equipment, Other - Own equipment - Platforms, Oil & Gas (O&G) industry	- Estimating the need of human resources - Improving risk management - Increasing availability - Increasing safety - Maintenance when needed – avoiding unnecessary work - Preventing breakdown - Spare part management
Case 6: Company F - Exploration and production company	Fleet: Ships, Other - Vessels serving platforms - O&G platforms	- Best practices - Increasing safety - Monitoring assets: real-time technical features, conditions and production rate - Observing changes, taking corrective actions on time - Optimizing spare part utilization - Preventing breakdowns - Supporting maintenance

The companies could see multiple different ways to utilize fleet data in their field of business. As **Table 3** shows, the usage examples can vary from fault detection to the optimization of the whole maintenance, and from fuel consumption management to the optimization of resource management. The resources may include the assets of the fleet, spare parts, fuel or human resources when planning e.g. maintenance or other operations. In general, fleet management is considered beneficial for identifying best practices, and when implemented to whole fleet, benefits such as increased availability, improved risk management, increased safety, and other cost savings can be achieved.

The potential of fleet management was recognized well by the case companies. Company D summed up *the advantage of fleet management into four phases: (1) collecting data about the fleet, (2) analyzing, (3) learning from the analysis, and (4) applying the data to the whole fleet*. According to the representative of Company D, O&G industry is advanced when it is a question of behavior of components at the component level, but there is still potential to gain more benefits when managing assets at the fleet level. In addition to improvements in maintenance and safety, the optimization of fuel efficiency was named as a significant development area where fleet-level benefits can be considerable. Also Company B mentioned the benefit of scalability when managing the fleet of assets. When the best practices are applied to the whole asset base, the benefits are considerable. Company C agreed with *the potential of identifying the best practices by taking advantage of widely collected and analyzed fleet data.* Company C also saw that the benefit of fleet-level analysis is *the optimization of resource utilization*. The utilization of resources, such as forklift trucks and human resources, including the expertise of the staff, can be managed inside and between the customer sites if fleet-level analysis can be used. Even though Company C operates in logistics, where vehicles traditionally form the fleet, they have a broader viewpoint on the definition of a fleet. For them, a fleet can consist of vehicles such as forklift trucks, but the fleet can also consist of a certain logistics process or entire customer sites. In the latter cases, fleet-level analysis enables *benchmarking and lessons learned* from one customer site to another similar process. In addition, this broader definition of the fleet makes it possible to optimize resource utilization and processes of several customer sites. Company C is a good example of a company which *considers a fleet at multiple levels*.

The potential of fleet management can be exploited at multiple levels, inside the company, but also at the network or ecosystem level. In addition to Company C, Company E saw that the fleet can be observed at different levels, and not all the potential of fleet-level consideration is tapped. Company E can consider *their products, remotely operated vehicles, as a fleet* but on the other hand, the interviewee *preferred to refer to platforms* when discussing fleet management, as they also offer comprehensive asset management service for their customers. According to Company E, fleet management is complicated in the O&G industry if platforms are considered as assets of fleet. The complexity is mostly related to the fragmented ownership of platforms. *There is potential if the platforms can be managed at fleet level, but the management of platform fleets requires* *fleet management at network or ecosystem level.* The interviewee mentioned *the optimization of spare part management as one example*. *With joint warehouses it would be possible to decrease the amount of money tied in storages and release the money for other productive purposes*. The representative of Company E also suggested that *the same idea as in spare part optimization can be applied to different groups of similar kinds of objects, such as components, people and equipment.* There is especially potential to improve availability when managing at fleet level.

However, companies acknowledged the dilemma of balancing between potential benefits and the costs of developing fleet-level analysis. Company F emphasized that the benefit of managing large sets of similar types of assets is *balancing with maximized revenues and minimized costs*. In the case of Company F, the key is to increase production and safety, and to decrease costs. To benefit from fleet management, data need to be gathered widely from the fleet and refined into a usable form to support decision making. Company F stated that *the predictive models and advanced analytics are a hot topic at the moment*. However, they underlined that *the costs of developing these kinds of models need to be considered and estimated where these models are needed and whether they are worth developing*. Also Company D reminded that the development of models and analyses takes resources and in striving for perfection, a lot of resources are required. It is important to keep in mind that the achievable benefits need to exceed the costs. For example, *sometimes 90 % accuracy or operating quality is enough if the better accuracy causes more costs than benefits,* according to Company D.

There seemed to be several challenges hindering the full exploitation of fleet-level management. According to Company A, a challenge in thorough exploitation of fleet data is the fact that *there are different generations of equipment in the field*. All the same data cannot be collected from old and new equipment, but investments in new equipment with modernizations are required by customers. This is partly related to the challenge acknowledged by Company B who had noticed that machinery and equipment with different ages and varying amount of gathered data underlines the importance of skillful staff. The accumulated knowledge and experience of workers are crucial when managing assets without detailed data and analysis. This tacit knowledge needs to be exploited when developing new fleet analysis models. *Therefore, the challenge is exploitation of tacit knowledge, or knowledge transfer in general*. Company D also emphasized the importance of *knowledge sharing between fleet managers*. In addition, Company A and E mentioned *data availability* as a challenge for enhanced utilization of fleet data. Company C mentioned a challenge of divergent assets in the fleet. It is challenging to measure indicators and implement best practices when the assets are not identical or similar. In the case of Company C, the assets can be logistics processes or entire customer sites, and thus the fleet is not homogenous. However, according to the literature (Medina-Oliva et al. 2014; Al-Dahidi et al. 2016), fleets can also be heterogeneous if the assets are not identical or similar but they share certain features, which makes it reasonable to consider the assets as a fleet.

3.3 *Discussion of the results*

According to the cases, fleet-level consideration makes it possible to gather increased amounts of data, to get extensive understanding about the behavior and the state of assets, to make accurate analyses and models, and to achieve multiplied benefits concerning the whole fleet. The assets of a fleet can vary, and fleets can be categorized at different levels on the basis of the purpose of fleet management. The assets of the fleet can be equipment or other relatively simple devices and assets, but there is potential to observe fleets consisting of complex systems, for example paper machines, platforms or customer sites. In fleets of complex assets, the assets often form a heterogeneous fleet where the features and conditions of the assets can vary. Despite this, there is potential to consider complex systems as a fleet if they share certain features that make it reasonable to consider them as a fleet. For example, companies can benefit from fleet management if best practices regarding maintenance as well as logistics processes can be applied to the whole fleet, or if spare part management of the whole fleet can be combined.

Although fleet management is advanced in traditional fleet industries, such as in the shipping industry, there is room for improvements. Improvements can be made regarding knowledge sharing and ownership issues, as the data concerning the fleet of assets is often fragmented, but also the assets can be owned by several actors (e.g. Case 6). Thus, there is untapped potential in developing fleet management practices and achieving scale advantages if the benefits of fleet management can be realized. The benefits can offer advantages to multiple actors if fleet management can be carried out at network level, and thus consider fleet management as a larger unity than an in-company activity. In traditional fleets, fleet management has often been considered an in-company activity (e.g. vessels owned, operated, maintained and managed by a single company), which leads to a simpler business ecosystem around the asset fleet. However, the trend in traditional fleets is also moving towards networks when e.g. maintenance is conducted by service providers. Thus the business ecosystems around traditional fleets are becoming more complex and the question is how and to whom the value is created during the life-cycle of asset fleets. In the case of extended fleets, e.g. platforms or harbors, the ecosystem around the fleet involves multiple actors to whom the maximum value should be created during the life-cycle of the assets. The efficient management of these kinds of fragmented fleets requires purposeful management over the boundaries of companies in business ecosystems.

Table 4. Different fleets and comparison of fleet management in literature and practice

Fleet	**Purpose of fleet management Theory/Literature**	**Purpose of fleet management Practice/Empirical results**
Traditional fleet - Aircrafts - Military - Vessels/ships - Vehicles - Machinery - Equipment	**O&M management** - Asset performance - Fuel consumption - Health management - Life-cycle analysis, remaining useful life estimation - Maintenance planning and optimization - Monitoring and proactive maintenance actions - Routing and scheduling problems - Resource management and allocation - Safety - Spare part management **Strategic management** - Investment and replacement decisions - Management strategy evaluation - Organizational performance - Risk management	**O&M management** - Automatized recommendations based on fleet data - Customer satisfaction - Fault detection and localizing - Increased availability - Life-cycle analysis - Maintenance planning - Monitoring - Optimization of fuel efficiency, including performance of a ship, fuel consumption, pollution and environmental costs - Performance analysis - Predictive models – proactive operations - Remote support and decision support (operational, tactical and strategic decisions) - Resource management - Safety, accident prevention - Spare part management **Strategic management** - Benchmarking - Investment decisions - Risk management
Other fleets – Extended fleets - Customers - Infrastructures (e.g. harbors) - Platforms - Plants - Processes - Resources (e.g. expertise of workforce)	**O&M management** - Asset performance **Strategic management** - Organizational performance - Benchmarking	**O&M management** - Best practices - Customer profiling - Increasing safety - Maintenance planning - Monitoring, corrective actions in time - Performance analysis - Predictions of future behavior - Resource management, including human resources, system resources etc. - Unified spare part management **Strategic management** - Benchmarking - Investment decisions

According to the literature and empirical evidence, there are different kinds of fleets, but the purposes of fleet management are similar, as can be seen in **Table 4**. It can be noticed that some of the purposes for fleet management can also be done on asset level, e.g. the optimization of fuel consumption, but the benefit of fleet level consideration is optimizing the consumption of the whole fleet and e.g. the benefit of wider knowledge or prioritizing the utilization of the assets that consume less fuel. Observing a fleet produces more data from the assets that can be utilized in analyses and models to support decision-making. The amount of data does not necessarily mean increased knowledge but to some extend the increased amount of data can bring more value if the data is utilized wisely and refined into analyses or models adding value to the decision-making situations. In fleet management, the management of larger asset groups is made purposefully and the aim is to find the potential situations where the benefits of observing a larger group of assets can bring advantage in decision-making. In traditional asset management, the focus is not necessary on observing and managing the assets as a fleet. Concerning traditional fleets, i.e. fleets of ships, vehicles and aircrafts, the purposes of fleet management are quite similar both in the literature and in the empirical evidence. The management situations are related to e.g. maintenance planning, resource utilization to maximize availability, and optimization of fuel consumption. In all cases the aim is to minimize unit costs and maximize profits, i.e. pursue economies of scale. The same note can be made for equipment fleet, where the literature and practice describe the same type of fleet management situations. The notes from the empirical evidence give detailed practical information about the usage of fleet management, and for example safety issues were emphasized by the case companies.

Concerning other fleets, or extended fleets, they have been mentioned in the literature (e.g. Tywoniak et al. 2008; Medina-Oliva et al. 2014), but special attention has not been paid to the potential of these kinds of fleets. Based on the interviews, the idea to consider complex assets or units as a fleet was approved and supported, and the same kind of management principles were mentioned in the management of these kinds of fleets. Especially monitoring the state of assets, benchmarking, and applying best practices were mentioned as valuable benefits from the fleet management of these kinds of complex assets. The empirical evidence raises the question of whether other assets could be considered as the assets of a fleet. As Company C is a service operator, for them the assets of fleets can be logistical processes, entire customer sites and human resources. According to Company C, it would be beneficial, for example, to manage human resources, especially the special skills and expertise of staff, as assets of the fleet, and they could be directed to tasks where there is a need to gain mission success with minimized costs. From their viewpoint, there is huge potential in applying fleet management practices from traditional fleets to *extended fleets* (see **Figure 2**).

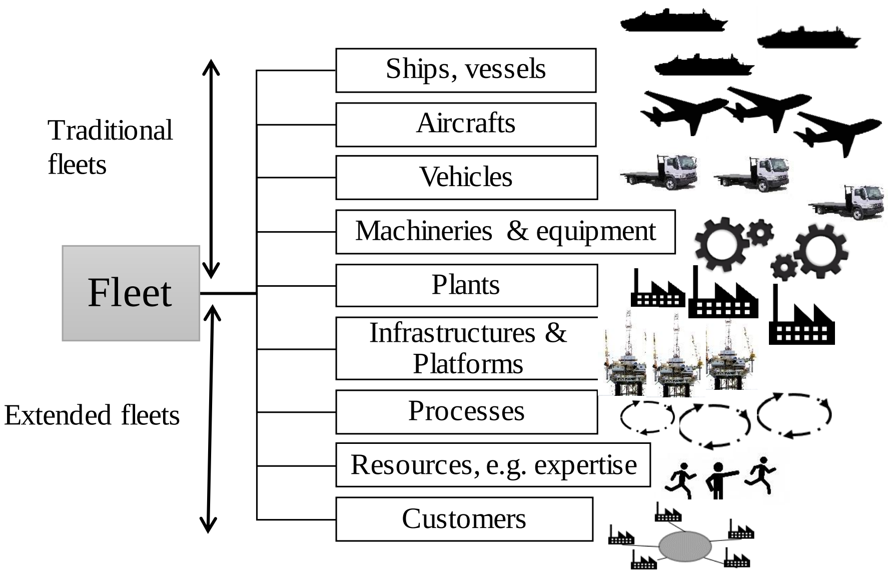

Figure 2. Traditional and extended fleets

4 CONCLUSIONS

Fleet management has been commonly related to military, marine, logistics and aviation industries, and fleet management practices are advanced in these sectors. However, there is untapped potential to apply fleet management practices when managing other kinds of fleets. This paper has increased the understanding of the value of traditional fleet management practices in new contexts by analyzing definitions in prior research and comparing findings from the literature to empirical findings (see **Table 4**). As an answer to the first research question, it can be concluded that the definition of a fleet in the literature is quite similar in the fields that the literature covers, but the current definitions do not respond to all the new fleets that have surfaced in recent years. Therefore, according to the empirical results, there is a need to extend the definition of a fleet. Our proposed extension to the definition of a fleet is to concern the assets of traditional fleets in extended fleets as well (see **Figure 2**).

According to the empirical results, there is untapped potential to apply fleet management practices and learnings from traditional fleet management to extended fleets. This can be seen as an answer to the second research question. Despite the asset group of the fleet, the same purposes of usages for fleet management can be applied (see **Table 4**). There is also potential to manage different levels of fleets more efficiently inside a company, but fleets and the management of fleets can also connect companies in networks or ecosystems. The developments in technologies have made it possible to gather data related to a fleet of assets. The challenge is to utilize the data to create business value.

The literature presents numerous examples of how to utilize and benefit from fleet data, but all the opportunities of fleet management in different business areas have not been recognized yet. Services based on fleet data has been developed e.g. in traditional fleet industries, but is it possible to apply these service ideas for the management of extended fleets? Based on the empirical results, the second research question can be answered by proposing that there is untapped potential in utilizing fleet data (1) in traditional fleet industries, where especially assets with complex ownership or where fleet data is fragmented in multiple companies hinder the exploitation, and (2) in unusual fleets where the assets can be other than traditional physical assets. Regardless of the fleet, the main target remains the same: to improve the management of assets to gain cost savings and to maximize profit during the life-cycle of an asset, which can be done either at company or ecosystem level or both. Fleets can be seen as a partly untapped object of accounting and analysis, or the decision-making level in a company or in business ecosystems.

Fleet management offers advantages to the internal management and decision making in companies, but in addition, various fleet services can be built around fleet data. In fleet management, the role of data is emphasized, and decision support or services are based on fleet-wide collected data. To benefit fully from fleet data in fleet management decisions, collaboration between companies is usually needed. This explains partly why the traditional fleet industries can still keep developing their fleet management actions further at more enhanced levels. These companies master the fleet management of their own fleets, but in the management of fleets or fleet data whose ownerships are complex, there is still potential to develop fleet management across company borders.

Further research is needed to explore the extended fleets. There are clearly multiple research gaps in the research of the management practices of extended fleets, and no one is currently aware of all the opportunities in applying fleet management in different fleets, and thus there is clearly more untapped potential around the issue. There could be benefits in managing different kinds of assets as a fleet with the aid of increasingly gathered data. For example, how large benefits could be achieved if the assets in the public sector, e.g. emergency vehicles or infrastructures, were managed as a fleet? The same applies to the assets in offshore or other extreme conditions, which are operated and managed more and more remotely from monitoring and control rooms in the future. Purposeful fleet management should be further researched in order to find the situations where fleet level analyses can bring benefits to decision-making. For example, spare part utilization is a good example, which also emphasizes the need of management over the boundaries of companies in business ecosystems. Another research subject could be the significance of collaboration to benefit from fleet data. The defining of fleet depends on the observers and what benefits they are aiming at. Different aims make the defining of fleet and sharing fleet data challenging between actors in ecosystem. This emphasizes the importance of contracts between companies in the ecosystem. The challenge is to exploit the fleet data and create value from it to different actors in business ecosystems.

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Appendix 1: Semi-structured interviews

Theme: Definition of a fleet

Describe shortly what is your business and what you do.
What is a fleet in your business?
What is the role of fleet management, i.e. managing multiple assets beyond an asset?

Theme: Fleet decision-making situations

What kind of analysis can be made based on fleet data?
   a. *The potential of real-time, predictive, optimization analyses?*
What kind of decision making would it facilitate?
   a. *What kind of fleet decision-making situations are there at operational, tactical, or strategic levels?*

Theme: Benefits of analyzing fleet life-cycle data

What benefits are there when managing large sets of similar types of assets?
What benefits do you think there would be if data concerning multiple assets (fleet) were available? The potential of cost savings vs. increased revenues?

Theme: Fleet data availability in an industrial ecosystem or network

Who collects and analyzes the fleet data? Is all the data available?

Publication 4

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A framework for creating value from fleet data at ecosystem level

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A FRAMEWORK FOR CREATING VALUE FROM FLEET DATA AT ECOSYSTEM LEVEL

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Abstract:
As companies have recently gotten more interested in utilizing the increasingly gathered data and realizing the potential of data analysis, the ability to upgrade data into value for business has been recognized as an advantage. Companies gain competitive advantage if they are able to benefit from the fleet data that is produced both in and outside the boundaries of the company. Benefits of fleet management are based on the possibility to have access to the massive amounts of asset data that can then be utilized e.g. to gain cost savings and to develop products and services. The ambition of the companies is to create value from fleet data but this requires that different actors in ecosystem are working together for a common goal – to get the most value out of fleet data for the ecosystem. In order that this could be possible, we need a framework to meet the requirements of the fleet life-cycle data utilization. This means that the different actors in the ecosystem need to understand their role in the fleet data refining process in order to promote the value creation from fleet data. The objective of this paper is to develop a framework for knowledge management in order to create value from fleet data in ecosystems. As a result, we present a conceptual framework which helps companies to develop their asset management practices related to the fleet of assets.

