Factors that determine costing system errors – a numerical simulation approach

Zur Erlangung des akademischen Grades eines
Doktors der Wirtschaftswissenschaften

Dr. rer. pol.

bei der KIT-Fakultät für Wirtschaftswissenschaften
des Karlsruher Instituts für Technologie (KIT)

genehmigte

DISSERTATION

von

M.Sc. Ana Mićković

Referent:	Prof. Dr. Ir. Marc Wouters
Korreferent:	Prof. Dr. Stefan Nickel
Tag der mündlichen Prüfung:	22.05.2019
Karlsruhe	

Content

List of figures

List of tables

1. Introduction

In this dissertation, we investigate the factors that determine the size of errors in costing systems. To model the influences of these factors on accuracy, we use numerical simulations.

Many companies use simplified methods for measuring and allocating costs and so their cost information is likely to be inaccurate. As a result, they may lack much of the information necessary for management, for example, for identifying opportunities for improving efficiency, for evaluating the financial benefits and costs of efficiency improvement investments, and for holding managers accountable for efficiency (Martin, Muûls, De Preux, & Wagner, 2012; Schleich, 2009; Schleich & Gruber, 2008). In many cases, the allocation of costs based on something as straightforward as direct product costs is not going to be too accurate. Being able to assess that inaccuracy is an important input for the cost-benefit tradeoff between the cost of generating more accurate cost information and the benefits of having that information.

However, because current research can only partly explain factors that influence errors in costing systems, and energy and other commodities cause some specific errors that have not been investigated so far, we focus on specific errors that are relevant in this context. We conduct three research projects that look at costing system accuracy: a literature review and two simulation studies. As a whole, the dissertation contributes to a more nuanced understanding of which factors can influence the accuracy of costing systems in the context of commodities.

The dissertation is structured into five chapters: this introduction, a systematic literature review on energy costs in manufacturing companies, a simulation study investigating the effect of activity cost pool interdependency on the accuracy of energy costing information, a simulation study on the impact of input market dynamics on the accuracy of costing systems over time, and a conclusion of the dissertation. We now present a short overview of chapters 2, 3, and 4.

The second chapter of this dissertation is a systematic literature review focusing on costing system errors regarding energy costs in manufacturing companies. Complex purchase pricing structures and large differences in usage among products make energy a particularly relevant commodity to study in the context of costing errors. Since there are almost no studies that provide a more nuanced description of measuring and allocating energy costs, this dissertation contributes to the literature by reviewing the availability and use of empirical information on energy costs in manufacturing companies.

The systematic literature review covers 51 papers from 22 journals in the fields of business, accounting, energy, and engineering. Our sample of papers has a focus on empirical studies that explore how companies measure and allocate energy costs, and furthermore, how is this information used in company's energy management. We explore how those practices may be different depending on the type of company, and therefore compare energy intensive with non-energy intensive companies, and large with small and medium sized enterprises. The findings suggest that most literature concerns energy intensive and large companies. Moreover, almost no studies provide a detailed description of practices on measuring and allocating energy costs in manufacturing companies.

The third chapter is a simulation study, in which we investigate the effect of activity cost pool interdependency on the accuracy of energy costing information. Previous research has focused on general errors of costing systems and divided these into measurement, aggregation and specification errors. The interdependency error can be seen as a special type of measurement error, which is occurring on the activity cost pool level, and that has not been investigated in prior research. The interdependency error may, for example, occur with energy costs if energy is transferred from one cost pool to another, either by design or because of insufficient insulation and other forms of "leakage". We use numerical simulations to investigate how the costing system accuracy is changing as a result of simplifications in costing systems that are ignoring these interdependencies. The main goal of this study is to address the issues of how energy specific costing system simplifications, caused by ignoring interdependencies, are influencing the accuracy of energy costing systems, and how those errors are changing with different settings and manufacturing environments.

The findings of this study suggest that simplifying energy costing systems and ignoring the influences of interdependencies between cost pools can result in large errors. We also report how these errors are changing with different properties and manufacturing environments. We conclude that the overall error of the costing systems increases in an environment where more cost pools are affected by the interdependency and where the density of cost driver matrix is lower.

The fourth chapter is also a simulation study, in which we investigate the impact of input market price dynamics on the accuracy of costing systems over time. Whereas the previous chapters focus on energy costs and costing system errors in connection with energy, this chapter focuses more generally on commodity prices. Previous research has focused on measurement, aggregation and specification errors in static simulations. We build on that research and observe how adding a time-component influences those errors. The research method is based on numerical simulations. Specifically, we focus on costing systems with resources that have a particularly complex purchase price structure, such as electricity. In order to observe those characteristics, it is not enough to observe costing systems at one time point. Instead, it is important to take their time properties into account. Because of that, we introduce the term dynamic activity-based costing. The main objective of this chapter is to investigate how the change in the level of dynamic pattern of resource prices influences the accuracy of costing systems.

