LAPPEENRANTA UNIVERSITY OF TECHNOLOGY

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ASSESSING CUSTOMER PROFITABILITY IN GARBAGE TRUCK ROUTES

Master’s Thesis - 2016

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ABSTRACT

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This thesis examines the customer profitability in garbage truck routes and especially the means to allocate the transportation costs among customers. The study reviews the customer profitability literature and applications and the practices to perform the calculations in the waste management industry. Cooperative game theory is reviewed and applied for transportation cost allocation, when the most suitable model is determined. This study also examines the customer profitability differences inside the routes and performs a worst case scenario analysis using VaR-type thinking. This thesis calculates the customer profitability as the difference of the revenues received and the sum of the costs, which serving the customer required. The transportation costs are allocated using the Shapley value approximation. The average standard deviation of the customer profitability is found to be 13,84 for routes and 2,17 for customers, which indicated that the significant profitability differences are relatively rare and emphasized in individual routes. The results from the VaR-type thinking show that on average, 51,4% of the profits is lost if 10% of the most profitable customers is lost. Thus, 10% of the customers brings over a half of the profits on average.

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Tässä tutkielmassa tarkastellaan asiakaskannattavuutta jäteautojen reiteillä ja erityisesti keinoja allokoida kuljetuskustannuksia asiakkaille. Tutkielma tekee katsauksen asiakaskannattavuuskirjallisuuteen ja sovelluksiin sekä käytäntöihin tehdä asiakaskannattavuusanalyysia jätteenkäsittelyn toimialalla. Tutkielma tarkastelee yhteistoiminnallisen peliteorian käsitteitä ja soveltaa niitä kuljetuskustannusten allokoimiseen sekä tekee suosituksia parhaasta asiakaskannattavuusmallista. Tutkielma määrittelee myös asiakaskannattavuuden eroja jäteauton reittien sisällä ja tekee pahimman skenaarion analyysia käyttäen hyväksi VaR-tyyppistä ajattelua. Lopputuloksena asiakaskannattavuus lasketaan tuottojen ja kustannusten erotuksena, jossa kuljetuskustannukset allokoidaan käyttämällä Shapleyn arvon likiarvoa. Keskimääräinen keskihajonta asiakaskannattavuudessa todettiin olevan 13,84 reiteillä ja 2,17 yksittäisten asiakkaiden tapauksessa. Tämä tarkoittaa, että merkittävät asiakaskannattavuuden erot ovat suhteellisen harvinaisia ja painottuvat vain tietyntyyppisille reiteille. VaR-tyyppisen ajattelun tulokset osoittivat, että keskimäärin 51,4% tuotoista menetetään, jos 10% kaikkien kannattavimmista asiakkaista kadotetaan. Tämä tarkoittaa myös sitä, että 10% asiakkaista tuo keskimäärin yli puolet voitoista reiteillä.

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First, I'd like to thank the community of LUT for all the education, challenges and tools that I received. Although they may not be enough for a lifetime, they are something to start with. A big thanks to my thesis examiner and supervisor Mikael Collan for inspiring lectures and helpful comments and ideas throughout this Master's thesis process. Thank you LTKY for two unforgettable years and incredible people. To sum up, thank you LUT for opening my mind and Student Unions around Finland for opening my eyes.

Second, I'd like to thank Lassila & Tikanoja Oyj for providing me support and an efficient environment to complete this thesis. A great thanks my supervisor Sebastian Aniszewski for conversations and ideas that boosted my work. I thank Elina Ahmasalo for providing me financial data and helping with calculations. I thank Jaakko Uuttu and Tuomas Honkonen for route information and encouraging conversations. Also, I'd like to thank Joni Niemiaho for driving me around with garbage truck for a day and showing the profession. Last, thanks to CEO Pekka Ojanpää and CFO Timo Leinonen for trusting me this subject.

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Faithfully,

Tomi Mankinen

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LIST OF SYMBOLS AND ABBREVIATIONS

ABC	Activity-based costing
ACAM	Alternative cost avoided method
AHP	Analytic hierarchy process
CAPM	Capital asset pricing model
CCPM	Contribution Constrained Packing Model
CGM	Cost gap method
CLV	Customer lifetime value
CP	Customer profitability
CRM	Customer relationship management
L&T	Lassila & Tikanoja Oyj
LP	Linear program
NBD	Negative binomial distribution
RFM	Recency, frequency, monetary value
SBU	Strategic business unit
SOM	Self-organizing map
SVM	Support vector machine
VaR	Value-at-risk
WACC	Weighted average cost of capital

1. INTRODUCTION

The purpose of this Master's thesis is to examine customer profitability in waste management industry. Especially, this thesis concentrates on customer profitability in garbage truck routes. Topic is approached by examining methods for calculating customer profitability in waste management industry and the results can be applied in companies operating in similar industries. This thesis also reviews customer profitability analysis in academic literature and presents a clear picture from ground level cost allocation possibilities to creating shareholder value. The main interest in cost allocation are the alternatives for transportation cost allocation. Thesis also applies value-at-risk (VaR) type thinking for route profitability sensitivity.

This thesis is made as an assignment to Lassila & Tikanoja Oyj (L&T), which is a large waste and environment management company operating in Finland and listed in Helsinki Stock Exchange. It is a service provider in environmental, industrial and facility industries, and renewable energy producer. L&T has over 850 heavy-duty vehicles that it uses for services and nearly 3000 optimized routes in the last five years. (Lassila & Tikanoja, 2016.) This assignment is part of their objective to increase customer understanding capabilities.

1.1 Background

In the 1990's, the need to have more effective management of relationships with customers emerged and customer relationship management (CRM) approach lead to development of new business environment. CRM integrated marketing, sales, supply chain, and customer service functions to achieve greater effectiveness in delivering customer value. (Soltani & Navimipour, 2016.) A crucial role in CRM framework is the concept of customer lifetime value (CLV) which includes a set of techniques that companies can use to evaluate their customer portfolios (Estrella-Ramón, Sánchez-Pérez, Swinnen, & VanHoof, 2013). At the base of CLV analysis is the understanding and knowledge of single period customer profitability, which is also sometimes used as part of CRM (Ryals & Knox, 2007). Thus, following the described hierarchy, understanding customer profitability is essential for successful CRM system and creating shareholder value in the long run.

Customer profitability has its roots in activity-based costing (ABC). In short, calculating customer profitability includes both defining profits and expenses according to activities and calculating their net value for each customer. (Cooper & Kaplan, 1991.) Especially in the waste management industry, understanding customer profitability can be challenging since customer relationships may be complex. They may include collecting waste from customer property, transporting it to waste processing plant, and selling it back to customer as raw material again. Moreover, the same process can take place simultaneously in different parts of country with different collecting and delivering routes.

Furthermore, transportation cost allocation increases the difficulty of customer profitability calculations in waste management industry. Revenues from customers, even though they differ from customer to customer, are easy to allocate, since they are all specified in the time of billing. The costs of waste collection, which mainly consists of the cost of the driver and the cost of the truck, are mostly affected by the location of the customers and their waste containers. The closer the customers are to each other, the more efficient and cheaper it is to collect their waste. When customers are located far away from each other, their waste collection costs increases. In addition, if even two customers are located close to each other, they affect each other’s profitability. Other customer may appear unprofitable, when the one in the neighbor seems extremely profitable. These profitability measures only apply, when waste collection is executed for both of the customers. Whenever one of them is not served or a third customer nearby is also served, their profitability changes. To be able to manage and increase shareholder value, waste collection companies should be able to allocate transportation costs fairly to customers in order to assess the customer profitability.

Moreover, customer profitability information enables the examination of the garbage truck route profitability. It has likewise a direct connection to shareholder value, since it is basically the sum of customer profits in the route. It is typical for the waste management industry that customers put service providers out to tender occasionally, so the chance that profitable customers are lost and the route becomes unprofitable exists. As the industry operates with contracts, the route may become unprofitable even during some customers’ contract period.

The customer profitability information enables the examination of this route profitability sensitivity. Because individual customers can be seen as assets (Gupta & Lehmann, 2003), garbage truck routes can be considered as assets as well. Financial risk management offers several tools for assessing customer risks, which can be applied in this study (Nenonen & Storbacka, 2016). Being able to measure the riskiness of the routes, the service provider can execute actions to decrease the risk.

1.2 Research focus and objectives

The customer profitability examination in the waste management industry is in the center of this research. To tackle the problem, the content of this thesis combines elements from different disciplines. First, marketing literature offers insights to understand the customer profitability and customer lifetime value in wider perspective. Second, accounting literature offers practices for profitability calculations. Third, transportation cost allocation has a long history in the discipline of cooperative game theory. These concepts are illustrated in the next figure.

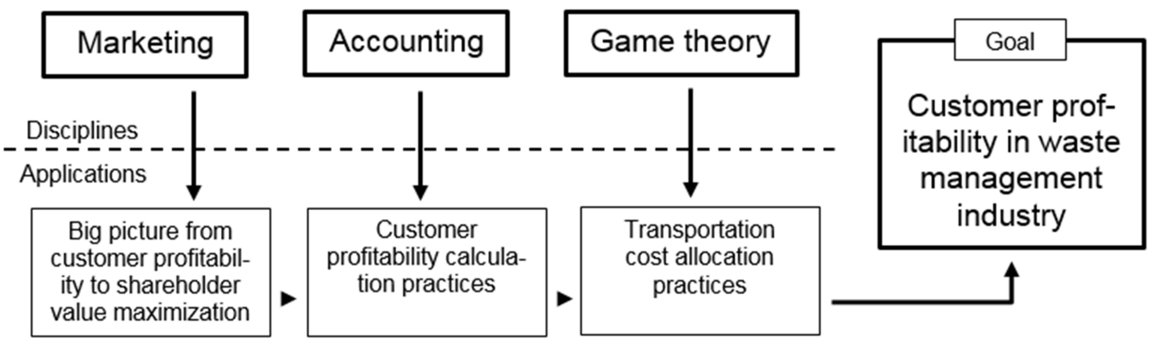


Figure 1. Main disciplines of the study

The problem is approach by familiarizing with the literature of the above disciplines. Then, customer profitability calculations are executed with real data. Thus, this thesis can supplement the studies of customer profitability and transportation cost allocation in garbage truck route cases with real data from Finland. However, the underlying problem is wide and can be applied to different data. Therefore, limitations for the data are necessary to be able to derive more consistent results.

The customers that are examined are corporate customers. In Finland, according to current law, municipality has a right to arrange their waste collection in a way they want (Finnish Waste Act 646/2011). This affects households markets, since municipality makes decisions for the households. Hence, the household waste collection markets vary from municipality to municipality. However, this does not apply in the corporate customer markets. Thus, corporate customers can arrange their waste collection freely. This makes corporate customer markets competitive in every part of Finland. Corporate customers have also contracts that vary from each other, since they have different needs and different contract periods. Some of them are likelier to put service providers out to tender and some just rely on the current service provider. This increases the possibility to have a great variety in customer profitability measures.

In addition, limiting to only corporate customers is not enough, since all kinds of waste cannot be collected simultaneously. In fact, waste fraction exclusions have to be made. The fraction of waste that is collected in the examined routes is mixed waste. Mixed waste is a common waste fraction that has to be collected from majority of the corporate customers. It does not have to be collected as often as bio waste, but the collected quantities are large and service is regularly needed. Since there are lot of mixed waste contracts and thus customers, large amount of data is easier to gather.

These two data limitations steer this study to have more practical implications. As described before, customer profitability analysis has a lot of managerial applications in waste management industry. The results of this research can thus be directly applied in garbage truck routes that include mixed waste and corporate customers. This can be formed as the underlying objective of this study, which is to *examine the customer profitability in garbage truck routes*. By combining the background problem, the disciplines and their applications and the limitations for data, the framework of the focus of this study can be described. It is presented in the next figure.

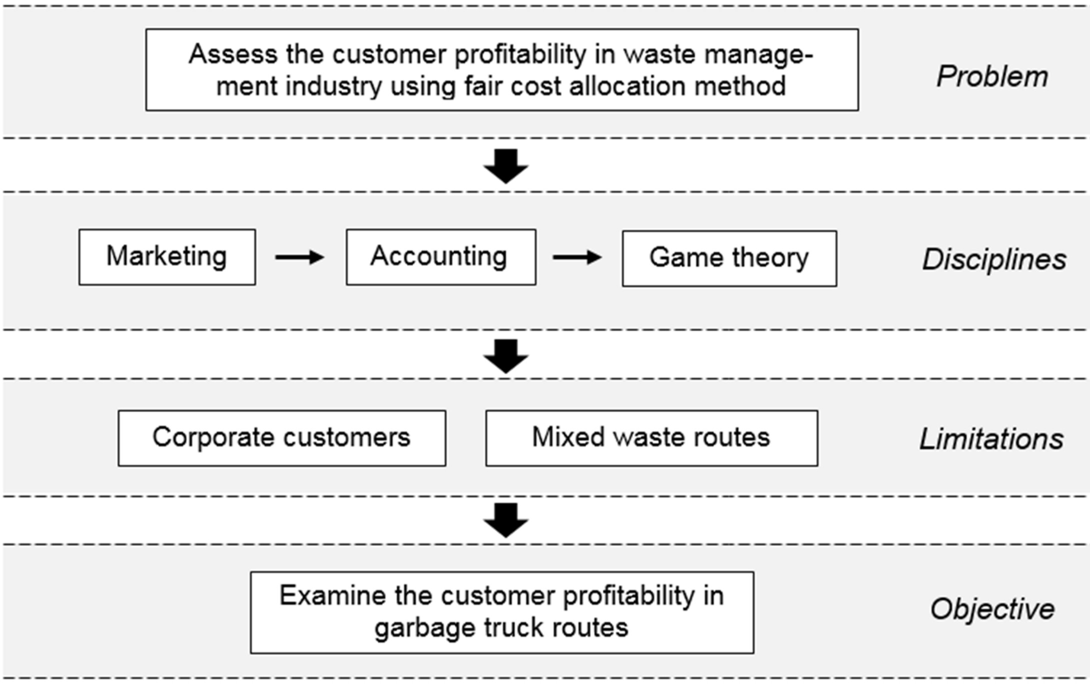


Figure 2. The focus of this study

The figure above summarizes the introduction so far. However, to be able to fulfill the main research objective, more detailed objectives have to be defined. Thereby, the main objective is broken down to research questions.

To be able to examine the main objective, the previous studies of the underlying problem have to be examined. They include empirical studies of the customer profitability and the customer lifetime value and empirical cost allocation cases. The more important are the previous empirical customer profitability studies conducted in waste management industry. These basics provide the current academic knowledge of the subject which can be used to examine the problem further. Thus, the first research question is:

1. How customer profitability in the waste management industry is previously studied in academic literature?

The answer here requires a broad review of theoretical literature of the subjects. With the theoretical basics, the appropriate method to calculate customer profitability can be derived. It requires defining allocation for different kinds of costs. The most difficult are the transportation costs, which can be allocated very differently among customers. Transportation costs form also the largest single costs for customer so appropriate allocation is necessary to reliably measure the customer profitability. To find the appropriate method for the customer profitability, different methods are compared. As a result, the best profitability method is chosen and applied to real data. Thus, the second research question is:

2. How should the customer profitability in garbage truck routes be calculated?

Using the appropriate profitability model, the customer profitability of single customers is obtained from routes and the whole route can be further examined. As mentioned in the background section, customers usually put service providers out to tender once in a while, which may lead to losing profitable customers and unprofitable routes. To assess the risk of route becoming unprofitable, the customer profitability differences need to be examined inside the routes. If no differences between customer profitability is found, route profitability would not change, if customers were lost. Using the appropriate way to calculate profitability and to assess the customer profitability differences in routes, the third question is:

3. How big are the customer profitability differences inside the garbage truck routes?

To get a broader view, the customer profitability differences inside routes are calculated in different cities of Finland and comparisons between the city centers and urban areas are also made. By knowing the differences inside the routes, the riskiest routes can be determined. To assess the severity of the risk that these routes become unprofitable, the route profitability is calculated without 1%, 3%, 5% and 10% of the most profitable customers in the route. This measures how bad things can get at worst, if the most profitable customers were lost at the same time. The fourth research question is thereby:

4. Do routes become unprofitable if 1%, 3%, 5% or 10% of the most profitable customers are lost?

This methodology is also known as value-at-risk in finance literature, where it is originally developed to portfolio risk management. Because this study considers customers, rather than financial portfolios, the concept is referred as VaR-type thinking. This approach is conservative, since it examines the situation where the worst case scenario occurs and most profitable customers are lost. Naturally, it is not likely that all of the most profitable customers are lost simultaneously, but the information can help managers to understand the severity of situation. The results may tell that if the routes are no longer profitable after some percent of the most profitable customers are lost, the risk of unprofitability is existing and actions can be considered. The smaller the percent is needed to make route unprofitable, the more severe the situation is.

Last, to get better view of the research objective, the research questions, their relations and hierarchy, are presented to following figure.

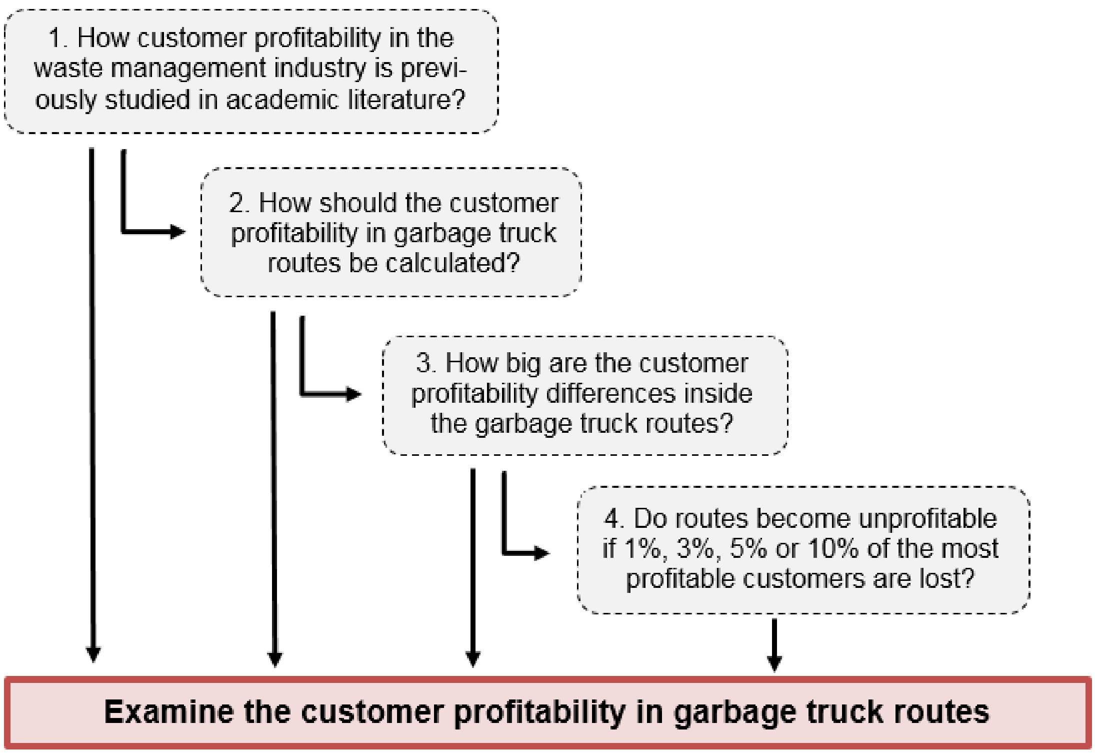


Figure 3. Summary of research questions of this study

Figure shows how all the questions supplement the underlying objective. Questions also have a certain hierarchy since the next question is based on the results of the previous one. Thus, questions have to be considered in the presented order.

1.3 Structure of the study

This thesis consists of six main chapters which all but conclusion include several subchapters. These are summarized in the next figure.

