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A Pricing Model for Internet of Things -Based Fleet Services to Support Equipment Sales

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ABSTRACT

Servitization and rapid technological development have made data-based services a feasible way for many manufacturing companies to increase their cash flow and support their core products. In this paper, an analytical model is presented for studying the development costs and pricing of new Internet of Things -based services for especially populations, or fleets, of industrial production equipment and machines. The model suggests the optimal price of a fleet service as a function of the life cycle of the service, the required rate of return, the size of the fleet, and the extent of economies of scale in fleet research and development. The paper contributes to the research on servitization of manufacturing, and sheds light on the different natures of service and equipment sales. Also a numerical study is presented to bring forward the managerial implications of the model.

Keywords: costing; investment; management; equipment; cost benefit

Introduction

Servitization of manufacturing has emerged as a way of producing stable cash flow to support the installed base of products, responding comprehensively to customer needs, and gaining novel competitive advantage (Oliva & Kallenberg 2003). According to the 2015 financial statements of big manufacturing companies, the share of their revenue created by services is extensive (for example Xerox with 56%, Rolls-Royce with 50%, and Konecranes with 44%). On the other hand, the Internet of Things (IoT) -based new service concepts can introduce smart, automated products to the markets (Pletikosa Cvijikj & Michahelles 2011). This development can be seen to have vast business potential for e.g. equipment manufacturing companies or information service providers both in B2C and B2B markets (see e.g. Gubbi et al. 2013). This is supported for example by Baines et al. (2009), who note that the financial potential of servitization is emphasized in industries with an extensive installed base, or fleet, of products.

According to Tywoniak et al. (2008, p. 1555), a fleet could be defined as “a population of similar entities”. The motivation behind fleet management is the potential to utilize data, technology, or other resources in managing these populations. Traditionally, the literature has discussed mainly truck fleets (Preble et al. 2015), aircraft fleets (Grampella et al. 2016) and ship fleets (Leger & Iung 2012) either in military or industrial contexts. However, also the idea of seeing industrial production equipment as fleets has been presented (see e.g. Kinnunen et al. 2016; Medina-Oliva et al. 2012) to absorb the benefits of fleet management in the logics of modern production.

So far, especially in industrial (B2B) settings, the adoption of new IoT-based technologies and service concepts has not met the high expectations. Uckelmann et al. (2011) describe the lack of models and logics to share the costs and benefits of IoT investments between companies as one of the main reasons hindering the adoption. Combined with the need to adopt the principles of service business, it is no wonder that many companies are struggling with assessing the profitability and pricing of their potential IoT-based new services. Regarding servitization of manufacturing, Neely (2008) has empirically shown that servitized companies tend to struggle in creating enough additional revenue to cover the development costs required when developing services to support the product installed base. In practice, data-based services have often been seen as an additional part to the physical product, and thus their business potential has not been even thought of.

In this paper we present a model for addressing the development costs and pricing of new IoT-based services, especially for equipment fleets. We study the impact of the size of the fleet, the economies of scale, the targeted life cycle, and the rate of return on the costs and pricing of IoT-based services. The features of service production are also set against those of equipment manufacturing business. A numerical study is used to bring forward the managerial implications of the model.

In the next section of the paper, the research background is addressed from the perspectives of costing and pricing IoT-based services, as well as fleet management models. After that, the model is presented, and later demonstrated with a numerical study. The paper ends with conclusions.

Background

Costs of investing in Internet of Things -based technologies

The IoT technologies provide a platform for introducing intelligence to products and services, e.g. via automatic status updates, service requests, operation optimization, spare part procurement, fault reports, and finally recycling (López et al. 2011). Niyato et al. (2015) present the IoT as a four-tier system, the tiers being: 1) devices, 2) communications and networking, 3) platform and data storage, and 4) software layer for data management and processing. These tiers can be used as a basis for investment appraisal, but so far the empirical examples of IoT cost assessments have been scarce. In practice the costs of adopting the IoT have been approached through e.g. the costs inherent in adopting radio-frequency identification (RFID, see Uckelmann & Scholz-Reiter 2011). These costs include mobile devices (e.g. RFID tags, sensors), aggregation hardware and software (e.g. readers, antennas, cabling), integration to middleware and updating existing systems (e.g. ERP, PLM, SCM), training, reorganizing the business processes, new system procurement (as well as installation and training), costs of inter-organizational communication (e.g. negotiations on data requirements and information security), as well as running and maintaining the system (including hardware and software updates, electricity, labor, data storage and analysis etc.). It should also be noted that, as stated by Huisman (2001) and Kärri (2007), the fast progress of information and communication technologies emphasizes the relevance of timing in technology investments.

The value and price of Internet of Things –based services

According to Rayport and Sviokla (1995) the emergence of virtual products and services has changed the notion of economies of scale and scope, as the value of digital assets can be reharvested in multiple business transactions. However, so far empirical research on the economies of scale present in digital services has not been presented. There are studies (e.g. Hadjinicola 1999) that refer to the classic economic theories presented by e.g. Hayes and Wheelwright (1984) when stating that the average unit cost is a convex function of the quantity produced. Bucherer and Uckelmann (2011) refer to several specific laws of information as an asset, originally presented by Moody and Walsh (2002).