The results of this chapter suggest that higher volatility of commodity prices causes errors of costing systems to increase, as does the existence of a stronger trend or more frequent seasonality pattern in time series of commodity prices. We also note that daily seasonality of commodity usage and lower density of consumption matrix negatively influence the accuracy of the costing system. Our results also show that having simplifications in costing systems, such as different simplified methods used for calculation of the prices based on less frequent measurement of the prices, will cause inaccuracies of costing systems.

2. Energy costs information in manufacturing companies – a systematic literature review

Abstract

Accurate, detailed, and up-to-date information on energy costs is crucial for energy management in manufacturing companies. That raises the question to what extent such energy costs information is actually available. This study reviews empirical information provided in papers published in research journals about the availability and use of energy costs information. The study focusses both on energy intensive companies as well as non-energy intensive companies, and we also distinguish between practices of small and medium enterprises (SMEs) vs. large companies. The literature review covers 22 journals in the fields of business, accounting, energy, and engineering, and the final sample includes 51 papers for the analysis. The findings suggest that most literature concerns energy intensive and large companies. The most striking result is that with few exceptions, there are almost no studies that provide a nuanced description of how measuring and allocating energy costs is being done. For example, almost no studies investigate specific cost allocation bases, the accuracy of cost allocations, or differentiation between first-stage allocation and second-stage allocation. Still, the overall impression is that many companies probably lack much of the cost information necessary for energy management, such as information needed for improving energy efficiency, evaluating the financial benefits and costs of energy efficiency improvement investments, and holding managers accountable for energy efficiency.

Keywords

Energy management, energy costs, energy intensity, manufacturing, energy metering

2.1. Introduction

Climate change and global energy consumption lead policy-makers to focus more on sustainability and energy efficiency. The goal of the European Union (EU) is to reduce greenhouse gas emissions by 20% until 2020, compared to the year 1990, to increase the share of energy consumption met by renewable energy sources to 20%, and to increase energy efficiency by 20% by 2020 (European Commission, 2018). The industrial sector, as one of the main consumers of energy as well as one of the largest emitters of CO_2, plays a crucial role in reaching that goal. The energy consumption of companies in the industrial sector in 2014 was 26% of the total energy consumption in the EU (Eurostat, 2016). Companies are also facing continuously rising energy prices and therefore internal incentives exist to reduce energy consumption and increase energy efficiency. One of the key enablers for achieving this is adequate information on the energy costs of a company—not just in total, but also at a more detailed level. Against this background, this chapter provides a focused literature review on empirical studies on the availability of energy costs information to support energy management initiatives of manufacturing companies.

Information on the energy costs of departments and products is an important resource for energy management (Aflaki, Kleindorfer, & De Miera Polvorinos, 2013) and, conversely, lack of adequate energy cost information can be significant barrier for improving a company's energy efficiency. "Energy management" is defined in various ways in the existing literature, but a common theme is the importance of information. O'Callaghan and Probert (1997) define energy management as applying "to resources as well as to the supply, conversion and utilization of energy. Essentially it involves monitoring, measuring, recording, analyzing, critically examining, controlling and redirecting energy and material flows through systems so that least power is expended to achieve worthwhile aims" (O'Callaghan & Probert, 1997, p. 128). Another definition of energy management, based on an extensive literature review is a combination of "systematic activities, procedures and routines within an industrial company including the elements strategy/planning, implementation/operation, controlling, organization and culture and involving both production and support processes, which aim to continuously reduce the company's energy consumption and its related energy costs" (Schulze, Nehler, Ottosson, & Thollander, 2016, p. 3704). Their paper also contains a list of selected definitions of energy management.

We present a systematic literature review of empirical studies of the availability of energy costs information for energy management in manufacturing companies. This review provides a contribution to the literature in several ways. First, we focus on a very specific topic and explore this in depth, namely empirical studies on *how companies measure and allocate energy costs*. Many of the existing papers address the topic of energy management much more broadly, and to the best of our knowledge, no literature review has focused specifically on empirical studies on the measurement and allocation of energy costs as an enabler for energy management. If companies are using only imprecise methods for measuring and allocating energy costs, their energy cost information is likely to be inaccurate and not detailed enough. Many companies still perceive energy as part of overhead costs that cannot be managed, leaving energy as the largest unmanaged potential (Zolkowski & Nichols, 2013). As a result, these companies may lack much of the information necessary for energy management, for example, in the form of avoiding consumption peaks, shifting energy consumption to moments when prices are lower (Bevilacqua, Ciarapica, Diamantini, & Potena, 2017), estimating the financial benefits and costs of energy efficiency improvement investments, measuring those actual benefits and costs, as well as holding managers accountable for energy efficiency (Sorrell et al. 2011) and avoiding the problem of split incentives (Thollander & Ottosson, 2010).