Key words: *fleet data, ecosystem, framework, value, data refining, asset management*

INTRODUCTION

Assets produced by an original equipment manufacturer (OEM) are often distributed to many customers and different locations. From the manufacturer's point of view the products or assets of fleet are often scattered to wide range of companies. Thus, the data related to fleet of assets are fragmented in an industrial ecosystem where e.g. a manufacturer has product data, an asset owner has process data and a service provider has the service data related to a certain fleet of assets. This fragmented data concerning the fleet is hindering the full exploitation of fleet data in the decision making and also in the service development.

Recently, the aim among industries has been to develop data processes in order to benefit from collected data in asset management decision making. Manufacturers are also willing to increasingly provide knowledge-based services alongside the products. Technologies have partly facilitated this movement but there are still challenges especially related to data sharing between companies in industrial network but the challenge is also to share data effectively even inside an organization. As the fleet of assets and the data related to the assets are often fragmented in different companies no one has the access to all the data concerning the fleet. In order to be able to generate fleet data based services these challenges need to be considered. The literature presents general frameworks to upgrade data into knowledge but they are lacking the perspective of company networks or ecosystems combined with the fleet management point of view. Therefore, there is a need for a framework which combines data refining process with ecosystem and fleet management perspectives. Thus, the purpose of this paper is to develop and illustrate the role of ecosystem when creating value from fleet data. The aim of this paper can be concluded into the following research question:

How can the process from fleet data to decisions in an ecosystem be illustrated?

Research question is answered by developing framework to meet the requirements of fleet data utilization in order that the value creation in ecosystem could be possible. By reviewing literature it has been acknowledged that the traditional knowledge management frameworks do not consider the development of modern ecosystem concept and the special characteristics of fleet data management. Thus, the research is conducted by developing analytically the existing data management and knowledge management frameworks. As a result a conceptual framework is developed and the results are discussed.

LITERATURE

Ecosystems in Literature

The developments in business environments are resulting in companies and other organizations networking in increasing pace. As the significance of networking has increased, companies are trying to develop powerful partnerships in order to fare in the competition between networks.

This increased interest in the subject can be noticed from the plentiful and multifaceted research conducted in the field. The subject is discussed with different terms such as industrial networks and value chains that often appear in the literature. In addition, the term of ecosystem has been used in business context as well as by several authors [1, 2, 3, 4, 5].

The term of ecosystem is used to represent the network and especially to highlight the interdependencies between network partners in order to achieve mutual effectiveness and survival [6]. The term ecosystem is also utilized to symbolize the sustainability and sustainable development aspects that are aimed in ecosystem level cooperation [1, 7]. There are different kinds of views to determine ecosystems and for example the terms of business ecosystem, industrial ecosystem, innovation ecosystem, and information technology (IT) ecosystem or digital ecosystem are presented in the literature. Peltoniemi and Vuori [8] have reviewed the different views of ecosystem in detail. For instance Moore [9] defines the business ecosystem as "an economic community supported by a foundation of interacting organizations and individuals – the organisms of the business world". IT ecosystem or digital ecosystem is founded on a platform where data and applications create the basis for the value creation in the ecosystem [10]. Industrial ecosystem can be defined as "a regional collection of industrial actors that cooperate in each other's waste material and waste energy utilization" [4]. Therefore industrial ecosystem can be regarded as an environmental ecosystem with the circle of material, energy and information. Despite the accurate term, the ecosystem can be concluded to refer to an interconnected population of organizations which can be small companies, large corporations, universities, research centers, public sector organizations, and other actors who influence the system [8].

As the definition for the ecosystem does not appear to be fully unambiguous and none of the definitions meets the requirements that we have when considering the ecosystem in the fleet context, we are regarding the ecosystem as the combination of three different ecosystem concepts: business ecosystem, IT ecosystem, and industrial ecosystem. In the Figure 1 the relation between these three definitions is presented. We define the value ecosystem around the fleet to contain the properties of business ecosystem, such as strong interdependencies between the actors of ecosystem and the aim of mutual value creation. The concept of industrial ecosystem highlights the importance of sustainability aspects which are significant as well for the fleet value ecosystem. The sustainability refers to the point that the ecosystem functions in a way where each actor is benefitting and no one's position in the ecosystem is indefensible. As the fleet data is the starting point for the value ecosystem around the fleet, the features of IT ecosystem, such as data and platform-centered approaches, are essential. Consequently, we define the value ecosystem around the fleet to be a combination of three subsystems including features of business ecosystem, IT ecosystem and industrial ecosystem. The ecosystem is formed around the fleet and basing on fleet data platform or corresponding information technology solutions. With the aid of information technological solutions a group of interconnected organizations are benefitting from fleet data and creating value in a sustainable way.

Ecosystem around the fleet is formed by several different actors which have different roles in the ecosystem interaction. Companies in the ecosystem may have roles such as equipment provider, customer or asset owner, and various service providers who all have certain relation to the fleet of assets and are involved in the fleet data based value creation. Especially, when it is a question about data refining in the ecosystem, the role of IT service providers is emphasized. Different actors in ecosystem are complementing the whole ecosystem and they have their role in the data refining process in order to create value from fleet data. The aim of value ecosystem around the fleet is the value creation for the whole ecosystem. The functionality of ecosystem is based on mutual trust and benefitting all the actors of ecosystem [11]. However, this characterization is representing the ideal ecosystem, and the common value creation and benefitting all the actors in ecosystem are more like the ambition than reality. There is still plenty to do before this kind of ecosystem could function as it is supposed and before the companies can create value for ecosystem around a fleet.

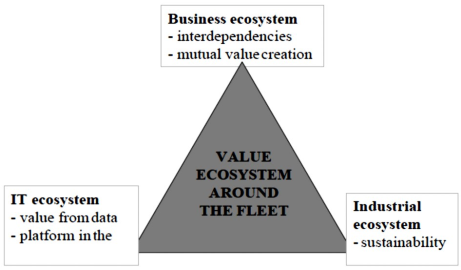

Fig. 1 The concept of value ecosystem around the fleet as a combination of different definitions of ecosystem

In order to get closer to the ambition state, the first step is to understand the roles of actors in ecosystem around a fleet. As the ecosystems and their interdependencies are often complex, this sets requirements for data acquisition and data sharing as well as for upgrading the data into valuable business knowledge for decision makers. These issues become relevant if companies in the ecosystems are willing to benefit from fleet-wide data and as the data can be owned by different companies they need to understand their role in the fleet data refining process. Figure 2 is presenting simply the roles of ecosystem actors in fleet data generation.

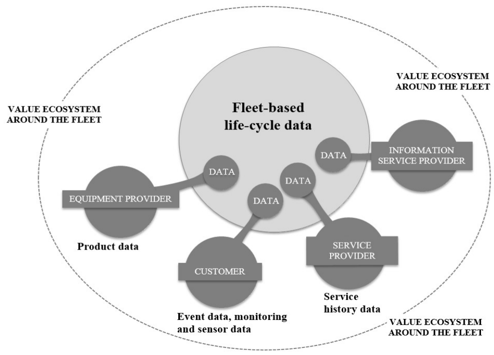

Fig. 2 Ecosystem around the fleet - the impact of ecosystem actors on fleet data

Information and Knowledge Management Models for Ecosystems to Manage Fleet Data

In the literature, general models for data management and data refining process are presented often in the fields of information and knowledge management research. General models and frameworks for knowledge management are presented by noted researches e.g. Nonaka and Takeuchi [12] as well as Davenport and Prusak [13]. When considering the process from data to knowledge the classifications for the data refining levels, also known as knowledge hierarchy, often appears in literature [14]. Knowledge hierarchy divides the levels of data, information, knowledge and wisdom. Data is regarded as unprocessed data or symbols, information is regarded as processed data that can be used, knowledge is refined from data and information, and wisdom refers to understanding. This kind of classification is essential when discussing the data to decision process.

Although the literature presents a large amount of models and frameworks for information and knowledge management, there is still a need for more specific frameworks in different business contexts and different levels of business. In other words, there are needs for the models for information management related to just a certain process, for the models related to information management at organizational level, and when the business networks and ecosystems are increasing, there is a need also for ecosystem level information models. Within the research program Service Solutions for Fleet management [15] researchers such as Kunttu et al. [16] have applied the data models to the knowledge-intensive service development by creating a framework (Figure 3) for information management in a single firm case. They present the framework for data-to-decision where the manufacturer manages the information flows from external and internal sources. The framework consists of six phases: data collection, data pre- treatment, descriptive data analysis, data modelling, soft and hard data combination and the comparison of decision options. The sequential phases result in the various levels of understanding to make the data useful for decision-making i.e. data, information, knowledge and wisdom [16].

When starting to develop the framework for fleet data management at ecosystem level, the data to decision framework presented by Kunttu et al. [16] is a good starting point. The framework presented by Kunttu et al. [16] illustrates the data refining process from data to decisions and the framework functions as a tool to develop knowledge-intensive services. However, the framework considers that the process is handled by a single company but it does not consider that the process from data to decisions is not always mastered by a single company. The process from data collection to decision making may be affected by several companies in ecosystem. Especially, when we are considering fleet-wide data, even the phase of data collection is executed by multiple companies as was presented in Figure 2. In addition, data pre-treatment and other data processing is often provided by information service providers. Another important aspect which is related to the ecosystem view is the value creation through data refining process. There is a need to clarify the roles of companies in the ecosystem around the fleet when creating value from fleet-wide data. Thus, who is benefitting or should we maximize the value for the whole ecosystem? The understanding of the roles in ecosystem is a step forward to create new business as well as sharing benefits and risks in ecosystems. Framework (Figure 3) could be developed further in a way which takes the role of collaboration in the ecosystem into account and considers challenges related to costs, benefits and information sharing.

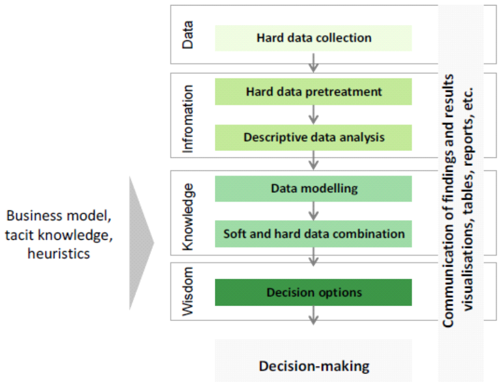

Fig. 3 Framework for information management and the relationship of data, information, knowledge and wisdom
Source: [36].

FRAMEWORK FOR CREATING VALUE FROM FLEET DATA AT ECOSYSTEM LEVEL

Existing knowledge management models which generally are known in information management context have been the basis for the development of the new framework in this paper. The general information and knowledge management frameworks presented in literature have now been integrated with IoT, ecosystem and fleet management viewpoints as a part of ongoing research program. Prior research, the research work during the research program and the collaboration with companies within the program, including workshops, have been the basis for the development work of the framework. Data to decisions framework developed by Kunttu et al. [16] is also a result of the research program and there are still possibilities to develop the ideas of data to business knowledge process further. Some ideas for further development were discussed in section 2.2.

In Figure 4, we are presenting the new framework which has influences also from the data-to-decision framework developed by Kunttu et al. [16]. The main need to develop the framework further is to clarify the roles of actors in data to decision process at ecosystem level. In other words, to clarify the process of how the fleet data can be turned into value in ecosystem. As there are several actors involved in the ecosystem, it is vital to be able to create value for the ecosystem as an entity but to create value for each actor in ecosystem as well. The actors in the ecosystem have different roles in the data refining process and thus in value creation. Figure 4 describes a swim lane flowchart where each actor has their own lanes describing their participation in the data to decision process. The black arrows are representing information flows between data refining phases and actors. It can be noticed that some of the actors have smaller roles in the process while the others might have important role in multiple phases in the process. In addition, in the top part of the figure, the stacked bars describe how the costs and benefits are generated through the process. Costs and benefits can be observed at actor level, as each actor has their own green and orange colors, and at the ecosystem level when the total costs and benefits can be observed. The value for ecosystem can be evaluated as the difference or ratio between discounted benefits and costs.

Figure 4 is representing an example how the process from data to decision in the ecosystem around fleet can be illustrated. However, the situation is often that each actor is managing the process from data collection to decisions by themselves inside the boundaries of company, i.e. companies are staying in their own swim lanes. However, this may lead to the situation where all the data is not available as fleet data is often fragmented to several actors in ecosystem. Therefore, it would be reasonable if the whole ecosystem was pursuing to benefit from the fleet data gathered by different actors. However, this requires that the actors of ecosystem are willing to cross the boundaries of their swim lanes and consider the roles of actors in data refining process. The mobility of data between actors in ecosystem is essential for fleet data utilization at ecosystem level.

Naturally, the whole process and each phase from data collection to decision making are not the core business for all the actors. Some actors might be specialized to some phases while others are mastering the other phases. It could be beneficial if the roles for different data refining phases were considered based on the core competencies of companies. This requires that the current situation in ecosystem can be illustrated and then developed and managed in order to create more value from fleet data for the ecosystem. Figure 4 is representing a suggestion for the data refining process in ecosystem where data are shared in ecosystem and each actor has their own roles in the process. For example, service provider I is taking care of data pretreatment collected by multiple actors and other actors are utilizing this data. It can be noticed as well that equipment provider and service provider II are providing analysis and models to support their own businesses but to support the customer's business as well. The costs and benefits are generated through the process for each actor and for the whole ecosystem. For example, different phases are causing different amount costs to each actor and the amounts of benefits are varying as well. Inspecting the value aspect is important as none of the actors should be in an indefensible position while others are gaining all the value. It is not beneficial either for the ecosystem. The ambition of ecosystem is to create value for each actor in ecosystem but for the whole ecosystem as well.

Figure 4 is a simplified description of an ecosystem. The purpose of the framework is to demonstrate how the actors could cross the boundaries of their own company and utilize the fleet data collected by other actors in order to create more value for the whole ecosystem. There could be more actors in real ecosystem and the situation is often more complex. The framework can be applied to different cases and the illustration needs to be done based on the case. Based on the illustration, the process from fleet data to decision making can be developed and managed at ecosystem level.

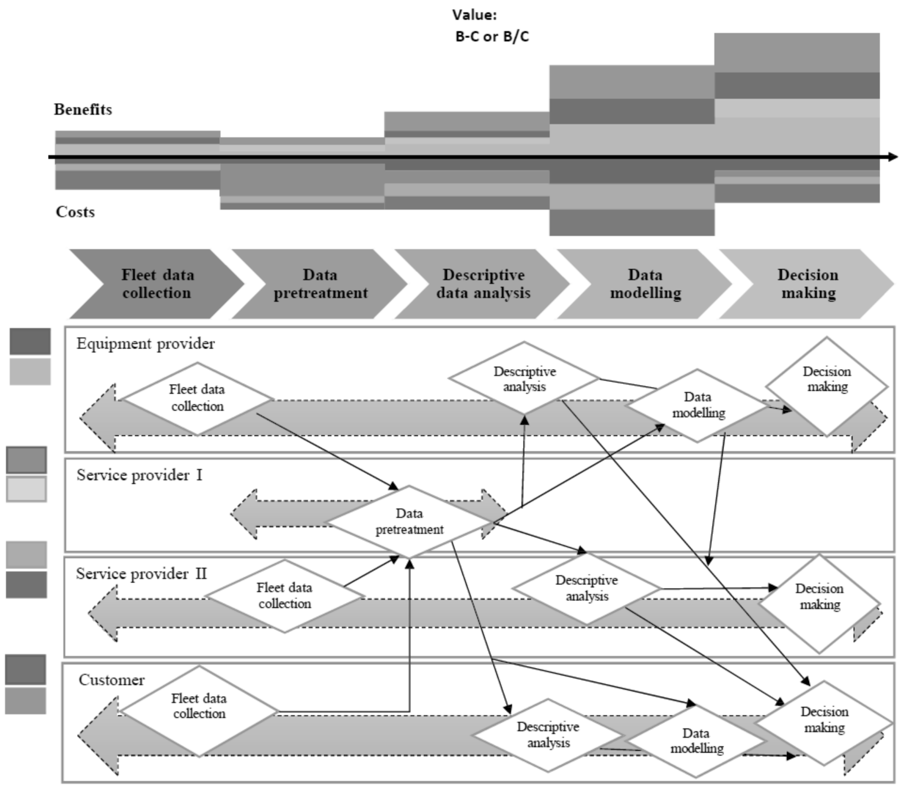

Fig. 4 Framework for exploiting fleet data at ecosystem level

DISCUSSION AND CONCLUSION

The potential to utilize fleet-wide data, which have been fragmented inside and outside organization, has been acknowledged and the need for understanding how to better manage the fleet data is recognized. This brings into discussion the data utilization at ecosystem level where the ecosystem is founded on the data of asset fleets. The value ecosystem around the fleet is founded on fleet data which highlights the IT ecosystem perspectives, but at the same time the interdependencies and value creation of business ecosystem definition are present, as well as sustainability considerations from industrial ecosystem approach are essential. Value from fleet data should be created in a way which benefits all the actors and the ecosystem as a whole. To respond this and the research question, a new framework is developed as a result of this paper. The framework is suggesting that the phases from fleet data collection to decision making could be realized by utilizing the core competencies of each actor and sharing the data between the actors in order to create value for each actor and for the whole ecosystem.

The framework can be used in many managerial purposes such as a tool of service development but also as a tool in fleet management related to asset management and as a help in information system descriptions where the information management model combined with ecosystem can be valuable. The framework can be used as a tool to evaluate the ecosystem around a fleet and the roles of actors in the data refining process. Companies can model their ecosystem around the fleet with the aid of the framework, and develop the data to decision process at ecosystem level in order to increase value creation. Companies can analyze the ecosystem and data refining process in order to recognize if there are overlapping processes which could then be improved by clarifying the roles of each actor. In addition, as the framework considers also value creation as the difference or ratio between discounted benefits and costs, it can also be used as a tool to develop the performance management of ecosystem.