Niyato et al. (2015) have studied the economics (e.g. cost-benefit analysis and pricing) of IoT-based services. They point out that some cost-benefit analyses on IoT adoption, usually based on RFID investments, have been documented (see Uckelmann 2012). They discuss the notion of an IoT application marketplace presented by Munjin and Morin (2012), where data brokers can sell the IoT data and applications. The utility theory is discussed as a feasible approach in pricing IoT-based services, and accordingly, a game theory –based model has been introduced for studying the price competition of these services. Other potential pricing logics for IoT-based services include incentives to rewarding information sharing (see Uckelmann et al. 2011), models for cost and benefit sharing (see Uckelmann & Scholz-Reiter 2011), market equilibrium approaches (see Chavali & Nehorai 2012), and auctions (see Zhang et al. 2013). Bucherer and Uckelmann (2011) note that the price for the information has typically been sunk to the price of the physical product because customers assume information to be free.

Existing models for fleet management

Various models for fleet management have been presented in the literature. However, the fleet described in existing work has invariably been limited to vehicle/transportation fleets such as cars, trucks, ships, airplanes etc., and the potential of fleet management in relation to production equipment has not been addressed extensively. The existing fleet management models include e.g. defining the optimal fleet size (see Eftekhar 2015; Pascual et al. 2013), optimizing fleet renewal through lease contracts (Neboian & Spinler 2015), pricing freight carrier services (King & Topaloglu 2007), and decreasing the size of the required prototype fleet in the automotive industry (Lockledge et al. 2002). Economies of scale have been addressed for instance by Cullinane and Khanna (2000), who have modeled operating large containerships as opposed to smaller ones in shipping. Fernández et al. (2005) have studied the existence and nature of economies of scale in bus fleet service production. They conclude that economies of scale emerge in this business through fixed and administrative costs. Desa and Christer (2001) have studied the maintenance of a bus fleet in a developing country where fleet maintenance data was not properly utilized. They report that the lack of fleet data and its analysis appeared to emphasize problems related to e.g. decreased fleet availability and increased maintenance costs.

The existing fleet management models do little to shed light on the investment and pricing of data-based fleet services. This is how we contribute to the academic discussion with our model. Unlike previous research, we take the management of production equipment fleets into account as well.

A model for estimating the costs and pricing of IoT-based fleet services

Service-oriented thinking emphasizes the role of measuring the value-in-use received by the service customers instead of value-in-exchange (see e.g. Vargo & Lusch 2004). However, value-in-use is highly dependent on the specific service and the context in which it is delivered. Pascual et al. (2017) present a quantitative model on use-based service pricing in product-service systems. They have linked the price of the service to product reliability. Ulloa et al. (2017) introduce a model to maximize the net present value of a performance-based maintenance service contract for each company in the supply chain. They have measured the performance of the service based on asset availability. In the context of this paper, depending on the specific IoT-based fleet service the value-in-use can also include several other tangible and intangible value creating elements. The intangible elements can be e.g. increased safety, improved flexibility, or higher customer satisfaction, the measuring of which would require qualitative methods in addition to numerical modeling (Bititci et al. 2011). At the moment the existing research and typology of fleet-based IoT services is not extensive enough to build a pricing model based on value-in-use. Instead, a cost-based pricing logic is adopted here to create a general model to contribute to the decision making of the fleet manufacturer.

Our model addresses IoT-based service development, based on investments focused on developing e.g. sensor technologies, software, databases, data transfer, or some other aspects of the IoT. We assume that a fleet manufacturer develops or purchases IoT-based software and/or hardware, which then incurs R&D costs, and gains revenue with economies of scale after installing the service concept to customers.

It can be presumed that the R&D costs of IoT technology (*C*) are defined through a polynomial function of the size of the fleet (q), as well as technology-related parameters a and b as follows:

$$C = aq^b. \tag{1}$$

It is thus assumed that when $b < 1$, the unit cost (*C/q*) decreases when the size of the fleet increases. On the other hand, when $b > 1$ there are diseconomies of scale. This assumption is consistent with the body of knowledge on learning curves (see e.g. Hayes & Weelwright 1984), and with the four-layer description of the IoT presented by Niyato et al. (2015), as at least two of the four layers (platform layer and software layer) can be viewed as sources of fixed costs not directly dependent on the number of assets in the fleet. The same equation has commonly been used to describe long term cost functions (see e.g. Naylor & Vernon 1969). Similar logic has also been adopted in estimating capital needs based on past capital costs. For instance Humphreys (1991) has reported a scale factor of 0.6 to represent the economies of scale. The R&D cost of the IoT technology, C, can be seen to comprise various cost components. Following the categorization by Uckelmann and Scholz-Reiter (2011) presented above, it can be said that

$$C = \sum_{d=1}^{9} C_d, \tag{2}$$

where C_1 is the cost of mobile devices,

C_2 is the cost of aggregation hardware and software,

C_3 is the cost of integrating to middleware and system updates,

C_4 is the training cost,

C_5 is the cost of reorganizing the related business processes,

C_6 is the procurement cost of new systems,

C_7 is the cost of inter-organizational communication,

C_8 is the cost of running and maintaining the system, and

C_9 is other possible costs.