Second, we focus on *small and medium size enterprises (SMEs)*[1] as well as on *non-energy intensive companies*, which have received much less attention by prior research regarding their information for energy management. Energy management is mostly addressed in the literature for large companies or energy intensive companies. These have a high share of energy costs as a proportion of total costs, such as iron and steel, cement, pulp and paper and chemicals industry (U.S. Energy Information Association (EIA), 2016). For example, foundries are facing costs between 5% and 15%, and pulp and paper mills are facing costs well beyond 20% (SFA, 2004, SEA, 2000).[2] While non-energy intensive companies may seem less exciting, they are actually still very important to study, because the untapped potential for energy efficiency improvements could be significant (Muller et al., 2007). Energy often has a lower management priority and these companies have fewer resources for energy monitoring and implementing energy

[1] Small and medium sized enterprises (SMEs) are defined as companies with less than 250 employees and with an annual turnover of less than 50 million euros, and/or an annual balance sheet total not exceeding 43 million euros (European Commission, 2015). Yet, as reported by the European Commission, SMEs in the non-financial business sector account for 99.8% of total enterprises in the EU-28, generating almost 57% of total value added, and employing 93 million people (66.6%, so two-thirds of total EU employment) (European Commission, 2017).

[2] These sources are written in Swedish and are cited in (Thollander & Ottosson, 2010).
The original sources are the following:
SEA (Swedish Energy Agency), 2000. Energianvändning Inom Industrin [Energy Use in Industry]. Swedish Energy Agency Publication Department, Eskilstuna. [In Swedish].
SFA (Swedish Foundry Association), 2004. Specialist Support for Scandinavian Foundries. Swedish Foundry Association, Jönköping. [In Swedish].

efficiency projects. This issue is even more pronounced at small and medium size enterprises (SMEs) (Gruber & Brand, 1991; Shipley & Elliot, 2001).

This chapter aims to systematically review a rather broad range of studies and contribute to a better understanding by teasing out information on how companies measure and allocate energy costs and how this depends on energy intensity and size of the company. The literature review was guided by the following four initial research questions:

- Research Question 1: What is known in the literature about how manufacturing companies are measuring and allocating energy costs?
- Research Question 2: What is known about how information about energy costs is used for energy management, in particular for an energy strategy, energy investments and energy audits?
- Research Question 3: What is known about differences between energy intensive companies and non-energy intensive companies, and between large companies and SMEs regarding measuring and allocating energy costs?
- Research Question 4: What are important areas for future research regarding the measurement and allocation of energy costs?

We conducted a systematic literature search that yielded 51 empirical papers in 22 journals in the field of energy and management accounting. After a systematic search process, we constructed an overview table to analyze characteristics of companies and methods observed in the sample of papers. In the next section, we describe the research method. In Section 3, we present the findings. In the last section, we discuss our findings and suggest implications for further research.

2.2. Research method

We conducted a systematic literature review using recent guidelines (Tranfield, Denyer, & Smart, 2003). To begin with, we defined our research objective: to provide a comprehensive overview of energy costs information in manufacturing companies with an emphasis on empirical data at the company level. We included research on both energy intensive and non-energy intensive companies, as well as on SMEs and large companies. We included only research articles and literature reviews published in peer-reviewed academic journals and disregarded other publications, such as conference papers, books, and working papers. Papers also needed to be written in English, be available online as full text, and have a publication year

1995 or later (in order to focus on reasonably contemporary practices). The literature search process is illustrated in Figure 1.

We used Elsevier's Scopus database and combined search terms and Boolean operators. Search terms included "energy measur*", "energy management" and "energy metering" in the title, and the terms "industry" and "manufacturing" in the title, abstract or keywords of a paper.[3] The asterisk (*) is used to include all variants of the word, such as measurement, measuring or measure. This search was not limited to particular journals because we would like the search query to return results from diverse research areas. This search yielded 700 publications, of which 642 were research articles and 58 were literature reviews. Moreover, we did two further searches across three journals[4] and four specific authors[5] that were particularly relevant for this topic: *Applied Energy*, *Energy*, *Journal of Cleaner Production*, and *Strategic Planning for Energy and the Environment*, and the authors Thollander, Johansson, Ottosson and Söderström.[6] We used the same search terms, which could be in the title, abstract, or keywords of papers. As indicated in Figure 1, these searches initially yielded 286 and 53 additional papers, respectively.

Reading the titles, keywords, abstracts and introductions of these papers revealed that most of these would not be useful for writing this review. Many of them focused on industries other than manufacturing, were not empirical studies, or the focus was on statistical analysis on the industry level without including company-specific data. This selection resulted in 135 papers. A full textual analysis was conducted on these papers. We searched for information at the company level about energy measurements, allocations of energy costs, energy strategy, and criteria for investments. Papers that did not include empirical data (in terms of case studies, questionnaires or surveys) or conducted statistical analysis on a sector or industry level were again excluded in this step, resulting in 45 relevant papers. Furthermore, we conducted a

[3] ((TITLE (energy measur*) OR TITLE (energy management) OR TITLE (energy metering) AND (TITLE-ABS-KEY (industry) OR TITLE-ABS-KEY (manufacturing))) AND DOCTYPE (ar OR re) AND PUBYEAR > 1994) AND (LIMIT-TO (LANGUAGE,"English"))