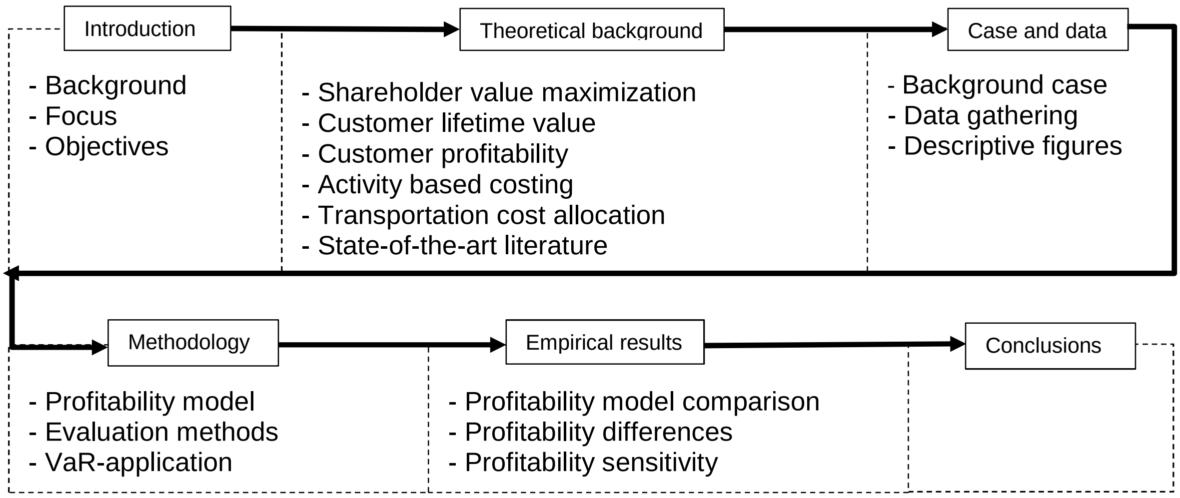


Figure 4. Structure of the study

The main contributions of this study, as the figure above presents, are presented in chapters 3, 4, and 5 in the middle of the thesis. This first part includes the background of the problem, the focus of the study, limitations, and research questions. Next chapter deals with the theoretical background of the topics of this study. Chapter presents the concepts of customer lifetime value and customer profitability, the activity based costing that is used as base of customer profitability, methods to allocate transportation costs, and the state-of-the-art literature from applications of the theoretical concepts. Third chapter presents the background case more in detail and the data used in the study. The fourth chapter includes the description of different customer profitability models used in this thesis as well as the VaR-methodology and its application in this study. Fifth chapter presents the results from data and the answers to research questions. Last, sixth chapter summarizes and concludes this research and proposes some future extensions.

2. THEORETICAL BACKGROUND

This chapter examines the theoretical background of this study. It holds the key concepts, findings, and results of current academic literature of the subject of this thesis. The chapter is also intended to give the big picture of the subject and is thus structured from wider subject to narrower as the figure below presents. At the last part of this chapter, the applications of these theoretical concepts are reviewed from academic literature.

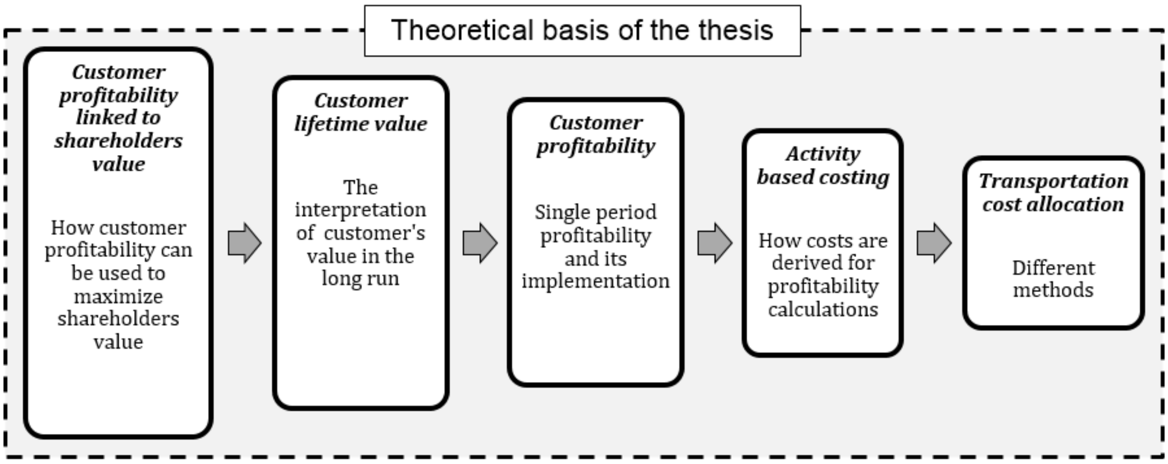


Figure 5. Theoretical background of the thesis

The figure shows the chain from firm level into detailed calculations. Each block is based on foundations of the previous ones in the figure and together they form the basics of this study. But first, since customer profitability and customer lifetime value are the key concepts in this chapter, it is important to clarify the meaning of the concepts. Academic literature mixes these consequently, which can cause confusion (Pfeifer, Haskins & Conroy, 2005). The definitions this thesis uses, follows Pfeifer et al. (2005) who examined this definition problem and ended up defining customer profitability as follows:

"Customer Profitability (CP) is the difference between the revenues earned from and the costs associated with the customer relationship during a specified period."

The definition is based on the word "profitability", which should match the concept on profitability in discipline of accounting. Thus, it is the accounting profit applied to individual customer relationship. Customer lifetime value on the other hand is defined as:

“Customer Lifetime Value (CLV) is the present value of the future cash flows attributed to the customer relationship.”

This definition uses the word “value” as base, which is referred to value concept in finance. So, the distinction between CP and CLV is fundamentally the distinction between profit and value in financial sense. Value is what something is worth and profit is the difference of revenues and costs. (Pfeifer et al. 2005.) Later on, Estrella-Ramón et al. (2013) contributed to same topic and provided broader comparison between the features of CP and CLV. Their comparison is presented in the next table.

Table 1. Comparison of CP and CLV (Estrella-Ramón et al., 2013)

Customer profitability	**Customer lifetime value**
Is arithmetic calculation of revenues minus costs for a specified period of time	Is the present value of future cash flow
This measure is calculated on a single period basis, usually the last economic year	This measure needs several time periods of data to be calculated
Is an accounting summary of events from the present and the past. Is not forward looking	Is forward looking, for this reason CLV is a more powerful measure than historic CP analysis; CLV looks at the future potential of the customer
Is not a good basis for developing marketing strategies	Is a good basis for developing marketing strategies
Treats marketing as expense, which leads to negative operating margin in the early stages of a high growth company	Treats customers as assets and marketing expenditure on them as investment

The table shows the same fundamental difference that was noted in the definitions. CLV is generally referred as more powerful measure than CP, although its usage has several difficulties, which will be discussed later. Moreover, the available data may not allow calculating reliable CLV's. Nevertheless, as shown above, CLV and CP have different interpretations and should not be mixed to each other. This division is also used along this study.

2.1 Customer profitability link to shareholder value

To start from the widest perspective, customer relationships can be viewed as very important part of shareholder value maximization, since customer profitability and customer lifetime value enables companies to think about the economic value of their customers. Some researchers even consider shareholder value and the sum of firm's CLVs as synonyms or close-enough proxies (Nenonen & Storbacka, 2016) and the present value of firm's customer base has been used to estimate the market value of the firm (Gupta, Lehmann & Stuart, 2004). On the other hand, Schulze, Skiera, and Wiesel (2012) argue that since CLV does not consider non-operating assets or debt, it cannot be viewed as direct proxy to shareholder value. Still, a lot of research is made regarding CLV and shareholder value and some have even linked financial measures into marketing measures (Hogan, Lehmann, Merino, Srivastava, Thomas, Verhoef, 2002).

First, an inclusive framework about marketing activities contribution to shareholder value was first proposed by Srivastava, Shervani and Fahey (1998). In their framework, the shareholder value is driven by:

1. An acceleration of cash flows (shareholders prefer earlier cash flows since risk and time reduce the value of later cash flows)
2. An increase in the level of cash flows (this can be higher revenues or lower costs, working capital and fixed investments)
3. A reduction in risk associated with cash flows (for example reduction of volatility and vulnerability of future cash flows)
4. The residual value of business (long-term value can be improved for instance by increasing the size of the customer base)

Applying these shareholder value drivers to CLV context, a comprehensive analysis framework can be build, which also takes into account the broad view of CLV, including base, growth, networking, and learning potential of customers. Stahl, Matzler and Hinterhuber (2003) examine means of creating shareholder value in case of all four shareholder value drivers and all four CLV components. Their 4 by 4 matrix can also be applied to calculate the CLV of customer and thus the CLV of all customers of the company.

Other approaches are also presented, although not so comprehensively. The economic value of customer can be thought as the return generated from customer relationship that has to more than compensate the cost of capital invested in that customer, or else the customer is not creating value. Some customers do not require any specific investment, others require a great deal and have significantly higher cost of capital. The return from customers of higher cost of capital must be larger to compensate this cost of capital. If companies use accounting profits to measure this value, they tend to have overstated estimates for created shareholder value in high cost of capital customers and understated shareholder value for low cost of capital customers. (Ryals, 2002)

When this thinking is applied to real customer portfolio, companies usually find that some customers create value and some destroy value. This can be illustrated with the figure below where customer value is examined with risk and return.

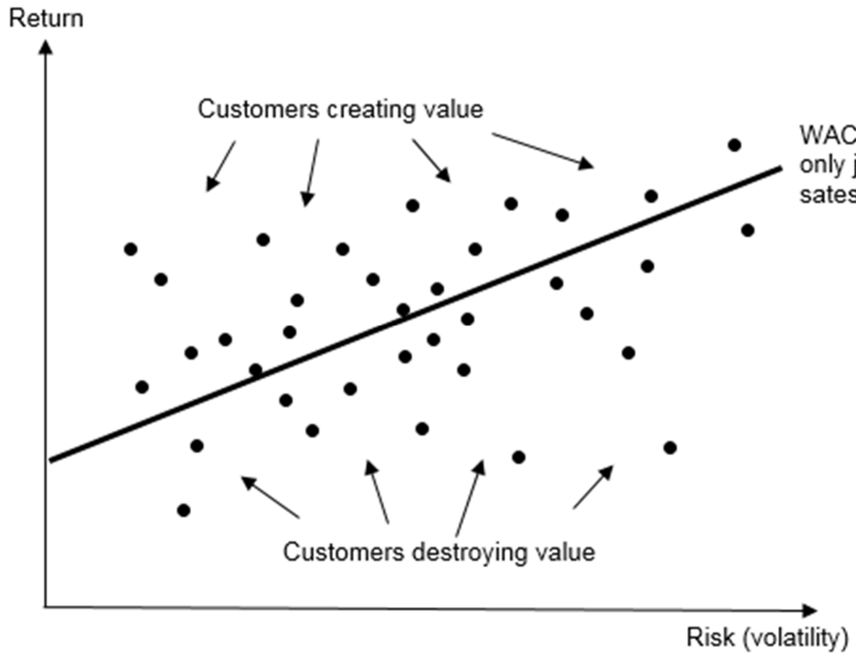


Figure 6. Customer portfolio with risk and return (Ryals, 2002)

The figure shown that when the risk increases, shareholders will require more return to compensate their investment. This increases company's WACC so the line slopes up and to the right. The dots are customers, which some are lying above the line and are thus creating value and some lie below the line and are destroying the value. As long as the average return from customer portfolio is above the company's WACC, the company is creating value to its shareholders. Although customers below the line may appear to be profitable, they are destroying value. (Ryals, 2002)

There are several things firm can do to manage the overall returns and the overall risk of customer portfolio. First, companies can increase revenues from customers. This includes enlarging the number of customers with customer acquisition and customer retention means, increasing revenues from existing customers by up-sales, cross-sales and price increases, and ensuring future revenues through firm renewal and innovations. In addition, companies can reduce the risk of the revenues by lowering the volatility of returns generated from customers (Ryals, 2002). This is especially important for customers that earn less than their cost of capital. Second, companies can decrease the customer related costs. This includes reducing the costs of serving existing customers, especially those who are destroying value, and reducing customer acquisition costs. Third, firms can optimize the capital invested in customer relationships and then manage their business volumes to take advantage of economies of scale. Last, companies can reduce the customer related risks by diversifying customer base and reducing risk correlations within the customer base. (Nenonen & Storbacka, 2016.) Revenue and risk management require the understanding the factors that drive customer behavior and is more important to companies with longer-term relationship with their customers (Ryals, 2002).

Managing customer related returns and risks is generally referred to as customer relationship management (CRM) and as stated before, it has a crucial part of creating shareholder value. However, it can be only managed effectively, if the CRM strategy is based upon measuring and managing risk-adjusted CLV's of key customers individually. Thus, CRM provides a clear link between customer profitability and shareholder value, which can be used for risk management in decision making. Ryals and Knox (2007) also argue that the domain of existing research is focused only on CP and CLV analysis, ignoring the bigger picture of the issue. Their suggested chain and conceptual framework, which shows the big picture, is presented in the next figure. (Ryals & Knox, 2007; Bermejo & Monroy, 2010)

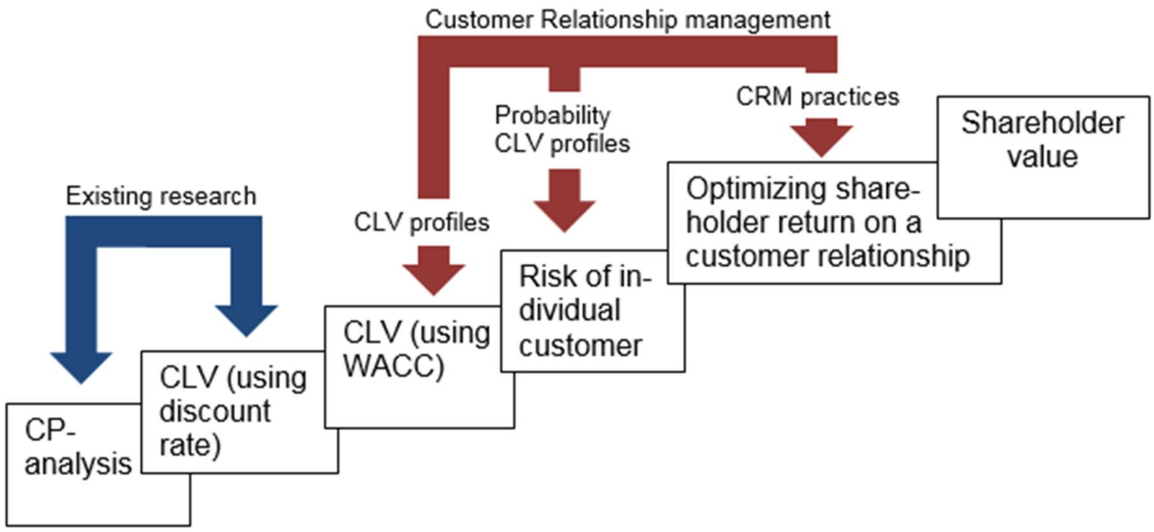


Figure 7. Linking CP-analysis with shareholder value (Ryals & Knox, 2007)

Figure shows how the analysis from CP goes on to calculating CLV, assigning it to appropriate company's risk, assigning each customers individual risk to better forecast future revenues, and optimizing the customer portfolio to generate shareholder value. To help assigning customer's individual risk, Ryals and Knox (2007) develop a relationship risk scorecard, which enables managers to measure the risk more precisely. The risk scorecard consists of overall relationship factors (number of customer relationships, number of business lines bought by customer, and longevity of relationship), account relationship factors, (company's relationship with broker, quality of relationship, and number of contact between company and customer) and company's knowledge of customer (how well company understands the customer's company and industry). With the scorecard, Ryals and Knox (2007) fulfill the research gap of CRM link to shareholder value and demonstrate the steps to make the analysis.

2.2 Customer lifetime value

After the need for customer relationship value maximizing is realized, the need for assessing the customer lifetime value for company arises. As above figure 7 from Ryals and Knox (2007) stated, risk adjusted CLV measures are the key components for understanding customer value. Thus, a huge quantity of academic literature exists to examine the concept. With broad range of research, broad range of CLV definitions are made, which makes understanding the big picture more difficult (Estrella-Ramón et al., 2013). Also in practice, CLV has its own limitations and requirements that are identified (Stahl et al., 2003). Estimating CLV can be challenging task to companies due to the allocating problems of standard accounting, limiting customer relationship benefits to only monetary ones, varying of costs over time or different times, and the risk levels of the cash flow streams. To tackle these problems, certain requirements are defined to measure the customer lifetime value accordingly (Stahl et al., 2003):

Requirement 1. All the costs have to be allocated to customers with the amount of resources they absorb. This hinders the usage of volume-based measures that are based on beliefs that customers with highest sales volumes are the most profitable ones. High-volume customers typically have the most bargaining power, so they can enjoy low prices and high level of service. Low-volume customers can also be unprofitable since they can absorb even more sales and service resources than high-volume customers. As a result, medium-volume customers tend to be the most profitable ones. To reach this result, customers need to be treated as a bundle of cost drivers.

Requirement 2. Both monetary and nonmonetary benefits have to be considered. Traditional, monetary-based customer evaluations tend to be underestimated since they do not take into account other benefit measures. Stahl et al. (2003) propose 4 value components that can be considered for each customer to solve this problem and improve evaluations: base potential, growth potential, networking potential, and learning potential of current customer relationship.

Requirement 3. Revenue and cost fluctuations during customer relationships need to be taken into account. Depending on the nature of customer relationship, the revenues and cost streams may be different at different part of relationship. It is a common belief that the longer the customer stay in a relationship, the higher profits she generates. Some studies support this concept (Loveman, 1998; Rucci, Kirn & Quinn, 1998) but some do not (Reinartz & Kumar, 2000), however if and when the changes in revenues and costs occur over time, they need to be estimated.

Requirement 4. Time value of money needs to be taken into account, so the cash flows generated in different time periods needs to be discounted to present value. Customers and channels have to be seen as investments and revenue streams and their values need to be projected and discounted to present. This allows firms to compare different relationships and allocate resources efficiently. Considering uncertainty and time value of money in customer relationships is the fundamental part in CLV calculations.

Requirement 5. The uncertainty related to customer relationships have to be considered. This includes the vulnerability of relationships, which are the occurrences that negatively affect the cash flow streams and the volatilities of the relationships, which are occurrences that cause fluctuations in cash flow streams. Moreover, these can be divided into macro-environmental level, industry level, and firm level vulnerability and volatility. High vulnerability and volatility relates to high customer relationship risk, thus decreasing the customer value.

Keeping these requirements in mind, the CLV estimation techniques are presented next. Although CLV methods vary, above requirements can be taken into account every time, thus increasing the reliability of the analysis. In addition, studying different CLV models increases the understanding of the subject, because it shows what is really possible to do with the existing models.

2.2.1 Basic CLV formula

Although there exists a wide range of different CLV models, which will be discussed later, the basic idea for all of them is quite the same. It is based on the definition that CLV is the present value of the future cash flows attributed to the customer relationship so it can be presented as simple formula as many researchers have proposed (Mulhern, 1999; Ryals, 2002; Ryals, 2003; Stahl et al., 2003; Rust, Kumar & Verkatesan, 2011). Thus, the basic formula for calculating CLV is:

$$CLV = \sum_{i=1}^{n} \frac{[(R_i * r_i) - C_i]}{(1+d)^i} \tag{1}$$

where

R_i= Revenue, the gross contribution from a customer or segment of customers at time i

C_i= Costs involved with acquiring, servicing, and maintaining the customer or segment of customers at time i. In most cases it does not include acquisition costs

r_i= customer retention rate, which represents the probability or proportion of customers expected to continue buying firm’s products or services in time period i

n = period or duration of customer relationship or time horizon

d = the discount rate used for calculations to determine the present value of future cash flows

The basic formula becomes even simpler if infinity is taken into account for revenue and costs streams and for retention rate. This may be appropriate because of simplification of formula, specifications about how long customers are staying don't have to be considered, retention rate is likely to decrease since probability for customers to change company increases over time, finite time horizon overestimates CLV and retention and discount rates will make distant future values contribute less to CLV. The formula of calculating CLV to infinity is thereby (Gupta et al., 2004):

$$CLV = \sum_{i=0}^{\infty} m_i \frac{r^i}{(1+d)^i} \tag{2}$$

where m_i is the constant margin $R_i - C_i$. The formula can be taken even further to include the whole customer base discounted to present value, the continuous process of customer acquisition and retention and continuous compound of discount rate, but the simplicity is unfortunately lost (Gupta et al., 2004).