It should be noted that according to the logic in equation (1), in order to assess the costs and feasible price of IoT-based fleet services, the size of the fleet must be known in advance. The pricing of the services can be analyzed through the cash flow diagram presented in Figure 1.

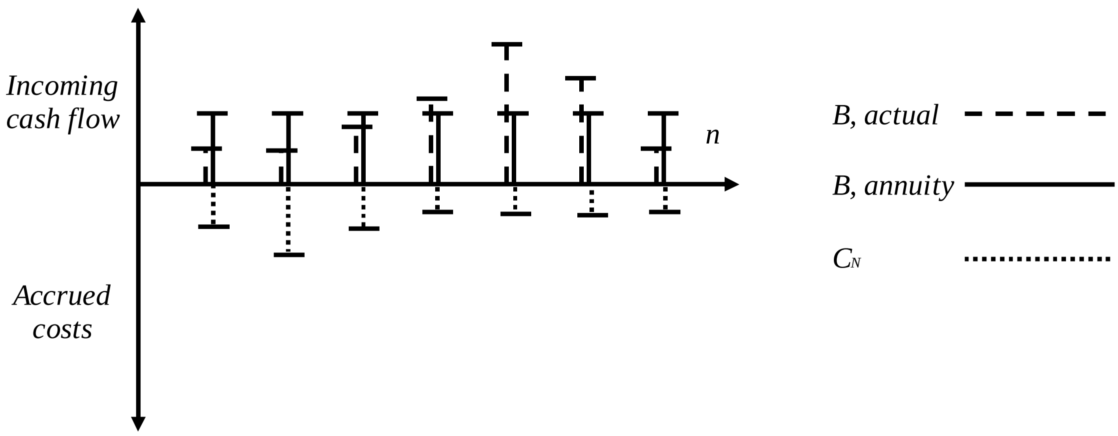

Figure 1. The benefits (*B*) and R&D costs (C_N) measured as the annual cash flow from IoT-based services during the life-cycle of the service (*n*).

R&D costs are typically accrued during a period of several years, or even during the whole life cycle of the service. The costs can be divided along the life-cycle of the service by using the annuity method, which is based on the principles of net present value calculation. The price of the service (*B*) can thus be presented as

$$B = \frac{i \sum_{N=1}^{n} \frac{\sum_{d=1}^{9} C_{dN}}{(1+i)^N}}{1-(1+i)^{-n}}, \tag{3}$$

where we denote by *i* the required nominal return of the investment, by C_N the R&D costs from each year, and by *n* the targeted life-cycle of the service. Next, the nominal return of the investment can be presented as a function of the real interest rate (i_R) and the inflation rate (i_F) as in

$$i = i_R + i_F + i_R i_F. \tag{4}$$

In this case, the real interest rate is chosen for the model. When equation (4) is presented accordingly and inserted into equation (3), we get

$$B = \frac{\frac{(i-i_F)}{(1+i_F)} \sum_{N=1}^{n} \frac{\sum_{d=1}^{9} C_{dN}}{(1+i_R)^N}}{1-[1+(i-i_F)/(1+i_F)]^{-n}}, \tag{5}$$

The annuity method as described in equation (3) presumes a discrete rate of return, compounded once a year. To study the impact of the targeted rate of return also in a context where cash flows are incurred on a continuous basis, the concept of continuously compounded interest can be introduced to the model as

$$\lim_{p/i \to \infty} \left[\left(1+\frac{i}{p}\right)^{p/i} \right]^i = e^i, \tag{6}$$

where p is the number of times i is compounded during the year. To differentiate the discrete rate of return from the continuous one, we from now on denote the continuous rate by j. The relation between i and j can be written as

$$1 + i = e^j, \tag{7}$$

resulting in

$$j = \ln(1 + i). \tag{8}$$

Thus equation (5) would transform into

$$B = \frac{\ln\left[1 + \frac{(i - i_F)}{(1 + i_F)}\right] \sum_{N=1}^{n} \frac{\sum_{d=1}^{9} C_{dN}}{(1 + i_R)^N}}{1 - \{1 + \ln[1 + (i - i_F)/(1 + i_F)]\}^{-n}}. \tag{9}$$

Introducing the cost function to the equation, it can be said that with the discrete rate of return

$$B = \frac{\frac{(i - i_F)}{(1 + i_F)} aq^b}{1 - [1 + (i - i_F)/(1 + i_F)]^{-n}}, \tag{10}$$

or with the continuously compounded rate of return

$$B = \frac{\ln[1 + (i - i_F)/(1 + i_F)]\, aq^b}{1 - \{1 + \ln[1 + (i - i_F)/(1 + i_F)]\}^{-n}}. \tag{11}$$

The future costs and capacity of IoT-supported fleets are uncertain and can be assumed to evolve over time. In addition to the possibility of repricing the services, this uncertainty related to e.g. technology and input costs could also be addressed through real options modeling by changing equation (1) into

$$C = aq^b + R, \tag{12}$$

where R is the (positive or negative) value of a specific real option, taking into account the uncertainty and learning included in the R&D investment. An interesting approach for strategic investment decisions has been presented by Smit and Trigeorgis (2017) who suggested the value of real options to be quantified as a tradeoff between flexibility and early commitment. Several authors have also studied IT related investments from the perspective of real options (see e.g. Benaroch 2017; Dimakopoulou et al. 2014).