[4] (ISSN (0306-2619) AND (TITLE-ABS-KEY ("energy measur*") OR TITLE-ABS-KEY ("energy management") OR TITLE-ABS-KEY ("energy metering") AND TITLE-ABS-KEY (industry) OR TITLE-ABS-KEY (manufacturing))) AND DOCTYPE (ar OR re) AND PUBYEAR > 1994 AND (LIMIT-TO (LANGUAGE,"English"))

[5] (AUTH (Thollander) AND (TITLE-ABS-KEY ("energy measur*") OR TITLE-ABS-KEY ("energy management") OR TITLE-ABS-KEY ("energy metering") AND TITLE-ABS-KEY (industry) OR TITLE-ABS-KEY (manufacturing))) AND DOCTYPE (ar OR re) AND PUBYEAR > 1994 AND (LIMIT-TO (LANGUAGE , "English"))

[6] These journals had provided three or more results and these authors had appeared two or more times in an earlier search. This search also led to including one conference paper were Thollander and Ottosson were co-authors.

backward and forward citation analysis based on these 45 papers. We analyzed the references (backward citation analysis) and used Google Scholar to identify more recent publications citing a paper (forward citation analysis). The entire process resulted in a final sample of 51 relevant papers distributed over 22 journals (Table 1).

The next step was to analyze the content of the final set of 51 papers. We coded and summarized information for each of these papers as shown in Table 2. We included categories of information that followed the logic of our research questions: on characteristics of companies, details about energy measurement practices, allocation of energy costs and available information on energy-related decisions. The findings are discussed in more detail in following sections.