The presented framework needs to be developed further and it needs to be tested with case ecosystem. The further research is focusing on the calculation of the costs and benefits of actors and on modelling the value of fleet data for ecosystem.

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Publication 5

Kinnunen, S.-K., Marttonen-Arola, S. and Kärri, T.
The value of fleet information: a cost-benefit model

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The value of fleet information: a cost-benefit model

Abstract: Internet of Things (IoT) technologies enable the collection of wide-ranging data related to industrial assets which can be used as a support of decision making in asset management, varying from operative maintenance decisions concerning one asset to the management of asset fleets. Technologies and data-refining processes need to be invested in to create knowledge from the massive amounts of data. However, it is not clear that the investments in technologies will pay back, as the data analysis and modelling processes need to be developed as well, and the potential benefits must be considerable. This paper contributes to this field by modelling the costs and benefits of IoT investments. As a result, we develop a model that evaluates the value of fleet information in the maintenance context by applying the cost-benefit approach. The costs consist of hardware, software and data processing -related work costs, while the benefits comprise savings in maintenance and quality costs, as well as other savings or increased revenues. Testing the model with a descriptive case demonstrates that the realized cost savings and other benefits need to be considerable for the investment in IoT technologies to be profitable. The results emphasize the importance of data utilization in decision making in order to gain benefits and to create value from data.

Keywords: fleet, cost-benefit, asset management, investment appraisal, maintenance, life-cycle analysis, Weibull, life-cycle data, cost savings, value of information

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1 Introduction

The emergence of new technologies and data makes it possible to develop different fields of business, and in the area of asset management, it enables effective maintenance and the achievement of various benefits, including cost savings and support for asset management -related decision making. In maintenance, the cost savings are related to e.g. improved reliability and safety, reduced maintenance work and spare part costs, reduced downtime, and improved availability (Yarn et al., 2001; Jantunen et al., 2011; Van

Horenbeek and Pintelon, 2013; Rashidi and Jenab, 2013; Amelian et al., 2015; Gavranis and Kozanidis, 2015; Öhman et al., 2015; de Jonge et al., 2017). The availability and utilization of data provide support for a variety of decision-making situations, for example investment decisions, service development and maintenance planning. According to El-Thalji and Jantunen (2016), there is a fundamental need for predictive intelligence tools to optimize asset utilization in a cost-effective manner. It has been stated that condition-based maintenance can reduce maintenance costs but requires data fusion and more real-time measurements (Laukka et al., 2016). Although data collection has increased due to the emergence of technologies, the benefits of data utilization are unclear (Raguseo, 2018), and the links between company performance, business value and data analytics need to be studied further (Ji-fan Ren et al., 2017). The potential benefits, e.g. cost effectiveness of maintenance actions, are recognized in general, but the systematic examination of benefits and the evaluation of monetary value that can be gained with the aid of advanced technologies and data-based decision support are discussed inadequately in the academic literature, and models quantifying the benefits of data utilization are limited. Thus, research is needed to understand more deeply how benefits and value can be derived from the collected asset data. The issue is topical, as companies are struggling with data and information overload, and consider whether they should invest in data refining processes. In addition, aging machinery and equipment set a challenge, because as modernizations and IoT investments are needed to get detailed and accurate data from machines of different ages. If modern data-driven models are implemented, it is essential that the potential benefits will outweigh the costs related to e.g. collecting, storing, processing, and analyzing the data over the life cycle of the asset (de Jonge et al., 2017). The profitability aspects of Internet of Things (IoT) investments are often neglected in the literature, as the research focuses on applications and utilization possibilities. The costs and profitability of IT investments are discussed in general in the literature (see e.g. Berghout and Tan, 2013; Kauffman et al., 2015; van der Pas and Furneaux, 2015). Miragliotta et al. (2009) and Dimakopoulou et al. (2014) have studied the profitability of IoT investment in RFID (Radio Frequency Identification) technology in supply chains. The present paper discusses investment in IoT technologies but also in different phases of the data refining process to convert the data into a usable form to support decision making. Modelling the costs and benefits of IoT technologies offers valuable knowledge for supporting decision making in strategic maintenance management.

Maintenance research has recently discussed the management of large asset groups, in other words fleets. Various models have been developed for different decision needs of fleet management, such as replacement investments of fleets (Stasko and Gao, 2012; Ansaripoor et al., 2014), defining the optimal fleet size (Klosterhalfen et al., 2014; Chaowasakoo et al., 2017), estimating the remaining useful life of a fleet (Al-Dahidi et al., 2016), planning the maintenance strategy for a fleet (Gavranis and Kozanidis, 2015; Wijk et al., 2017; Feng et al., 2017), proactive maintenance (Borguet et al., 2016), and optimal spare part inventory management (Yongquan et al., 2016). Especially in the field of logistics, models have been developed to support routing, capacity, and inventory management decisions for vehicle and ship fleets (Buxey, 2006; Wu, 2009; Pedraza Martinez et al., 2011; Ngai et al., 2012; Mishra et al., 2013; Tran and Haasis, 2015; Raa, 2015). The development of data collection practices and information systems, e.g. the development of a maintenance management information system, enables managing assets also at fleet level (Chiang and Torng, 2014). Technologies enable the collection of fleet-wide data and the utilization of them in order to achieve cost savings. Pedroza Martinez et al. (2011) discuss the significance of fleet management to reduce fleet-related costs and to increase the efficiency of the fleet. However, the full potential of collected data has not been captured, as the value for business is difficult to define and calculate. Research is needed to clarify how data utilization can affect the maintenance costs at the fleet level. Maintenance costs have been modelled with various models, e.g. Weibull distribution (Yang et al., 2006) and Net Present Value (NPV) (Marais and Saleh, 2009; Sinkkonen et al., 2016). In asset management, the costs and benefits related to IoT investments and data utilization have not been discussed widely. The theorization of value from IoT-based data is limited and analytical modelling can be a useful method to build theories in this field. It is important to discuss the value potential of utilizing the data collected from asset fleets because companies will invest significantly in IoT-related investments in the near future. Therefore, tools to evaluate the costs, benefits and profitability of those investments are needed.

This paper contributes to the previous discussion by exploring the costs of data refining and the benefits that can be achieved through data utilization in maintenance management at the fleet level. The objective of the paper is to create a model to increase the understanding of how the value of fleet information and its components, benefits and costs, are generated when the data is utilized to support maintenance-related decision making. The research method of the paper is analytical modelling. Analytical modelling is considered as a suitable method in management research to perceive phenomena and to observe the effects of variables. Modelling has been considered as a useful tool for decision making in many research areas related to management research (Mun, 2008). Models are tools for decision-makers to analyze and observe the results and consequences of changing variables. In this research, the cost-benefit method is utilized as the method of valuation. The central idea is to create a general model for IoT investments that illustrates the relationships between the key components: costs, benefits and the effects of fleet-level considerations and data refining level. The developed model works also as a managerial tool to evaluate the value of IoT investment projects concerning a fleet. The proposed model considers the perspectives of fleet-level benefits, the impact of the data refining level, and the costs of investments and the data refining process. The results of the model are demonstrated with a descriptive case that concerns the modernization of a pulp drying machine fleet. The purpose of the descriptive case is to evaluate the logic of the model and demonstrate the effects of the variables.

The rest of the paper is structured as follows: Section 2 presents the development of the model from a theoretical basis, Section 3 presents the results of the model by testing it with a descriptive case and discusses the results, and Section 4 presents conclusions and ideas for further research.

2 Model for the value of fleet information

2.1 Benefits

There is constant pressure to increase the performance of assets, as industrial assets are expected to function in a way that they create value for their owner. Maintenance can be seen as an essential part of improving the performance of assets when better availability is required with low maintenance costs. The advanced technologies, IoT and data-driven models receive more attention among researchers as support for maintenance planning (see e.g. Macchi et al., 2016). The emergence of IoT technologies and increasingly gathered data make it possible to take maintenance planning to a more advanced level, where e.g. predictive models and condition-based strategies for maintenance planning can provide various benefits, such as savings in maintenance costs, improved reliability, diminished production losses, and improved safety (Yanr et al., 2001; Jantunen et al., 2011; Van Horenbeek and Pintelon, 2013; Amelian et al., 2015; Gavranis and Kozanidis, 2015; Öhman et al., 2015; Chopra et al., 2016; Laukka et al., 2016; de Jonge et al., 2017; Wijk et al., 2017). The value of potential benefits from data utilization is challenging to determine, but it is important for companies to understand the potential benefits in order to maximize the returns of their investment in information technology and to create value from the data (Raguseo, 2018). Therefore, the benefits of utilizing IoT-enabled data and technologies as support for maintenance decision-making need to be evaluated when planning to invest in technologies. The present value of the total benefits when taking advantage of advanced technologies and data refining in the maintenance context can be modelled as follows:

$$PV(B_{total}) = PV(B_1 + B_2 + B_3) \tag{1}$$

where B_1 are savings in maintenance costs, B_2 are savings in quality costs, and B_3 are other benefits. Thus, the present value of the total benefits are the discounted sum of savings in maintenance costs, savings in quality costs, and other benefits, including e.g. savings in service development or increased revenues. The major benefits can be viewed as reduced maintenance costs, and thus the level of data refining can reduce failures, unnecessary maintenance work, spare part consumption and inventories, and therefore reduce the total maintenance costs. To be able to calculate the savings in maintenance costs, a failure model is needed. As mentioned above, the literature presents different cost models for calculating maintenance costs (Zhang and Wang, 2014; Jung et al., 2010; Marais and Saleh, 2009; Yang et al., 2006). In this paper, we apply the Weibull distribution to represent the failure behavior and the maintenance costs that are comparable to the failure rate. The connection between the failure rate and maintenance costs has been studied by several researchers (e.g. Yang et al., 2006; Popova et al., 2006;

Crespo Márquez, 2007; Afsharnia et al., 2014). The Weibull distribution is generally utilized in reliability analysis to represent failures in different phases of the asset life cycle (Abernethy, 2006). The three phases of Weibull are 1) early failures, 2) constant failures and 3) wear-out failures, which together form a bathtub curve (see Figure 1). The Weibull failure rate function is well suited for the purpose of this research, and it is utilized as a basis for the calculation of benefits in maintenance costs. In the case of different failure behaviors, other distributions can be utilized instead of the Weibull distribution.

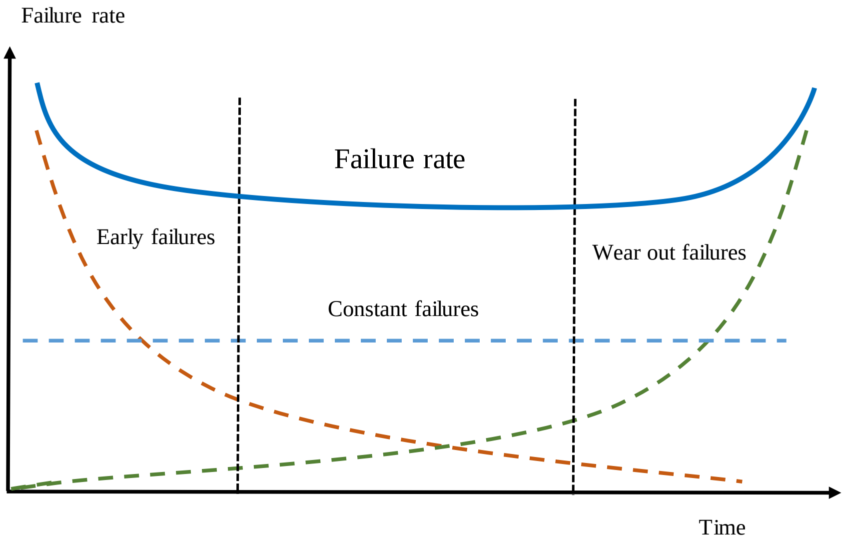

Figure 1. General presentation of the Weibull failure rate function, i.e. the bathtub curve

In order to model the benefits B_1, i.e. the potential savings in maintenance costs, the bathtub curve is utilized to illustrate the failure rate and maintenance costs. The bathtub curve represents the maintenance costs of a certain asset fleet. In Figure 2, the m_1 curve represents the maintenance costs at the starting point, in other words before taking advantage of fleet data analysis. The utilization of fleet data enables better maintenance decisions, which can then reduce failures and maintenance costs. The savings in maintenance costs can be illustrated by the transition from cost level m_1 to the lower level m_2. The idea is presented in Figure 2, and the equation for B_1 can be presented as:

$$B_1 = m_1 - m_2 \qquad (2)$$

where m_1 represents the starting level of maintenance costs over the life cycle of the assets and m_2 represents the maintenance costs after utilizing refined fleet data in decision making. It can be assumed that the fleet-wide data and high level of data refining can bring benefits such as savings in unscheduled maintenance costs, when better predictions can be made due to the fleet data analysis (Feng et al., 2017; Borguet et al., 2016). The theoretical maximum transition from m_1 to m_2 can be achieved when the data refining level is 100 %, and the maximum transition depends on the starting level of the maintenance costs m_1.

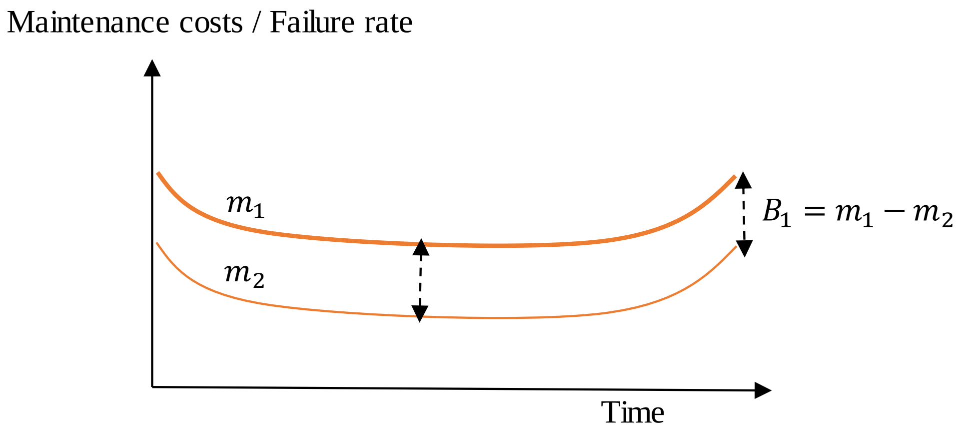

Figure 2. Savings in maintenance costs

An equation for the maintenance costs m_1 and m_2 can be stated according to the Weibull failure rate function, given by:

$$\lambda(t) = \frac{f(t)}{R(t)} = \frac{\beta}{\eta}(\frac{t-\gamma}{\eta})^{\beta-1} \quad (3)$$

where $f(t)$ is the failure probability density function and $R(t)$ is the reliability function, while t represents time. β is the shape parameter, η is the scale parameter, and γ is the location parameter. The bathtub curve gets its shape with different values of β. In the burn-in or infant-mortality failure phase $\beta < 1$, in the constant failure phase $\beta \cong 1$, and in the wear-out failure phase $\beta > 1$. (Abernethy, 2006) The Weibull failure rate function acts as a basis for the equation for maintenance costs m_1 and m_2, and the exact shape needs to be determined for each fleet separately for the shape to represent the failure behavior and maintenance cost structure of the fleet.

The major benefits are based on the savings potential related to the maintenance costs, but other savings are possible as well when utilizing refined fleet data. Benefits B_2 can be seen as savings in quality costs, and they can be assumed to be annual cost savings that depend on the data refining level. The level of data refining affects the amount of benefits and costs. The level of data refining can be viewed as an input to the phases of data utilization, including data collection and preprocessing, as well as analysis and modelling work. The level of data refining represents how much resources are invested in data refining. The data refining level can be viewed as a measure that illustrates the improvement in data refining compared to the starting point. In other words, the data refining level of 0 % means that data refining is at the same level as it was before the investment and therefore there are no improvements in the data refining processes compared to the starting point. The level of 100 % illustrates maximum improvement compared to the starting level of data refining.

It can be assumed that at least up to a certain point, the number of benefits increases significantly when the level of data refining increases. It has been stated that the knowledge of experts with the power of analytical decision techniques and more accurate analysis can improve the quality of decisions, and thus cost savings can be achieved (Yarn et al., 2001; Moody and Walsh, 2002). Savings in quality costs may include e.g. decreased production losses, reduced waste, and savings in safety costs. These benefits can be achieved if fleet data are analyzed and models to support decision making are developed (Jantunen et al., 2011; Yarn et al., 2001). It is assumed that the data refining level affects the number of benefits as follows:

$$B_2 = D \times q \tag{4}$$

where D refers to the data refining level and q to the quality costs that can be potentially reduced, e.g. production losses and waste caused by misuse failures. It can be assumed that if data refining and analytics are taken to the advanced level and theoretically right decisions can be made based on the models and predictions, the theoretical maximum cost savings can be achieved with the data refining level of 100 %. This means that all quality costs can be avoided. In reality, the quality costs are hardly entirely avoidable.

The other benefits B_3 can also be seen as annual cost savings or increased revenues that depend on the data refining level. It can be assumed that if fleet data are available and utilized, benefits other than direct maintenance-related savings, such as savings in logistics and inventory costs, reduced resource utilization or reduced service development costs, can be achieved (Mishra et al., 2013; Yongquan et al., 2016). Reduced service development costs or increases in revenues related to service sales can be generated if new fleet services have been developed based on the fleet data, and fleet service can be offered to other fleets of assets. The equation for other benefits can be presented as:

$$B_3 = D \times s \tag{5}$$

where D is the data refining level and s refers to the other costs that can be avoided when taking advantage of fleet data analysis. For simplicity, the benefits are expected to be realized immediately in this model. In reality, the benefits can be achieved after knowledge and collected data accumulate with time.

2.2 Costs

After presenting the components of benefits, the present value of total costs can be presented as follows:

$$PV(C_{total}) = PV(C_1 + C_2 + C_3) \qquad (6)$$

where C_1 consists of investments in hardware, and these costs can be seen as non-recurring costs. C_2 are software costs which can be viewed as annual license costs, and C_3 are working costs related to data refining. Thus, the present value of total costs is the discounted sum of hardware costs, software costs and working hours related to data refining. Investments in hardware are non-recurring by nature and can be then viewed as acquisition costs. Hardware costs consist of e.g. sensors and other technologies and equipment. Software costs are related to e.g. data analysis software, which are usually annual licenses. The costs of IT investments in general have been discussed in the literature (e.g. Berghout and Tan, 2013; Kauffman et al., 2015; van der Pas and Furneaux, 2015). The costs of IT investments are often divided into hardware, software, and project management costs. However, Moody and Walsh (2002) approach costs from a different perspective. According to Moody and Walsh, the major costs are related to the capture, storage and maintenance of information. The costs related to data collection include hardware costs, such as sensor technologies, but they may include also working costs, such as entering task information manually. The maintenance of information consists of e.g. data preprocessing -related costs, which can include software-related costs but also work-related costs.