While real options modeling can provide valuable insight into decision-making situations with respectively detailed data, the method is highly sensitive to changes in the model parameters and might not be the best approach in situations where the data is based on rough estimates and does not provide a solid ground for addressing the option values. As Dimakopoulou et al. (2014) have noticed, many real options modeling studies have used hypothetical data and cases. Trigeorgis and Reuer (2017) also note that real options models often use assumptions that make it challenging to implement them in practical, real-life contexts.

To address the uncertainty related to the future costs and capacity of the fleets, we link the size of the fleet with a time variable *t* and a fleet-specific parameter *M:*

$$q = e^{Mt}. \tag{13}$$

This supports the trends and forecasts of the exponentially growing amount of connected devices presented by e.g. Forbes (Press 2016), Gartner (2017), and Statista (2017). Many researchers have foreseen the end of the exponential technical improvements predicted by Moore's law, but in a way the vast connectivity provided by the IoT is seen to extend the development in the future (see e.g. Freeman & Drobot 2016; Page 2016). This assumption is also congruent with the theories of learning curves, discussed e.g. by Hayes and Weelwright (1984). When equation (13) is inserted into equation (10) for the discrete rate of return, we get

$$B = \frac{\frac{(i - i_F)}{(1 + i_F)} a e^{Mtb}}{1 - [1 + (i - i_F)/(1 + i_F)]^{-n}}, \tag{14}$$

and similarly with the continuously compounded rate of return

$$B = \frac{\ln[1 + (i - i_F)/(1 + i_F)]\, a e^{Mtb}}{1 - \{1 + \ln[1 + (i - i_F)/(1 + i_F)]\}^{-n}}. \tag{15}$$

Thus the price of the service depends on the life-cycle of the service (n), the required real rate of return (i_R), time (t), as well as the fleet- and technology-related parameters a, b and M, which define the extent of the economies of scale and the growth of various equipment fleets.

Finally, the payback period for the service development can be calculated as C/B, and the objective criteria is

$$C/_B \leq n. \tag{16}$$

A payback period close to the length of the service life cycle would of course not result in feasible profitability. In practice the payback period must be significantly shorter than the life cycle for the service to create profit. Although the payback period does not assess the profitability of the service investment as such, it links the development costs and annual cash flows to the life-cycle of the service. This provides a valuable insight as the targeted length of the life-cycle can be regarded as one of the most important variables in developing dynamic technology-based services.

Numerical study

Introduction to the numerical data

In this section our model is used for a numerical study with case data from the financial statements of Konecranes, a large equipment and service provider in the lifting business that has recently acquired Terex MHPS and become the world leader in the industry. Konecranes' investments are studied separately for equipment and service sales to show the main differences between the two.

To verify our assumption of the relation between costs and the size of the fleet described in equation (1), we plotted the costs and volume (net sales) of Konecranes' equipment and service sales respectively from years 2000 to 2015. The costs were plotted as sums of both the variable and fixed costs of each business segment. We then assessed the goodness of fit of our model to the data as opposed to several alternative models. The coefficients of determination calculated during this assessment are presented in Table 1 below. Konecranes' business is stable, and the scale factors *b* are relatively close to 1, which caused the R^2 to be very high for all of the tested models, making them applicable for the study. However, the highest coefficients of determination were received with the original model, and thus it was used in the numerical study.

Table 1 The goodness of fit of alternative models to the data

Model		Coefficient of determination	
		Equipment sales	*Service sales*
Power	$\boldsymbol{C = aq^b}$	$\mathbf{R^2 = 0.9964}$	$\mathbf{R^2 = 0.9967}$
Polynomial	$C = aq^2 + bq + x$	$R^2 = 0.9912$	$R^2 = 0.9961$
Linear	$C = aq + b$	$R^2 = 0.9910$	$R^2 = 0.9957$
Exponential	$C = ae^{bq}$	$R^2 = 0.9754$	$R^2 = 0.9873$
Logarithmic	$C = a\ln q + b$	$R^2 = 0.9725$	$R^2 = 0.9760$

To determine the economies-of-scale parameters *a* and *b* for service and equipment development at the company, the volume (representing *q*) and accrued costs (representing *C*) of the service business and equipment sales were plotted for the period 2000-2015, and least squares approximation was used to fit aq^b to the data. The results showed that the service development had benefited from small economies of scale (the *b* being 0.96), while in the equipment sales, clear economies of scale could not be found. On the other hand, parameter *a* was found to be 1.18 for services and 0.85 for equipment. The target real rate of return, i_R, was calculated for service- and equipment-related investments by dividing the earnings before interest and taxes (EBIT) with the invested capital and eliminating the effect of inflation, as shown e.g. in equation (5). The inflation rates used were those documented by the World Bank (2016). The rates of return were calculated for the period 2010–2015, and the average values were used in the numerical study. For the fleet size (q), the starting level of 10 was used for both services and equipment. In the analysis to follow, the size is varied up to 20 000 units to inspect the importance of the fleet. The targeted life-cycle (n) was set to 5 years for IoT-based services and 15 years for equipment development. Table 2 below summarizes the basic levels of the various parameters for the two types of investments.