Figure 1 – Literature search process

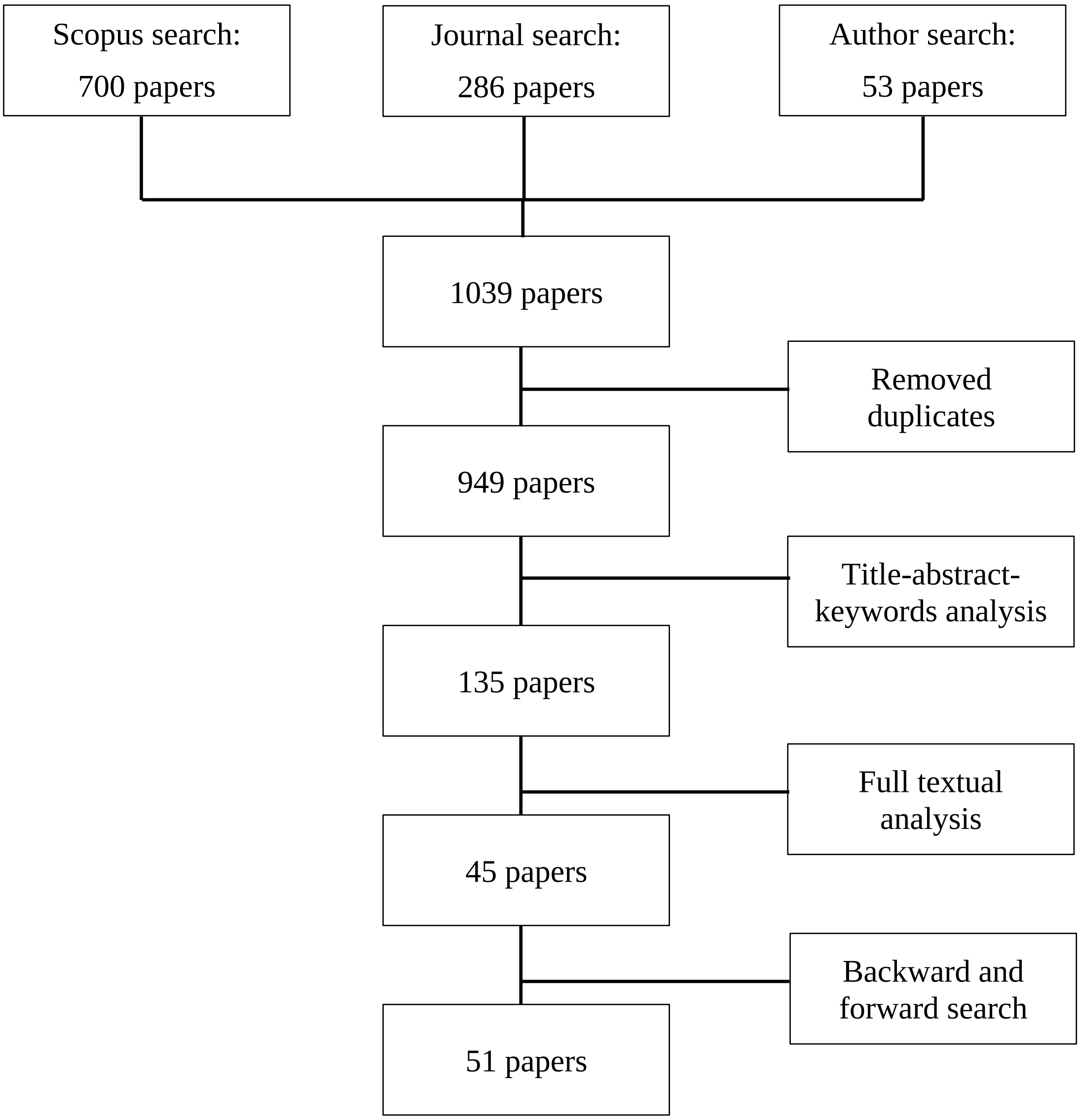


Table 1 – Sample of 51 papers from 22 journals for this literature review

Journal	Number of papers in the sample
Applied Energy	8
Applied Thermal Engineering	1
Chemical Engineering and Processing: Process Intensification	1
Energy	5
Energy Conversion and Management	2
Energy Efficiency	2
Energy Engineering	2
Energy Policy	1
Energy Procedia	2
International Energy Journal	1
International Journal of Energy Research	1
International Journal of Engineering Research in Africa	1
International Journal of RF Technologies: Research and Applications	1
International Journal of Scientific & Technology Research	1
Journal of Cleaner Production	12
Journal of Environmental Economics and Management	1
Management Accounting Research	1
Procedia CIRP	1
Production and Operations Management	1
Strategic Planning for Energy and the Environment	3
Sustainable Energy Technologies and Assessments	1
Summer Study on energy efficiency in industry (ECEEE)	1
World Journal of Engineering	1
Total	51

Table 2 – Summarized data for the literature review on energy cost information in manufacturing companies

<table>
<tr><th>Authors</th><th>Year</th><th>Research method [A]</th><th>How many companies [B]</th><th>Industry focus [C]</th><th>EI /NEI [D]</th><th>Company size [E]</th><th>Measuring energy consumption [F]</th><th>Second stage allocation [K]</th></tr>
<tr><td></td><td></td><td colspan="7">Types of energy measured [G]</td></tr>
<tr><td></td><td></td><td colspan="7">Summary of measurement details [H]</td></tr>
<tr><td></td><td></td><td colspan="7">Specific Energy Consumption [I]</td></tr>
<tr><td></td><td></td><td colspan="7">Allocation of energy costs [J]</td></tr>
<tr><td></td><td></td><td colspan="7">Explicit energy strategy [L]</td></tr>
<tr><td></td><td></td><td colspan="7">Investment projects [M]</td></tr>
<tr><td></td><td></td><td colspan="7">Criteria for investment projects [N]</td></tr>
<tr><td></td><td></td><td colspan="7">Energy audit [O]</td></tr>
<tr><td>Abolarin, Shitta, Gbadegesin, Nna, Eguma, Onafeso, Adegbenro</td><td>2015</td><td>Case study</td><td>1</td><td>Manufacturing industry</td><td>Not specified</td><td>SME</td><td>Basic</td><td>Not mentioned</td></tr>
<tr><td></td><td></td><td colspan="7">Not specified</td></tr>
<tr><td></td><td></td><td colspan="7">Utility company meters for entire company, manually collecting energy consumption data monthly</td></tr>
<tr><td></td><td></td><td colspan="7">Not specified</td></tr>
<tr><td></td><td></td><td colspan="7">Not specified</td></tr>
<tr><td></td><td></td><td colspan="7">Not specified</td></tr>
<tr><td></td><td></td><td colspan="7">This is only the economic evaluation, but the company did not actually implement the energy management measures.</td></tr>
<tr><td></td><td></td><td colspan="7">Payback period</td></tr>
<tr><td></td><td></td><td colspan="7">Yes</td></tr>
<tr><td>Afkhami, Akbarian, Beheshti, Kakaee, Shabani</td><td>2015</td><td>Case study*</td><td>1</td><td>Cement industry</td><td>EI</td><td>Large</td><td>Both</td><td>Not mentioned</td></tr>
</table>

		Electricity, Gas						
		Metering largest consuming processes (calciner and kilns) every 10 minutes. Daily thermal energy consumption shown on process charts.						
		Per kg of final product (cement)						
		Not specified						
		Not specified						
		Some equipment repaired or replaced in order to reduce electrical and thermal energy consumption. New and more efficient solutions were implemented.						
		Not specified						
		Not specified						
Aflaki, Kleindorfer, de Miera Polvorinos	2013	Case study	1	Pharmaceutical	NEI	Large	Detailed	Not mentioned
		Electricity, Fossil fuels, Gas, Biomass, Hot water						
		Facility-wide measurement system. No further details are provided but it seems that detailed measurement for separate processes is conducted.						
		Not specified						
		Not specified						
		Not specified						
		A master plan was developed containing some 200 projects, which were split into two categories: 1st with low investments, direct benefits and short payback time, 2nd with higher risk and longer payback times.						
		For each of the projects an assessment of projected energy savings, carbon savings and cost savings was conducted. Also expected to satisfy capital expenditure limits and required payback periods.						
		Not specified						
Alkaya, Demirer	2014	Case study	1	Textile industry	EI	SME	Basic	Not mentioned
		Electricity, Water, Gas, Steam, Other						
		Not specified what measurement is done at a more detailed level than the entire company.						
		Per ton of final product (fabric)						