The third cost component is working costs, including the work hours used in data treatment, data analysis and modelling. The assumption is that the working costs increase when the data is refined further. More accurate data treatment, advanced analysis and modelling require more working hours and cause therefore more working costs. It can be presumed that the costs of data refining increase significantly if the models are to be extremely predictive and reliable. There is a limit to when it needs to be considered whether it is profitable to develop the models further and whether the additional benefits can still outweigh the costs of data refining. It is often enough that the models give adequately reliable information for decision makers, but in some cases more accurate predictions are required.

2.3 Structure of the model

In this paper we develop a cost model which models the value of fleet information. The model represents the relation of IoT investment costs and benefits that can be achieved when fleet-wide data is analyzed and utilized to support maintenance and asset management decisions. The components of the benefits and costs were discussed in detail above. In this section we combine the benefits and costs to a model which presents the value of fleet information.

The value of fleet information can be seen as the difference between the discounted total benefits and the total costs. The level of data refining illustrates how much is invested in the phases of data refining, and the level is represented as percentage defined through expert judgement. Although this parameter is prone to some error due to the subjective process, it was considered to be the best available option for assessing the status of the vast and multifaceted data. The level of data refining affects the costs related to data refining, but on the other hand, the level of data refining affects the number of benefits as well: refined data can be used better in decision making, compared to disorganized and big raw data. The size of the fleet and time also have an effect on the outcome.

The fleet affects the number of benefits in two ways 1) the size of the fleet has a positive impact on the quality of the analyses and models (Yarn et al., 2001; Moody and Walsh, 2002), and 2) the achieved value (e.g. an optimized maintenance schedule) can be multiplied to the whole fleet, and therefore the benefits will increase. The size of the fleet affects the amount of costs as well, as the costs can be assumed to grow along with the size of the fleet. This applies when regarding the costs related to data treatment, including data gathering, data pretreatment and warehousing, as the amount of produced data increases with the size of the fleet. However, the larger size of the fleet can be assumed to have advantages when e.g. prediction models are developed and the development costs can be divided to all the assets in the fleet. Thus, there can be economies of scale when utilizing fleet data in the development of models or services for large-sized fleets of assets. It can be assumed that the benefits will increase significantly when the size of the fleet increases, but there is a limit when a larger fleet size does not increase the accuracy of analysis any more. This can be concluded on the basis of the laws of information presented by Moody and Walsh (2002).

Time has an impact on the costs and benefits in the form of interest or required rate of return, when costs and benefits are considered over a certain life cycle. Thus, the selected time period has a significant impact on the value of fleet information. For example, some benefits are realized after a longer time period, and therefore the time period needs to be selected according to the asset features, such as typical life-cycle and failure behavior, and according to the purpose of the value assessment. Costs related to data gathering, data processing and analysis work can be assumed to be constant over time, except for the impact of the interest.

The value of fleet information is the result of the cumulative present value of total costs and benefits. The same can be expressed with equations, and the net present value of fleet information is formed as follows:

$$NPV = PV(B_{total}) - PV(C_{total}) \qquad (7)$$

where $PV(B_{total})$ is the present value of the total benefits and $PV(C_{total})$ is the present value of the total costs. The time-discrete formula of the net present value is utilized when modelling the total benefits and costs. The time-discrete formula of net present value is defined as:

$$NPV = \sum_{t=0}^{N} \frac{B_t}{(1+i)^t} - \sum_{t=0}^{N} \frac{C_t}{(1+i)^t} \quad (8)$$

where t is the time of the cash flow, B_t is the total benefits at time t, C_t is the total costs at time t, and i represents the interest rate. Thus, the value of fleet information is formed as the difference between the discounted total benefits and total costs. The structure of the model is presented in Figure 3. The model is unique and combines the costs and benefits of IoT investments and the effects of fleet-level analysis and data refining level. The structure of the model also describes the theoretical framework constructed during the literature review. Previous literature has discussed some specific parts of the model in detail (e.g. individual cost categories, investment appraisal methods and interest rates), whereas some aspects are still mostly unexplored (e.g. the level of data refining, the impact of the size of the fleet, and some benefits of fleet information). Due to these unexplored parameters, not much previous research exists to address the value of fleet information. The model responds to the lack of research to evaluate the value of data analytics for business (see e.g. Ji-fan Ren et al., 2017; Raguseo, 2018).

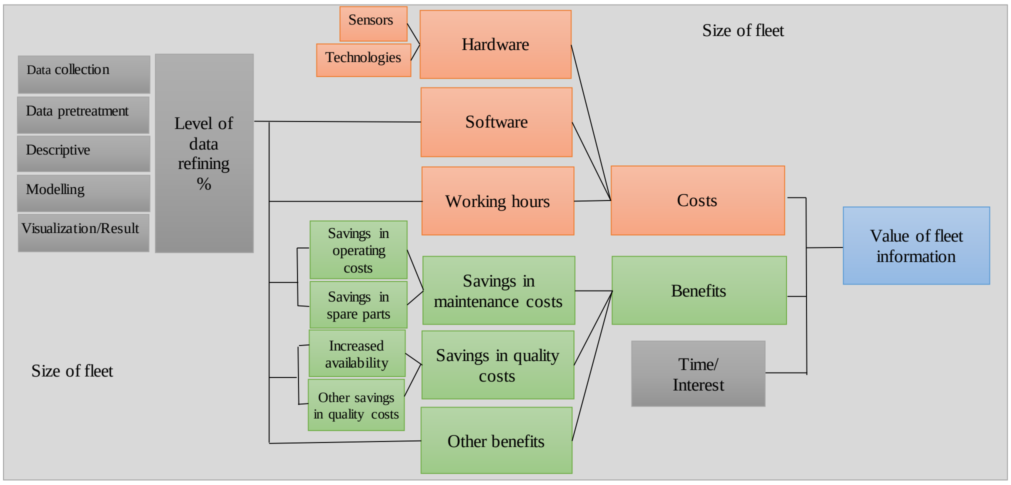

Figure 3. Structure of the model

3 Results and Discussion

3.1 Case description

In this section, the presented model is tested with a descriptive case study. The case concerns the modernization of a pulp dryer machine fleet. The case is based on the real maintenance costs of one pulp drying machine in a specific year. As comprehensive case data was not available, some assumptions have been made in order to test the proposed model. The complementary data has been selected in a way that it represents the reality as realistically as possible.

The case covers the drying phase of a complex pulp manufacturing process, where the pulp dryer is the critical piece of equipment. Thus, in the case of asset breakdown, the whole pulp manufacturing process stops. The pulp manufacturing process is presented in Figure 4, where it can be seen that the pulp drying phase is located at the end part of the manufacturing process. The pulp dryer has typically a lifetime of approximately 50 years. Due to the long lifetime, several modernizations need to be considered during this lifetime in order to keep the machine in a competitive condition. At the moment of the study, the case pulp dryer had reached the age of 20 years, and modernization related to the technologies of data collection and analyzing needed to be considered. The emergence of new technologies in data collection will improve the availability of data and can bring along benefits if the data are processed and utilized effectively to support the decision making. Additional benefits can be gained if fleet-wide data can be gathered, better analysis of fleet data, e.g. fault predictions, can be made, and the analysis is utilized in the management of the whole fleet. In this case, we model whether investment in IoT technologies and in fleet data refining is profitable in the case of a pulp drying machine fleet. In addition, we make sensitivity analysis on which factors have significant influence on the results. The case is observed from the pulp manufacturer's perspective, who is the asset owner as well.

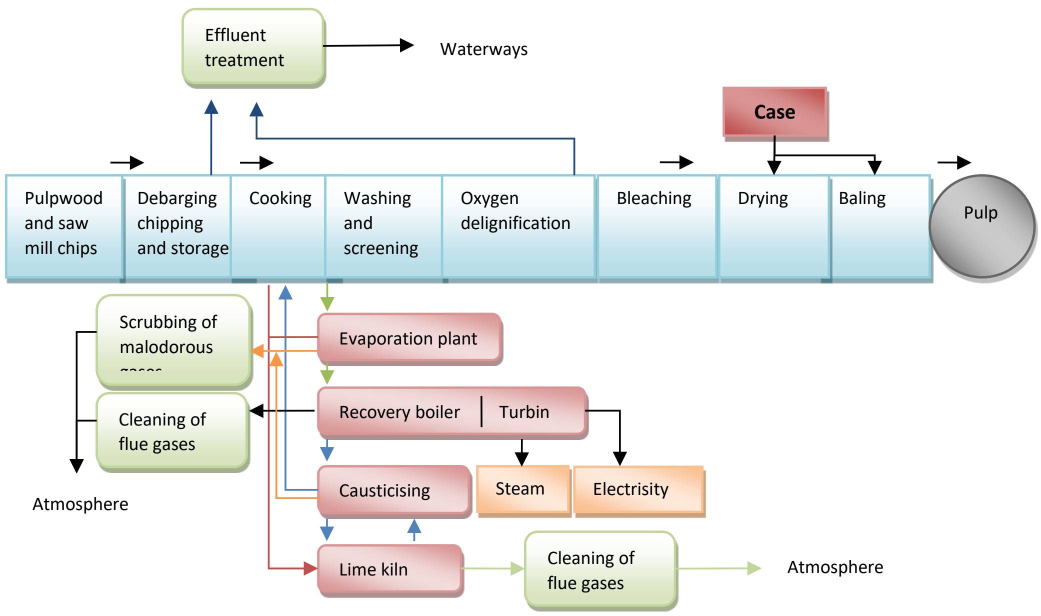

Figure 4. Pulp manufacturing process (Source: Sinkkonen et al., 2013)

As the basis for testing the model, we utilize the cost structure of the pulp dryer machine presented in Table 1. The cost data has been collected from the year 2010 and the cost data represents the typical maintenance cost structure of a pulp drying machine. The cost occurred are the basis for the evaluation of potential benefits that can be achieved with modernization and data utilization. Some of the costs are inevitable, but there is potential to diminish some of them. Next, we discuss in detail the components of the model applied to the case. As a result, the net present value of fleet information is presented and sensitivity analysis made.

Table 1. Cost structure of the case pulp dryer machine

MAINTENANCE COSTS	**€/year**	
Operative maintenance costs	**1 507 800**	**Total maintenance costs**
Workforce total	13 800	
Equipment total	279 000	
Subcontracting total	1 215 000	
(subc. Annual maintenance)	260 000	
(subc. Condition based maintenance)	240 000	
(subc. Preventive maintenence)	95 000	
(subc. Unscheduled reactive breakdowns)	620 000	
Spare part costs	**138 000**	
Quality costs	**2 114 000**	**Total quality costs**
Loss of production total	1 565 000	
Loss of production (Annual maintenance)	465 000	
Loss of production (Unscheduled reactive breakdowns)	1 100 000	
Misuse failures total	549 000	
Other maintenance costs	**67 000**	**Other costs**
Machine and tools	10 000	
Logistics costs	40 000	
Environmental costs	17 000	
TOTAL COSTS	**3 826 800**	**Total**

3.2 Benefits

The pulp mill aims at high availability of the pulp drying machine, as downtime causes loss of production and lost revenues. By observing the cost structure of the drying machine (Table 1), it can be noticed that there is a significant amount of unnecessary costs which could be reduced by efficient maintenance planning. For example, costs related to unscheduled reactive breakdowns, loss of production, and misuse failures can be reduced if more accurate data, also fleet-level data, is available. Then more exact analyses and predictions can be made to support the decision making related to the case drying machine, and the whole fleet of drying machines as well. The case company has 20 similar or nearly similar kind of drying machines, and thus the size of the drying machine fleet is 20 assets.

3.2.1 Savings in maintenance costs B_1

In order to quantify the present value of total benefits, we need to define B_1, B_2, and B_3 separately. First, the savings in maintenance B_1 need to be modelled with the Weibull distribution. Here we use the maintenance costs presented in Table 1 as the starting point. These costs can be assumed to be typical costs for a 20-year-old pulp drying machine. The failure rate of the pulp drying machine is expected to follow the shape of the bathtub curve, and the costs of maintenance follow the same shape as discussed in section 2.1.

The exact shape of the bathtub curve needs to be determined to the pulp machine fleet for the shape to represent the failure behavior and maintenance cost structure of the fleet. A typical lifetime for a drying machine is approximately 50 years. Therefore, the scale parameter η, which is also known as the life parameter, is selected in the way that it reflects the lifetime of the pulp drying machine. The scale parameter is selected to represent the lifetime for which the equipment is expected to fail with 63.2% probability (Crespo Márquez, 2007). Based on the available information, η can presumed to be 55. In many cases the location parameter γ is often set as 0, and the values for shape parameter β are selected in a way that in the early failure phase $\beta = 0.5$, in the constant failure phase $\beta = 1$, and in the wear-out phase $\beta = 8$ (Crespo Márquez, 2007).

Based on the information of a 20-year-old pulp drying machine, the maintenance costs m_1 are fitted to the shape of the bathtub curve. The equation for maintenance costs at the starting point is:

$$m_1 = x_1 \text{€} \times \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} \tag{9}$$

When the maintenance costs of year t are known, x_1 can be determined. The bathtub curve is fitted to the shape in a way that the maintenance costs of the 20-year-old drying machine are settled in the curve. In order to determine x_2 for the maintenance costs, m_2 after modernization needs to be evaluated. It can be assumed that the level of m_2 is determined by the level of data refining after the modernization. In the case of $B_{1,}$ the maximum transition from m_1 to m_2 can be achieved when the data refining level is 100%, which means in the case of the pulp drying machine case that the costs related to unscheduled reactive breakdowns (620 t€) can be avoided. Unscheduled reactive breakdowns -related costs are the potentially diminished costs which can be affected by better data utilization. The new x_2 can be determined by reducing the unscheduled reactive maintenance multiplied with the data refining level D from the total maintenance costs in Table 1. The new factor is calculated and the equation for m_2 is:

$$m_2 = x_2 \text{ €} \times \frac{\beta}{\eta}(\frac{t-\gamma}{\eta})^{\beta-1} \quad (10)$$

Figure 5 presents the maintenance costs m_1 and m_2. Benefits B_1 is the difference between the values of m_1 and m_2 each year. For example, at the age of 30, the savings are 496 t€. The transition from m_1 to m_2 is caused by the data refining level D, which is selected to be 82% in the case. The data refining level indicates the improvement in data refining processes compared to the starting level of data refining before an investment. A 82 % data refining level can indicate that a lot has been invested in advanced data analytics in the analyzing of process and maintenance data, but there more could be done to achieve the level of 100%, such as more accurate data quality or integration to other information systems in the company.

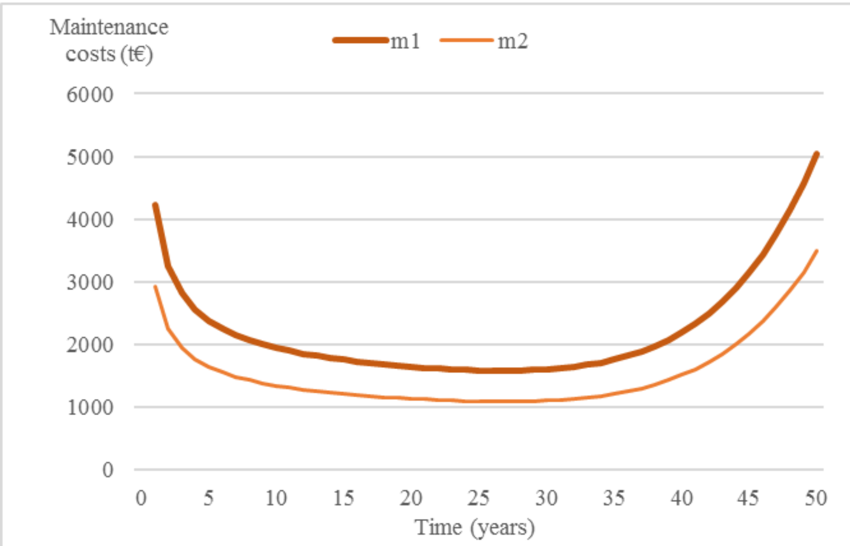

Figure 5. Maintenance costs m_1 and m_2 for a pulp drying machine

3.2.2 Savings in quality costs B_2

It can be seen in Table 1 that the total quality costs consist of losses in production and misuse failure costs. The loss of production related to unscheduled reactive breakdowns and the costs related to misuse failures are costs where savings are achievable with a higher data refining level. In other words, these costs can be avoided if more analytics and accurate predictive models are utilized, and thus better decisions can be made. By utilizing equation (4) where $D = 82\%$ and q is the sum of the losses of production caused by unscheduled reactive breakdowns and the costs related to misuse failures, the savings in quality costs are 1 352 t€ annually with an 82 % data refining level.

3.2.3 Other benefits B_3

When considering the other benefits B_3 in the case, we can assume that there is potential to reduce the logistics costs and environmental costs with a higher level of data refining. With equation (5), where the data refining level $D = 82\%$ and s is the sum of logistics costs and environmental costs, the other benefits can be defined. Thus, the other savings are 47 t€ annually with an 82 % data refining level.

3.3 Costs

The costs related to modernization and future data processing and analyzing consist of hardware, software and working costs. It can be presumed that this kind of investment needs to be repeated in a few years, when technologies have developed further, and new modernization will be needed in order to keep up with the competition. Therefore, we can set the time frame of 5 years after which a new modernization needs to be considered.

The investment cost of modernization consists of hardware costs, including sensors and other technologies. The investment cost C_1 is non-recurring and it is evaluated to be 5 000 t€ per a pulp dryer machine. The software costs C_2 are expected to be 50 t€ annually, the working costs depend on the data refining level $D = 82\%$, and thus the working costs C_3 are expected to be 328 t€ annually. When improving the data refining level more workers are needed. We have assumed that the data refining level of 82 % requires five additional fulltime workers to accomplish the improvement in data utilization in this case.