Table 2 The basic levels of modelling parameters for the numerical study

	Service development parameters	*Equipment development parameters*
a	1.18	0.85
b	0.96	1.00
q	10	10
i_R	36%	14%
n	5 years	15 years
B	5.3772 euros	1.5965 euros

In the following analysis, only the discreet rates of return have been used. The model can also be used to study the continuously compounded interest rates, but since the difference between the two tend to be relatively small they are not addressed here. In general, it can be said that compared with the discreet interest rates, smaller unit prices are required with the continuously compounded interest rate to achieve the targeted benefits and profitability. This is because the interest rate is compounded more frequently, and with time there is more interest gained on the interest itself.

Economies of scale in IoT-based fleet services

The role of economies of scale in IoT-based fleet service investments is addressed through studying the technology-related economies of scale -parameter (*b*), as well as the size of the fleet (*q*). Figure 2 shows how the extent of the economies of scale, measured through *b*, impacts the required unit price (*B/q*) in service and equipment development, respectively. The dashed lines depict the basic levels of *b* for both categories.

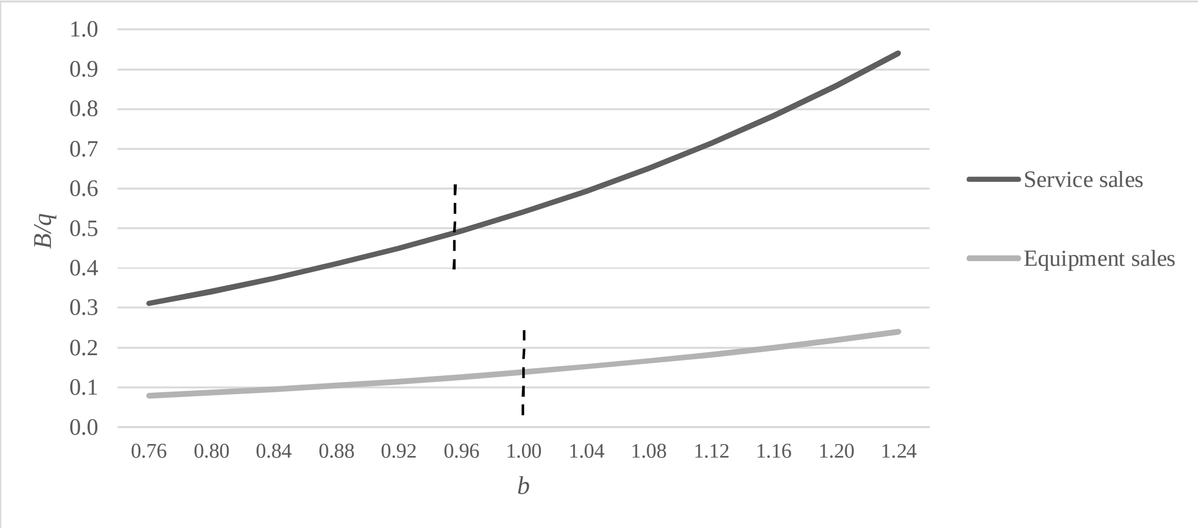

Figure 2 The impact of the economies of scale (*b*) on the required unit price (*B/q*).

The role of the economies of scale seems to be more extensive in the service business than in equipment sales. The proclivity for economies of scale creates potential for achieving lower unit prices in IoT-based services, but on the other hand, their sensitivity for diseconomies of scale create a risk for higher required unit prices, compared to equipment business. However, the causes and repercussions of this difference on the business of an equipment-service provider are likely to be complex and cannot be analyzed based on this data. Some insight into the topic has been previously presented by e.g. Kastalli and Van Looy (2013), who noted that some resources and capabilities obtained through the manufacturing business actually enable companies to achieve economies of scale and scope in their service production. They also concluded that an increase in equipment sales helped generate more service sales for their case company, and vice versa. Further research is needed on the topic before service and equipment businesses can be optimized based on their perceived economies of scale.