2.2.2 CLV models

Defining CLV may seem like an easy task, since basic formulas are relatively simple, but estimating revenues, costs, profit margin, retention rate, discount rate, and length of the relationship are proven to be complicated. Over the years, research community has developed several techniques to estimate CLV variables, which none have proven to be always superior to others. Next, used models in literature are presented and the big picture of field is outlined. Discount rates for models are presented in the next chapter.

Several attempts are proposed to classify the CLV models. They have divided into basic CLV models, customer base analysis models, and normative CLV models (Jain & Singh, 2002) and past customer behavior models and future-past customer behavior models with or without acquisition costs (Hiziroglu & Sengul, 2012). Estrella-Ramón et al. (2013) provides the most comprehensive classification of models. In their division, different CLV models can be considered in the case of relationship type between customers and company, analysis type, sources of data, inclusion of competition, and the level of aggregation in the data for CLV calculation. Analysis type models can still be divided into historical and predictive models, deterministic equations, such as RFM (recency, frequency, monetary value) models and growth and diffusion models, and stochastic processes like probability, econometric, persistence, and computer science models. A lot of contribution and research is conducted to these deterministic and stochastic models so further examination about these techniques is important to understand more about the CLV analysis. Next, these models are described more in detail.

RFM models are traditionally used for target marketing since they have shown to be better predictors for customer future purchase behavior than demographic profiles of customers. RFM models create several groups of customers based on three variables: recency, frequency, and monetary value. A model can classify customers into five groups based on each of these variables creating 125 groups, which can also be weighted, thus scoring customers according to their success. This scoring helps determining actions for each customer groups. Due to its simplicity, RFM models lack predictability for several periods ahead, their variables are imperfect indicators of true underlying behavior and they ignore that customers' past behavior may be a result of past marketing activities. (Gupta, Hanssens, Hardie, Kahn, Kumar, Lin & Sriram, 2006.) Other CLV models have shown to be superior to RFM models (Reinartz & Kumar, 2003; Venkatesan & Kumar, 2004), but RFM variables can also be used to build model that overcome many of its limitations (Fader, Hardie & Lee, 2005).

Probability models assume that customers' behavior varies across the population according to some probability distribution. For CLV purposes, predictions about whether an individual will still be an active customer in the future and what will be his or her purchasing behavior, are made. One model that explicitly address these issues is the Pareto/NBD (negative binomial distribution) model, which requires only two historic pieces of information about customer: the time when the last transaction of customer occurred and how many transactions the customer has made in a specified time period. Other models include beta-binomial/beta-geometric model by

Fader, Hardie and Berger, brand loyal with exit model by Morrison, Chen, Karpis & Britney (Gupta et al., 2006), and Hierarchical Bayesian approach (Borle, Singh & Jain, 2008).

Econometric models are generally modelling customer acquisition, retention, and expansion and then combining them to estimate CLV. Customer acquisition models focus on factors that influence buying decisions of first-time purchases by new or lapsed customers. Basic modes are usually a probit or a logit models (Thomas, Blattberg & Fox, 2004), which also try to link acquisition to customer retention behavior. Customer retention refers to the probability that customer is alive or active buyer. In contractual settings, customer informs the firm when relationship terminates (for example in the case of cellular phones or magazine subscriptions) but in non-contractual settings there are no clear ending for relationship (such as book shops) and determining active customers becomes a difficult task. In general, there are two broad classes to tackle this problem: the first considers that customers' defection is permanent or "lost for good" and uses hazard models to predict the probability of this defection to competitor (Venkatesan & Kumar, 2004), the second considers customer switching as transient or "always a share" and uses migration or Markov models (Pfeifer & Carraway, 2000). The third component is the expansion of relationship or margin generated by customer in each time period. It depends on customers past purchases and firm's efforts in cross-selling and up-selling products. (Gupta et al., 2006.) Margin can be modelled as constant over future (Gupta et al., 2004) and cross-selling as multivariate probit model (Li, Sun & Wilcox, 2005).

Persistence models are dynamic systems that use the same components (acquisition, retention, and cross-selling) as econometric models to model CLV. These models are developed together with multivariate time-series analysis since they take advantage of vector autoregressive (VAR) models, unit roots, and cointegration to study how changes in one component affects other components over time. Thus, the major contribution of persistence models is their long-run or equilibrium behavior projection using several variables. On the other hand, they require lots of time-series data to work correctly. (Gupta et al., 2006.) Rust et al. (2011) build a simulation model to predict customer profitability and lifetime value. They used past and current marketing contacts, past and current purchase behavior, and customer characteristics to predict purchase propensity and gross profit from customers. Other previous studies in CLV context include advertising, discounts, and product quality impact on customer equity (Yoo & Hanssens, 2005) and examination of differences in CLV between customers acquired through different marketing channels (Villaneuva, Yoo & Hanssens, 2008).

Computer science models rely on data mining, machine learning, and non-parametric statistics to approach the prediction problems, unlike structured parametric models such as logit, probit, or hazard models, which marketing literature has typically favored. In CLV context, computer science models may be the most suitable for studying customer churn, which typically includes large numbers of variables. (Gupta et al., 2006.) Oliveira Lima (2009) applied logistic regression, decision trees, k-nearest neighbors, and neural networks to customer churn predictions. She found that logistic regression and decision trees are most suitable techniques for churn predictions. Neural networks could also be applied, but they include lots of complexity, which would make them difficult to interpret. Also, the use of support vector machine (SVM) has gained popularity in classification purposes since it has shown to outperform the traditional logit model (Cui & Curry, 2005).

Growth and diffusion models refer to forecasting the acquisition of customer that firm is likely to acquire in the future. This is based on an idea to use customer equity as strategic metric which is defined as the CLV of current and future customers. (Gupta et al., 2006.) This customer equity can then be used as approximation of firm value (Gupta et al., 2004). Diffusion model has also been used to assess the value of lost customers. According to Hogan, Lemon and Libai (2003) the loss of customer is not only equal to the direct profitability of that customer but also the word-of-mouth effect that could have generated from customer.

2.2.3 CLV discount rates

In addition to estimating revenues, costs, retention and length of relationship, discount rate is as crucial for successful CLV estimate. Discount rate calculations can be done with several different models, most of them familiar from finance literature.

Researchers have applied weighted average cost of capital (WACC), capital asset pricing model (CAPM), and risk scorecard to derive the appropriate discount rate for customers.

The most commonly used discount rate in CLV calculation is firm's WACC. As the capital used by business comes either from debt or equity funding, the whole cost of capital of the firm is the weighted average of the cost of its debt and the cost of its equity. (Ryals & Knox, 2007.) The cost of debt is generally the appropriate market rate the firm is paying for its debt. On the other hand, the cost of equity includes business and financial risk and can be calculated with CAPM. It considers the current risk free rate summed with the firm's market sensitivity (noted as beta) times the market excess return. Naturally, if the firm has no debt, the CAPM discount rate is used as the discount rate for the whole company. CAPM combined with the cost of debt, WACC, can be used as the risk measure in projects, where the total risk of project is the same as the company's, the project is financed so the long-term capital structure of the company remains unchained or the project value is not significant for the overall value of the company. (Oliveira Lima, 2009)

To improve the WACC's relevance for customer relationship, McNamara and Bromiley (1999) assessed certain customer risk factors for each customers. They were based on the review of company's CRM capabilities, general insights about the customers, growth potential, customer defection, and competitive intensity. Each factors were defined a certain weighting and customers were scored according to these factors and weights. These scores could then be used to calculate more precise WACC for CLV calculations. Ryals and Knox (2007) argue that unless the predicted lifetime is very long or WACC for customer is very high, even huge changes in discount rate have a little impact on the actual CLV. Thus, they present a risk scorecard for addressing customer relationship risk, which could be used to estimate the riskiness of customers' future revenues, rather than discount rate.

To improve CAPM's estimate for cost of equity, the concept of customer beta was developed. Like the traditional firm beta, which measures the sensitivity of firm's stock return to market return, customer beta measures the sensitivity of returns from customer to overall market return movement. Thus, the riskiness of individual customer could be better measured. (Nenonen & Storbacka, 2016.) However, the applicability of CAPM for assessing customer related return and risk is noted to have several conceptual drawbacks (Buhl & Heinrich, 2008). Moreover, inspired by financial portfolio theory, the customer base can be developed such way that it maximizes the return at a certain level of risk (Groening, Yildirim, Mittal & Tadikamalla, 2014). That portfolio risk may as well be appropriate risk measure and used as discount rate in CLV calculations.

2.3 Customer profitability

When moving to more detailed calculations, static customer profitability calculation is always in the center of CLV. When the difficult of CLV calculations were predicting customer's future behavior, CP-measures are struggling to find the sufficient amount of revenues and costs that should be allocated to each customer. Therefore, CP calculations are not so straightforward and many researchers have proposed their practices and considerable aspects to calculations.

Cooper & Kaplan (1991) suggest that when calculating customer profitability, first all production related expenses are subtracted from sales revenues for all products sold to an individual customer. Then customer sustaining expenses are subtracted. These are the costs that are traceable to individual customers, but are independent of the volume and mix purchases such as travelling, calling costs of customer, and background information maintaining for customer. Boyce (2000) presents more detailed list that includes

- discounts and commissions
- marketing and sales support
- packaging and documentation
- inventory holding costs
- delivery
- technical and administrative support
- quality control
- credit terms

- accounts receivable days
- financing
- collection costs
- order entry processing
- handling customer inquiries
- customer service

Mulhern (1999) approaches CP in different angle and suggests one of the most comprehensive list of profitability measurement components, although his analysis is not completely consistent with the CP and CLV definitions. These components are presented in the next figure.

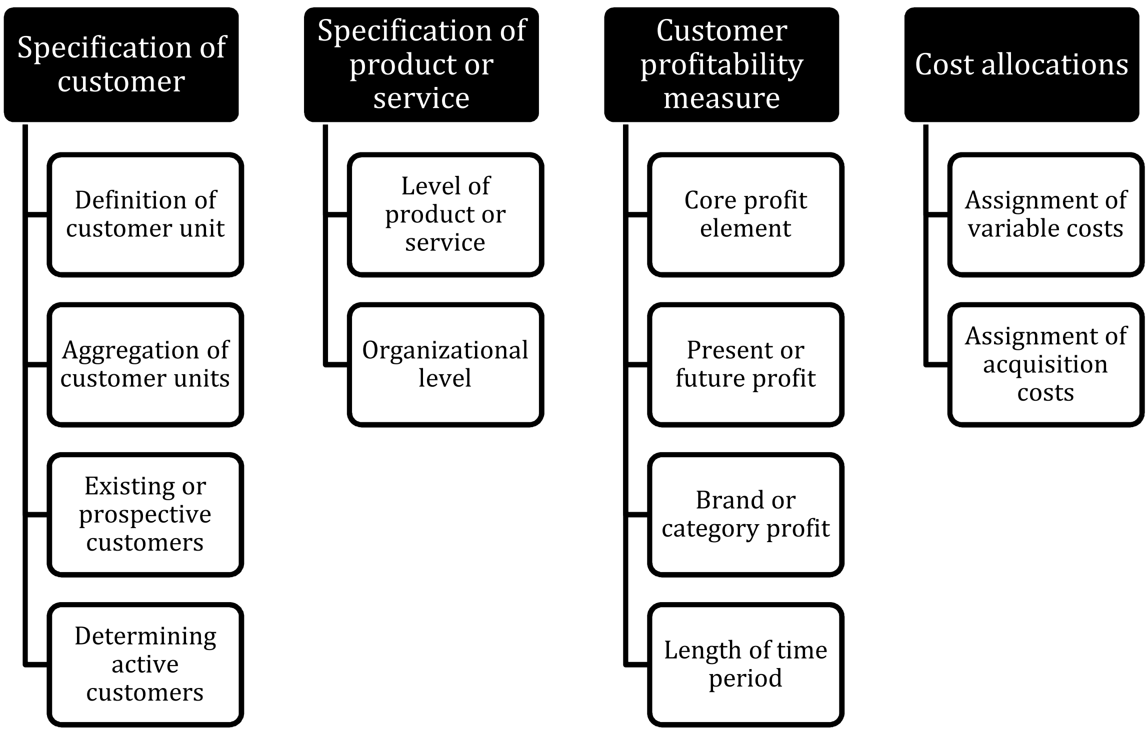


Figure 8. Customer profitability components (Mulhern, 1999)

First, the specifications of customers have to be done. It includes defining the customer unit, which can be for example consumers or corporate customers. Depending on the application, CP calculations can be performed for all customers or certain customer unit, which also determines the scope of the study. Sometimes it's not practical to calculate the profitability of all individual customers, so aggregation specifications of customer units needs to be done. This can be especially complex in business marketing, where customer unit can represent for instance the entire company, strategic business units (SBU), division of SBU's or specific corporate locations. Customer unit specification also covers defining the use of existing customers or possible future customers and determining which customers are “active”.

Second, specifications about products or services that are included to CP calculations are as important. These include determining the level of products or services and the level of organization. Separate profitability analysis can be made for individual products and brands, if analysis level needs to be very specific, or calculations can be performed such that every element of the relationship between an organization and customer is included in a single profitability measurement. Organizational level can cover minor sales territory, local sales offices, regional sales offices or national level.

Third, the analysis has to specify the CP measure. There, the core profit element is first determined. Usually CP calculations uses just monetary contribution but it can also be some other profit contribution depending on the situation. Then the analysis has to specify between present or future profits that it includes. Calculations that take into account the future profits are usually made in industries, where customers are naturally bound to supplier for a long time, because of high switching costs. Thus, when the length of the relationship is shorter, it is reasonable to avoid including lots of future profits. It also means that the length of time period used in calculations is important. Typically it should be based on the time-related aspects of customer lifetime and an organizational planning cycle. Finally, CP analysis can be constructed to measure realized profits from one company or from category of companies, where categorized level profit is represented by the sum of customer's purchases from all companies selling in that category. This allows to analyze the portion of the customer's profit that one company possesses.

Fourth, and last, cost allocation specifications are mandatory. They include the assignment of variable costs and customer acquisition costs. Mulhern (1999) agrees that variable costs should be assigned to each customers to use the fully developed profitability calculations. If it is not possible, the CP analysis would not be very good, even if they are collapsed into fixed costs. Customer acquisition costs are typically even harder to assign to individual customer. In some cases, the only possible allocation would be to apply an average cost to all customers. Sometimes it is even best to leave out the acquisition costs from profitability analysis.

As can be seen, the problem of CP analysis is well described and its limitations are well understood. There are also different approaches when implementing CP analysis into practice. One proposed general method divides the implementation of CP analysis into six step model. The model is presented in the next figure. (van Raaij, Vernooij & van Triest, 2002)

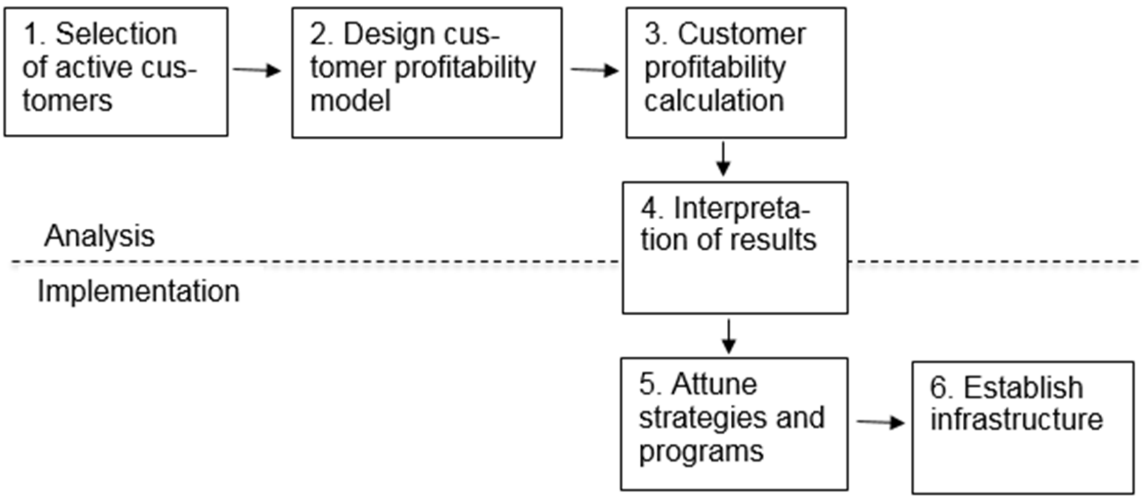


Figure 9. Customer profitability analysis implementation (van Raaij et al., 2002)

As figure 9 shows, first active customers have to be selected from overall customer base, so that the costs are allocated to only active customers. In the application, active customers had place at least one order during considered time period. Second, customer profitability model is designed. This means examining the performed activities and what drives the costs of these activities so that all costs can be assigned to some activity. Third, the CP calculations are executed using the gathered data. The level of detail is determined by the available data so that calculations are not too costly to perform. With actual results, fourth step consists of interpreting results. Here the choices made in second step can be reconsidered and calculations can be revisited. In fifth step, customer relationship strategies are improved using the results. This also includes improving of cost management and pricing programs according to customers' contribution. Last, infrastructure for continuing analysis in the future is established.

Developing the same idea further, Wang & Hong (2006) propose practical customer profitability management system that is based on continuous data mining. The system calculates the customer profitability (although they don't specify how) and then uses a neuro-fuzzy classification technique to categorize customers as unprofitable or different sort of profitable. The system calculates the customer beta to assess the quality of customer profitability. If customer beta is below or equal to 1, she is considered as "safe", otherwise she is considered as "significant" to draw attention. In addition, the system examines the trend of customer profitability by using customer betas. System also includes the accessibility of customer to be able to point reasonable marketing activities to customers. Thus, as a whole, system monitors customer base and behavior and refers different actions according to customer profitability and behavior. The system is a great example of how customer profitability analysis can be taken forward and integrate to managerial decision making.

The realization of customer profitability differences have naturally caused actions from companies. For example, AT&T offered different levels of customer service in long-distance telephone business depending upon customer profitability. Highly profitable customers were offered personalized service and less profitable got only automated, menu-driven service. PageNet, the wireless provider, raised monthly rates for unprofitable subscribers after analyzing their CP. The strategic motivation was likely to turn them into profitable or drive them away. Similarly, Federal Express raised shipping costs for customers in expensive-to-serve area where their volume did not justify the normal rates. (Winer, 2001)

2.4 Activity based costing

Activity based costing (ABC) is the technique that is most commonly used as a base for customer profitability analyzes (Holm, Kumar & Rohde, 2012). The need to improve the usefulness of accounting information in controlling increasing indirect costs arose in GE at 1960's and the field of activity based management was developed (Latshaw & Cortese-Danile, 2002). The field developed in 1970's and 80's and the ABC that we now know was first described by Cooper and Kaplan (1988). Traditional systems worked well when costs of direct labor and materials could be easily traced to individual products. ABC approach is based on the idea that all of the company's activities exists to support the production and delivery of today's goods and services. Thus, all costs could be considered as product costs.

Companies are usually good at measuring direct labor and material costs to products and services, but the hardness of ABC calculations comes when the overhead costs are included. To help this, Cooper and Kaplan (1988) suggest three rules to guide the process. First, firms have to focus on expensive resources. This leads to resource categories that have the potential to make the biggest difference. So, industrial goods producer would be most interested tracing manufacturing overheads, consumer goods producer would like to measure marketing and distributing costs and high technology company is potentially most interested about its R&D costs. Second rule is to concentrate on resources whose consumption varies significantly by product and product type. Third rule is to focus on resources whose demand patterns are uncorrelated with traditional allocation measures like labor and materials. Together these rules encourage to focus on resources that have the greatest potential for distortion under traditional systems. It may be difficult to measure or allocate costs precisely, but it is better to be correct within 5% to 10% of the actual demand than to be completely wrong using outdated allocation techniques.