3.4. Net present value of fleet information

The profitability of the IoT investment related to the pulp drying machine is appraised according to the net present value of fleet information. The costs, benefits, and discounted present value have been collected to table 2 with the expected time frame of 25 years, and the need for modernization is assumed to appear every 5 years. The interest rate is 10 %. The calculation is made for the whole fleet, i.e. modernization is made for each dryer machine in the fleet. Therefore, the investment costs are multiplied by the size of the fleet, but the costs of software and data processing work are presumed to remain the same as for one dryer machine. In practice it is likely that at least the costs of data processing work would increase somewhat, but would still result in significant economies of scale at the fleet level. However, there is no empirical evidence of this, and for simplicity we have assumed that the costs will stay constant for different sizes of fleet. The benefits are multiplied by the size of the fleet because the same developed analysis and models can support the decision making concerning each dryer machine of the fleet. Thus, the same benefits can be achieved with each dryer machine.

On the basis of Table 2, it can be concluded that the investment is profitable with the case values. The net present value after the first modernization after 4 years is 19 094 t€. If modernizations are made at five-year intervals, the net present value at the end of life of the dryer machine is 107 450 t€. The payback period for the first modernizations is 3.6 years. The payback period should be in the size range of 2-3 years, as new modernizations are expected in order to keep the machine in a competitive condition. The payback period should be relatively short because the technologies develop rapidly. In addition, companies expect return and profit for their investments. The utilized interest rate (10 %) is low if we assume that the company tries to achieve profit for the investments. Therefore, the payback period with the case values (3.6 years) is barely profitable, and the expected benefits will have to be achieved.

Table 2. Cash flow and net present value

Age of drying machine (years)	Time (years)	Investment (t€)	Costs (t€)	Benefits (t€)	Net cash flow (t€)	Discounted cash flow (t€)	Cumulative net present value (t€)
20	0	-100 000	0	0	-100 000	-100 000	-100 000
21	1		-378	38 051	37 673	34 249	-65 751
22	2		-378	37 969	37 591	31 067	-34 685
23	3		-378	37 899	37 521	28 190	-6 495
24	4		-378	37 843	37 465	25 589	19 094
25	5	-100 000	-378	37 803	-62 575	-38 854	-19 760
26	6		-378	37 779	37 401	21 112	1 352
27	7		-378	37 774	37 396	19 190	20 542
28	8		-378	37 791	37 413	17 454	37 995
29	9		-378	37 833	37 455	15 885	53 880
30	10	-100 000	-378	37 903	-62 475	-24 087	29 793
31	11		-378	38 007	37 629	13 189	42 982
32	12		-378	38 148	37 770	12 035	55 017
33	13		-378	38 333	37 955	10 994	66 011
34	14		-378	38 568	38 190	10 057	76 068
35	15	-100 000	-378	38 861	-61 517	-14 727	61 341
36	16		-378	39 221	38 843	8 453	69 794
37	17		-378	39 657	39 279	7 771	77 565
38	18		-378	40 179	39 801	7 159	84 724
39	19		-378	40 800	40 422	6 609	91 333
40	20	-100 000	-378	41 533	-58 845	-8 747	82 586
41	21		-378	42 393	42 015	5 678	88 264
42	22		-378	43 396	43 018	5 285	93 548
43	23		-378	44 561	44 183	4 934	98 483
44	24		-378	45 906	45 528	4 622	103 105
45	25		-378	47 454	47 076	4 345	107 450

3.5. Sensitivity analysis

As discussed above, the net present value of the case investment is positive with the starting values if we choose the time frame of 25 years, but the model enables analyzing the changes of different factors and their impacts on the net present value. For example, the impacts of the data refining level and investments, as well as the impact of changes in the costs and benefits on the final result can be analyzed. By analyzing the impacts of different factors separately we noticed that the following factors, the sensitivity analyses of which is presented in Figure 6, are the most critical for the value of the investment:

- the data refining level,
- savings in quality costs, and
- investment costs.

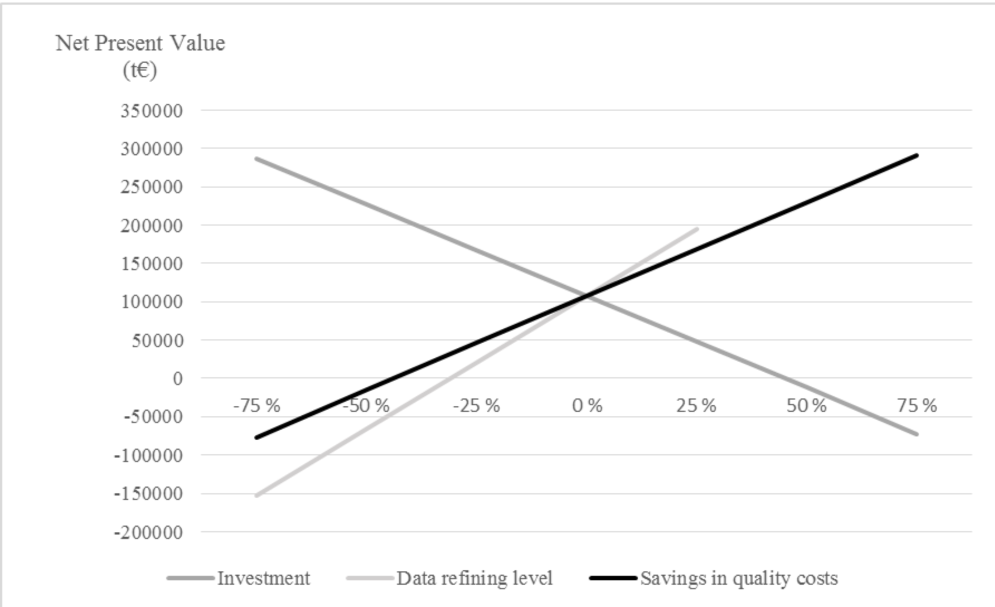

Figure 6. The impact of different factors on the net present value

Consequently, the value of fleet information depends significantly on the realization of benefits that should be achievable with the refined data. It can be concluded that the data refining level needs to be relatively high in order to achieve savings that are expected with the aid of the fleet data analysis and models. The potential benefits of fleet analysis cannot be achieved adequately if the development of analyses and models is not invested in and the models are not accurate enough. However, it needs to be acknowledged that both costs and benefits will increase if the data refining level increases. In the case of the drying machine, especially the savings in quality costs are important for the investment to be profitable. This is because of the large amount of production losses caused by unscheduled reactive breakdowns and costs caused by misuse failures. The quality costs are emphasized in this case, as high availability is important for the drying machine, which is a critical equipment in the pulp manufacturing process. In addition, the cost of investment has a significant impact on profitability. The changes in the prices of technologies, sensors etc., may have a significant impact on the amount of investment and thus on the net present value. Technologies are developing rapidly and becoming less expensive, which makes the timing of the investment relevant. Is it reasonable to invest this year or a few years later when the prices might be lower and technologies more advanced, but on the other hand, the benefits of investment cannot be achieved until the investment is made and the analyses and models are utilized in decision making?

With the model, companies can assess if they should invest in IoT and data refining processes. The model works as a tool to analyze the costs and benefits of collecting, analyzing and utilizing data to support decision making in asset management. The model takes modernization at the fleet level into account. There are significant benefits if IoT modernizations are made to the whole fleet of assets, as this enables the exploitation of fleet-wide data analysis and making better decisions concerning the whole fleet. When the investment is made concerning the whole fleet, some costs can be divided to all the assets of the fleet, and thus economies of scale can be achieved to some extent.

4 Conclusions

This paper has extended the discussion about the value of information by appraising an IoT investment with the cost-benefit approach. The purpose was to model the value of fleet-wide data. As a result, we developed a model where the value consists of the costs of data refining including hardware, software and data processing work, and the benefits that can be achieved through data utilization in maintenance management at the fleet level. New technologies in data collection and data utilization are topical in scientific discussion, but the profitability of these investments has been studied inadequately so far. As theoretical implications, we contribute to the field by modelling the costs and benefits of an IoT investment, adopting the perspective of maintenance and asset management. Our model is multidisciplinary by nature, integrating theories from the areas of investment appraisal, maintenance management and information management. The logic in modelling the value of information is unique and our model responds to the need of understanding the benefits of data utilization (see e.g. Raguseo, 2018). As a practical implication, managers can gain better understanding of the business value of data refining. It is important to acknowledge that the benefits are not self-evident when investing in IoT technologies, but accurate analyses and practical models are needed in order to make better decisions and achieve benefits.

In the developed model, the value of fleet information is based on the presumption that more accurate and multifaceted fleet level data enable better decisions, which are converted into cost savings and other benefits. The realization of cost savings depends on the quality of decision support analysis and models. The case study stresses the importance of different factors in the formation of value. In the case of the drying machine, components such as savings in quality costs, the data refining level and the size of the investment are emphasized. The case also demonstrates that IoT modernizations are expected to pay pack in a relatively short time, and the purpose of collected data needs to be clear for the benefits to be reached.

In further research, the model needs to be tested with other cases in order to validate the results. Limitations of this paper are that many of the values were estimated in the case, as real data of the IoT investment and the realized benefits were lacking. However, sensitivity analysis was utilized to compensate for the estimations of certain values. In addition, the data refining level as a percentage is a quite abstract parameter, and estimating the level precisely is challenging. The level has some resemblance to the capacity utilization rate and it would be interesting to define the data refining level and its effects further (see e.g. McNair and Vangermeersch, 1998). Thus, more research is needed to define the effect of data refining on the amount of costs and benefits.

The developed model concerns only one company and the value that can be achieved by that company. However, the nature of the fleet data requires that other stakeholders dealing with the asset fleet and fleet data need to be taken into consideration. In other words, the fleet data are accumulated in many companies, and the value of fleet information should be observed from a network or ecosystem perspective. Considering the value of fleet information from the ecosystem perspective makes it possible to divide the costs of data collection and other data processing between the actors of the ecosystem, which then could influence the profitability of the IoT investment. Miragliotta et al. (2009) have discussed the profitability of RFID investment for different stakeholders in a supply chain. The main questions concern who pays for the investments and who gets the benefits. This idea needs to be discussed further. Therefore, further research is needed to evaluate the value of fleet information at the ecosystem level.

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Publication 6

Kinnunen, S-K., Marttonen-Arola, S. and Kärri, T.
The value of ecosystem collaboration: fleet life-cycle data -based cost-benefit model

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The value of ecosystem collaboration: fleet life cycle data -based cost-benefit model

Abstract: To successfully manage a fleet of assets requires data collection from a fleet that can be distributed globally and into several companies. Thus, data collection is often conducted by multiple actors in a business ecosystem, which makes it difficult to get access to all the data concerning a fleet. It is important to demonstrate the value that can be achieved by systematically utilizing fleet data as a support of fleet-level decision-making. There is huge potential to benefit from fleet data due to increasingly gathered data, Internet of Things technologies, and data analysis tools. In this paper, a model is proposed to illustrate the ecosystem around a fleet and how to evaluate the costs and benefits of fleet data utilization in an ecosystem. An example ecosystem is proposed, formed by an equipment manufacturer, its customer company, and an information service provider. The model demonstrates the costs and benefits for each actor in the ecosystem and works as a managerial tool to develop collaboration, fleet data utilization, service development, and value creation from the data in the ecosystem. The model is tested with illustrative data in a maintenance context in which the fleet data from pulp drying machines are refined into analyses and models to support maintenance related decision-making. The results deepen the scientific discussion on the value of information and emphasize the importance of understanding how value can be created from fleet life-cycle data for the actors and for the whole ecosystem. The challenge lies in determining whose value should be maximized and how the ecosystem could develop collaboration in data utilization to create value for the ecosystem.

Key words: fleet, asset management, data utilization, benefits, costs, ecosystem, collaboration, value creation

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1 Introduction

Data from industrial assets are increasingly gathered with advanced technologies, and Internet of Things (IoT) applications and services are developed based on the data. Technologies for data collection are developed but the focus is shifting to the utilization of the data in decision-making. The massive amounts of data need to be refined and utilized to create value rather than only be stored in data warehouses and systems. In asset management, the technologies have enabled analyzing the state of assets and managing large groups of assets, i.e. fleets. The benefit of managing asset fleets is to improve the management of assets in a way that enables the gaining of cost savings and the maximization of profit during the life cycle of an asset. Cost savings and increased revenues can be related e.g. to improved maintenance planning (Feng et al., 2017), improved resource and capacity utilization (Archetti et al., 2017), increased asset availability (Gavranis and Kozanidis, 2015), and learned best practices (Galletti et al., 2010). However, the challenge in fleet-level analysis is that the data concerning a fleet is often fragmented and none of the actors has access to the full life-cycle data of the assets. Often the asset manufacturer has certain technical data on their products, but the process and event data related to the operations and maintenance phase of the asset life cycle are stored in the customer's systems. In addition, other actors, such as service providers, might be involved. Thus, fleet level consideration requires the reviewing of the ecosystem, i.e. who has been involved in producing, storing and refining the data. It is meaningful to look into the data refining process in order to develop value creation from the data.

The literature lacks models and frameworks that present how fleet data can be turned into value in business ecosystems. In order to develop data utilization to create value for business, research is needed to increase the understanding on how the costs and benefits of data utilization are realized and how value is created. There is a need to further study the benefits of data utilization and how data analytics is linked with company performance and business value (Ji-fan Ren et al., 2017; Raguseo, 2018). In fleet data utilization, the key is to increase understanding on how the actors of the ecosystem around the fleet are involved in the data refining process and what are the costs and benefits for each actor. To respond to this need, this paper aims at clarifying the generation of costs and benefits in the ecosystem around a fleet. The research question is as follows:

How can the value i.e. the costs and benefits of utilizing fleet data in decision-making be modeled for each actor in an ecosystem?

The research question is answered by developing a model that illustrates the generation of costs and benefits of fleet data in the ecosystem around a fleet. The research applies analytical modeling as a research method. Analytical modeling is considered a suitable method in management research to perceive phenomena and to observe the effects of variables. Modeling is considered a useful tool for decision-making in many research areas related to management research (Mun, 2008). Models are tools for decision-makers to analyze and observe the results and consequences of changing variables. The central idea is to create a general model for IoT investments that illustrates the relationships among the key components: costs, benefits and the effects of fleet-level consideration and data refining level. The previously presented model (Kinnunen et al., *in press*) is extended to an ecosystem level in this paper. The extended model illustrates the value formation of fleet data for the actors of an ecosystem. We have developed the model for an example ecosystem consisting of an equipment provider, its customer company, and an information service provider. The logic of the model is then tested with illustrative data. The illustrative data were utilized as the real data of IoT investments and realized cost and benefit data were lacking. The illustrative data concern the modernization of a pulp drying machine fleet and the ecosystem around the fleet and the fleet-level analysis.

The model is developed based on research conducted in a research program dealing with the topic of service solutions for fleet management. The themes have been studied in close collaboration with companies involved in the program. Different types of working methods, such as seminars, focus groups, and workshops, have been used, and empirical materials, such as interviews and secondary data (e.g. discussions, company brochures), have had an effect on the research process.

The theoretical background for the model is discussed in section 2 in which the literature is reviewed and a theoretical frame is presented. Section 3 presents the structure of the model and describes how value can be modeled. In section 4, the illustrative case is described and the model is tested with the illustrative data. The findings from the testing are discussed and analyzed with the sensitivity analysis at the end of section 4. Section 5 concludes the results and proposes ideas for further research.

2 The theoretical frame of benefits and costs in fleet-level decision-making

The benefits of fleet management are recognized in literature, and the basic idea is to improve the management of assets so that cost savings and maximized profits can be achieved during the life cycle of an asset. Fleets are widely discussed in the marine, military, logistics, and aviation industries, where fleets consist of ships, aircrafts, trucks, or other vehicles (Archetti et al., 2017; Feng et al., 2017; Tran and Haasis, 2015). Machineries and equipment are also considered fleets in asset management and maintenance contexts (Al-Dahidi et al., 2016). Fleet management and decisions concerning fleets are often related to optimization problems, including capacity and routing problems, but also to proactive and real-time decisions e.g. in maintenance planning and performance monitoring, as well as to strategic decisions, including e.g. investment management (Al-Dahidi et al., 2016; Archetti et al., 2017; Feng et al., 2017; Richardson et al., 2013; Tran and Haasis, 2015). There is potential to develop predictive intelligence tools to optimize asset utilization in cost effective manner (El-Thalji and Jantunen, 2016) and for example develop preventive maintenance practicalities with the aid of increased data collection and tools for decision support (see e.g. Amelian et al., 2015; Laukka et al., 2016). Fleet management and decisions at fleet level pursue the economies of scale, the minimization of unit costs, and the maximization of profits during the lifetime of assets (Tran and Haasis, 2015; Archetti et al., 2017). Savings can be e.g. savings in maintenance operations, spare parts, quality costs, and decreased downtime (Al-Dahidi et al., 2016; Feng et al., 2017; Gavranis and Kozanidis, 2015; Yongquan et al., 2016). Other benefits can be e.g. increased revenues in the form of new service sales and new product development (Kortelainen et al., 2016). The connection between fleet-level decision-making, supportive analyses and models, achievable benefits and generated costs is described in Figure 1. Literature has presented pieces of this puzzle (see e.g. Al-Dahidi et al., 2016; Berghout and Tan, 2013; Feng et al., 2017; Gavranis and Kozanidis, 2015; Miragliotta et al., 2009; Richardson et al., 2013) but the pieces have not been previously put together, as is presented in Figure 1. Generally, literature describes a certain fleet decision-making problem (e.g. maintenance planning) and then proposes a fleet analysis tool or model (e.g. a predictive model) to support the decision-making need in order to achieve benefits, such as savings in maintenance costs. Instead, the theoretical framework described in Figure 1 gives a broader, general view on the matter of how fleet decision-making situations can be supported with fleet analyses and categorizes what kinds of benefits can be achieved and what kinds of costs are generated when the fleet analyses are utilized.