Table 3 The impact of the size of the fleet (q) on the development unit cost (C/q)

Size of the fleet (*q*)	**1**	**10**	**50**	**100**	**200**	**500**	**1 000**	**2 000**	**5 000**	**10 000**	**20 000**
Development cost (*C*) for services, €	1	**11**	**50**	**98**	**191**	460	895	1 741	4 197	8 164	15 881
Development cost (*C*) for equipment, €	1	9	43	85	170	425	850	1 700	4 250	8 500	17 000
Unit cost (*C/q*) for services, €	1.18	**1.08**	**1.01**	**0.98**	**0.95**	0.92	0.90	0.87	0.84	0.82	0.79
Unit cost (*C/q*) for equipment, €	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85

Table 3 presents the impact of the size of the fleet (q) on the development unit cost (C/q). The table shows that the size of the fleet does not impact the unit cost of equipment. This is due to the fact that when defining the modeling parameters constant returns of scale were assumed for equipment development. For service production, the unit costs decrease when the size of the fleet increases. In practice the impact is largest when dealing with fleets of 10 to 200 units; with bigger fleets the economies of scale have a smaller effect on the unit price.

Life cycles and rates of return in manufacturing business and service sales

Figure 3 and Table 4 show how the targeted life-cycle (n) of the developed service or equipment affects the payback period of the investment (C/B) and the required unit price (B/q).

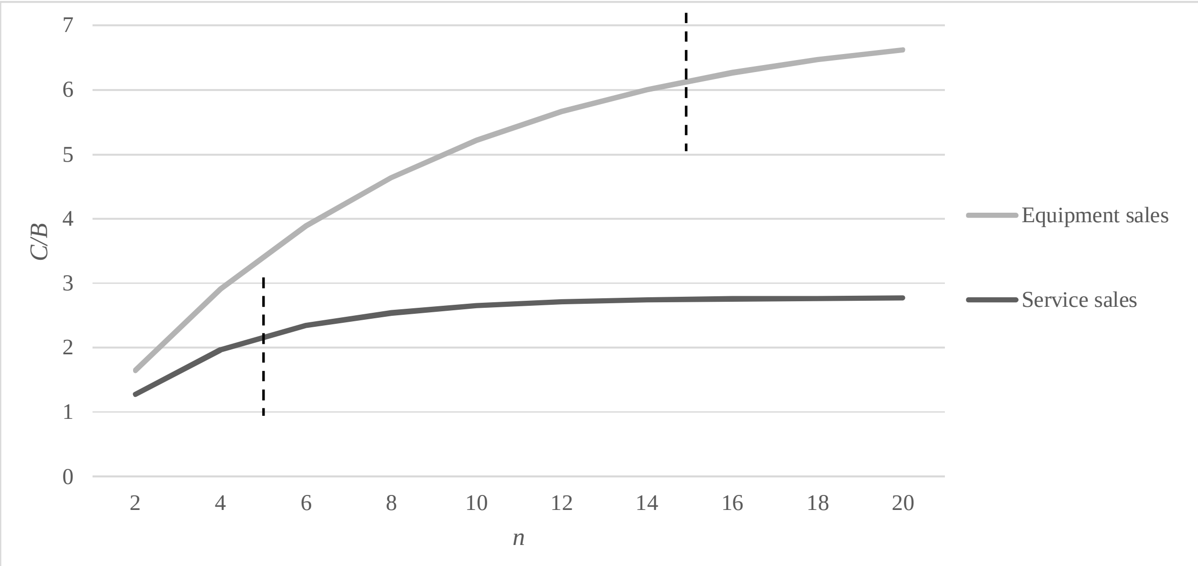

Figure 3 The impact of the targeted life-cycle of the service or equipment (*n*) on the payback period of the investment (*C/B*).

It can be concluded from figure 3 that compared to equipment sales, service development has a potential for significantly shorter payback periods. The payback periods for services also stabilize quickly, already with service life cycles of 6 years or more. Regarding equipment sales, stability in payback periods is only achieved after life cycles of around 20 years. Thus the difference between the two is highlighted when the life cycle is over 6 years. This also means that from the basic level of the service life cycle, 5 years, only quite small increases in service life cycles are needed to achieve "cast inflow –creating" years after the investment has already paid itself back. In practice companies can create extensive business by selling several consecutive IoT-based services to support the life cycle of an individual piece of equipment.

Table 4 The impact of the targeted life-cycle of the service or equipment (*n*) on the required unit price (*B/q*)

Targeted life cycle (*n*), years	**2**	**4**	**6**	**8**	**10**	**12**	**14**	**16**	**18**	**20**
Required unit price (*B/q*) for services, €	**0.84**	**0.55**	**0.46**	**0.42**	0.41	0.40	0.39	0.39	0.39	0.39
Required unit price (*B/q*) for equipment, €	**0.52**	**0.29**	**0.22**	**0.18**	**0.16**	0.15	0.14	0.14	0.13	0.13

Table 4 shows that the difference between services and equipment is not as extensive as above when measured with the required unit price. This is at least partly caused by the higher required rate of return of services (36%) compared to equipment sales (14%). The table also shows that for both services and equipment, the decrease in the required unit price reduces with life cycles longer than 8 to 10 years. The impact is greatest with short life cycles, thus especially in service development the significant role of life cycle planning should be acknowledged.