In addition, there are two types of costs that should be excluded from ABC calculations. First are the costs of excess capacity which should not be charged from individual products. This prevents for making biased cost estimations. If company spreads capacity costs over budgeted volume, the production costs appear to be much higher than they actually are just because sales volumes were not as large. This can lead to "death spiral" where decreasing demand forecasts create idle capacity, so accounting system reports higher costs, which leads management to increase prices, which lowers the demand again. Second, research and development costs of completely new products and lines should not be included to individual product costs. Thus, R&D costs should be divided into costs that are related to improving existing products and costs that are related to developing entirely new products. Existing product development costs should naturally be included into product calculations but new product development costs should be treated as investments. (Cooper & Kaplan, 1988)

After Cooper and Kaplan, more practical rules are proposed for implementing ABC. A general method is executed in six steps. First, all the direct material and labor costs associated with each products and services are determined. Then, overhead costs are grouped to four categories following Cooper's (1990) framework: output unit-level costs, batch-level costs, product/service sustaining costs, and facility sustaining costs. Third step is identifying cost drivers (or cost activities) that may have a causal affection on the costs. Then, the costs that are affected by the same activities are grouped within each cost level. Fifth, the rates that activity units consume costs is defined by dividing total costs in each cost pool by the total number of activity units in each cost pool. Last, overhead costs are divided into products and services based on the activity rates by the time each product or service consume activities. (Latshaw & Cortese-Danile, 2002.) Similarly, a widely used cost accounting book by Stanford and Harvard professors describes ABC implementation process in general as follows (Horngren, Datar & Rajan, 2012, 150-153):

Step 1: Identify the products that are the chosen cost objects
Step 2: Identify the direct costs of the products
Step 3: Select the activities for allocating overhead costs
Step 4: Identify overheads associated with each cost-allocation activities
Step 5: Compute the rate per unit of each cost-allocation activities
Step 6: Compute the overhead costs allocated to the products
Step 7: Compute the total cost of the product by adding all direct and overhead costs assigned to product

These general guidelines are also applied in the logistic industry. There ABC application is however not so straightforward since there are several challenges that do not generally exist in manufacturing. In logistic industry the output is usually harder to define, determining activities and cost drivers may be difficult, data collection and measurement are more complicated, and activities in response to service requests may be less predictable. (Rotch, 1990.) Nevertheless, studies have presented detailed descriptions about ABC implementation to transportation industry. First, the ABC system was developed to Portuguese warehouse and logistic operator. The application started by identifying the resources that was used to produce the service, the activities that are using resources, and cost objects which are the final services. The application is made in firm level, since although they examined the sources of transportation costs, the identified resources were only number of transportations. Overhead costs were allocated using informed guess of the percentage of management time dedicated to each activity, although recognizing that it was the biggest weakness of the model. As a result, the model was able to calculate the costs for each distribution service. (Themido, Arantes, Fernandes & Guedes, 2000)

Another application of ABC in logistics is made for Turkish transportation service provider. First, the activities that company uses in its business is determined by mapping the business processes and interviewing firm’s employees. The goal was to gather as much activities as possible and then group similar activities together to get sufficient amount of information. Next, since activities consume resources to form processes, resources were determined. These are basically support resources that are treated as overheads. Overall 19 of them were identified. Direct costs were assigned to cost objects after ABC analysis. As third step, since activities consume resources according to cost drivers, these consumption rates are determined. Cost drivers are named as first-stage cost drivers and they are, for example, number of personnel and vehicles or distance travelled. In addition, since consumption rate of some activities cannot be easily estimated, they are systematically analyzed with analytic hierarchy process (AHP) to obtain allocation of cost drivers for all overhead costs. Next, each activity in process is matched with required amount of resources according their consumption rates to create a cost pool. Last, cost pools are allocated to cost objects according to their activity cost pool usage. (Baykasoglu & Kaplanoglu, 2008)

To get clearer picture from subject, next figure presents and compares the ABC method used by Latshaw and Cortese-Danile (2002) for general ABC implementing and Themido et al. (2000) and Baykasoglu and Kaplanoglu (2008) for implementing ABC into transportation case. The general process is described in the black background and transportation processes are described in the white backgrounds.

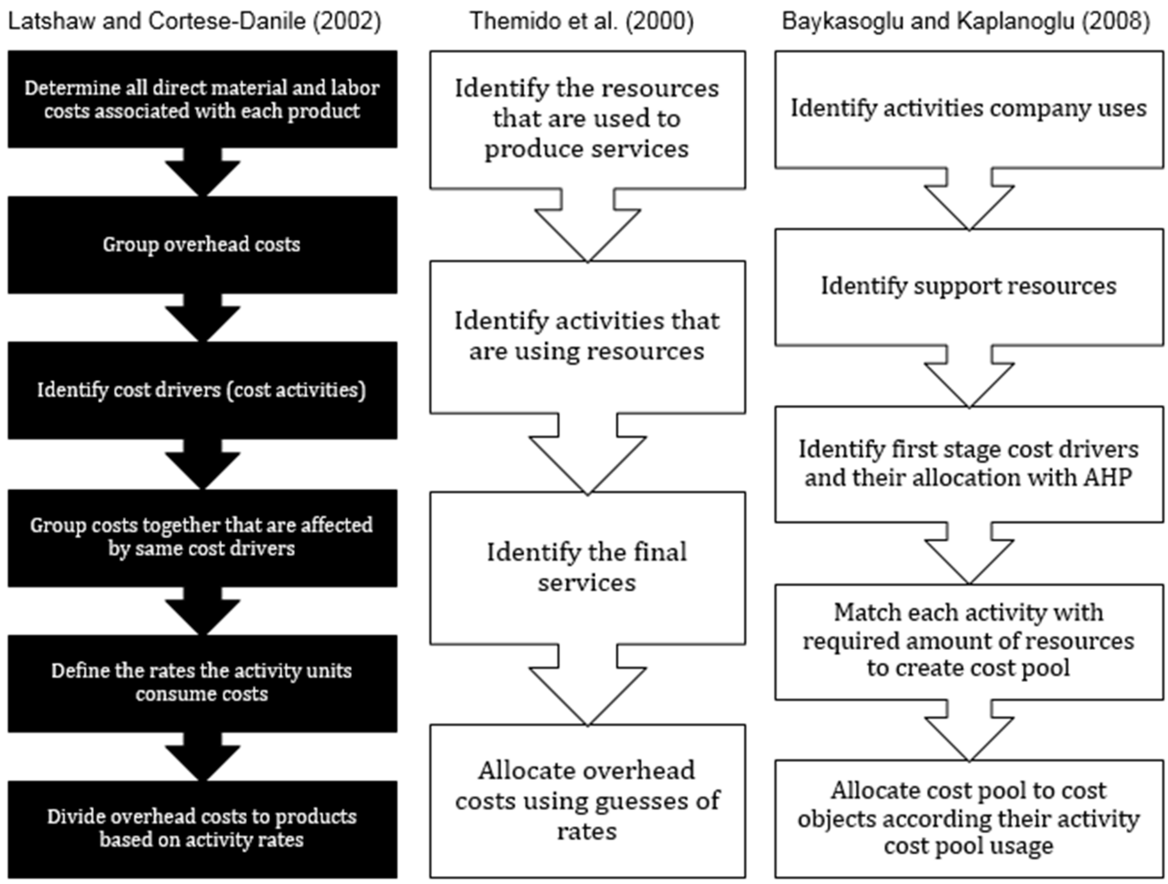


Figure 10. Comparison of the ABC implementations

The figure shows that ABC implementations in transportation field have followed the basic principles of implementation although there are some differences. The need to define the final service or the activity is present in the transportation field. In general process, it is assumed that firm is aware of its final service, which is not always that simple in the transportation field. When general implementation has some focus on defining and grouping overhead costs, transportation implementation uses most of its time determining activities and their consumption rates, which shows the difference between theory and practice.

Apart from transportation, ABC has also been applied to numerous targets over the years. Kennedy and Affleck-Graves (2001) studied ABC's relation to firm value and found that over the three year research period, firms that adopted ABC performed on average 27% better than firms who used traditional cost accounting. ABC applications are common especially in healthcare industry and hospitals. ABC is used to understand production functions in order to improve the quality of provided services (Esmalifalak, Albin, & Behzadpoor, 2015; Chen, Sabharwal, Akhtar, Makaram, & Gupte, 2015; Kaplan, Agarwal et al., 2015; Gregorio, Russo, Lapão, 2016). Academic community has also been conducted studies of ABC for example in case of academic libraries (Siguenza-Guzman, Auquilla, Van den Abbeele & Cattrysse, 2016), international airlines, (Lin, 2012), farm management (Carli & Canavari, 2013), and green building projects (Tsai, Yang, Chang & Lee, 2014). Calculations of ABC have also developed recent application to include uncertainties to cost allocation and analysis using fuzzy and Monte Carlo approach to ABC (Esmalifalak et al. 2015).

2.5 Transportation cost allocation

Although there are detailed descriptions on how costs are assigned to different activities in transportation, they all simplify the allocation of transportation costs to customers. The typical allocation method is calculating average cost per shipment for customer (Roth & Sims, 1991; Baykasoglu & Kaplanoglu, 2008) or average travelled distance between customers (Themido et al., 2000). Thus, these ABC studies lose some of their information as they allocate the same amount of transportation costs to customers although the allocation is considerably more complex in reality. This also leads to biased cost estimates and may not serve as a good base for customer profitability calculations. Since the costs of transportation depends on the locations of customers, the fair way to split the costs among customers is desirable. Moreover, the method should be easy enough to implement in practice, so it can be applied in large amount of customer profitability calculations.

However, the method of average costs divided for customers is common and can be considered as one of the options. It is normally applied especially in mass transportation, where the service provider charges the same fee from anyone who uses it. It is also assumed that the number of users is so large that their individually travelled distance can be ignored. Some mass transportation providers have attempted to refine the fares by “zones”, where customers are charged certain payment by crossing the zone. Thus, the travelled distance is partly included in the payment. On the other hand, if the number of users is extremely small (i.e. 1), the whole travelled distance and its costs can be allocated directly to that user. This is generally applied in taxies. (Faigle, Fekete, Hochstättler & Kern, 1998)

The three above methods are commonly used, because they are easy to understand and interpret. However, the transportation cost allocation problem is also widely studied in the field of cooperative game theory. Next, the basic concepts of cooperative game theory are presented. Then, cost allocation models are described including the traditional models according to Guajardo & Rönnqvist (2016). These traditional methods include proportional methods, marginal cost based models, duality method, method based on Shapley value and nucleolus method.

2.5.1 Introduction to cooperative game theory

The transportation cost allocation problem is widely studied in the field of operational research and game theory. There, it was first considered as cost allocation fairness problem (Fishburn & Pollak, 1983) and was modelled using concepts of cooperative game theory (Tamir, 1989) and later through travelling salesman problem modification known as travelling salesman game (Potters, Curiel & Tijs, 1992). As an introduction to notations used in models, let $N = \{1, \dots, n\}$ be the set of all players (or participants, or customers) called the “grand coalition”, and K be the set of all subsets of N. The characteristic function $C: K \to \mathbb{R}$ assigns to each coalition S in K the costs of coalition S by solving some optimization problem. The cost allocation vector $x = (x_1, \dots, x_n)$ assigns to each player j in N a quantity that $x_j \in \mathbb{R}$ such that the sum of x_j equals $C(N)$. This means that all the costs for grand coalition N is split among its members using the allocation x. When all costs are allocated, the division is said to be efficient. (Guajardo & Rönnqvist, 2016)

The allocation vector x satisfies the rationality if there are no subsets S of players where the players in coalition S perceive less total costs than the total costs allocated to them by x. This is known as individual rationality condition. Naturally, the cost allocation is not sufficient, if some players would be better off by forming their own coalition. If S is only one player j, the cost assigned to her should not be greater her stand-alone costs $C(\{j\})$, which are the costs she would have to pay if she buys the service only for herself. Thus the constrain is formed as

$$\sum_{j \in S} x_j \leq C(S)\ \forall S \in K \tag{3}$$

The core of the game is a set of cost allocation vectors that satisfy the previously described conditions of efficiency and individual rationality, that is

$$Core(C) = \left\{ x \in \mathbb{R}^n : \sum_{j \in N} x_j = C(N), \sum_{j \in S} x_j \leq C(S)\ \forall S \in K \right\} \tag{4}$$

This allocation also provides stability since there are no subsets S such that the player would be better off by deviating the grand coalition N. (Guajardo & Rönnqvist, 2016.) The core is said to be "empty", if no allocation vector x is found and "non-empty" if there is at least one allocation vector that fills the conditions (Engevall, Göthe-Lundgren & Värbrand, 1998). In addition to condition of efficiency (all cost are allocated to players) and individual rationality (no player pays more than her stand-alone costs and is better off by forming own coalition), other principles or axioms are also defined that the optimal solution should fulfill. The condition of additivity states that if the allocation problem decomposes into sub problems, their added solutions should equal the solution of the whole game. The condition of symmetry states that the two players who contribute equally to every coalition, can be swapped without affecting the solution. Last, the dummy player property states that if one player contributes her stand-alone value to every coalition, she should be assigned with that value. (Besozzi, Ruschetti, Rossignoli & Strozzi, 2014; Guajardo & Rönnqvist, 2016)

Calculating the core of the game is NP-hard problem, since it demands calculating the optimal costs for $2^N - 1$ coalitions. Thus, methods to assess the fairness of allocations that lessens the computational complexity are proposed. One of them is the concept of semicore, where the coalitions that include only the single-player coalitions and their complement coalitions are considered. It requires calculating the allocations for only $2|N| + 1$ coalitions and thus is more practical for larger data sets. (Flisberg, Frisk, Rönnqvist & Guajardo, 2015.) Other weaker version of the core are the ϵ-approximation core, which lessens the rationality constraint by ϵ value (Faigle et al., 1998; Sun, Rangarajan, Karwan & Pinto, 2015).

2.5.2 Cost allocation methods

The first and probably simplest class of traditional methods are proportional methods. They are quite straightforward methods where each player is assigned a share of total costs according to some criteria. The costs for each player j are thus

$$x_j = \alpha_j * C(N), \qquad \forall j \in N \tag{5}$$

where α_j is the proportion of total costs $C(N)$ and $\sum_{j \in N} \alpha_j = 1$. The simplest criterion that is used is the egalitarian method, which allocates equal cost shares to all players (Berger & Bierwirth, 2010), which makes the method same as calculating average cost per transport per customer. Other options is to define the proportion based on demand rate of each player, which is calculated as the proportion of player j's transport volume from whole transport volume (Wong, Van Oudheusden & Cattrysse, 2007; Flisberg et al., 2015) or the stand alone cost, which is calculated as the proportion of j's distance from starting point from the sum of all players distance from starting point (Sun et al., 2015). However, as Özener and Ergun (2008) notes, there are no guarantee that proportional methods deliver the solution that is optimal to all players. Efficiency is reached, since all costs are allocated, but even their simple example with only three players proved that the individual rationality may not be satisfied.

Using some of the principles of proportional methods, methods based on marginal and separable and non-separable costs are another way of allocating the costs. Here, the marginal or separable cost of one player j is the marginal cost m_j when she joins the grand coalition and is defined as $m_j = C(N) - C(N \setminus \{j\})$. So the marginal cost for new player is the cost of whole coalition including new player subtracted the cost of grand coalition without new player. The non-separable costs $g(N)$ are the costs that are left, when all the marginal or separable costs are subtracted from grand coalition costs and can be noted as $g(N) = C(N) - \sum_{j\in N} m_j$. (Guajardo & Rönnqvist, 2016; Besozzi et al., 2014.) These methods allocate each player their marginal cost plus a share of the non-separable costs. Non-separable cost allocation can be done equally or based on volumes or stand-alone costs like in case of proportional methods. (Flisberg et al., 2015)

The non-separable costs can also be allocated using alternative costs avoided method (ACAM). There, the cost allocated to single player j is

$$x_j = m_j + \left(\frac{r_j}{\sum_{i\in N} r_i}\right) * g(N) \tag{6}$$

where $r_j = C(\{j\}) - m_j$. So each players' cost is her marginal cost plus the part of non-separable costs, that are determined by the amount of costs the player avoided (i.e. difference of player's stand-alone and marginal costs) by joining the coalition compared to other players. (Flisberg et al., 2015.) However, ACAM can be seen as rough form of more general cost gap method (CGM) which allocates non-separable costs according to minimum of maximum costs player j is willing to pay by joining the coalition (Tijs & Driessen, 1986). As the non-separable costs of grand coalition are defined as the difference of total costs and sum of all marginal costs, the non-separable costs of one coalition S are defined as $g(S) = C(S) - \sum_{j\in S} m_j$, so the maximum that new player would be willing to pay to join the coalition would be $m_j +$

$g(S)$. Thus, the player would not agree not pay more than her marginal costs and all non-separable costs of coalition. To join the grand coalition, the player would only agree to pay $m_j + min_{S:i\in S} g(S)$. The costs allocated to single player are then (Besozzi et al., 2014):

$$x_j = m_j + \left(\frac{min_{S:j\in S} g(S)}{\sum_{i\in N} min_{S:j\in S} g(S)}\right) * g(N) \tag{7}$$

Cost allocations based on basic marginal methods, including ACAM, generally satisfy the conditions of efficiency and symmetry although Engevall, Göthe-Lundgren & Värbrand (2004) noted that they also may not lead to efficiency. CGM method satisfy also the individual rationality and the dummy property (Frisk, Göthe-Lundgren, Jörnsten & Rönnqvist, 2010).

Cost allocation methods based on duality are another set of allocation methods. They use the relationship between core allocation and linear program (LP) duality to obtain cost allocation. (Özener, 2014.) Since transportation problems are usually solved using LP, the cost function of these problems can be used to allocate costs among players (Guajardo & Rönnqvist, 2016). To form the solution, the original LP problem's constraints are used as part of the new maximizing problem. Duality methods are claimed to be simple and fast, not depending on routing solution of the carrier and including synergies among the customers but they require the underlying vehicle routing problem to be modified. (Özener, 2014)

The most used cost allocation method in travelling salesman games in recent years is the Shapley value, which was published by L. S. Shapley in 1953. Later, Shapley received the Nobel Memorial Prize in Economic Sciences 2012 together with A. E. Roth. (Guajardo & Rönnqvist, 2016.) Imagine that every player is rational and will be signing up to route in some random order. Then each player have to pay the incremental cost of being included in the route at the moment of signing. The payment is thereby depended on the order the players are signing up. Because the player cannot know the order and thus the payment, she may as well calculate the average payment assuming that every ordering is equally alike. (Young, 1985.) So allocated cost for each player j is (Guajardo & Rönnqvist, 2016):

$$x_j = \sum_{S \subseteq N : j \in S} \left[\frac{(n - |S|)!\,(|S| - 1)!}{n!} \right] * [C(S) - C(S \setminus \{j\})] \quad \forall j \in N \tag{8}$$

where |·| represents the number of elements in the indicated set and $[C(S) - C(S \setminus \{j\})]$ is the marginal cost of player j joining the coalition S as the last (Besozzi et al., 2014). Thus, the value can be interpreted as the average marginal contribution each player would make to grand coalition if it were to form one player at a time (Young, 1985).

The main drawback for Shapley value is that it is computationally complex, since every marginal contribution of each player in each possible coalition have to be calculated. This makes the Shapley value NP-hard (Sun et al., 2015) since the number of coalitions is equal to $2^N - 1$ (Flisberg et al., 2015). Furthermore, Shapley value may not belong to core even if the problem has non-empty core. Only when the game is convex (so that $c(S \cup T) + c(S \cap T) \leq c(S) + c(T)$ for all $S, T \subseteq N$), Shapley value has always a solution that is included in core but travelling salesman games are generally not convex. (Engevall et al., 1998.) Still, Shapley value is the only one that can satisfy the five conditions or axioms and as answer, it is unique (Guajardo & Rönnqvist, 2016). Due to this, Özener (2014) applied approximation of Shapley value by calculating the average marginal contribution of five closest players thus leasing the computational complexity but providing relatively good answer.