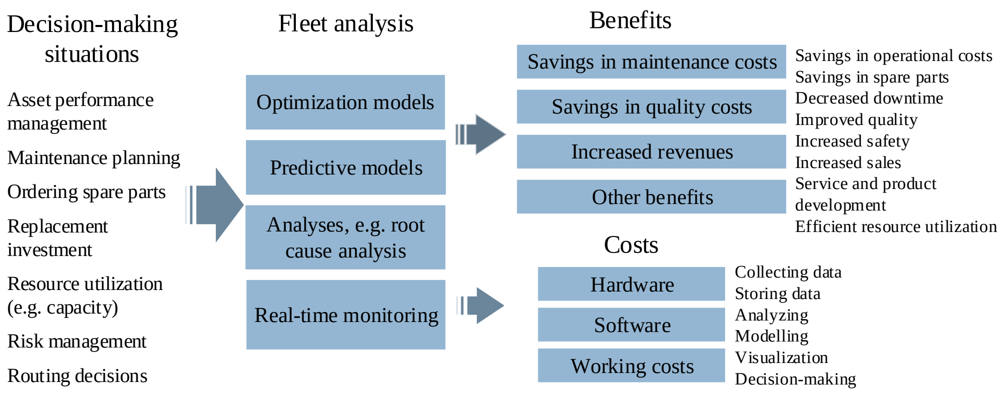

Figure 1. Theoretical frame of the benefits and costs in fleet-level decision-making

Although the benefits of fleet-level analysis are seen, comprehensive understanding of the value of fleet information is limited. The value of information is challenging to determine which can be seen as relatively mild attempts to evaluate the value of data or information. Research on defining the benefits of data utilization and the effects of data analytics to company performance and business value is limited (Ji-fan Ren et al., 2017; Raguseo, 2018; Raguseo and Vitari, 2018). Instead, the discussion is focused on describing single applications, models or services to solve certain decision-making needs (see e.g. Archetti et al., 2017; Kortelainen et al., 2017b). However, there is literature that describes the principles to the value of information in general (Evans and Price, 2012; Moody and Walsh, 2002). For example, it can be said that the value of information increases with accuracy and use and it is valuable only when utilized in decision-making (Moody and Walsh 2002). When discussing the value of fleet data, we need to bring other aspects into discussion as well due to the nature of fragmented fleet data (Kinnunen et al., 2017). The challenge is that the value is often contextual (Evans and Price, 2012) and the value of fleet data varies depending on the perspective from which it is evaluated. In the case of fleet information, data is generated, processed and utilized by multiple actors in an ecosystem around a fleet. Thus, it is important to understand and model how the value is created in network or ecosystem. For example, Sinkkonen et al. (2016) have combined value thinking and an industrial maintenance network in their life-cycle model whereas Miragliotta et al. (2009) have discussed the costs of technology investment in a supply chain. In the case where multiple actors are involved, who should actually benefit from the data and to whom should the value be maximized? Should the asset owner get the most value from information concerning the fleet (Archetti et al., 2017) or should it be the equipment provider, who delivers the assets and can e.g. utilize the data in product development to gain value from fleet-wide data in the form of an improved product and increased new product or service sales (Kortelainen et al., 2017a)? And what is the role of the information service provider, who refines the fleet data into analyses and models, in this value formation?

When considering the value of information, the costs of data processing need to be considered. Costs are generated throughout the whole process from data collection to storage, maintenance, and utilization of information (Miragliotta et al., 2009; Moody and Walsh, 2002). The costs of data utilization can include initial (e.g. hardware), running (e.g. software licenses and maintenance), and other organizational (e.g. personnel working and training) costs (Berghout and Tan, 2013). In the case of fleet information, it is essential to acknowledge that the costs and benefits are realized for multiple actors in the ecosystem depending on which phases and to which extent they participate in the data refining process (Kinnunen et al., 2017). However, the ecosystems around fleets are distinctive and the roles in the fleet data refining process may differ depending on the case, and thus the roles need to be defined and modeled separately in each case.

3 Model to determine the value of fleet information in an ecosystem

3.1 Structure of the model

The ecosystem consisting of three actors represents a simplified example of the fragmented fleet data refining process from data collection to the value for each actor. The ecosystem comprised of three actors is utilized because of simplicity but it involves the essential actors and clearly illustrates the situation and the interdependencies in the fleet ecosystem. In reality, the ecosystem around a fleet consists of numerous actors, including e.g. several customers, but developing and applying the model for more complex ecosystems becomes more difficult. When considering the fleet ecosystem of three actors, the ecosystem around a fleet typically includes an equipment provider who manufactures the assets and owns e.g. product development data concerning the assets. A customer company usually owns the assets and has the most extensive data from the operations phase of the assets' life cycle. In addition, service providers are often involved in the fleet life cycle data generation by producing and mastering e.g. service history data.

In this model, we have an information service provider as the third actor. The information service provider provides e.g. the technical solution for fleet-level analysis. As a presumption in the model, the fleet is the same for each actor: the assets owned by the customer and provided by the equipment provider. It needs to be acknowledged that the fleet could be defined differently, and each actor may consider the fleet from a different perspective and the fleet-level analysis and decision-making situations could be different for each actor (Kortelainen et al., 2017a). However, this would complicate the model, and as this is the first attempt to model the value of fleet information at ecosystem level, the fleet is limited to being the same for each actor and encompassing the assets owned by the customer and provided by the equipment provider.

The actors of the ecosystem have different roles in the fleet data refining process and varying decision-making needs where the fleet-level analysis can be utilized. The customer is the one who owns the assets of the fleet and pursues to use the assets efficiently throughout the entire life cycle of the assets and maximize the profit from their business processes. The role of the equipment provider is to support the customer's maintenance decisions by providing fleet-level analysis and support for optimal asset utilization to keep the assets in good condition. Both the customer and the equipment provider utilize fleet life cycle data also for their own decision-making, e.g. the equipment provider can use fleet data to support product development. A service provider is responsible for the technical realization of the fleet analyses and models, and the structures and the lessons learned from the technical realization can be utilized in their business when developing solutions for other customers as well.

In Figure 2, the value for each actor is illustrated as the components of costs and benefits followed from data processing and data utilization in fleet decisions. Defining the roles of each actor, and thus the cost and benefit components for each actor, requires that the service level of data-based services are defined in the ecosystem. The service levels of data-based services can be classified as data-as-a-service (DaaS), information-as-a-service (IaaS) and knowledge-as-a-service (KaaS) (Kortelainen et al. 2017a). The provided service levels define e.g. how the costs of data processing are realized for the actors. For example, if the equipment provider offers KaaS-level service for the customer, the costs of analysis and modeling are generated to the equipment provider and the customer can only focus on decision-making. Naturally, the actors can produce analyses and models based on fleet data to support their own decision-making. In that case, the costs from data analysis and modeling are also generated to those actors. The service level also reflects the data refining level, i.e. how advanced the data processing is and thus how detailed the support for decision-making is. This has an effect on the extent of benefits. Next, the components of the model, e.g. size of the fleet, the data refining level and the valuation of fleet information, are discussed.

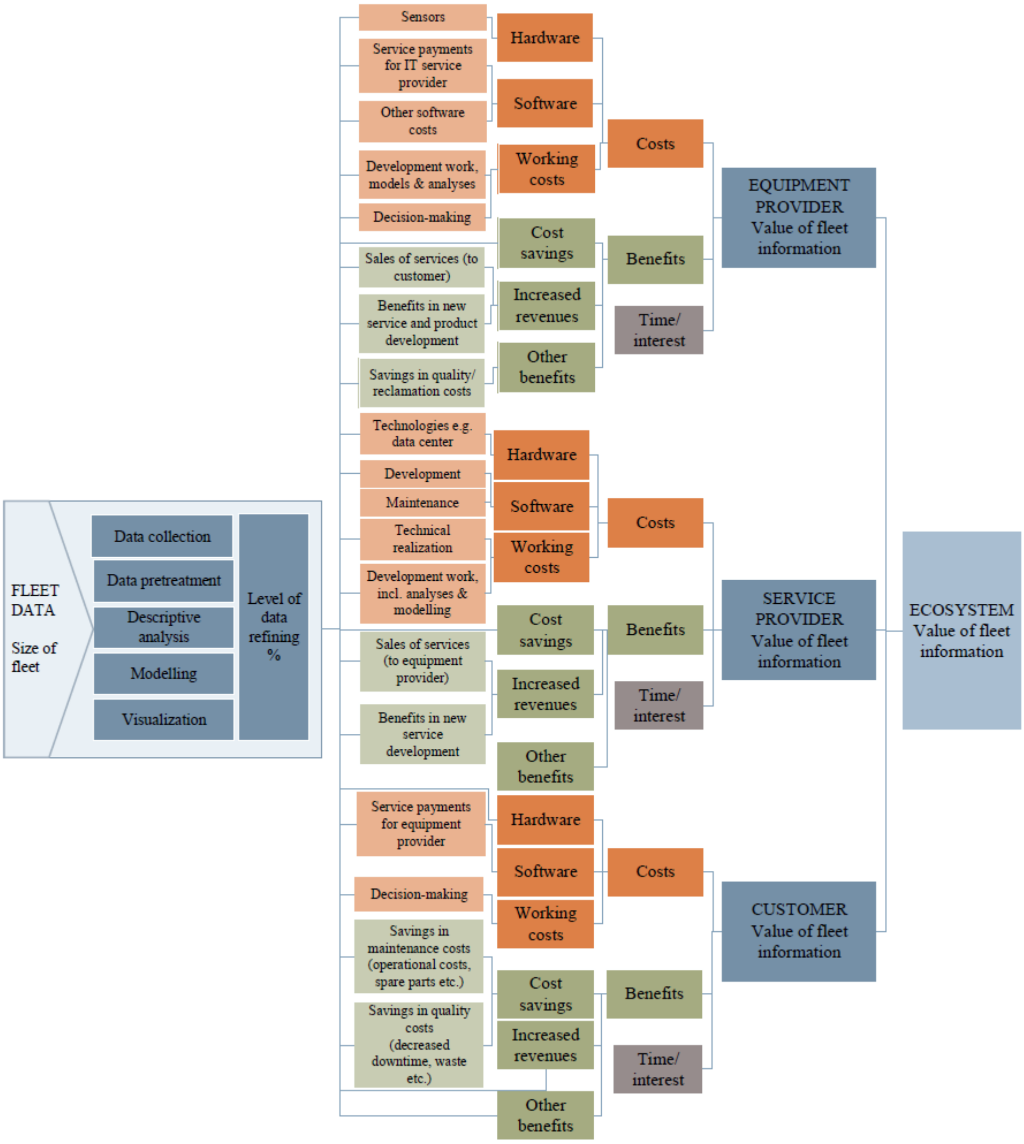

Figure 2. Structure of the model

Fleet data utilization and the size of the fleet

The assumption behind the model is based on the benefit of utilizing fleet data in decision-making. If data is collected from a fleet of assets, it can be assumed that the more assets from which the data is collected, the more accurate analyses and models can be made to support decision-making. Better decisions are converted into benefits, such as cost savings and increased revenues. This assumption can be derived from the laws of information presented by Moody and Walsh (2002). In addition, the number of assets in a fleet increases the amount of benefits when the decisions can be made concerning every asset of the fleet, and thus the benefits are multiplied. The benefits increase significantly to some extent with the amount of assets and data, but there is a limit when a larger amount of data no longer improves the accuracy of the analysis.

The costs can be assumed to grow with the size of the fleet. This applies to costs related to data gathering, data pretreatment and warehousing, as the amount of produced data increases with the size of the fleet. However, the larger size of the fleet can be assumed to have advantages when e.g. predictive models are developed and the development costs can be divided between all the assets in the fleet. Thus, there can be economies of scale when utilizing fleet data in the development of models or services into large-sized fleets of assets.

Data refining level

The model is based on the assumption that the data refining level affects the amount of benefits and costs. It can be assumed that benefits and costs increase the more processed and refined the data is for decision-makers (Kortelainen et al., 2017a). The relation of data refining level to benefits and costs is presented in Figure 3. The data-to-decision process can be divided into data collection, data pretreatment, descriptive analysis, modeling and visualization or decision-making phases (Kunttu et al., 2016). The level of data refining depends on how thoroughly the phases of data processing have been performed. In other words, how much effort is made to accurately conduct the phases from data collection to visualized solutions. Better decisions can be made when decision-making is supported with detailed analyses and models, and thus more benefits can be achieved along with better decisions. Although the benefits increase with detailed analyses and models, so do the costs. If 100 % accuracy and reliability, regarding e.g. data quality, are pursued, the costs may increase significantly as perfection requires plenty of resources. It needs to be considered what is a satisfactory accuracy for the analyses and models, and what is the point where the amount of additional benefits does not cover the costs. Often it is enough that the models give adequately reliable information for decision-makers, but in some cases more accurate predictions are required. In this paper, we utilize an abstract expression to describe the level of data refining. We propose that the level of data refining can be expressed with the percentage of how far the phases of data processing are developed. The phases of data refining consist of data collection, data pretreatment, analyzing, modeling and visualization or decision-making, as presented in Figure 3.

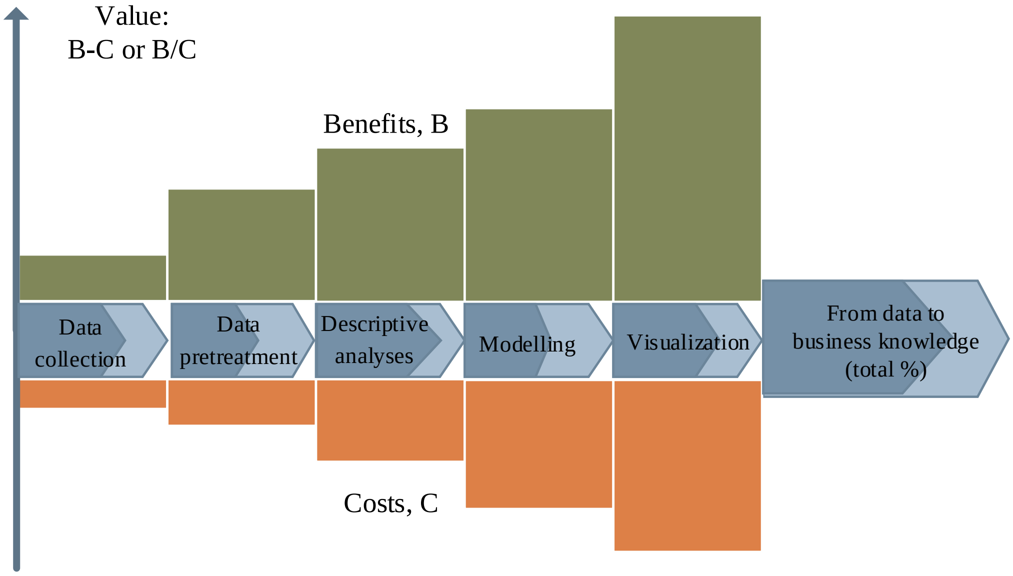

Figure 3. Data to knowledge and the relation to the accumulated costs and benefits

The value of information over time

The value of information can be examined with the cost-benefit approach. In the cost-benefit approach, total costs and total benefits are expressed in monetary terms. Benefits are realized after a longer time, and the situation can be considered as an investment that needs to pay itself back during a defined time period. Thus, the selected time period needs to be defined according to the purpose of the value assessment. Net present value is a suitable method for valuation over a time period as it takes into account the time value of money. The effect of time is taken into account by defining a suitable interest or discount rate. Discount rate is often defined at least at the level of the company's weighted average cost of capital. The value of information for each actor can be defined as the net present value of the discounted total benefits and total costs.

The value can be evaluated for each actor separately, but the value of fleet information can be defined for the whole ecosystem. However, if the value of the ecosystem is considered as a whole, it is not obvious which value should be maximized. The model can be adapted to other ecosystems but the fleet and the actors in the ecosystem need to be defined. The roles in the fleet data refining process may vary, as well as the benefits and costs for each actor.

3.2 Value of fleet information for the customer

The components of the model (Figure 2) can be expressed with equations. As the value can be defined for each actor, the formation of the value can be presented separately for each actor. After that, it can be considered whether it is reasonable to observe the value of fleet information at ecosystem level as well. In this section, the value of fleet information for the customer is presented with equations. According to the structure of the model, in order to reach a value, benefits, costs and the components of both need to be analyzed. First, the benefits from exploiting fleet-level analyses and models for the customer are discussed. From the customer's perspective, the total benefits can be presented as follows:

$$B_{total\_customer} = B_{1C} + B_{2C} + B_{3C} \tag{1}$$

where B_{1C} is cost savings, including savings in maintenance costs (B_{1CM}) and savings in quality costs (B_{1CQ}), B_{2C} is increased revenues, and B_{3C} is other benefits for the customer. The benefits are related to asset management decisions and include e.g. savings in maintenance costs, quality costs and other benefits that can be achieved with better decisions with the aid of fleet-level analysis and models.

Cost savings in maintenance costs can be e.g. the result of improved maintenance planning and reduced spare part consumption (Al-Dahidi et al., 2016; Feng et al., 2017; Gavranis and Kozanidis, 2015; Yongquan et al., 2016). Savings in maintenance costs can be seen as a transition from the maintenance cost level before the modernization is made to the lower cost level that can be achieved when the fleet analyses and models are utilized as the support of maintenance decision-making. This can be presented as:

$$B_{1CM} = m_{1c} - m_{2c} \tag{2}$$

where m_{1c} is the maintenance cost level of the customer before the modernization and m_{2c} is the cost level of the customer after benefitting from fleet information. To model the maintenance costs for a fleet of assets, we need to have a pattern that represents the behavior of typical maintenance costs during the asset's life cycle. A different type of failure model can be utilized to illustrate the maintenance costs throughout the lifetime of the assets. In this model, we utilize the Weibull function to represent the maintenance costs of a fleet. The Weibull function, i.e. bathtub curve, can be utilized to represent the maintenance costs of a fleet during the lifetime of the assets (see e.g. Popova et al., 2006; Yang et al., 2006; Crespo Márquez, 2007; Afsharnia et al., 2014). The cost savings in maintenance costs can be presented as the transition from m_{1C} to m_{2C} as presented in Figure 4.

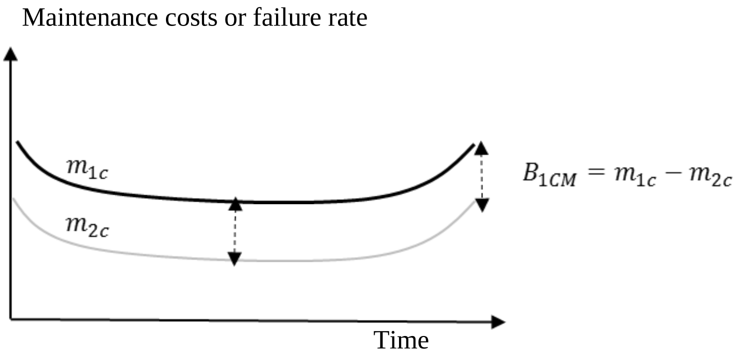

Figure 4. Savings in maintenance costs as the transition from higher cost level to lower level.