Figure 4 shows how the targeted rate of return (i_R) impacts the payback period of the investment (*C/B*). The figure highlights the fact that the service business seems to be less sensitive to changes in the required rate of return. This makes service sales a profitable way of creating stable cash flow to support equipment sales, even in dynamic financial situations. On their website Konecranes has set their long-term operating margin target to 10%, which during 2010–2015 would have coincided with a real rate of return of about 34% for all business in total. This objective is considerably closer to their current rate of return of service sales (36%), compared to their equipment sales (14%). Thus the future investments of the company will most likely be directed to the development of supporting services. On the other hand, it can be seen that if the rate of return for equipment sales could be increased e.g. from 14% to 25%, the respective payback period would decrease from around 6 to 4 years. Thus the importance of the targeted rate of return should be acknowledged in equipment-related investments.

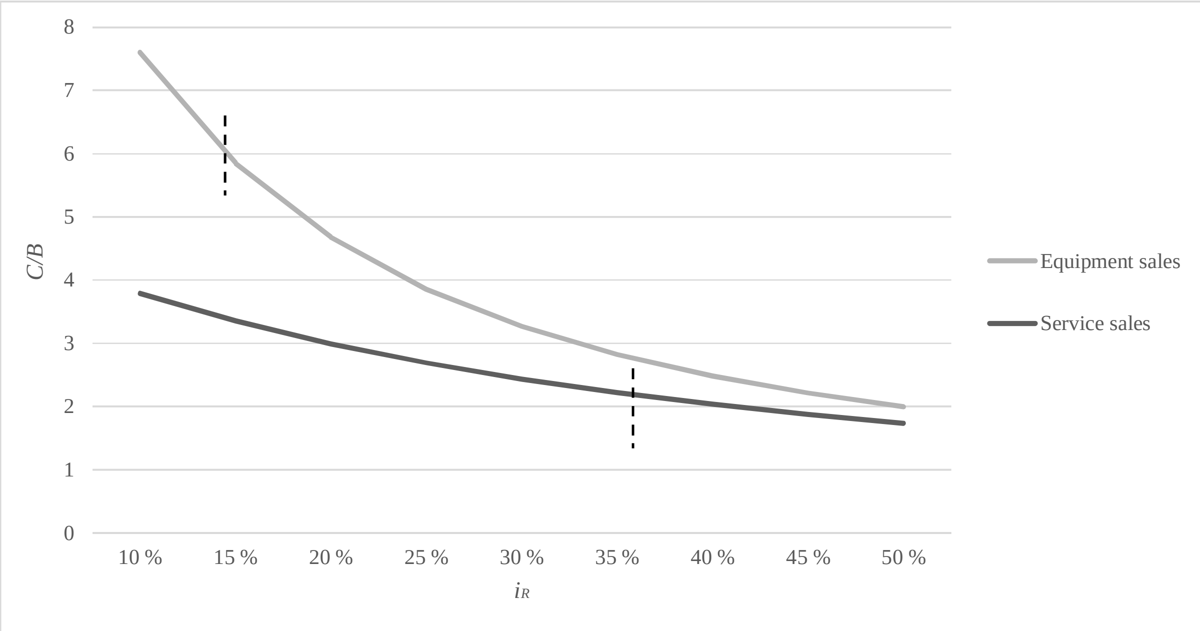

Figure 4 The impact of the targeted rate of return (i_R) on the payback period of the investment (C/B).

Finally, Figure 5 depicts how the data used in the numerical analysis fits the authors' assumption on the connection between the size of the fleet (q) and time (t) as described in equation (13). For equipment sales, the R^2 is 0.7495, and for service sales 0.9275. Thus the assumed exponential time-sensitivity of the fleet seems to concern especially the service business of the selected case. It is to be noted that the goodness of fit for equipment sales would improve to 0.8175 if the years 2008 to 2011 (9 to 12 in Figure 5), strongly affected by the economic recession, would be ignored. In practice, most companies are well aware of the dependence of equipment sales on the current economic conditions, however forecasting future demand reliably has proven to be a challenge. Many companies strive for more stable cash flows through increasing the share of service sales in their business. In future research real options modeling could be applied to address the changes in equipment sales caused by potential significant market changes.