Like Shapley value, nucleolus is another NP-hard method which always finds the unique solution to cost allocation problem. Moreover, the nucleolus solution belongs to core always, when the core is non-empty. The method is based on maximizing the satisfaction of coalitions with proposed allocation x. The satisfaction for collation S is measured by excess ε as the difference of total cost of coalition $C(S)$ and the sum of allocated costs to S noted as $\varepsilon(x, C, S) = C(S) - \sum_{j \in S} x_j$. The larger the excess is, the happier players are in collation S since they achieve larger savings. In a game consisting of all players N, the excess vector is defined as $e(x, C) = (\varepsilon(x, C, S_1), \dots, \varepsilon(x, C, S_p))$, where $p = 2^n - 1$ and S_i are the coalitions in $K \setminus \{N\}$. In game, all allocations that satisfy the individual rationality are called imputations and are defined as $x_j \leq C(\{j\})\ \forall j \in N$. In addition, a vector $y \in \mathbb{R}^p$ is lexicographically greater than $\bar{y}$ (i.e. $y \succcurlyeq \bar{y}$) if either $y = \bar{y}$ or there exists $h \in \{1, \dots, p\}$ such that $y_h > \bar{y}_h$ and $y_i = \bar{y}_i \forall < h$. Thus the nucleolus of cost sharing game with the set of imputations $\mathcal{X}$ can be defined as (Guajardo & Rönnqvist, 2016)

$$\mathcal{N} = \{x \in \mathcal{X}: \theta(e(x, C)) \succcurlyeq \theta(e(y, C))\ \ \forall y \in \mathcal{X}\} \tag{9}$$

where $\theta(e(x, C))$ is the vector that is result from arranging the components of the excess vector $e(x, C)$ in non-decreasing order. So, the nucleolus is a set of imputations that lexicographically maximizes the excess vector. (Guajardo & Rönnqvist, 2016.) The nucleolus satisfies the conditions of symmetry and dummy player property and if the solution is in the core, also the conditions of individual rationality and efficiency (Frisk et al., 2010). Nucleolus can also be modified by as normalized nucleolus, where the excess vectors are divided by the sizes of coalition and the demand nucleolus, where the excess vectors are multiplied by the total demand of the coalition (Engevall et al., 1998).

In addition to these traditional methods that were presented above, there are several other methods that are more of ad hoc. For cost allocation among customers, the closest are the moat model proposed by Faigle et al. (1998) and the contribution constrained packing model (CCPM) by Sun et al. (2015). They are based on geometric cost allocation in two dimensional space and try to approximate the core. They involve a certain optimization function with constraints and CCPM requires certain algorithm to include slack. Although these methods claim to yield appropriate allocation, they have not studied since and thus they are excluded from methodologies in this study.

To help reader get a better overview of cost allocation methods, their basic principles are collected in the next table.

Table 2. Cost allocation methods

Method class	**Basic principle**	**Modifications**
Proportional methods	Assign a share of total cost to each player according to some criteria	Criteria can be according egalitarian, transport volume, stand-alone costs
Marginal cost methods	Each player are allocated their marginal cost plus some share of non-separable costs	Non-separable costs shared according to proportional methods, ACAM or CGM
Duality methods	Modify the underlying LP problem and use it to allocate costs	
Shapley value	Assign the average marginal contribution to each player they would make if the grand coalition were formed one player at a time	To lease the computational complexity, the value can be approximate
Nucleolus	Calculate the set of imputations that lexicographically maximizes the excess vector	Excess vector modifications by normalizing or demand adjusting

Table sums up the findings from cost allocation methods. Although fairness criteria are proposed, there are no broad consensus of the acceptance of the different models. Özener, Ergun and Savelsbergh (2013) found in their study that proportional methods have high number of instable subsets and extremely high maximum instability values and the Shapley value approximation was found to perform only a slightly better. On the contrary, duality method was found to be considerably better than other methods. When Frisk et al. (2010) studied duality methods, they found their numerical answers did not belong to core as well as proportional allocation method and marginal method, where non-separable costs were divided equally. However, Shapley value, ACAM, and CGM belonged to the core. The findings of Flisberg et al. (2015) reported that proportional methods did not even belong to semicore when ACAM and nucleolus belonged to semicore. As academic community has produced mixed results, Guajardo and Rönnqvist (2016) conclude in their review article that there is no single best method that would always work.

2.6 State-of-the-art literature

Before applying theoretical basics into practice, the systematic state-of-the-art literature review is conducted to examine the applications of the previous concepts in academic literature. Especially, search focuses on applications in the waste management industry. Thus, academic articles are searched from online databases. Since the topic covers concepts of customer profitability, customer lifetime value, activity based costing in transportation, and transportation cost allocation, articles related to these keywords were first searched from databases. Search were conducted from three different databases: Elsevier Science Direct, Emerald Journals, and EBSCO – business source complete. Only journal articles written in English were included in results.

Search was conducted as an iterative process. Each keyword was first combined with “waste management” or “garbage truck” (for example, keyword could be customer profitability AND waste management) and searched in all three databases. Then, the most relevant articles according to abstract were selected for examination. After studying articles, their most relevant references were also examined. If no relevant articles were found, the initial search was conducted by mixing more keywords together. Relevant results were divided into three groups: studies from customer profitability differences and customer lifetime value, studies from activity based costing in transportation and studies from transportation cost allocations. Overall, 42 articles were covered in this review.

First, studies from customer profitability differences are made with rather interesting results. Study on Kanthal, a manufacturer of heating wire, showed that 20% of most profitable customers brought 225% of profits when 10% of least profitable customers were losing 125% of profits (Cooper & Kaplan, 1991). A study on pharmaceutical manufacturer in July 1995 to December 1996 revealed the customer profitability ranging from -12 000 dollars to 62 000 dollars profits with most customer profits concentrating on little over zero (Mulher, 1999). From the customer base of nationwide wholesaler/distributor, top 2% of customers generated 80% of revenues and profits and 32% of customers were unprofitable (Niraj, Gupta & Narasimhan, 2001). The data from Nordic banks in 1991 and 1992 reveals that 1,41% of customers bring almost 50% of bank’s profitability and 12% of customers brings 140% of customer base’s profitability (Storbacka, 1997). The customer profitability study on exporter in Norwegian fishing industry considering 176 customers revealed that 86 customers were profitable at range of 10%-90% and 90 were unprofitable (Helgesen, 2007).

In Australian telecom industry, the geographical location of customers was found to affect their profitability. All customers were found to be profitable, but customers in metropolitan area were the most profitable as the minor rural customer contributed the least. (McManus, 2007.) The cost-to-serve calculations were performed for a Brazilian consumer product manufacturer including customer profitability. The results showed that only 6% of customer provided 80% of the margin. (Guerreiro, Bio, Vazquez & Merschmann, 2008.) In Czech markets during 2010-2014, the market leader in its industry generated 104% of profits and 94% of turnover from its 20% of most profitable customers. On the contrary, least 10% of profitable customers generated only 4% loss and 6% of turnover. (Cermák, 2015.) Thus, empirical studies have shown that there are significant differences between customer profitability across and within industries.

In addition to customer profitability, empirical customer lifetime value cases are examined across different industries. CLV is applied in the case of Internet companies (Gupta et al., 2004), financial services (Ryals, 2005; Haenlein, Kaplan & Beeser, 2007; Ryals, 2008), cruise ship company (Berger, Weinberg & Hanna, 2003), retailing (Kumar, Shah & Venkatesan, 2006; Kumar, Petersen & Leone, 2010), and high tech companies (Venkatesan & Kumar, 2004; Reinartz, Thomas & Kumar, 2005; Kumar, Venkatesan, Bohling & Beckmann, 2008). However, no empirical cases of customer profitability nor CLV were found in the waste management industry.

Activity based costing has drawn interest in several industries and case studies in the field of transportation, logistics, and supply chain are regularly conducted. Researchers have presented their implementations of ABC to warehousing and distribution (Roth & Sims, 1991), logistics (Pohlen & La Londe, 1994; Pirttilä & Hautaniemi, 1995; Manunen, 2000; Stapleton, Pati, Beach & Julmanichoti, 2004), and similarly to supply chain management (Lin, Collins & Su, 2001; Schulze, Seuring &

Ewering, 2012). There are also detailed described applications of ABC into transportation that were detailed described previously (Themido et al., 2000; Baykasoglu & Kaplanoglu, 2008). Even though the search was limited to land transportation, waste management industry did not appear in the results.

The current solutions on transportation cost allocations are deeply studied in the field of co-operative game theory. There are number of studies using empirical cases in the field of ground carrier service providers (Berger & Bierwirth, 2010; Liu, Wu & Xu, 2010; Dahl & Derigs, 2011; Özener, 2014), railcar companies (Cheng, Tan & Lin, 2013), and maritime transportation sector (Yilmaz & Savasaneril, 2012). Some applications include logistic service providers (Vanovermeire & Sörensen, 2014), or retailers (Cruijssen, Borm, Fleuren & Hamers, 2010), or both (Anily & Haviv, 2007). Furthermore, natural resource sector has applied cost allocation in the case of agriculture (Nguyen, Dessouky & Toriello, 2014), forestry (Frisk et al., 2010; Flisberg et al., 2015), and oil and gas industry (Engevall et al., 1998; Engevall et al., 2004; Özener et al., 2013). Again, although research has been conducted in several industries, no applications in waste management industry or garbage truck routes were found. All in all, the tools for this research exists and are widely used in other industries, but no previous studies about customer profitability or transportation cost allocation, that are the most relevant for this thesis, were found in current literature.

3. BACKGROUND CASE AND DATA

Moving from theoretical basics to practical application, this chapter presents the case that motivates this study and describes the data that is used to derive the results. The information in this chapter is gathered through conversations with the experts of L&T.

3.1 Background case

As stated before, this study examines the customer profitability in garbage truck routes. Thus, understanding the basic business logic in the industry is important. It allows focusing on right things and building a profitability model that has practical implications. The case has shortly been presented in the introduction chapter, but this description intends to give more comprehensive view on the waste management industry and the underlying case.

According to the experts of L&T, the waste management industry is based on contracts between customers and service providers. Contracts can cover collecting different waste fractions, for example mixed, bio, glass, metal or cardboard waste and it can include some other services, for instance renting the waste container or washing the waste container. Typically a garbage truck goes to customer locations and executes the agreed service. When customer's waste is collected (or some other service is executed), the service provider charges the appropriate amount of money according to the contract. The billing is done for waste collection service and the quantity of waste separately. Thus, service provider receives money from the service but also from the collected waste.

Since service provider has contracts with several customers simultaneously, he will try to minimize the costs by collecting as much of the same waste fraction from different customers as possible during one shift. Once the garbage truck is full, it is emptied at landfill or at some waste treatment plant. Landfill charges the garbage truck for the quantity of waste it is emptying. Garbage trucks are weighted before and after emptying and the payment of waste is defined according the weighting.

Other costs that service provider has, includes salaries for its employees, maintenance of trucks, gasoline, and sustaining the necessary administration.

The day of the garbage truck driver starts from the depot where she is given the truck and the customers she has to serve during the shift. The driver can also work overtime and serve more customers, since typically a part of her salary is based on the quantity of waste containers she empties. Thus, the more work she does, the more she earns. From the depot, the driver goes to customer locations and executes the agreed service. One truck can usually deal with only one waste fraction at a time. Normally, the day of the driver also includes a visit to landfill at least once and a possible lunch and other breaks. Depending on the locations of the customers, the amount of breaks, and landfill visits, a driver can empty hundreds of waste containers during her shift. After the customers have served, the driver returns to depot and the truck may be taken by another driver. This process goes on from day to day. The business process described above including the real process and cash flows between customers, landfill, and service provider is presented in the next figure.

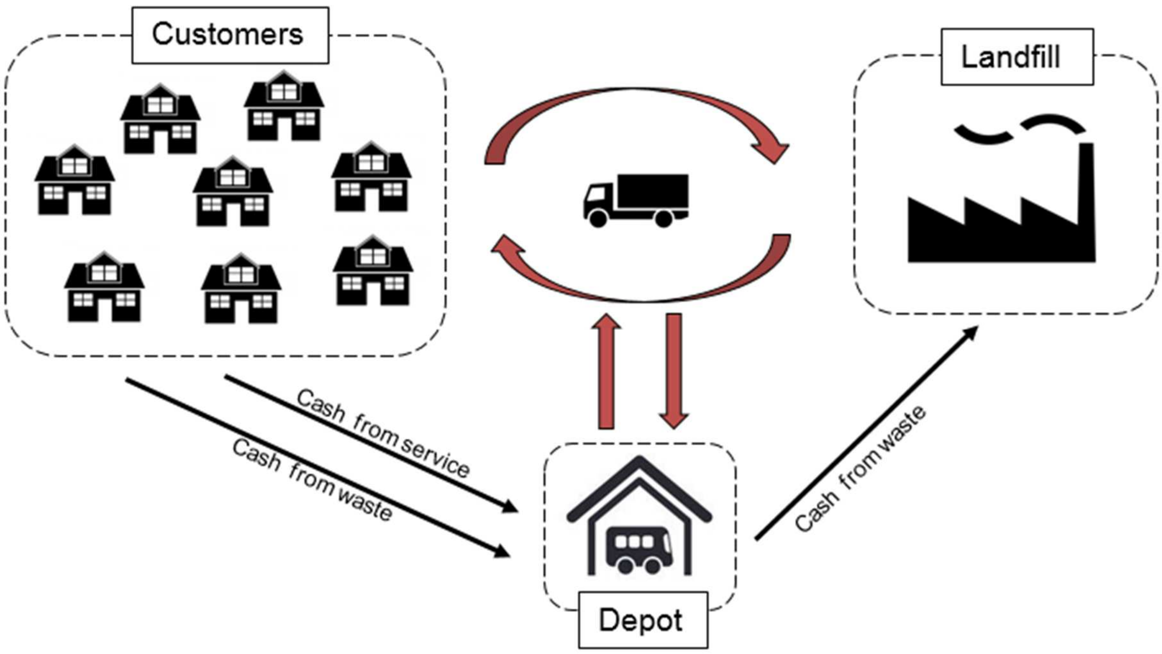


Figure 11. Business process of the waste management industry

As noted above, the distinguishing feature of the industry is the usage of contracts, which also includes risks. In these contracts, service provider agrees to carry all the costs of service during the contract period. Moreover, the contract is made and the price is determined before the service provider is aware of all the costs of servicing each customer. Thus, when pricing the contract, the contract price should cover still the unknown costs. Service provider can raise prices afterwards, but too large raises also increases the possibility of losing the customers. The most uncertain cost relates to transportation cost for individual customer. As stated in the introduction chapter, these costs depend on the locations of the customers. When customers are located close to each other, their servicing costs are low since driving to one customer decreases the distance to the closest customers also. When customer are located far from each other, their servicing takes time and fuel, which increases their costs. Servicing cost of existing customers are also changing, if new customers are acquired or current customers are lost on the route during the contract period. This complicates the customer profitability calculations.

To be able to increase shareholder value, company should focus on value creating customers. The knowledge of which customers are creating value and which are destroying is essential and customer profitability analysis is the basis of it. By examining ways to allocate transportation costs among customers, analyzing customer profitability differences and studying the sensitivity of the route profitability, this thesis intends to apply customer profitability analysis to waste management industry. Results can give more information to management for whether to increase customer acquisition actions in some areas or whether price increases are more desirable step. The rest of the thesis intends to give answers to this underlying case.

3.2 Data collection and processing

The data this study uses is a real data from L&T's databases. It is collected from route database, where the information of truck routes is and from financial database, where the information of the cash flows is. The data is processed with Microsoft Excel 2013 spreadsheet software.

Data collecting starts by discussing with truck route expert, who manages the route database. First, the information about five routes are imported to get an example sample. By working with the sample, data processing practices and possible problems can be solved before gathering the actual data. The truck route data includes the customer number, the map coordinates of the customer, the service that is executed and the time the driver checked the service to be completed for each customers in the route. To illustrate one of the routes, the time from first customer to second, the second customer to third and so on is presented in the next figure.

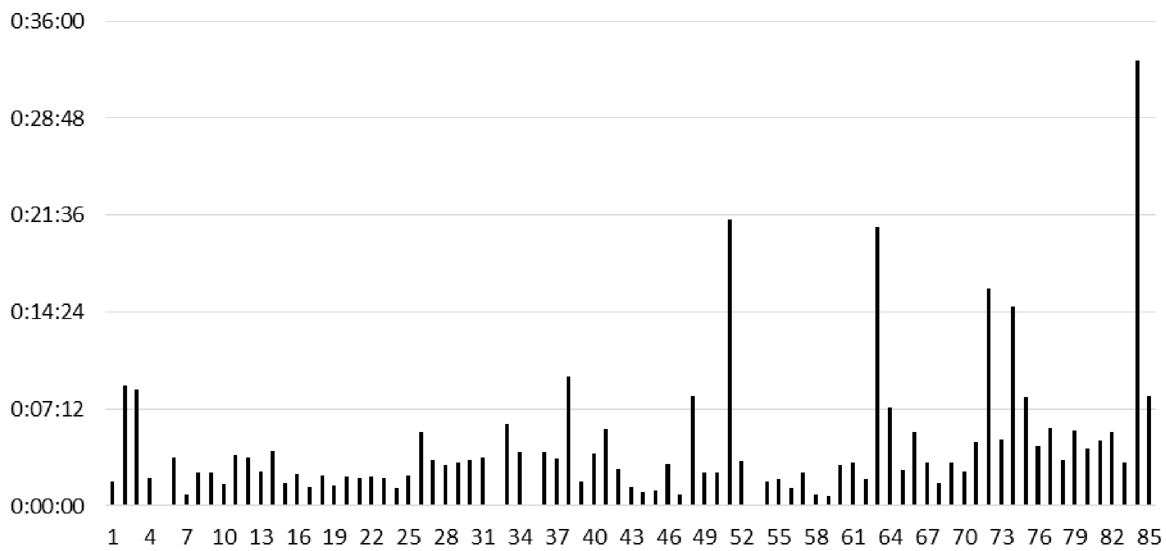


Figure 12. An example of time between customers in route

The figure shows how much time did it took for garbage collector to get from one customer to next one in minutes. The numbers in x-axis are the ordinal numbers of the customers in route. As can be seen, most of the customers are located quite close to each other so the time from customer to customer is only a couple minutes. Some customers, for instance 5, 32, 35 and 53 are located so close to previous customer, it took only seconds to serve them. On the other hand, the longest times between customers were around 20 to 35 minutes. It may be due to the long distance for those customers, the drivers visit to landfill or the driver having a break before those customers. A similar figure is repeated for all the routes analyzed.

The route data also includes the latitude and longitude coordinates of the customers and depots. Using these coordinates, the single distance between the depot and the customer as well as the single distances between customers can be calculated. The distance calculations are done using the Haversine formula, which calculates the approximate distance of two points taking earth's spherical shape into account. The Haversine formula is:

$$SD_i = 2r \arcsin \sqrt{sin^2\left(\frac{\phi_j - \phi_i}{2}\right) + \cos\phi_j \cos\phi_i \, sin^2\left(\frac{\lambda_j - \lambda_i}{2}\right)} \quad (10)$$

where r is the radius of the earth, ϕ_j and ϕ_i are the latitudes of the customers or the depot, and λ_j and λ_i are the longitudes of the customers or the depot. (Sun, Karwan, Gemici-Ozkan & Pinto, 2015.) The time from depot to first customer and the time from last customer back to depot was estimated using the single distance and the approximate average truck speed. Thus, the entire time from the depot to serving customers and back to the depot could also be estimated.

The financial data for the customers in sample routes was gathered from different database. The data included the information of the customer, revenues for the service and for the waste, and the type of service that was executed. Thus, the financial and route data could be combined in a single Excel file. The example calculation revealed plenty of problems in data processing since some data had to be modified for right format, some had to be filtered, and a lot had to be individually examined since there were multiple services executed during the sample time. When the best practices for data processing were obtained, the main data for this study could be collected.

The main data was obtained in similar manner as the sample data. The route data and the financial data was gathered from different databases using the same limitations as described in introduction chapter. The waste fraction that was included was mixed waste, which is the most common waste fraction. The customers that are considered are corporate customers, since their contracts have the most variations but they also hold the largest business opportunities. Also learned from the sample data, all the information in collected from only one day. This makes the data processing easier since customers are generally visited only once in a day. Thus, the financial data does not include a lot of other information than that is needed for this study. The selected day is Monday 16.5.2016. There are no holidays close to that day so it reflects the normal situation on the route. It is also a day from late spring, so the weather conditions should not play a big part in the route. Routes in winter may take more time to complete because of the snow so the service costs would be larger. There are no particular reasons that the day is Monday and it could also be any other day from Monday to Friday.

The data that fulfills these limitations is imported to Microsoft Excel 2013 and processed to final form where analysis can be made. As a result, 7935 customers in 67 routes are analyzed in this study. The next figure illustrates the described process.