		Not specified						
		Not specified						
		Some equipment repaired or replaced in order to reduce energy consumption. Optimization of energy usage in certain processes.						
		Payback period						
		A "walk-through audit" is mentioned, but details are not provided.						
Amundsen	2000	Case study*	4	Food industry	EI	Diverse	Both	Not mentioned
		Electricity, Water						
		Monitoring system database which meters water and energy consumption for each production department on a weekly basis.						
		Per kg of final product						
		Not specified						
		Not specified						
		Calculation of Environmental Performance Indicators (EPI) and performing corrective actions based on EPI, key statistics and consumption figures.						
		Not specified						
		Yes, every three years. Including energy flow audits, improvement possibilities and evaluating performance indicators.						
Apeaning, Thollander	2013	Both	34	Multiple	EI	Not specified	Detailed	Not mentioned
		Electricity						
		24 companies are metering electricity use at both site and building levels, remaining 10 companies are metering at equipment level.						
		Not specified						
		Not specified						
		Not specified						
		Six companies use monitoring and targeting schemes to manage their electricity use, four companies have benchmarks to compare their energy use against.						

		Not specified						
		Five companies from the sample had conducted energy audit within the last 10 years.						
Askounis, Psarras	1998	Case study	1	Food industry	EI	Large	Both	Yes
		Electricity, Water, Fossil fuels, Steam						
		Sub-metering conducted regularly on various process levels. Calculation of specific energy consumption and comparing to the standards.						
		Per unit of final product (beer)						
		First stage: not specified. Second stage: Calculation of SEC for one product for each section as the base product and converting the other outputs to energy (or water) consumption equivalent of this base product.						
		Not specified						
		Using energy monitoring and targeting system to generate detailed reports.						
		Not specified						
		Not specified						
Ates, Durakbasa	2012	Structured questionnaire	40	Multiple	EI	Diverse	Not mentioned	Not mentioned
		Not specified						
		Not specified since metering is considered to be a part of energy management activities. It is stated that 24% of the companies in the sample practice energy management.						
		Per ton of final product						
		Not specified						
		40% of the companies have formal (written) energy strategy. The rest of the companies has communicated energy-related goals and principles orally.						
		80% of the companies have implemented an energy efficiency project within the previous 2 years.						
		Not specified						
		Not specified						
Backlund, Broberg, Ottosson, Thollander	2012	Structured questionnaire	18	Manufacturing industry	Both	Not specified	Not mentioned	Not mentioned

		Electricity, Fossil fuels, Other						
		Not specified						
		Not specified						
		Not at all: 60% x, 63% y. Sub-metering: 10% x, 13% y. Per m2: 10% x, 13% y. Per product: 10% x, 0% y. Per department: 10% x, 0% y. Other: 0% x, 13% y. Explanation: x - companies that participated in the program for improving energy efficiency or had energy audit in the last three years, y - companies that did not participate in such programs nor did conduct energy audit in the last three years.						
		No long term energy strategy: 33% x and 50% y. Energy strategy between 1-4 years: 44% x and 26% y. 4+ years strategy: 22% x and 13% y. Do not know: 13% y.						
		56% of the companies have participated in the program for improving energy efficiency in energy intensive industries or had energy audit in the last three years						
		No criteria: 40% x and 25% y. Payback period between 1-4 years: 60% x and 26% y. 4+ years payback period: 0% x and 25% y. Do not know: 25% y.						
		Some						
Beecroft	2007	Case study	1	Cement industry	EI	Large	Both	Not mentioned
		Electricity, Fossil fuels						
		Metering largest consumers (grinding) and incoming power on process level for daily, monthly and yearly reports.						
		Per ton of final product						
		Not specified						
		Targets related to energy reduction initiatives are integrated into overall plant improvement plans.						
		Optimization of process controls and plant standard operating procedures as a result of more accurate tracking.						
		Same criteria as for all general projects, with the exception of investments for improving power metering in the plants.						
		Not specified						
Bevilacqua, Ciarapica, Diamantini, Potena	2017	Case study	1	Manufacturing industry	EI	SME	Both	Not mentioned

		Electricity						
		Detailed sub-metering on machine level (sensors for active power, reactive power and energy consumption), metering in 15 minutes intervals.						
		Not specified						
		Not specified						
		Not specified						
		Detailed measurements and analysis of consumption data enabled changes in production schedule and provided more efficient configuration of the machines.						
		Payback period						
		Not specified						
Boutaghriout, Hamouda, Smadi, Malek	2016	Case study*	3	Food industry	EI	Not specified	Detailed	Not mentioned
		Electricity, Gas						
		Electricity consumption data measured on process level.						
		Per kg of final product						
		Not specified						
		Not specified						
		Not specified						
		Not specified						
		Yes						
Brunke, Johansson, Thollander	2014	Both	23	Iron and steel industry	EI	Diverse	Mixed (in a sample)	Not mentioned
		Electricity, Water, Fossil fuels, Steam						
		17% annually or quarterly, 63% monthly or weekly, 20% daily metering. 100% of companies measure electricity, 70% measure fuel and 60% measure steam and water.						
		Not specified						
		65% of participating companies allocate their energy consumption per ton, 26% use sub-metering, none use per square meter or per employee.						