The extent of the transition depends on the data refining level D. The relation can be presented as follows:

$$m_{2C} = m_{1C} - D * m_{1C*} \tag{3}$$

where m_{1C*} is the part of the customer's maintenance costs that can potentially be diminished after modernization. It cannot be assumed that all the maintenance costs can be avoided just by developing the data refining level up to 100%. The maintenance costs that can be diminished are maintenance costs that are caused by malfunction and unscheduled maintenance but also excessive maintenance work that can be reduced by optimizing maintenance intervals.

Cost savings in quality costs can be defined as a transition from the initial quality cost level

q_{1C} to the lower cost level q_{2C} that can be achieved with the aid of fleet information as the support for decision-making. Usually, better maintenance decisions result in lower maintenance costs but lower quality costs as well, including decreased downtime, diminished losses in production and waste. The following formula can be used to represent cost savings in quality costs:

$$B_{1CQ} = q_{1C} - q_{2C} \tag{4}$$

and the new improved level of quality costs can be calculated with the data refining level D:

$$q_{2C} = q_{1C} - D * q_{1C} \tag{5}$$

Increased revenues B_{2C} can be evaluated as annual increase in revenues, but it is important to acknowledge that the loss of production due to downtime has already been taken into account in the savings in quality costs. Other benefits B_{3C} can result from e.g. improved safety or effective resource utilization, and they can be calculated for example as the sum of annually earned savings, or the benefits can be non-recurring, depending on the case.

After discussing the benefits for the customer, the costs of exploiting fleet data are discussed. From the customer's point of view, the total costs of processing fleet data can be formulated:

$$C_{total\_customer} = C_{1C} + C_{2C} + C_{3C} \tag{6}$$

where C_{1C} is hardware costs, C_{2C} is software costs, and C_{3C} is working costs. The costs of these cost groups depend on how the service levels of fleet data -based analysis services and the roles of the actors in the ecosystem are defined. There might not be any hardware costs for the customer if all the analyses and models are purchased as services from the equipment provider. In that case, software costs are emphasized and they can consist of service payments to the equipment provider. The service level of purchased services affects the amount of working costs, i.e. whether the customer is doing some of the analyses or models themselves for other purposes based on the fleet data or whether working costs are related only to the utilization of analyses and decision-making based on the purchased analyses and models.

Finally, the value of fleet information for the customer can be defined as the net present value of discounted total benefits and costs. The time-discrete formula of the net present value can be utilized in the model and is suitable to be used when appraising IoT modernization investments with clear time periods, e.g. years. The time-discrete formula of net present value for the customer is formulated as:

$$NPV_{Customer} = \sum_{n=0}^{k} \left(\frac{B_{total\_customer_n}}{(1+i)^n} \right) - \sum_{n=0}^{k} \left(\frac{C_{total\_customer\,n}}{(1+i)^n} \right) \tag{7}$$

where n is the time of the cash flow, $B_{total\_customer_n}$ is the total benefits at time n for the customer, $C_{total\_customer_n}$ is the total costs at time n for the customer, and i is the discount rate. The value of fleet information for the customer is the difference between the cumulative discounted total benefits and the cumulative discounted total costs.

3.3 Value of fleet information for the equipment provider

Secondly, the value of fleet information is defined for the equipment provider. The components of total benefits and total costs are discussed, as well as the formation of value for the equipment provider. From the equipment provider's perspective, the total benefits can be presented as follows:

$$B_{total\_equipment} = B_{1E} + B_{2E} + B_{3E} \tag{8}$$

where B_{1E} is cost savings, B_{2E} is increased revenues and B_{3E} is other benefits for the equipment provider. Cost savings can be e.g. costs savings in reclamation costs. The increased revenues can be gained e.g. from increased product and service sales when better products and services can be offered to customers because of the support from fleet-level information and analyses. Other benefits can be e.g. benefits in product development. These kinds of benefits can be achieved when the equipment provider can respond to the needs of customers in real-time and the gained knowledge can be exploited in future product development. All benefit components can be expressed as annual benefits, such as annual cost savings or annual increased sales. The amount of benefits, especially cost savings –related benefits, are connected to the data refining level according to equations (4) and (5), and increased sales can be estimated as annual benefits.

The cost components of the equipment provider depend on the agreement with the information service provider. The roles and responsibilities in the fleet data refining process define which costs are realized for the equipment provider and which for the information service provider. The total costs for the equipment provider are as follows:

$$C_{total\_equipment} = C_{1E} + C_{2E} + C_{3E} \tag{9}$$

where C_{1E} is hardware costs, C_{2E} is software costs, and C_{3E} is working costs. Hardware costs can include e.g. sensors installed in the assets. Generally, hardware costs are investment-type non-recurring costs that are realized at the beginning of the time period. Software costs are payments to the information service provider for providing the technical solution for fleet analyses and services. Software costs can be e.g. annual licenses. Working costs include development work used to develop the analyses and models in collaboration with the information service provider and the utilization of analyses and information e.g. in one's own product development decisions. Working costs include human working hours used to process data and develop the analyses and models. Working costs depend on the data refining level, i.e. the further the analyses and models are developed, the more working hours are required. The need for working costs can be assumed to be higher at the beginning when the service solutions are developed but some development work is needed in the future as well.

The value of fleet information for the equipment provider can be modeled with the same logic as for the customer. The value can be viewed as a net present value of total discounted benefits and costs. The time-discrete formula of the net present value is:

$$NPV_{Equipment} = \sum_{n=0}^{k} \left(\frac{B_{total\_equipment_n}}{(1+i)^n}\right) - \sum_{n=0}^{k} \left(\frac{C_{total\_equipment\,n}}{(1+i)^n}\right) \tag{10}$$

where n is the time of the cash flow, $B_{total\_equipment_n}$ is the total benefits at time n for the equipment provider, $C_{total\_equipment_n}$ is the total costs at time n for the equipment provider, and i is the discount rate.

3.4 Value of fleet information for the information service provider

Thirdly, the value of fleet information is defined for the information service provider. The components of total benefits and total costs are discussed, as well as the formation of value for the information service provider. From the information service provider's perspective, the total benefits can be presented as follows:

$$B_{total\_service} = B_{1S} + B_{2S} + B_{3S} \tag{11}$$

where B_{1S} is cost savings, B_{2S} is increased revenues and B_{3S} is other benefits for the information service provider. Increased revenues for the information service provider include revenues from service sales to the equipment provider. Other benefits may be e.g. benefits for service development in the future or references. All the benefit components can be evaluated as annual benefits, and they may vary yearly.

The costs for the information service provider depend on the agreement with the equipment provider and on the agreed service levels, but the essential part of costs includes the technical realization of the fleet services, such as programming and maintaining a server or a cloud. The total costs for the information service provider can be presented as:

$$C_{total\_service} = C_{1S} + C_{2S} + C_{3S} \tag{12}$$

where C_{1S} is hardware costs, C_{2S} is software costs, and C_{3S} is working costs. The costs of the information service provider are mostly generated by the technical solution development of fleet analyses, including hardware costs (e.g. data center), software development and maintaining costs, and working costs of technical realization and development. These costs include non-recurring costs for developing the solution realized at the beginning of the time period, but also continuous annual costs such as maintenance costs.

The value of fleet information for the information service provider is presented with the same logic as the value for other actors. The time-discrete formula is as follows:

$$NPV_{Service} = \sum_{n=0}^{k} \left(\frac{B_{total\_service_n}}{(1+i)^n} \right) - \sum_{n=0}^{k} \left(\frac{C_{total\_service\ n}}{(1+i)^n} \right) \tag{13}$$

where n is the time of the cash flow, $B_{total\_service_n}$ is the total benefits at time n for the information service provider, $C_{total\_service_n}$ is the total costs at time n for the information service provider, and i is the discount rate.

3.5 Value of fleet information for the ecosystem

Value for each actor has been discussed but because the actors of an ecosystem share an interest for creating value from fleet information also in the future and in the long run, it is important to be able to create value for the ecosystem as a whole. The amount of value differs for each actor, but the position should not be unbearable for any actor while other actors gain remarkable value (Adner, 2017). Instead, value should be created for the whole ecosystem. This way, the ecosystem remains viable.

The value for the ecosystem can be assessed as the sum of its actors' values. The value of an ecosystem $NPV_{Ecosystem}$, i.e. the sum of net present values of each actor, can be shaped as follows:

$$NPV_{Ecosystem} = NPV_{Customer} + NPV_{Equipment} + NPV_{Service} \tag{14}$$

The sum of net present values should be positive in order for the investment in data refining to be profitable. The bigger the value, the more profitable the investment is for the ecosystem as a whole. It needs to be acknowledged that the value for the ecosystem can be positive even if the value is negative for some actors. It would be beneficial to utilize other measures as well and consider which measures and values should be maximized. Another option is to examine the B/C ratio (benefit-cost ratio) that is defined as the total discounted benefits divided by the total discounted costs. The ratio can be defined for each actor separately but also for the whole ecosystem. The B/C ratio should be more than 1 for the investment to be profitable. The B/C ratio is a suitable measure when comparing the profitability of investments of different size. In the case of IoT investments, the amount of investments of different actors can vary remarkably, and the achieved benefits are compared to the sizes of the inputs. The B/C ratio can be formulated as follows:

$$B/_{C} - ratio = \frac{\sum_{n=0}^{k}(\frac{B_{total_n}}{(1+i)^n})}{\sum_{n=0}^{k}(\frac{C_{total_n}}{(1+i)^n})} \tag{15}$$

where the numerator is the cumulative total benefits of the selected time period and the denominator is the cumulative total costs during the period including the initial investment. The ratio can be calculated for each actor by changing the actor-specific values. It is possible to calculate the ratio for the whole ecosystem by summing up the cumulative benefits and costs of each actor.

As the B/C ratio shows whether the total benefits overrun the total costs of investment, it also shows the ratio of the benefits overrunning the costs. The ecosystem should aim at making an investment with a net present value of more than 0, but NPV as a single measure does not provide enough information about the viability of the investment. The objective of the ecosystem is to create more value than the companies alone could gain. This can be achieved e.g. by taking advantage of synergy benefits. In fleet data utilization, synergy benefits can be gained e.g. by defining the roles of the actors in the data refining process in order to minimize the unit costs of the data refining process. Thus, more benefits could be gained with lower data refining costs at an ecosystem level, which can be seen as an increase in the B/C ratio. The B/C ratio can be utilized as a tool or measure to develop collaboration in the data utilization of the ecosystem.

4 Testing the model with illustrative data

4.1 Fleet analysis services for a pulp dryer machine

Illustrative data is utilized to demonstrate the logic of the model. The case examines the modernization of a pulp dryer machine fleet owned by the customer. The fleet consist of 20 similar or nearly similar pulp drying machines. Thus, the size of the fleet is 20 assets. The customer invests in modernization, including sensors to all the dryer machines and data analyses and models built upon fleet data. The equipment provider is a specialist of pulp dryer machines and offers analysis and modeling services to the customer to prevent faults and breakdowns, thus reducing the costs of unscheduled maintenance and loss of production. The equipment provider has the expertise on machine behavior and features, and thus is able to develop the logic for recognizing anomalies in the asset's behavior and predict faults and the need for maintenance activities. The equipment provider does not usually have the expertise to process the data, and therefore an information service provider is needed to execute the technical realization of the analyses and models. The information service provider is responsible for e.g. data treatment, maintaining a cloud server, modeling, programming, etc.

As discussed in section 3.1, the level of data services (knowledge-as-a-service, information-as-a-service etc.) affects the roles of the actors in the data refining process as well as the costs and benefits. In this case, it is assumed that the equipment provider offers knowledge-as-a-service type of services to the customer, which means that the equipment provider offers advanced analyses and models with visualizations and finished decision propositions to the decision-makers. The objective of the customer is to use machines in a cost-effective way during their life cycle, and the equipment provider provides their expertise as a service to the customer. The role of the information service provider is to act as a link to enable the realization of the service by building the technical solution. The costs and benefits of each actor are determined by their roles in the ecosystem.

4.2 Simulation of the value of fleet information

In this section, the value of fleet information is simulated for each actor using illustrative data. The roles of the actors in the fleet ecosystem are presented in Tables 1–3, and the cost and benefit components are described. Some of the costs are equivalent to the benefits of another actor. For example, the software costs of the equipment provider are the same as the benefits from increased revenues for the information service provider. Thus, the benefits of one actor may be costs to another. In the tables, the initial costs are expected to occur at the beginning of the time period, and the annual costs and benefits are expected to occur each year after the investment.

Table 1. Costs and benefits of the customer

Customer		
Costs		
Hardware	-	
Software	Service payments for equipment provider	Initial costs 500 000 € Annual costs 100 000 €
Working costs	Decision-making	Initial costs 30 000 € Annual costs 160 000 €
Benefits		
Cost savings	Cost savings in maintenance costs, Cost savings in quality costs	Annual savings in maintenance according to Weibull, depend on asset life cycle, approx. 363 000 € annually Annual savings in quality costs 989 000 €
Increased revenues	-	
Other benefits	E.g. decreased environmental costs	Annual benefits 34 000 €

Table 2. Costs and benefits of the equipment provider

Equipment provider		
Costs		
Hardware	Sensors	Initial costs 4 000 €
Software	Service payments to the information service provider	Initial costs 1 000 000 € Annual costs 50 000 €
Working costs	Development work, decision-making	Initial working costs 160 000 € Annual costs 104 000 €
Benefits		
Cost savings	Savings in quality costs	Annual savings 500 000 €
Increased revenues	Sales of services (to customer)	Initial revenues 500 000 € Annual revenues 100 000 €
Other benefits	New service and product development	Annual benefits 10 000 €

Table 3. Costs and benefits of the information service provider

Information service provider		
Costs		
Hardware	Technologies	Initial costs 100 000 € Annual costs 10 000€
Software	Development, maintenance	Initial costs 10 000 € Annual costs 40 000 €
Working costs	Technical realization, development work (incl. modeling), data treatment	Initial costs 400 000 € Annual costs 150 000 €
Benefits		
Costs savings	-	
Increased revenues	Sales of services (to equipment provider)	Initial revenues 1 000 000 € Annual revenues 50 000€
Other benefits	New service development	Annual benefits 50 000 €

To evaluate the value of information for each actor other parameters are required, such as the time period, the interest or discount rate, and the data refining level. In this case, the time period has been selected to be five years, as the need for reinvestments in these kinds of technology investments is repeated relatively often and new investments are needed to keep up with the competition. The interest rate or discount rate has been selected to be 10 %. This interest rate is appropriate if a significant rate of return is not required. The utilized interest reflects the risk of the investment project (Götze et al., 2015, p. 13). For example, the rate of return could be higher in technology investments where the risks are high, for example 15–25 %. In regard to the data refining level, it was defined according to Table 4 where the phases 1–5 are estimated, and the data refining level D is calculated as the average of the phases. The data refining level of 0 % means that nothing is developed compared to the starting point, whereas the level of 100 % is the maximum level the available technologies and know-how could enable. The level of each phase can be estimated by expert judgment in the companies. The same data refining level can be utilized for all the actors, but it is possible to define the level for each actor separately. However, this increases the complexity of the model. In Table 4, the defined data refining level has affected the amount of costs and benefits described in Tables 1–3. For example, it can be assumed that the data refining level affects the development costs of fleet analyses and models.

Table 4. Defining the data refining level D

Data refining level (0–100 %)	
Phase 1: Data collection	70 %
Phase 2: Data pretreatment	60 %
Phase 3: Descriptive analysis	60 %
Phase 4: Modeling	50 %
Phase 5: Visualization & decision-making	60 %
Data refining level D	**60 %**

The above mentioned parameters, costs and benefits are put to equations (7), (10) and (13), and the value of fleet information for each actor can be determined. When the value of fleet information for each actor is calculated, the components of net present values can be explored as well. In Figure 5, the discounted benefits and costs are presented for each actor during the five-year period. It can be noticed that the major costs are at the beginning, and the costs occur steadily among the actors in the following years. Instead, there are significant differences in regard to the benefits for the actors during the time period. The benefits for the customer are considerable starting from year one and are significantly higher than the benefits for other actors. The benefits for the information service provider focus on the beginning and the benefits are low in the following years. The benefits for the equipment provider remain fairly constant over time.

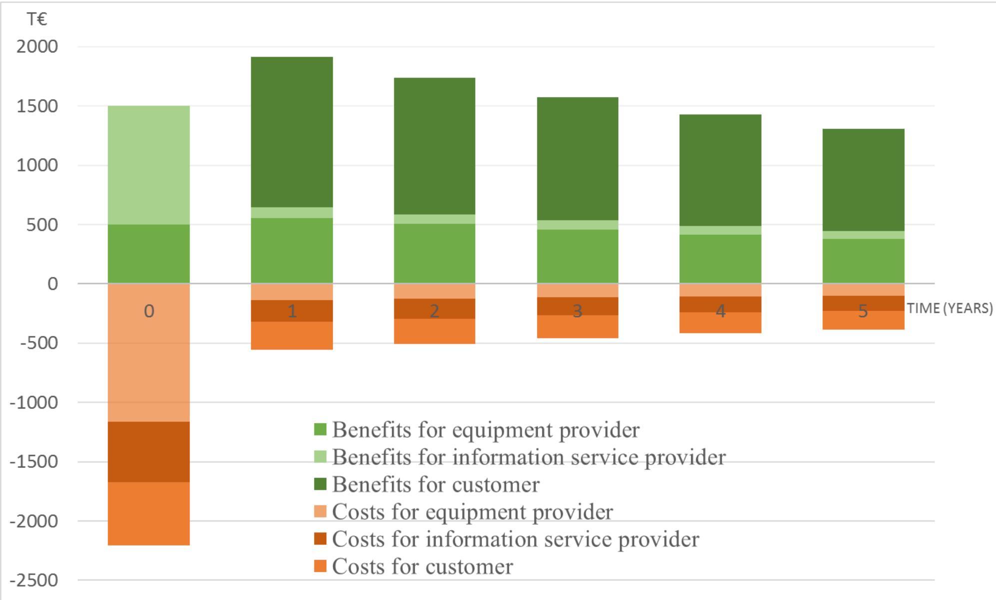

Figure 5. Discounted benefits and costs for each actor

The values of fleet information for each actor are presented in Figure 6. The value is presented as cumulative present value during the five-year period. For the information service provider, the value is positive from the beginning but remains low the entire time. The value for the customer is positive after one year and increases significantly with time. The value for the equipment provider is positive after two years and increases steadily. Investments in IoT modernization and data analyses seem to be profitable especially for the customer as most of the benefits are benefitting the customer's business. The benefits for the equipment provider and information service provider consist mainly of service payments from the other actors. It would be beneficial if the equipment provider and information service provider found more ways to exploit the fleet data to support their own business as well, e.g. by developing their products and services and by also offering them to other customers.