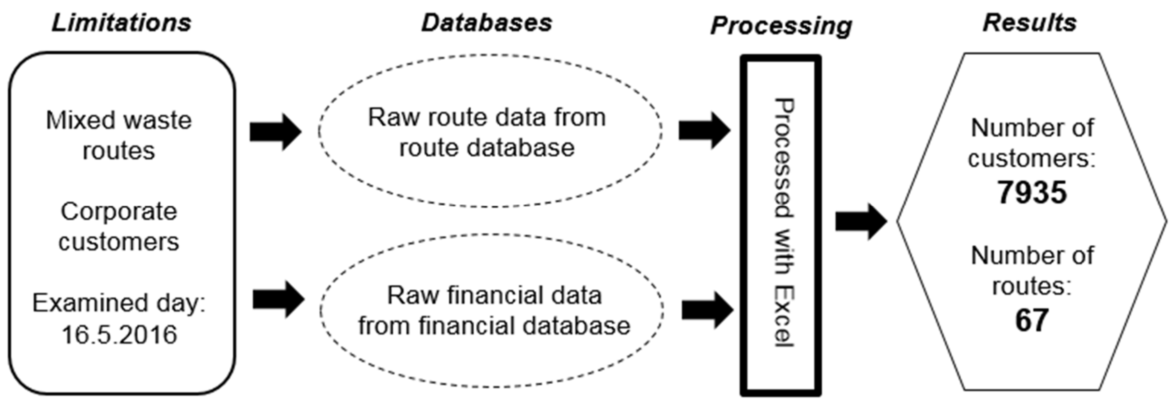


Figure 13. Data gathering process

After the data is gathered, it can be used to derive customer profitability model, calculate the customer profitability differences on routes, and apply the VaR-type methodology for profitability sensitivity. However, the data should also be critically evaluated. The route data includes all the customers that were served in the examined day. Also using the estimated times from depot to customers and back to depot, the time of the route could also be estimated. This includes all the breaks and visits to landfills, if they were not the first or the last thing the driver did after leaving the depot. Thus the data includes all the possible route information that was possible to include or estimate.

As the data is obtained from only one business day, one should be careful when implementing the results to practice. One day cannot reflect the state of the whole company, although the day is selected to be as normal as possible and the number of routes and customers are kept as high as possible. The data still represents a single snapshot of the state of the company, which limits the customer profitability to be only a static profitability and no time dependence is considered. However, since the data represents the reality and there is plenty of it, answers to research questions proposed in first chapter can be derived.

3.3 Descriptive figures

As the previous chapter described the data collecting process and the amount of data that was gathered, here more detailed figures of data is presented. The following figures and measures are produced to give a better view of the data that is used for analysis. By understanding the underlying data, analysis can be done more reliably and results can be evaluated more critically.

First, to get a broader view of the customers' locations, they are presented on a map. This is done using the latitudes and longitudes and the customers the drawing them on the map of Finland using Excel's Power Map tool. The resulted map can be seen in the Appendix 1. The map shows that most of the customers are located in the southern part of Finland and none of them represent the northern Finland. The map was also used to group routes into city center routes and urban area routes. Each route was examined individually to see whether it was driven in the center of examined city or in the urban area around the city center.

Second, descriptive statistics are presented. They are divided into three levels: cities, routes and customers. They are intended to give another broad view of the data so more detailed statistics can be presented later.

Table 3. Descriptive statistics of the data

Customers		
	Total number of customers	7935
	Average number of customers on route	118,43
Routes		
	Total amount of routes	67
	Number of routes in city centers	33
	Number of routes in urban areas	34
	Average duration of route	7h 15min 51s
Cities		
	Number of cities	19
	Average number of routes per city	3,53

The table shows again the total number of customers and routes. The average number of customers on route is high and causes problems for some cost allocation methods. Routes are evenly distributed between routes in city centers and urban areas. Also, the average duration of the route is approximately the length of the workday. As the map of the customers showed, the routes are located in various different cities and thus cover significant part of Finland. However, the number of routes per city is not divided evenly between cities. This division is presented in the next figure.

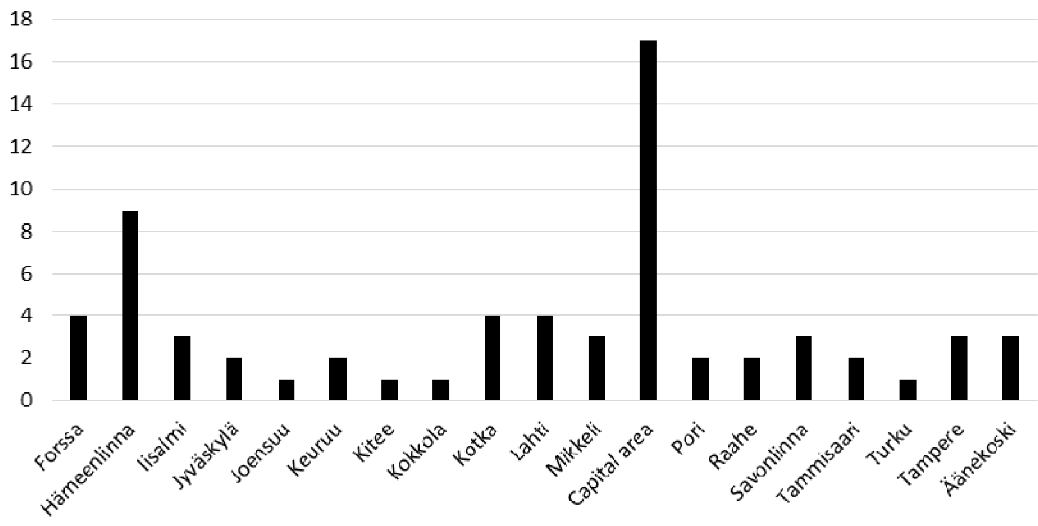


Figure 14. Number of routes in each examined city

The figure shows that the most routes analyzed in this study are located in capital area of Finland. This covers the cities of Helsinki, Espoo and Vantaa and some close municipalities around them. Four cities are represented by only one route and five cities have just two routes. In addition to capital area, Hämeenlinna is the second largest city in the data of this study by nine routes. Nevertheless, the previous table and the figure do not provide any of the information about the revenue and cost data, so they are presented in different way.

To get broader view of the whole data, it is presented as self-organizing map (SOM). SOM was first proposed by Teuvo Kohonen in 1982 and it is intended to visualize high-dimensional data. This is done by converting the non-linear statistical relationships between high-dimensional data into geometric relationships. (Kohonen, 2001, 106) The SOM functions with competitive unsupervised learning algorithm, which trains neurons by going through number of training cycles starting from randomly chosen weights and adjusting weight vectors in each training cycle. The winning neuron in each cycle is determined by measuring the minimal Euclidian distance of the neuron to input data value and adjusting its weights as well its nearest neighbor's weights closer to input data value. This also requires standardization of input data before feeding into network. (Hanafizadeh & Mirzazadeh, 2011.) More information about SOM methodology is provided by Kohonen (2001).

The result of SOM is usually reported by presenting the maps for each variable and their unified distance matrix (U-matrix). The U-matrix shows the distance of weight vectors of adjacent neurons as its elements. (Hanafizadeh & Mirzazadeh, 2011.) Thus, it can be interpreted as combined map of all maps. For this study, SOM of the underlying data was built using Matlab and SOM toolbox, which is developed by the researchers of the Laboratory of Computer and Information Science of Helsinki University of Technology in 1996. Before training the network, the data is standardized using variance standardization. The U-matrix and the maps of other parts of the data are presented in the Appendix 2.

The SOM of the data gives more insights to the data and shows the relative amounts of the values. The large values are rare compared to the vast majority of the small values. Only the distance from the depot includes approximately as much large values as small values. The U-matrix shows that in the whole data set, there are two potential clusters that are mainly characterized by large revenues from the service. These customers differ from other customers only by their large revenues from service. For information confidential reasons, the actual revenue and cost numbers were deleted from the SOM figures. Expectedly, the biggest waste containers, the largest revenues and the largest costs from waste are found in the same customers. Similarly, the distance from depot does not have any connection to other variable, which should be natural. However, the longest travelled time from previous customer and the longest distance from previous customer are generally not the features of the same customer although there are some connection. All in all, the SOM works well by visualizing the data and the features of customers.

4. CUSTOMER PROFITABILITY METHODOLOGY

So far, the theoretical basics of the subject is presented and the available data for this study is described. This chapter carries on the research by combining these previous chapters to form the methodology. Chapter presents the customer profitability model that is used, different cost allocation methods that are applied and the methodology for VaR-type application.

4.1 Customer profitability model

As stated in chapter 2 in this thesis, CP calculations can be executed in different way and there is no single right approach. Adjustments regarding the available data and the examined problem are necessary to be able to perform calculation accurately. Also some assumptions for calculations are necessary. Following Mulhern's (1999) CP component framework (Figure 8, p.25), the customer profitability components in this study are defined as follows.

Customer specification are quite clear and they are already discussed in previous sections. Examined customers are corporate customers, which are measured individually as they are located on the route. Thus, no aggregations of same customers in different cities is done, so CP calculations consider effectively the individual customer profitability on route. In addition, since data covers customers that are served in one day, calculating CP for single customers that are served in different parts of the Finland would not be possible, because the service can be done in different days. Customers are also existing customers, since their data is available for calculations. Including prospective customers would require additional route analysis, since they can be located practically anywhere on the map and the optimal truck route would change every time a new customer is added. Last, selected customers are always active customers, since inactive customers would not have contract with the firm.

The selected product or service is only the waste collection service for mixed waste, even though customer and firm may be in relationship in other branches and waste fractions also. If service includes washing service or rent payments for waste container, they are also included in the whole service. Organizational level is ignored and analysis only concentrates on the individual customer profitability.

The core profit element that calculations consider, is only the monetary profit for the service and the waste in the single visit. The service profit is composed by the revenues received for service and the costs of the labor. The waste profit is composed by the revenues received from the waste and the waste treatment fees of the waste that firm pays to landfill. All profits are present profits since the data is measured for only one day. Including future profits would require additional data for expected customer lifetime and emptying frequency. Since corporate customers have different contracts and their emptying frequency may vary, providing results for data set as large as used in this study would be very time consuming. Last, calculations measure the customer profit which is aggregated profit from service and waste. No upper category profit is included.

Cost allocation for service and waste costs is done by means of ABC and following the implementation practices that was presented in the chapter 2.4. First, the waste collection service in route is selected as the object, which costs are calculated. The direct costs that can be assigned to customers are the costs of waste, since they are only depended for the quantity of waste the customer produces. The costs of the driver and the truck, which are the service costs, are classified as overhead costs, since their allocation is not so straightforward. The activities that drive these overhead costs are the time used for driving from the depot to customers and back to depot at the end of the day, driving from customer to customer to collect the waste, the time it takes for driver to actually empty the customer’s waste container, the breaks the driver have during the day, and the trip to landfill for emptying whenever it is necessary. Since the cost object is only one service, the above overhead costs form the cost pool that can be assigned to activities according their usage rates. The assignment can be done in different ways, which are considered later. Last, by summarizing the amount of cost the activities use and the direct costs, the whole costs of the service can be defined.

Due to the limitations of data, only the costs that were listed above were included in the calculations. Thus, no customer acquisition and sustaining costs as well as administrative costs were included. However, as the purpose is to measure the route and customer profitability, the most important costs are included as Cooper and Kaplan (1988) highlighted. Since there are other costs as well that can be assigned to customers, the CP calculations are likely to overestimate the profitability, which reader should be aware of. After all the components are defined, the profitability model for customer profitability can be presented in the next figure.

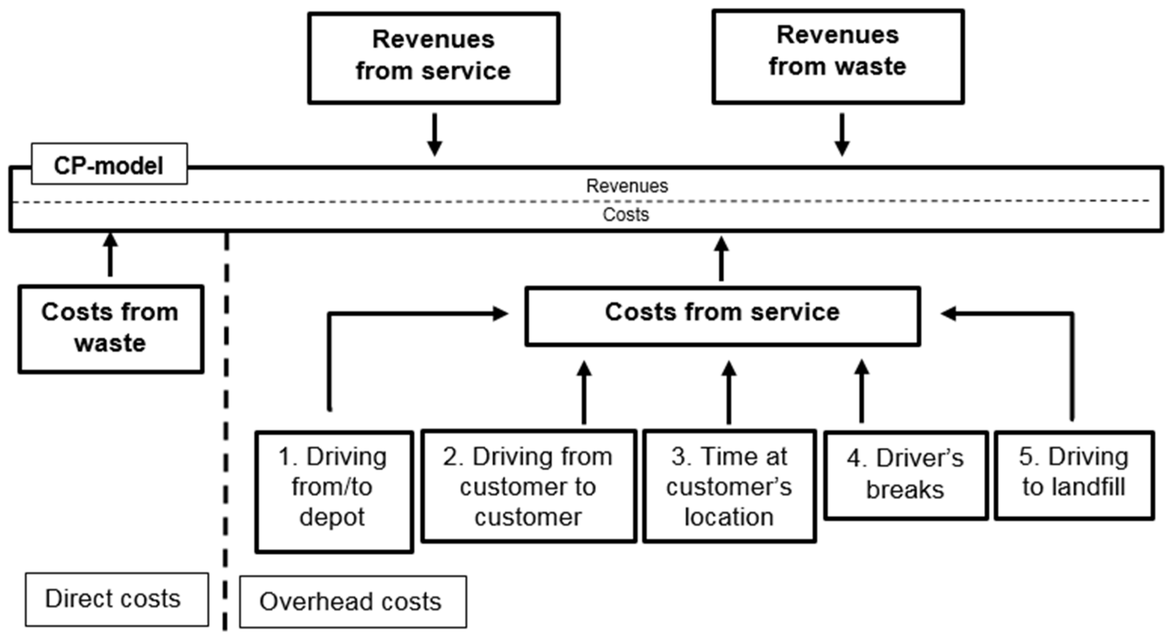


Figure 15. Customer profitability model combining revenues and ABC

The above figure shows the detailed model. However as stated in chapter 3.2, the data does not include specifications of time in customer's location, breaks or landfill visits. Instead, these activities are included in the time the truck spends on the route. Since that time is used for deriving the allocation of servicing costs, all these activities will be taken into account in calculations (except if the landfill visit occurred first or last in the day). Thus, the model can be shrunk to a formula, which is used to calculate the profitability of the individual customer. The customer profitability (CP) for individual customer i is therefore:

$$CP_i = R_{si} + R_{gi} - C_s - (C_g * Q_{gi}) \quad (11)$$

where

R_{si} = Revenue from serving individual customer (euros)

R_{gi} = Revenue of waste from individual customer (euros)

C_s = Cost from service (euros)

C_g = Waste treatment fee (euros/thousand kilograms)

Q_{gi} = Quantity of waste collected from customer (thousand kilograms)

When considering the formula components more in detail, the revenue from service is the amount of money charged for the waste collection service. Revenues from waste is the amount of money charged from customer for the waste that was in the container. The cost from service is some proportion of the total cost of the route, which is determined using the game theoretic methods. These are considered next. The waste treatment fee is the fee the landfill charges from service provider. Finally, the quantity of waste collected is the product of the number of the customer's waste containers, the size of the containers, and the average fill rate of the container.

Transportation cost allocations can be done in several ways. This study applies the cooperative game theoretic approach and models that are presented in chapter 2.5.2. As the description of the data showed, the number of the customers on route is generally very large (118,4 on average), so NP-hard methods cannot be applied. Hence, this study compares proportional methods, marginal methods and the approximation of Shapley value.

Proportional methods allocate the proportion of the costs of the route according to some criteria. The criteria that this study uses are considered in chapter 2.5.2 and they are the average (egalitarian) based, volume based and stand-alone based proportional allocations. In the average based allocation, each customers are assigned the same amount of total costs of the route, which is the average cost per customer. In the volume based allocation, each customer is allocated the proportion, which is equal to the relative number of waste containers of the customer. In stand-alone based allocation, each customer is allocated the amount of costs according to their relative distance from the depot.

Marginal methods allocate each player their marginal costs and the share of non-separable costs according to some criteria. Again, the criteria that are used are the average based, volume based, stand-alone based and the ACAM based proportions of the non-separable costs. To be able to assess the marginal cost for customer, their increase to route length is determined by the time it took from previous customer to examined customer. This time is illustrated in the Figure 12 (p.48). Time is then multiplied by the average cost of the driver and the truck for the company. In the ACAM method, the non-separable costs are allocated by the relative proportions of the costs that customer “avoided” when she was included in the route (the difference of her stand-alone costs and marginal costs).

Last, the approximation of Shapley value is calculated in a similar manner as Özener (2014). There, the allocation is calculated for only five nearest customers to lessen the computational complexity. Calculations are done using Matlab. The Shapley value calculations are conducted with the code developed by Twan Burg (2014), which calculates the Shapley value using the costs of all coalitions. The code that calculates the costs of all possible coalitions for five closest customers on route using the Haversine formula is developed for this study. The proportion of the total route costs that is allocated to each customers is the relative proportion of each customer’s Shapley value.

4.2 Evaluation methodology

To be able to evaluate the fairness of the cost allocation methods and select the most suitable one for customer profitability calculations, the concept of semicore is applied. Although the semicore is weaker concept than the core, it is practical for this study, since the amount of customers on routes is large. Thus, it would not be possible to calculate the core for any route this study considered. Semicore has similar methodology than the core, but it lessens the computational complexity by considering only simple group rationality.

The semicore of the game (N, C) is defined as the set of allocations that satisfies the individual rationality condition, that no player pays more than her stand-alone cost, that is

$$x_j \leq C(\{j\}), \qquad \forall j \in N \tag{12}$$

the group rationality condition, that the complement coalition pays no more than their total costs, that is

$$\sum_{i \in N \setminus \{j\}} x_i \leq C(N \setminus \{j\}), \qquad \forall j \in N \tag{13}$$

and the efficiency condition, that all costs of the route are allocated, that is

$$\sum_{j \in N} x_j = C(N). \tag{14}$$

Semicore is claimed to include all the essential fairness criteria and it is possible to calculate for larger data sets since the amount of coalitions needed is only $2|N| + 1$. (Flisberg et al. 2015.) Hence, the semicore is calculated for all compared allocation methods. Calculations are done using Matlab and the code to test the allocation belonging to semicore is developed for this study.

To test whether the allocation of different methodology belong to semicore, a sample of customers is chosen, where all the methods are tested. Thus, allocations do not have to be calculated 8 times for the whole data. The sample is not randomly chosen. The routes are picked so that the test sample represents the whole route data as well as it can. Thus, the test sample consists of five routes, which are picked from different cities, one routes from each. The cities are Forssa, Hämeenlinna, Lahti, Helsinki and Savonlinna, which all have more than one route in the whole data. The selected routes have different amount of customers and different lengths. This information about the sample data is presented in the next table.

Table 4. Descriptive values of the sample routes

City	Number of customers on route	Length of the route
Forssa	174	7h 23min 29s
Hämeenlinna	192	7h 21min 55s
Lahti	131	6h 36min 34s
Helsinki	232	9h 41min 7s
Savonlinna	97	5h 43min

The table shows that the number of customers and the length of the route vary between the routes that are selected to sample. Although testing the allocation methods for these five routes only, does not equal to testing the allocations for whole data, it does give a signal if some method is better than others. Moreover, it can point out methods that are not suitable for allocating transportation costs in waste management industry.

After the desirable allocation method is determined, the customer profitability can be calculated and the profitability differences can be examined. Thus, to measure profitability differences within route, the metric for difference is required. A simply difference metric used widely in finance and considering especially return variability is variance and standard deviation of the returns. The variance is defined as

$$\sigma^2(\tilde{r}_m) = the\ expected\ value\ of\ (\tilde{r}_m - r_m)^2 \tag{15}$$

where $\tilde{r}_m$ is the actual return and r_m is the expected or average return. The standard deviation is simply the square root of the variance:

$$\sigma(\tilde{r}_m) = \sqrt{\sigma^2(\tilde{r}_m)} \tag{16}$$

Sometimes actual returns are thought as a sample that represents the actual population. Then, when calculating the expected value of squared differences, it is not divided by number of individual returns N but by $N - 1$, which corrects for what is called the loss of degree of freedom. (Brealey, Myers & Allen, 2011, 163-164.) However, in this study, the route profitability is calculated from all customers on route, so the standard deviation can be calculated from whole population and no corrections are thus needed.