		32% with a long-term energy strategy (>3 years), 32% (1-3 years), 36% no policy.						
		13% of companies organize personnel trainings and promote energy efficiency on a regular basis.						
		Investments based on payback time (19 companies, of which only 4 with payback period of 3 years and longer), internal rate of return (3 companies) and net present value (1 company).						
		89% of the steel producers and 62% of the downstream actors had conducted energy audits.						
Christoffersen, Larsen, Togeby	2006	Structured questionnaire	304	Manufacturing industry	Not specified	Diverse	Mixed (in a sample)	Not mentioned
		Not specified						
		61% regularly measuring energy consumption in detail, but no further details provided.						
		Not specified						
		Not specified						
		Not specified						
		65% are implementing specific energy-saving projects, 44% actively involving employees in the energy-saving work.						
		Not specified						
		Not specified						
Dobes	2013	Case study*	2	Multiple	EI	Diverse	Basic	Not mentioned
		Electricity, Gas						
		Only invoice data for total use of electricity and natural gas available.						
		Not specified						
		Not specified						
		The investments mentioned in the paper are made as a result of energy efficiency project. Further energy strategy is not mentioned.						
		In the scope of Monitoring and Targeting project, sub-meters are installed on department level and monitoring of external conditions like climatic conditions or humidity of interior air. Based on the gathered data saving measures were implemented.						
		Payback period						
		Yes						

Dongellini, Marinosci, Morini	2014	Case study	1	Automotive industry	NEI	Large	Detailed	Not mentioned
		Electricity, Gas						
		Electricity metered on invoice level, natural gas by the flow meters installed in the company.						
		Per unit of final product (car)						
		Not specified						
		Not specified						
		As a part of energy audit, gas and electricity are metered on a building level, along with other measures like indoor temperature. Based on energy audit energy saving measures are proposed, feasibility study was conducted and estimation of energy savings was made.						
		Payback period of less than 5 years for energy saving actions.						
		Yes. Measures in this paper are implemented as a result of energy audit, but they are not part of the routine practices of the company						
Drumm, Busch, Dietrich, Eickmans, Jupke	2013	Case study	1	Chemical industry	EI	Large	Not mentioned	Not mentioned
		Electricity, Gas, Steam						
		Steam, electricity are metered on consumer level as part of energy efficiency check.						
		Per ton of final product						
		Not specified						
		The paper shows first time implementation of the new energy management system. No further data regarding energy strategies provided.						
		Possible improvements were identified based on the new energy management system and energy consumption measurements. Some of the improvements were implemented.						
		Energy investment projects evaluated based on their feasibility and profitability.						
		Not specified						
Fernandes, Capehart, Capehart	1997	Case study*	1	Manufacturing industry	NEI	SME	Basic	Yes
		Electricity						

		Metering on facility level, and further allocations based on calculations and estimations for each department.						
		Not specified						
		First stage: calculations based on square meters and number of hours consumed by each activity. Second stage: calculations based on number of hours consumed and volume.						
		Not specified						
		Not specified						
		Not specified						
		Yes						
Gordić, Babić, Jovičić, Šušteršič, Končalović, Jelić	2010	Case study	1	Automotive industry	NEI	Large	Both	Not mentioned
		Audit: steam, hot water, electricity, natural gas, compressed air, propane, demi water, water						
		Before the audit: metering based on invoices, no detailed data, Audit: very detailed sub-metering and ultrasonic metering. Types of energy measured during audit: steam, hot water, electricity, natural gas, compressed air, propane, demi water, water.						
		Per unit of final product (car)						
		Not specified						
		Not specified						
		Implementation of energy saving measures as a result of energy audit → 25% reduction of total energy consumption						
		Before the audit: only low budget projects (less than 10.000 €), After: technical and economic feasibility, payback period						
		Yes, energy audit described in detail and conducted as a background for energy management improvements.						
Hildreth, Oh	2014	Case study	1	Automotive industry	NEI	Large	Both	Not mentioned
		Electricity, Water						
		Utility company meters at facility level on a monthly basis. Further, sub-meters are used at department level, which provide highly accurate energy use rates for activities.						