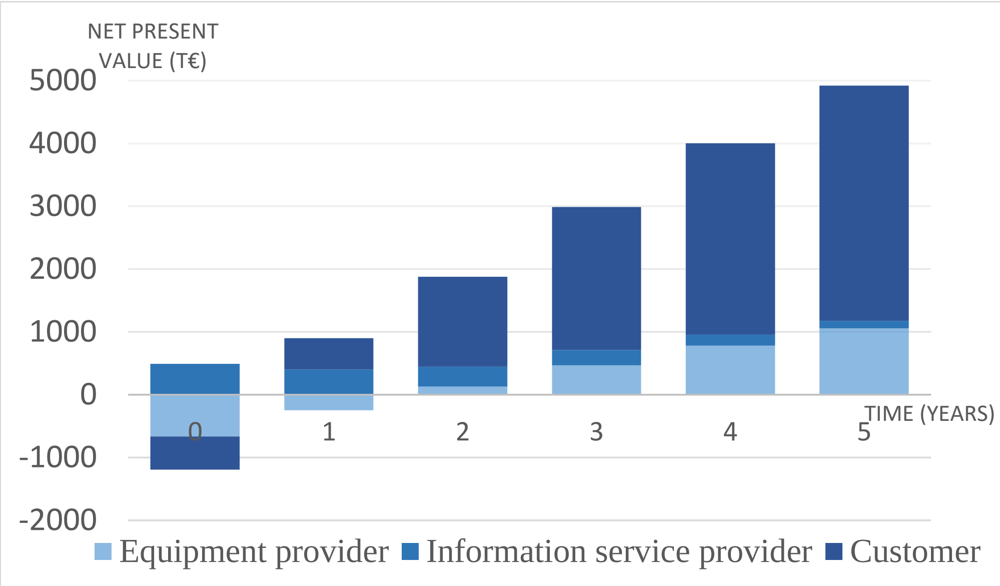

Figure 6. Net present value for each actor

Table 5 summarizes the net present values and the benefit-cost-ratios of each actor and shows the ecosystem level indicators. The B/C ratio of the customer is significantly higher than the ratios of the equipment provider and information service provider. The B/C ratio of the information service provider is barely over 1.0, and thus the project is barely profitable to them. The ecosystem level ratio is higher than the ratios of the equipment provider and information service provider, but that is caused by the high net present value of the customer. This kind of modernization seems to be profitable especially to the customer with these kinds of agreements and roles in the ecosystem. Naturally, the pricing of services between actors needs to be considered, and pondered whether the utilized illustrative pricing data are reasonable as the reality might be different than the assumed values.

Table 5. Net present values and benefit-cost ratios

	NPV (€)	B/C ratio
Equipment provider	1 060 000	1.60
Information service provider	117 000	1.10
Customer	3 744 000	3.47
Ecosystem level	4 920 000	2.09

4.3 Sensitivity analysis

As the model is tested with illustrative data in section 4.2, a sensitivity analysis was used to illustrate how the changes in starting values affect the results and enable the analysis of the risks of utilizing illustrative data. It was noticed that the changes in the data refining level (Figure 7), interest rate (Figure 8) and costs of data refining (Figure 9) have an effect on the value created.

The changes in the benefits of the customer significantly affect the value for the customer but also the value at the ecosystem level. In terms of the value of the equipment provider and service provider, the changes in the benefits mainly depend on the contracts between the actors, as a remarkable amount of benefits originate from the sale of services to another actor. The sales prices are traced back to the costs of data refining, and the changes in the costs of data refining significantly affect the value for the equipment provider and service provider, as can be seen from Figure 9.

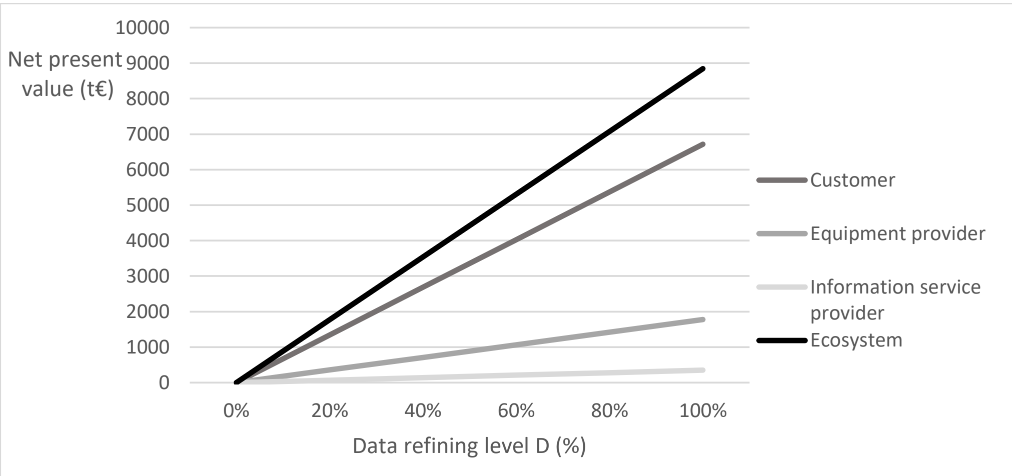

Figure 7. The effect of the data refining level to the net present value for the actors and the ecosystem.

In Figure 7, the value for the customer and the ecosystem increases significantly as the data refining level increases. For example, a change from a 20% data refining level to 60% increases the value for the customer and ecosystem significantly, and if it was decided to develop the data refining process, it would be reasonable to invest in a higher data refining level. The effect on the equipment provider and service provider seems to be lighter. On the other hand, Figure 7 reveals the differences in the values for the actors and raises the question of whether the pricing or value sharing policies between the actors are fair.

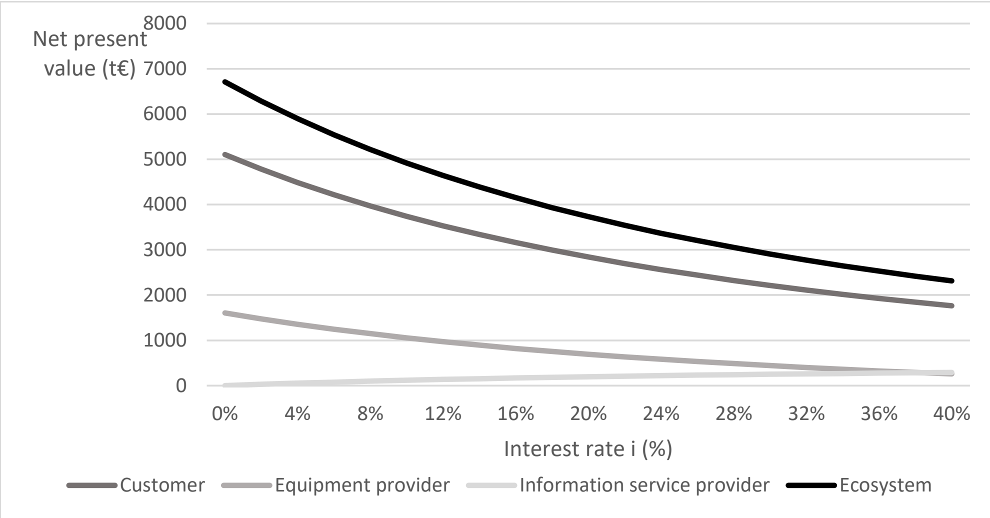

Figure 8. The effect of interest rate to the net present value for the actors and the ecosystem.

As can be seen in Figure 8, the interest rate affects the value, and the higher the rate, the lower the value. The interest rate does not have a negative effect on the service provider who gains its profit mainly at the beginning of the time period. For the other actors and the ecosystem, the interest rate has a more significant effect, and it is interesting to consider what the suitable return requirement for this kind of an IoT investment is. In addition, different actors may have different return requirements for these kinds of investments. However, when calculating with default values, even considerable changes in the interest rate do not easily make the investment unprofitable.

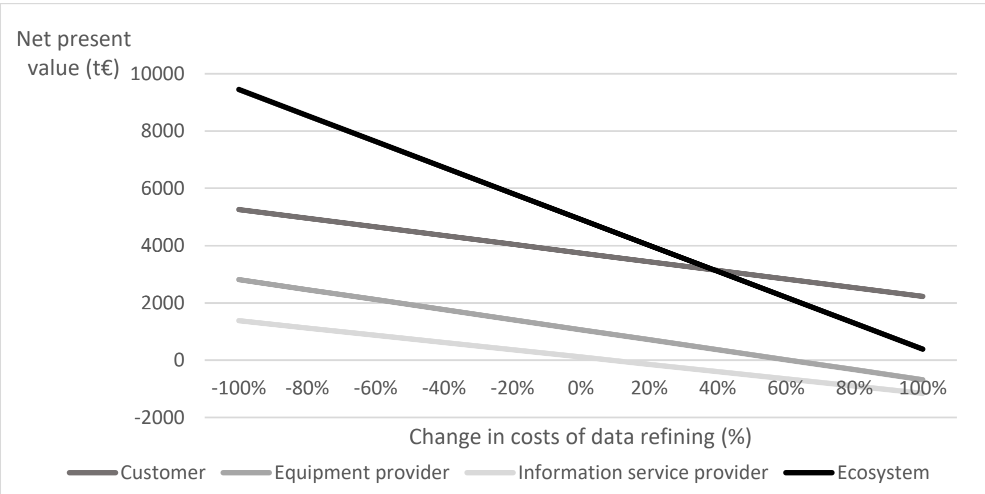

Figure 9. The effect of changes in the costs of data refining on the value for the actors and the ecosystem.

Figure 9 shows how changes in the costs of data refining affect the value for each actor and the ecosystem. The changes in the costs of data refining include e.g. the changes in the costs of hardware, software and work costs. As the illustrative data of costs were estimated and there is limited research available, it is reasonable to examine how the changes in data refining -related costs affect the net present value. In Figure 9, 0% stands for the value calculated with the starting values and e.g. 20% stands for the increase in the costs of data refining. It can be seen that the value for the service provider turns negative when the costs increase by 20%, and the value is negative for the equipment provider when the costs increase by more than 60%. The value for the ecosystem is less than for the customer when the costs increase by 40%.

If the changes in the costs of data refining are examined with the B/C ratio, the trends shown in Figure 10 can be seen. The slight decrease in the costs makes the B/C ratios increase remarkably. On the other hand, if the costs are higher than expected, the B/C ratios do not decrease relatively as much. However, the B/C ratios remain very low in that case.

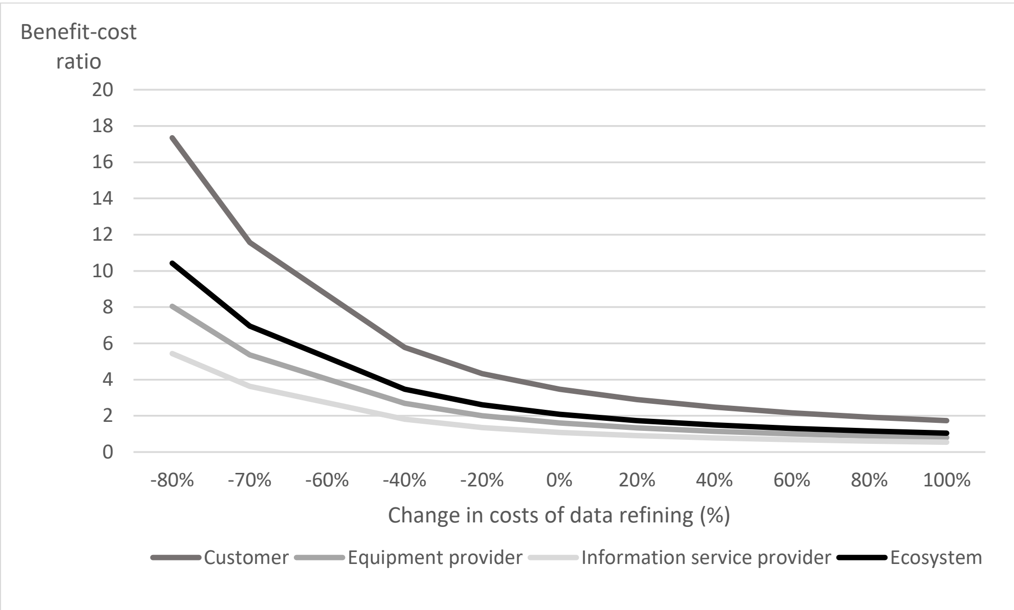

Figure 10. Benefit-cost ratio of the actors and the ecosystem when the costs of data refining change.

4.4 Discussion

The results of testing the model depend on the selected starting values, and with different values, such as real company values, the results could be different. The model is created for an ecosystem of three actors, but it can be applied to an ecosystem consisting of more actors as well, and the actor-specific roles, benefits and costs then need to be defined. However, in this paper the illustrative data demonstrates the logic of the model and the importance of the roles in the ecosystem from data to decision-making. For example, the roles of the actors in data processing and in developing the analyses and models affect how the costs are divided. The distribution of benefits between the actors affects the pricing models and those whose decision-making the analyses and models support. It is important to understand the costs and benefits of data utilization for the actors in order to build collaboration on a sustainable basis.

When we can examine the costs and benefits of each actor, we can consider whether the distribution of costs and benefits are equitable. The balance between the actors affects the sustainability of the ecosystem. It is important that data collection, processing, analyses and models are developed in the future as well, which requires the actors of the ecosystem to be in a sustainable position and committed to their roles in developing data utilization. The illustrative data provides an example, and the position of the information service provider is not particularly good in this case. The positions of the actors can be taken into account by entering into contracts which satisfy the actors and by agreeing on pricing methods. However, the challenges are inevitable when e.g. balancing the benefits between the actors, because it is challenging to define which benefits result from the analyses and models and which result e.g. from the company's internal development. The unequal distribution of benefits could be compensated with fair pricing models, ensuring that the benefits and costs, and thus the cash flow, is divided evenly during the time period and between the actors. The challenge is that, at the same time, the actors pursue the maximization of their own profit, which can lead to disagreements. However, the issue should be considered from a wider perspective, taking the ecosystem level into consideration.

Typical situations between the actors in these kinds of data-based services cannot be stated based on the results of testing the model. Instead, more research is needed with real cases. The model enables discussion on the value of data and information. It is essential that data refining benefit the decision-making of the actors and that the analyses and models can be turned into business value or benefits, such as cost savings and increased revenues.

5 Conclusions

The model was developed to demonstrate the value of fleet life cycle data for the actors in a fleet ecosystem. Understanding the value of fleet data is important for companies in order for them to develop fleet data utilization both inside the company but also with the stakeholders in their fleet ecosystem. Fleet data are usually fragmented between multiple actors, and the actors in the ecosystem need to develop their fleet life cycle data management process to generate value. Because the data only has value when used, it is important to promote the utilization of the data in decision-making, instead of just storing the data in data warehouses. Also, the efforts to assess the value of information in literature are scarce, and thus more research is needed to evaluate and model the value of information. This paper contributes to the theoretical discussion by increasing understanding on the value of information and creating a logic for modeling the value in collaboration within the fleet ecosystem. As for managerial implications, the developed tool can be utilized by managers in developing data utilization in their business operations. The model enables analyzing the benefits, costs and value of IoT and data analysis investments for business and developing collaboration in data utilization and data-based services with the stakeholders.

The developed model presents a simplified example of a fleet ecosystem and the value of fleet data for each actor in the ecosystem. The model can work as a tool to understand the relations of the actors in the fleet data refining process and how the ecosystem can create value more efficiently from fleet data that is currently fragmented and the full potential of which remains unused. If we consider the value of information in the ecosystem, we need to remember that the objectives of the actors may differ and the value that should be maximized needs to be considered case-specifically. The model can be used by the actors, e.g. the equipment provider, when developing new fleet analysis services or other data-based services and when the profitability of developing and maintaining those services need to be understood. The profitability can be viewed for each actor or for the ecosystem as a whole. Thus, the model can also been used as a tool for developing collaboration between companies. For researchers, the model can work as a tool to study the effects of data utilization on business and to increase knowledge about the value of information.

The results of testing the model demonstrate the complexity of fleet data utilization and valuation in an ecosystem. The roles in the data refining process affect the costs and benefits of each actor, and the role of each actor should be meaningful in order to sustainably develop data management in the ecosystem. Thus, service agreements and pricing policies are essential, but the vital starting point is to understand the costs and benefits of each actor. The model can be used as a tool to test different pricing scenarios and service agreements to maximize the value of collaboration.

As for the limitations of this paper, the model is tested with illustrative data from a fleet ecosystem consisting of three actors. The illustrative data is compensated with sensitivity analysis to deepen the discussion and analysis of the results. In addition, a simplified and general presentation of the model is presented but it enables applying the model to other kinds of fleet ecosystems as well. The fleet could be more complex and more actors involved in the value creation. However, the presented model and testing it with illustrative data emphasize the main variables and effects of the model. More research is also needed in defining the data refining level and its effects on costs and benefits. The presented method of evaluating the data refining level as a percentage defined by expert judgment creates an interesting point for further research.

Further research should continue to examine the value of data for businesses in ecosystems, which can be done e.g. by modeling the logic of valuation further and by testing and simulating case ecosystems. Research is needed to examine the costs of data processing in detail, i.e. what are the real costs of different actors. In addition, defining the benefits and verifying which benefits result specifically from the developments in data utilization is challenging, and thus further research is needed. The topic is highly interesting from both academic and managerial perspectives, while collaboration between companies in data utilization is becoming ever more essential when creating value for business.

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