4.3 VaR-application

To be able to assess the risk of customer profitability, VaR-type thinking is applied in this study. In finance and especially in portfolio risk management Value-at-risk (VaR) is often applied for risk measurement due to its simplicity. It attempts to summarize all risks of portfolio of financial assets into a single number. In the simplest way, it answers to question “how bad can things get”. VaR-measure approaches this by calculating the possibility of losing more than certain amount of money in certain amount of time. For example, VaR could be calculated to find out that we have 1% probability to lose 10 000 euros in the next day. (Hull, 2015, 494-495)

In general, VaR can be defined as the loss that is expected to be exceeded with the probability of only x percent during the next t days. There is no right way to choose x and t but typical used value can be 1%, 2%, 5% or 10% as the probability x and 1, 2, 10 business days or 1 business month as the holding period t. Naturally, the loss is larger for probability of only 1% than probability of 5% (in some systems approximately 1,414 times as large) and for shorter time periods t than longer time periods t (approximately $\sqrt{t}$ times larger than 1-day holding period). In addition to probability and time estimate, VaR assumes that the underlying portfolio or asset remains unchanged during the holding period. (Linsmeier & Pearson, 2000)

There are different approaches for calculating VaR but they can roughly be categorized into two groups. These are model building approach and historical simulation approach. The historical simulation assumes that past will represent future. First, for example 501 days of historical price data are considered, then the returns of each day is computed and applied to today’s portfolio. Then, the distribution of what would happen if the past represented future can be computed. Taking the five smallest portfolio losses, it can be determined that there is 1% chance of losing at least the fifth smallest amount of euros in the next day. The model building approach uses portfolio's expected returns and volatilities to determine possible loss supposing that the returns are normally distributed. It can be calculated as linear model, quadratic model or as Monte Carlo simulation. (Hull, 2015, 494-512) This thesis applies the approach similar to historical simulation.

As seen, VaR is a powerful methodology in risk management since it presents complex information in a simple package. This study considers CP and VaR methodology can be easily interpreted to CP analysis also. However, since VaR is purely a measure for risk of financial assets, this study refers rather to VaR-type thinking to avoid confusion with concepts. With VaR-type thinking it is possible to measure how much the route profitability would decrease if certain amount of the most profitable customer are lost during the measured period. With the results, profitability sensitivity can be measured and repairing actions can be considered if the loss of profitability seems too obvious.

As denoted above, two important measures have to be defined when applying VaR-type thinking: the probability of the loss and the holding period. For CP, there are no clear probabilities of loss that are reasonable to consider. Thus, several probabilities are calculated to understand the sensitivity of the profitability. For company, the most crucial quantity of customers would be the amount that makes the route unprofitable. Moreover, the examination of whether the route is still profitable after certain amount of the most profitable customers are lost is interesting. The larger the quantity or probability, the more confident firm can be that its profitability will remain in the future. Using this assumption, this thesis considers the probabilities of 1%, 3%, 5% and 10%. Bigger probabilities would increase the need to adjust the collecting route and thus the underlying data would not apply anymore. If the route is still profitable after these amount of losses, CP can be thought to be at good state.

Since CP is calculated from single day data only, the time period used is the time between the day the data was gathered and the day the route is driven next time. If customers' contract would all end simultaneously, the contract period could be used as the time period. However, since contract periods differ, assessing single contract period would be impossible. In addition, the route may not be driven identically next time, because there may be some different customers due to their various emptying frequency. Thus, the time period for VaR-measure will be more of a theoretical since the same identical route may not be ever driven. Nevertheless, it should give appropriate risk information for the current state of the route profitability.

5. EMPIRICAL RESULTS

Previous chapters discussed the base of this study. Here, the results according to data that was previously presented are introduced and analyzed. This chapter also intends to answer the research questions proposed in the first chapter.

5.1 Customer profitability model comparison

First, to be able to examine the customer's profitability on routes, the best transportation allocation method is determined. The methods that are compared are presented theoretically in the section 2.5.2 and practically in section 4.1. The fairness of the methods is tested by calculating whether the allocation belongs to semicore. By using the methodology described in sections 4.1 and 4.2, the results are derived.

Detailed results are presented in the Appendix 3. There, each route is tested for all the conditions of the semicore. This is done for all 8 methods that are compared. The x-mark signifies whether the allocation fulfills the condition that is tested. The last column concludes if the allocation belongs to semicore. The allocation belongs to semicore only if all the conditions are fulfilled.

Appendix 3 shows that each method is able to fulfill the group rationality and efficiency conditions. Thus, the only condition that made differences between methods was the individual rationality condition. The proportional methods and the Shapley value approximation could fulfill this condition at some parts, but marginal methods all failed in each route. Hence, none of the allocations of marginal methods belonged to semicore. The failure is explained because of some customers' long distance from other customers. In many cases, the long distance is especially the distance from the depot to the first customer. Then, the marginal costs of that customer are larger than the stand-alone costs of the customer and the allocation of the non-separable costs does not make a difference.

Proportional methods and Shapley value produced the allocations that could fulfill all the conditions. The best of them were the proportional method, where the allocation is based on the customers' distance from the depot (stand-alone based allocation) and the Shapley value approximation. The stand-alone based allocation was able to produce allocation that belonged to semicore in each case and Shapley value only failed in the case of Hämeenlinna. Closer examination of results showed that Shapley value failed only because one customer is located very close to depot and her stand-alone costs are then very low. Only the stand-alone based allocation could take this into account. To give a summary of the results, next table is composed based on the results of the Appendix 3. Here, the x-mark signifies that the allocation belonged to the semicore.

Table 5. Summary of results of cost allocation models

	Proportional methods			Marginal methods				Shapley value
	Average	Volume	Stand-alone	Average	Volume	Stand-alone	ACAM	
Forssa	x	x	x					x
Hämeenlinna			x					
Lahti			x					x
Helsinki	x	x	x					x
Savonlinna	x		x					x

Table shows the summary of the methods in the sample data. The proportional methods where the allocation is based on volume and the average of the costs did not perform poorly, but they were not the best ones either. The allocation in Forssa and Helsinki proved to be the easiest since all the methods, except marginal methods, were able to allocate them fairly.

By combining theoretical basics and empirical results of the transportation cost allocation, the most suitable method can be concluded. Proportional methods are relatively easy to calculate and the stand-alone based allocation produced the best results in the test sample. However, the stand-alone criterion does not take the locations of the customers into account. Although it divides costs to customers according to their distance from depot, the customers that are located in different ways of the depot but in the same distance will be assigned the same costs, even though the other may have lots of other customers nearby and the other may be all alone. Hence, the interconnection of customers are not considered sufficiently well to ensure the fair allocation.

The Shapley value solves these problems by taking interconnections of the customers better into account. It is computationally more challenging than the proportional methods, but by simplifying it to consider only the five closest customers, the computational complexity can be lessen. In addition, even five closest customers are enough to include the most relevant interconnections between customers. Shapley value is not the best method to take the distance from the depot into consideration as it failed once the individual rationality condition in the test sample. Nevertheless, it allocates the costs more fairly for all the customers in the route than stand-alone based allocation because the distances between the customers are included in the calculations. Thus, Shapley value, and even the Shapley value approximation is more recommendable allocation measure than other measures considered in this study. The following calculations in this study are done using the allocations based on the Shapley value approximation.

When the transportation cost allocation problem is solved, the appropriate way to determine customer profitability can be derived. Customer profitability model should include all the revenues that are generated from customers. These can be the revenues from service, waste and the additional services that are sold to customers. Model should also include all the relevant costs. The direct costs, such as the cost from waste can be directly subtracted from individual customers. The service costs can be assigned to customers using Shapley value approximation. If the number of customers on the area is so small, that the original Shapley value is computationally possible to calculate, it can also be used. As this is not the case in the majority of the cases, the approximation should be used by limiting to only small number of the closest customers at a time. In addition, to improve the model, the other costs, such as the administrative costs and the customer acquisition costs can be included. After the appropriate profitability is derived for customers, company can focus on the unprofitable existing customers, predict which customer would be the most desirable to acquire and monitor the success of business units.

5.2 Customer profitability differences in routes

Using the Shapley value approximation as the transportation cost allocation method, the customer profitability calculations are executed for all 7935 customers. Since the number of routes is high, the customer profitability differences in routes is examined in city level. Standard deviation of the customer profitability is used as the measure of difference and it is calculated at the route level for the profit measured in euros. The loss of degree of freedom was not taken into account. The results of the differences are presented in the next figure. For comparison, the figure also includes the average standard deviation for all routes and the standard deviation for all customers.

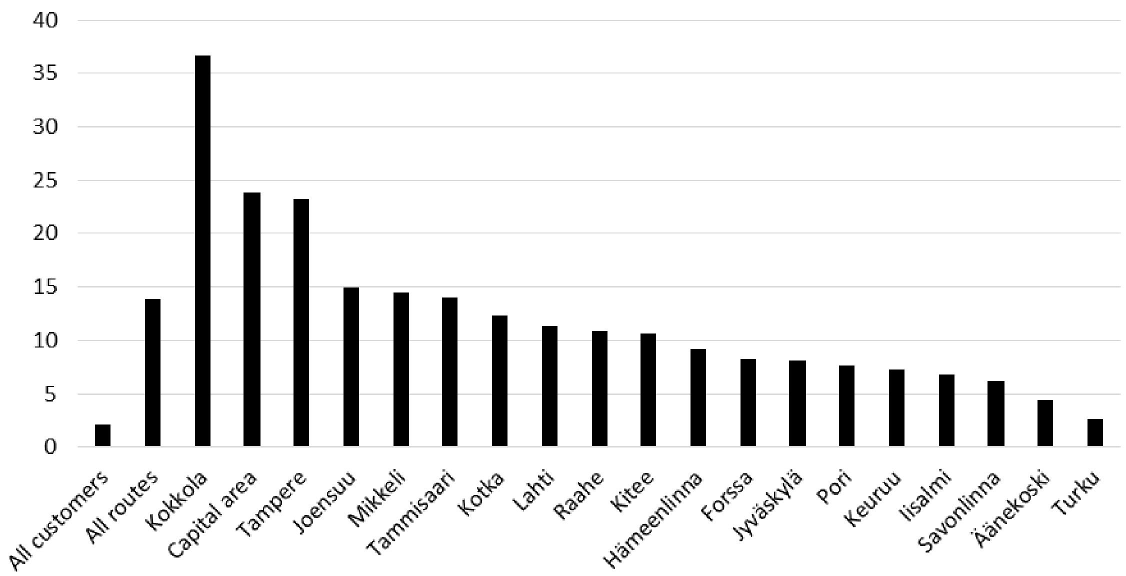


Figure 16. Standard deviations of routes in different cities

The figure shows the great variety of customer profitability in different cities. The largest differences are in Kokkola, where the standard deviation is over 36 and the smallest are in Turku with the standard deviation of approximately 2,5. However, as the Figure 14 (p.52) showed, only one route is included in both cities in this data. Thus, sweeping conclusions about these results cannot be made since they only represent the situation in one route in one day. The capital area, which included 17 routes and Hämeenlinna, which included 9 routes, can be used to draw some conclusions about customer profitability differences. In the capital area, customer profitability differences are relatively large, when compared to the average of all routes. In Hämeenlinna, the profitability differences are over two times smaller than in capital area and significantly smaller than the average of all routes.

More comprehensive results are the standard deviations of all customers and all routes. The standard deviation of all customers is very small (2,17) which indicates that there is large amount of customers with quite similar profitability. Hence, the profitability of all customers is on average only 2,17 euros larger or smaller than the average profitability. This average profitability cannot be presented due to the information confidential reasons. The small standard deviation for all customers also means that the huge profits or the big losses are rare in the whole customer base. This is also supported by the self-organizing map of the data (Appendix 2), which shows that the largest revenues and costs are very rare. The largest part of the customers by far, are the ones with small revenues and costs.

The data set includes half of the routes, which are driven in the city centers where customers are naturally closer to each other and half of the routes are driven outside the centers, in urban areas, where the distances are generally much larger. Therefore it is interesting to examine the profitability differences between the city center routes and the urban area routes since they have significantly different transportation costs. The next figure shows the comparison of city center routes, which included 33 routes in different cities and urban area routes, which included 34 routes.

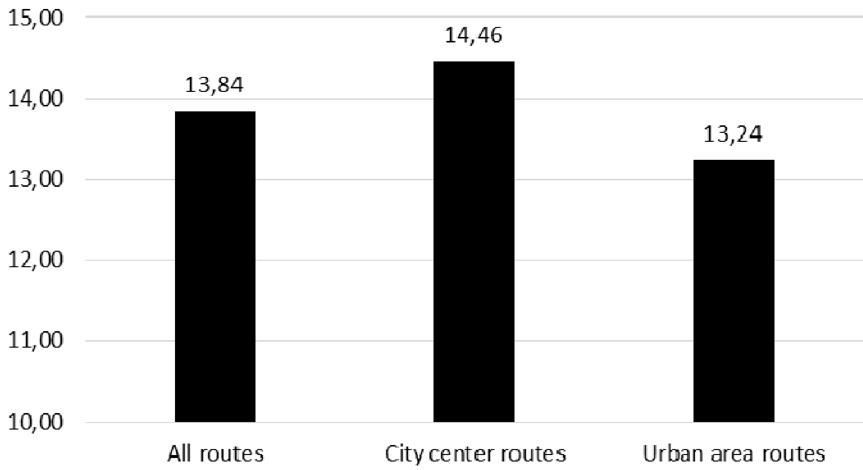


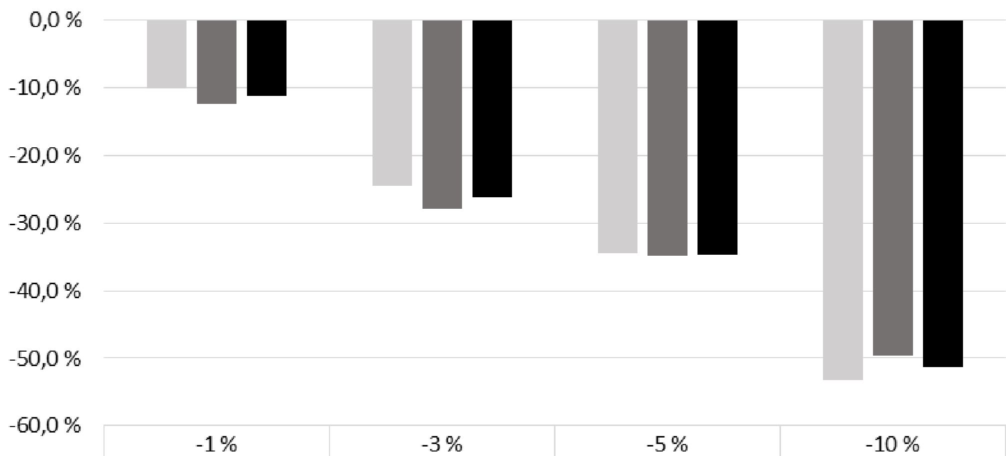
Figure 17. Comparison of the standard deviations

The figure shows that there is only a little difference between the customer profitability in city centers and urban areas routes. The customer profitability in urban areas differs from the average profitability 1,22 euros less than in the city center routes. This could imply that pricing in the urban areas is done more consistently than in the case of city center customers.

However, since the difference is small, the customer profitability differs almost as much from the average in both routes. Moreover, as the number of routes in both category is still relatively small, the difference may disappear or turn the other way around if more data is analyzed. This study did not revealed any large differences between cities, which can indicate that both routes are equally risky and neither of them should be avoided. On the other hand, this may be due to the company’s ability to manage customer relationships and keep both route types equally risky. More data would be required to confirm these perceptions.

5.3 Route profitability sensitivity

Last, to assess the real risk that arises from customer profitability differences, the VaR-type application is executed. As stated before, the route profitability is calculated without 1%, 3%, 5% and 10% of the most profitable customers. Since the data set of routes is relatively small, the unprofitable routes and routes that become unprofitable when some customers are lost, are first deleted from the data. Including them would produce huge percentage losses that distorted results substantially. For information confidential reasons, the exact number of removed routes cannot be displayed. Nevertheless, the vast majority of routes did not fulfill these conditions so the loss of the routes was not significant. Now, using this data, it is possible to quantify the sensitivity of the route profitability. To have statistical reliability, the VaR-type application is calculated for city center routes, for urban area routes and for all routes and not in the city level. The sensitivity is calculated as the percentage loss from the overall route profit. Again, for information confidential reasons, the actual route profit numbers cannot be reported. The next figure presents the results.



	-1 %	-3 %	-5 %	-10 %
City center routes	-10,1 %	-24,4 %	-34,5 %	-53,2 %
Urban area routes	-12,4 %	-28,0 %	-34,9 %	-49,7 %
All routes	-11,2 %	-26,2 %	-34,7 %	-51,4 %

Figure 18. Route profitability sensitivity

The figure shows that there are so large profitability differences, that even small losses of the most profitable customers have significant impact on the route profitability. The decrease is naturally the largest when the first 1% of the most profitable customers is lost and the effect dilutes when more of the customers are lost. If 10% of the most profitable customers are lost, more than half of the profits is also lost on average, which implies a great risk. However, as the results represents the worst case scenario, routes are still profitable after losing even 10% of the most profitable customers. All the other customer losses as big would not decrease the profits so much. In addition, when comparing to results of other customer profitability studies, the findings of this study shows much smaller risk. Even after severe customer losses, the routes would still generate some profit.

When comparing city center routes and urban area routes, the figure shows mixed results. The loss in urban area routes is a little larger in 1% and 3% cases. When the loss is increased, city center routes are first tie with urban area routes at 5% and suffer from greater loss at 10%. If these results are compared with the risk of the routes that are measured by the customer profitability standard deviations, no significant connection can be seen. As their standard deviations are almost identical, the losses with VaR-type application are also almost identical. The differences are likelier to be explained by the coincidence than some fundamental phenomenon. More reliable results would require more data.

Since this connection between the standard deviation of the customer profitability in the route and the route profitability sensitivity is rather interesting, it can be further studied with the data of this research. To examine this, the profitability losses can be studied in different standard deviation segments. First, the data is divided into three equal sized sets according to the customer profitability standard deviations. For information confidential reasons, the exact number of routes in each set cannot be shown, since it would expose the amount of unprofitable routes, which were previously removed from the data. The first set consists of routes with the smallest standard deviations of at most 6, the second set consists of routes with the medium standard deviations of 6 to 12 and the third set consists of routes with the largest standard deviations that are larger than 12. Then, the VaR-type application is executed for all three data sets. The next figure present the results of this comparison.

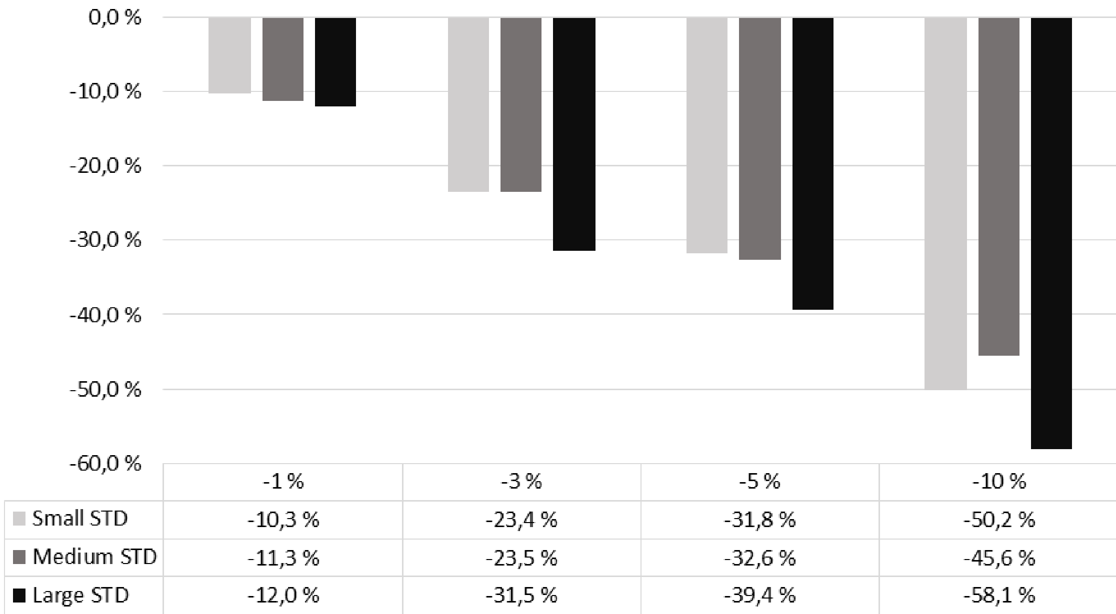


Figure 19. Sensitivity comparison between different standard deviations

The figure shows a little connection between these measures. As the standard deviation of customer profitability increases the worst case losses also increase. This applies in every case but the last 10% case. The large standard deviation routes suffer always the most ending up to 58,1% loss at 10%. The small standard deviation routes suffer the least in every case but the last, where the medium standard deviation routes suffer the least. Thus, the standard deviation and the route profitability loss do have a slight connection, although the scarcity of data decreases the reliability of the results. To confirm the connection, more routes should be analyzed. Nevertheless, the data used in this study indicates that the connection exists and increase in the standard deviation of customer profitability of the route also increases the loss if the most profitable customer are lost.