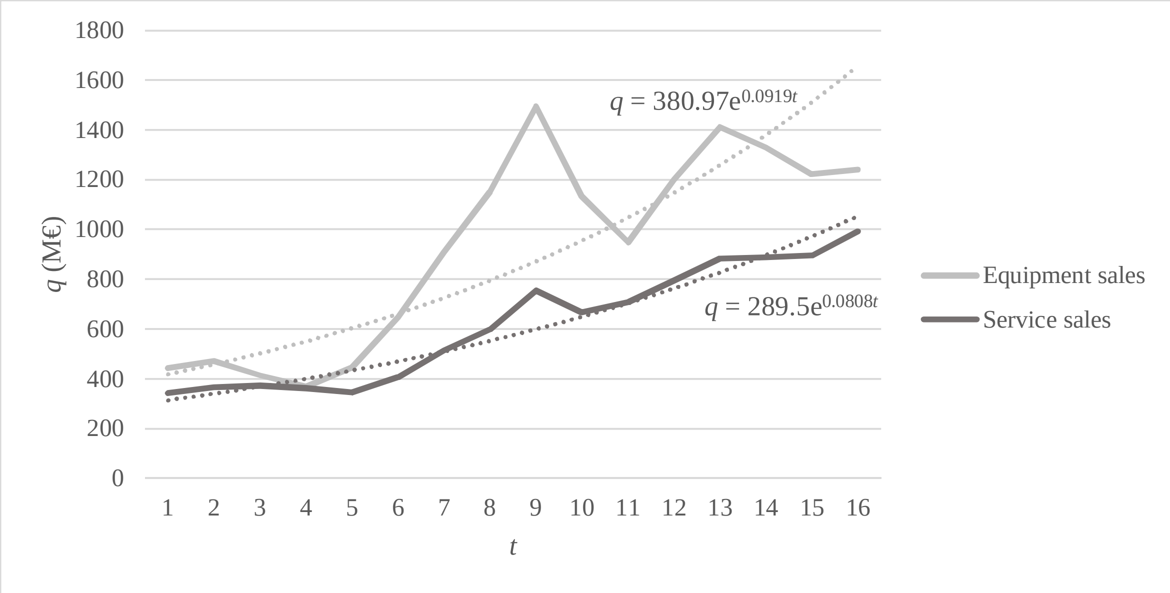

Figure 5 The impact of time (t, 2000-2015) on the size of the fleet (q) on the equipment and service sales of Konecranes.

It needs to be remembered that Figure 5, and the data used in the numerical study, only provides a limited view of the equipment and services produced by Konecranes. In practice, the company's offering includes rapidly developing IoT-based services and smart devices but also a large amount of "traditional" services and unconnected equipment. To reach reliable conclusions, it should thus be included in future research to study the various types of IoT-related investments and their connection to time in more detail.

Conclusions

We have presented a model for studying the target price and life-cycle costs of developing IoT technology -based services for fleets. It can be concluded that the optimal price of an IoT-based fleet service depends on the life cycle of the service, the required return, the size of the fleet, and the extent of economies of scale in fleet R&D. Our numerical study shows how the variables impact the required price and development costs of the service in a context where small economies of scale exist in service production. Services, compared to equipment sales, can lead to bigger economies of scale, shorter payback periods, and higher rates of return. It is also noted that the investment payback periods in service business are less sensitive to changes in the targeted rate of return.

Our model contributes to previous research by taking account of the concepts of pricing and costing of IoT-based service development in fleet environments. It also enables analyzing the differences between service and equipment sales. The business implications of this paper include providing transparency into the profitability of fleet-based IoT investments. In order to optimally support equipment sales with IoT-based services, it is crucial to understand which parameters the profitability is the most sensitive to. Of the parameters discussed in this paper, the size of the equipment fleets and the economies of scale have not usually been included in investment appraisal models, and it is not evident how they should be exploited to create additional business value. So far most companies have not properly analyzed their decisions to invest in IoT because accurate forecasts on costs and profits have not been available. This paper aims to encourage industry to model their pricing and investment decisions with the data and estimates they have, rather than only rely on subjective decision making criteria. The model contributes especially to contexts where IoT-based services are being designed to support critical, expensive products with long life cycles. This kind of contexts can usually be found in for instance oil and gas, railway, utility, and heavy process industries such as mining (see Parida & Kumar 2009).

The limitations of the study include ambiguity in calculating the parameters of the model. In the numerical study, financial statement data was used, but for coherent managerial conclusions the quality and accuracy of the data should be paid more attention to. The pricing model presented in this paper is cost-based and does not take the value-in-use of the customer or the service provider into account. Topics for further research include validating the model with more extensive data and addressing the various parameters in different contexts in closer detail. A typology of IoT investments would be needed to understand the potential and challenges of different investment appraisal techniques (including value-based pricing and real options modeling). As presented by Smit and Trigeorgis (2017), strategic decisions can be seen as trade-offs between long-term commitment and flexibility, and the decision-making context defines the optimal methods and techniques for each investment. When designing IoT-based fleet services, early commitment creates value through e.g. ensuring an adequate size of the fleet which then enables reaching economies of scale in fleet R&D. Flexibility, on the other hand, is needed regarding for instance the life cycle of the service. The optimal life cycle can change at any time due to a number of factors some of which are exogenous and thus difficult to quantify reliably. To address both commitment and flexibility value, the optimal model to support fleet service pricing decisions should, based on Smit and Trigeorgis' (2017) view, include elements of both real options and game theory. In addition to optimizing the price of the fleet service, this kind of model could be used in defining the optimal timing for the investment as well as the optimal size of the fleet.

It should also be noted that in practice the fleet can comprise e.g. assets of various ages, the data of which should be analyzed at least partly independently to optimize the reliability and accuracy of the consequential managerial decisions, but their IoT-based development costs are assessed best on the level of the larger fleet. This creates further challenges for the pricing logic and should be studied in detail in the future.

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