6. CONCLUSIONS

The purpose of this study is to examine the customer profitability in garbage truck routes. The thesis covers this subject by reading up on the current academic literature of customer profitability analysis and its applications in different industries. Especially, this research studies the transportation allocation methods that can be used at the basis of the customer profitability analysis. Thesis draws the big picture from the connection between customer profitability and shareholder value down to specific cost allocations, which take advantage of the cooperation game theory concepts.

By using real data of the big Finnish waste management company L&T, this study develops a customer profitability model to assess the customer profitability in garbage truck routes. First, by interviewing experts in company, the business logic behind the numbers is presented. Then, using the practices of academic literature, the knowledge of the business and the raw route and financial data, the customer profitability framework is developed. The framework is completed by comparing different transportation cost allocation methods. The best allocation method is selected and customer profitability is calculated for whole data set covering 7935 individual customers in 67 routes in 19 different cities around Finland.

Customer profitability data is used to examine the profitability differences on routes in order to assess the riskiness of the routes. Large profitability differences is assumed to increase the risk of the route since losing profitable customer would have more effect on the profitability of the routes with large differences than routes with small differences. Profitability differences are studied using the standard deviation of the customer profitability on the route. In addition, profitability differences are also compared in the case of city center routes and urban area routes to analyze whether the location of the route affects its risk.

Last, the affection of customer losses on route profitability is examined by VaR-type methodology. The route profitability is calculated without 1%, 3%, 5% and 10% of the most profitable customers to find out the risk tolerance of the routes. Moreover, VaR-type methodology can be used to examine the connection between the profitability differences and the customer loss tolerance of the routes. To see the big picture of the objectives and their main results of this study, all research questions and their answers are first summarized in the next table.

Table 6. Summary of the research questions and the results

Research questions	**Answers**
1. How customer profitability in the waste management industry is previously studied in academic literature?	Several customer profitability and customer lifetime value studies were found. None was conducted in waste management industry, but their documented methodology could be applied.
2. How should the customer profitability in garbage truck routes be calculated?	The customer profitability is the difference of the revenues received and the sum of the costs, which serving the customer required. The most suitable method for transportation cost allocation is the Shapley value approximation.
3. How big are the customer profitability differences inside the garbage truck routes?	The average standard deviation in all routes is 13,84 and in all customers 2,17.
4. Do routes become unprofitable if 1%, 3%, 5% or 10% of the most profitable customers are lost?	On average, for 1% customer losses, the route profitability decreases 11,2%, for 3% losses, 26,2%, for 5% losses, 34,7% and for 10% losses, 51,4%.

The table above shows the brief summary of the results. Nevertheless, to get more comprehensive conclusions, each result is examined more in detail. The literature review of the subject found several customer profitability and customer lifetime value studies. Significant customer profitability differences are found throughout the industries, which indicates the importance of the subject. Search did not come across with any customer profitability study made in waste management industry but the methodology is explained well and it could be transferred to garbage truck route cases. A large part of customer profitability analysis is assigning the direct and overhead costs to customers using activity based costing. Literature review found several applications of activity based costing in logistics and transportation industry. Although none of them was found to be conducted in the waste management industry, their documented methodology could be applied in this study. Finally, transportation cost allocation problem is examined in several industries where transportation costs form a large part of the total costs. Studies presented different methods but none of them were applied in waste management industry.

The literature review did not find any applications of customer profitability in the waste management industry. Moreover, most of the customer profitability studies used activity based costing as the cost allocation method, but none of the activity based costing applications in transportation industry used the cooperative game theoretic approach to transportation cost allocations. This may be due to the computational complexity of some of the allocation methods. Since computational complexity can be lessen without losing the most important features, these methods can be applied in customer profitability analysis. Thus, literature review found useful practices that can be applied when conducting customer profitability calculations in the waste management industry, but corresponding studies were not found. Combining these concepts, customer profitability can be calculated in waste management industry using existing practices.

To decide the best transportation cost allocation method, which can be applied in the real data in the waste management industry, eight methods were compared. According to test sample, the best methods were the stand-alone cost based proportional method and the Shapley value approximation method. Both of them were able to allocate costs so that the result belonged to semicore almost every time. Although semicore is weaker concept of fairness than the core, it is possible to apply in large data sets and remain the computational efficiency. Combining the theoretical knowledge and the empirical results, the most suitable method is found to be the Shapley value approximation. It is better for considering the interconnections between the customers, which stand-alone based proportional method is not able to take into account. Hence, it solves the underlying problem of dynamic costs more reliably than proportional methods. Shapley value approximation is not as good at taking stand-alone costs into account as stand-alone based method, which decreases its reliability for customers that are located very near the depot compared to other customers. However, since the majority of the customers cannot be relatively the closest customers of the depot, the Shapley value approximation serves as the fairer cost allocation method for most of the customers, which makes it recommendable.

Using the best cost allocation method, the customer profitability model can be formed for the waste management industry. The customer profitability is simply the difference of the revenues that is received from customer and the sum of the costs, which serving the customer required. The costs can be divided into direct costs, that are directly assigned from each customers and overhead costs that should be allocated to customers by their rate of consuming. In the waste management industry, the transportation costs are usually the largest costs that should be treated as overhead costs since they cannot be directly assigned to customers. When the number of the served customers is usually very large, Shapley value approximation is used to assign the transportation costs. Other costs, such as administrative costs should also be assigned to customers using the means of activity based costing if the corresponding data is available for calculations.

The profitability differences were studied in all cities and in city center routes and urban area routes. The average standard deviation in 67 routes is found to be 13,84. The standard deviation of all 7935 customers is 2,17, which indicated that the profitability of the vast majority of the customers is close to the average profitability. The significant profitability differences are thus relatively rare and they are emphasized in individual routes. Large conclusions cannot be made when individual cities are considered since majority of cities have only a couple of routes in the whole data. To compare more reliably the profitability differences between cities, much more data is needed.

When the customer profitability differences in city center routes and urban area routes are compared, no significant difference is found. City center routes had only a little larger standard deviation than urban area routes, but the difference may disappear if the data is increased. This can indicate that city center routes and urban area routes are equally as risky and neither of them should be avoided because of profitability risk. Another interpretation is that the company has managed to build its routes and price its service contract in such way that there are no differences between the locations of the customers. All in all, even if the profitability differences are small in the whole customer base, there are significant differences in routes which may expose to risk of unprofitability.

The results from the VaR-type thinking show that on average, 51,4% of the profits is lost if 10% of the most profitable customers is lost. The loss is the largest for the first 1%, where it is 11,2%. The results show that the impact is significant but on average the routes stay quite profitable after 10% of the most profitable customers is lost. Especially, when compared to the findings of the literature review, the route profitability can be thought to be at good level. As in the case of the standard deviations, city center routes and urban area routes are affected approximately as much in all customer losses. Since the route data is relatively small, no general conclusions can be made.

Last, the additional experiment of the connection between standard deviation of customer profitability in route and the profit loss if the most profitable customers is lost, showed a little connection. Although the samples were relatively small, the results roughly followed the intuition that small standard deviation routes suffer less than larger standard deviation routes in case of customer losses. Only in the case of 10% customer losses, the routes with medium standard deviations suffered the less. This result is more likely to be caused by the scarcity of data than some real phenomenon behind it. Results indicates that standard deviation of customer profitability in route may be a valid risk measure in waste management industry although more data is required to confirm this perception.

This research can have several managerial implications in the waste management industry. First, studying customer profitability can point out the customers that are unprofitable. Since this has a direct connection to shareholder value, companies should sustain only profitable customers and try to turn unprofitable ones into profitable. By having the information about profitable and unprofitable customers, the company can clarify the reasons behind unprofitability and design actions to turn unprofitable customers into profitable. Second, customer profitability analysis can help pricing new or current contracts better. Thus, it decreases the possibility to make unprofitable contracts. By knowing the costs of each customers in each case, managers can be aware of the limits of the contract prices, which helps designing contracts that create shareholder value.

Third, by understanding the drivers of customer profitability in the waste management industry, company can identify potential customers, which would be very profitable if they were acquired. As the major part of the customers' cost are not determined very straightforward, certain customers can be relatively much profitable than others. Managers can then concentrate customer acquisition actions to potential customers that really matter for the company. Last, customer profitability information can help sharing best practices inside the company. If the same type of customers have different profitability in firm's customer portfolio, something may be done better in the case of the most profitable customers. Spreading the best practices can help the company to accomplish higher customer profitability in different parts of the customer portfolio. Therefore, understanding customer profitability may be difficult, since it demands a lot of work but it steers the operations to more efficient direction.

This thesis holds a lot of limitations and it is aimed to solve a rather specific problem. Although a comprehensive answer is derived, the future research can expand the research by including more costs, more customers, more waste fractions and more alternative transportation cost allocation methods. Moreover, the customer profitability model used in this study allocates the costs of the service only using the transportation costs. However as seen in the background of the model, some of the service costs comes from the time used in customer's locations. Hence, the future models should include also the number of waste containers as part of the allocation principles.

Large part of the results of the profitability differences were conducted with too little of the data. A larger study would provide more reliable results that could confirm the city related differences and the connection between route profitability differences and route profitability sensitivity. Thus, more research about the valid risk measures for customer assets is required. This research showed that even the simplest standard deviation can capture some of the riskiness of the customer profitability. Finance literature and portfolio risk management have studied a lot of different methods to measure the riskiness of the asset portfolio, which may offer a better proxy for the risk.

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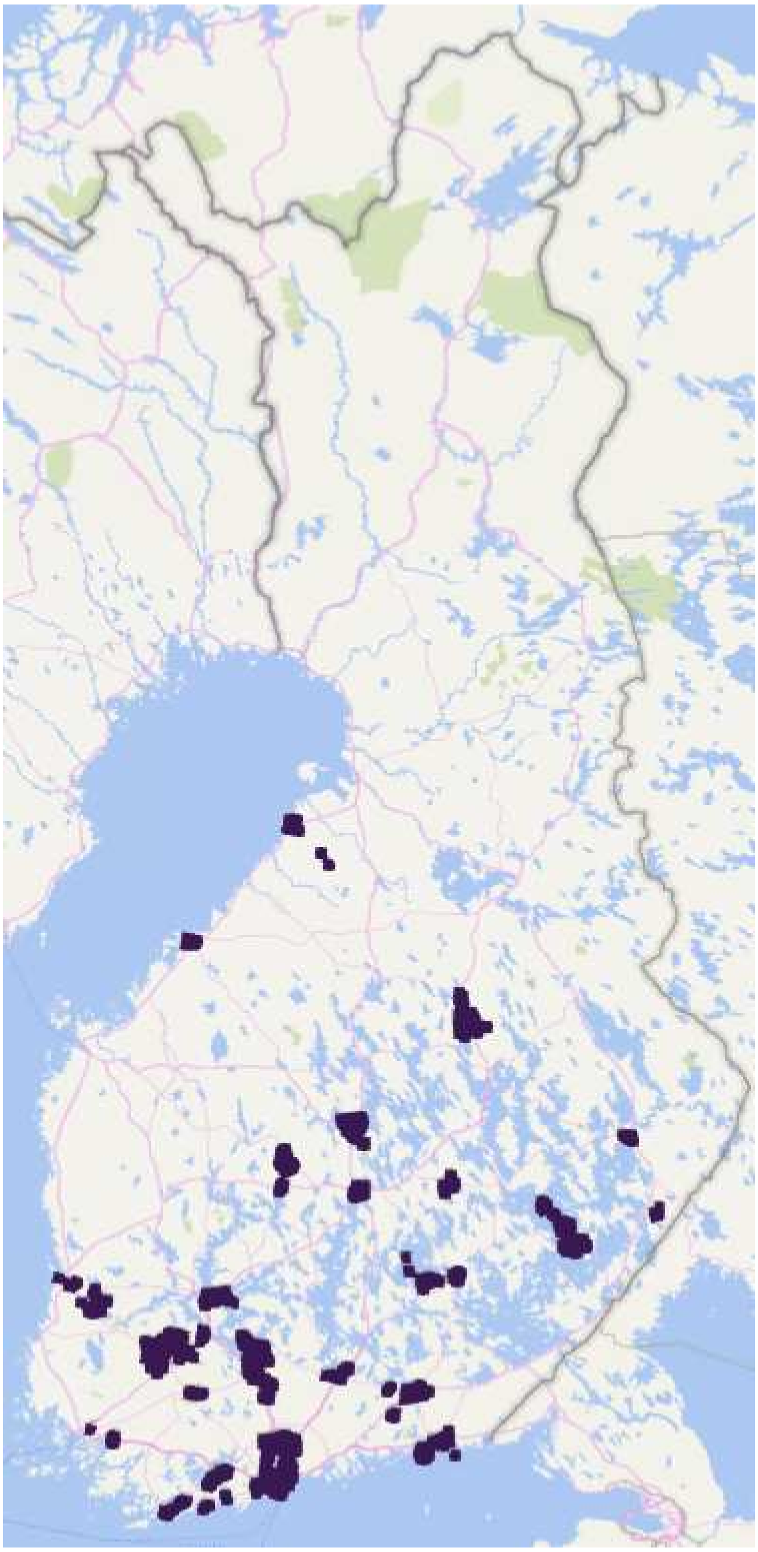
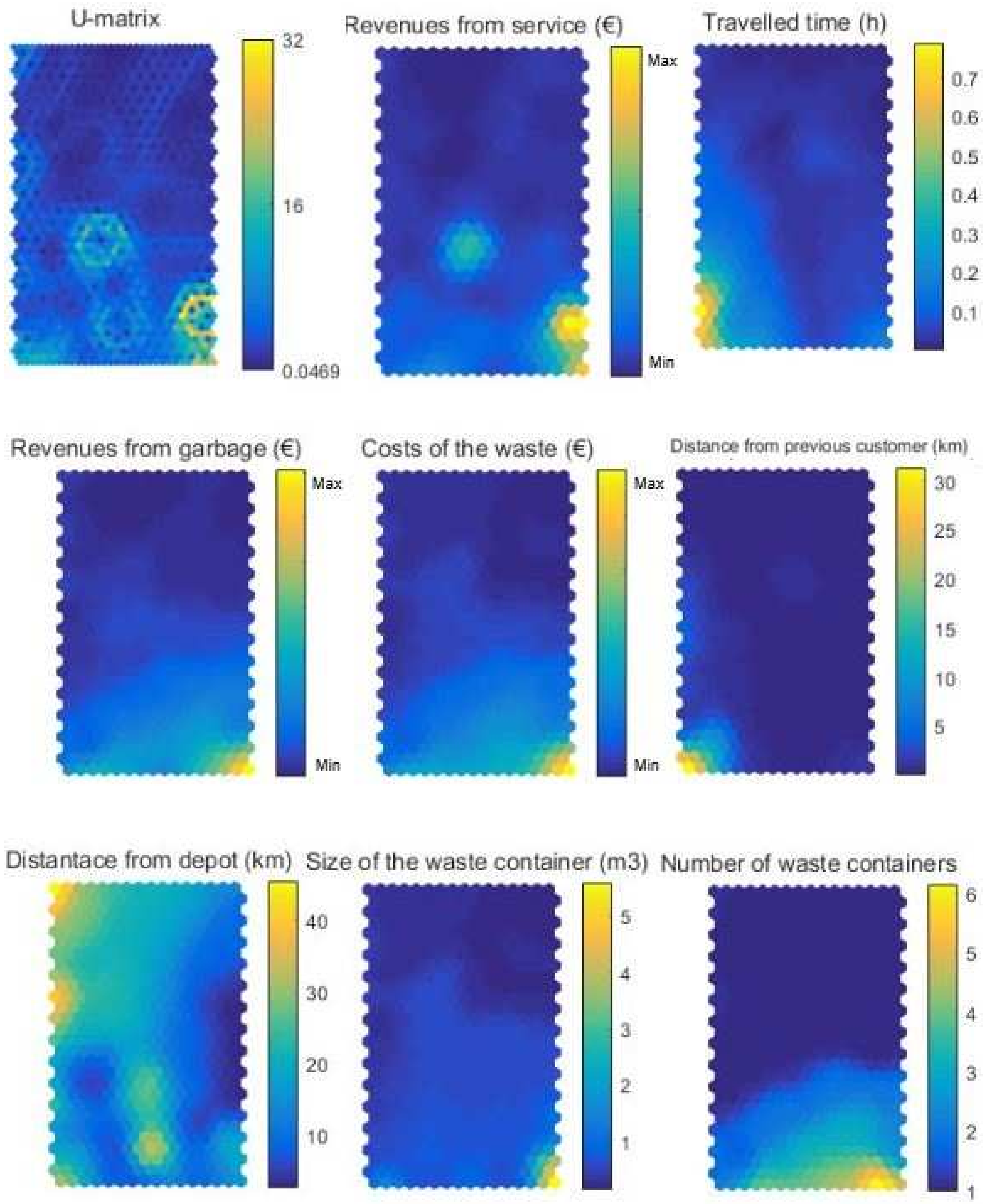
APPENDIX 1. Examined customers on a map



APPENDIX 2. SOM of the data



APPENDIX 3. Comparison of the allocation methods

Proportional methods

Allocation based on average	No more than stand-alone costs	No more than total group costs	All costs allocated	Belongs to semicore
Forssa	x	x	x	yes
Hämeenlinna		x	x	no
Lahti		x	x	no
Helsinki	x	x	x	yes
Savonlinna	x	x	x	yes

Allocation based on volume	No more than stand-alone costs	No more than total group costs	All costs allocated	Belongs to semicore
Forssa	x	x	x	yes
Hämeenlinna		x	x	no
Lahti		x	x	no
Helsinki	x	x	x	yes
Savonlinna		x	x	no

Allocation based on stand-alone costs	No more than stand-alone costs	No more than total group costs	All costs allocated	Belongs to semicore
Forssa	x	x	x	yes
Hämeenlinna	x	x	x	yes
Lahti	x	x	x	yes
Helsinki	x	x	x	yes
Savonlinna	x	x	x	yes

Marginal methods

Allocation based on average	No more than stand-alone costs	No more than total group costs	All costs allocated	Belongs to semicore
Forssa		x	x	no
Hämeenlinna		x	x	no
Lahti		x	x	no
Helsinki		x	x	no
Savonlinna		x	x	no

Allocation based on volume	No more than stand-alone costs	No more than total group costs	All costs allocated	Belongs to semicore
Forssa		x	x	no
Hämeenlinna		x	x	no
Lahti		x	x	no
Helsinki		x	x	no
Savonlinna		x	x	no

Allocation based on stand-alone costs	No more than stand-alone costs	No more than total group costs	All costs allocated	Belongs to semicore
Forssa		x	x	no
Hämeenlinna		x	x	no
Lahti		x	x	no
Helsinki		x	x	no
Savonlinna		x	x	no

Allocation based on ACAM	No more than stand-alone costs	No more than total group costs	All costs allocated	Belongs to semicore
Forssa		x	x	no
Hämeenlinna		x	x	no
Lahti		x	x	no
Helsinki		x	x	no
Savonlinna		x	x	no

Method based on Shapley value approximation

Allocation based on Shapley value	No more than stand-alone costs	No more than total group costs	All costs allocated	Belongs to semicore
Forssa	x	x	x	yes
Hämeenlinna		x	x	no
Lahti	x	x	x	yes
Helsinki	x	x	x	yes
Savonlinna	x	x	x	yes