		Not specified						
		Not specified						
		Yes, 10 year goals for energy reduction.						
		Various investments in energy efficiency (in processes and buildings) and energy conservation. Regular meetings are held in order to improve efficiency and evaluate progress.						
		Project implementation plan is developed based on prioritization of projects on their return on investment and the probability of successful implementation.						
		Not specified						
Huang, Luo, Xia	2013	Case study	1	Ceramic industry	EI	Large	Detailed	Not mentioned
		Electricity, Water, Fossil fuels						
		Sub-metering is conducted on a process level (powder preparation, pressing, sintering, polishing, others).						
		Per ton of final product						
		Not specified						
		Not specified						
		Different measures are proposed as a result of conducted cleaner production audit, in different categories. Plans are established based on difficulty of technical feasibility and estimated costs.						
		Investment projects are divided based on investment cost and implementation time on: no/low cost, medium and high cost measures. Also, payback period and internal rate of return are calculated.						
		Yes, conducted as a part of cleaner production audit.						
Johansson	2015	Interviews	11	Iron and steel industry	EI	Diverse	Not mentioned	Not mentioned
		Not specified						
		Not specified						
		Not specified						
		Not specified						
		5 companies have long term strategy of more than 3 years.						
		Some of the companies introduced sub-metering and new equipment to improve energy efficiency.						

		Payback period, profitability						
		Some: 10 of the companies in the sample have conducted energy audits.						
Kannan, Boie	2003	Case study	1	Food industry	EI	SME	Basic	Yes
		Electricity, Fossil fuels						
		Electricity costs are gathered on invoice level based on measurements from utility company. Data for furnace oil consumption is not available, so the costs are based on estimation. Further data for energy balance sheet is based on estimations and calculations.						
		Per kg of processed flour						
		First stage: Allocations of energy costs to department level are based on estimations and calculations Second stage: Allocation to products based on kg of processed flour (so the same as SEC)						
		Not specified						
		Recommendation of energy saving measures and regular periodic monitoring as a result of the conducted energy management project.						
		Life cycle analysis, payback period						
		Yes						
Kirabira, Nalweyiso, Makumbi	2014	Both	7	Iron and steel industry	EI	SME	Mixed (in a sample)	Not mentioned
		Electricity, Fossil fuels, Biomass						
		It seems that metering is done only on basic level, based on invoices from utility companies. Most of the companies from the sample lacked sub-meters to monitor energy consumption on process level. Biomass is also not measured.						
		Per kg of final product						
		Allocations of energy costs to department level are based on estimations and calculations.						
		Not specified						
		Not specified						
		Not specified						
		Not specified						

Klugman, Karlsson, Moshfegh	2007	Case study	1	Pulp and paper industry	EI	Large	Detailed	Not mentioned
		Electricity, Steam						
		As a part of energy audit, electricity and steam are measured with data logs, generic processes and waste-water heat are measured, and other energy data and plant specifications are based on estimations.						
		Per ton of final product						
		Further allocations of energy costs to departments or processes are based on calculations and estimations.						
		Not specified						
		As a result of energy audit and analysis, the potential investment projects were identified.						
		Payback period of 2 years						
		Yes, the paper describes energy audit.						
Kong, Price, Hasanbeigi, Liu, Li	2013	Case study	1	Pulp and paper industry	EI	Large	Basic	Not mentioned
		Electricity, Water, Fossil fuels, Steam						
		Energy metering is done only on basic level, based on invoices from utility companies. For energy audit purposes also was used: statistical reports, plant energy bills, field measurements and discussions with plant operators.						
		Per ton of final product (paper)						
		Further allocations of energy costs to departments or processes are based on calculations and estimations.						
		Not specified						
		As a result of energy audit and analysis, the potential investment projects were identified.						
		Payback period, profitability						
		Yes, the paper describes energy audit.						

Krenn, Weichbold, Korp, Meixner, Stockner, Berger, Bernreiter, Bleicher, Geiger, Fresner	2015	Case study*	1	Iron and steel industry	EI	Large	Basic	Not mentioned
		Electricity, Water, Gas, Hot water						
		Energy metering is based on invoices from utility companies, and the data is collected electronically or read manually from meters, on a monthly basis.						
		Not specified						
		Not specified						
		Not specified						
		Potential investment projects are identified as a result of the economic evaluation and comparison of theoretical modeling with company's results.						
		Payback period						
		Not specified						
Lampret, Bukovec, Paternost, Krizman, Lojk, Golobic	2007	Case study	1	Pharmaceutical	NEI	Large	Basic	Not mentioned
		Electricity, Water, Fossil fuels, Gas						
		It seems that metering was previously done only on basic level, based on invoices from utility companies. Energy management project and calculations done in the paper are based on detailed measurements.						
		Per unit of net sales revenues						
		Not specified						
		Not specified						
		Potential investment projects are identified as a result of the economic evaluation and calculations conducted in the scope of energy management project.						
		Calculations of possible energy savings as a part of energy management project.						
		Not specified						

Li, Li, Qiu, Xu	2010	Case study*	1	Glass industry	EI	Large	Detailed	Not mentioned
		Electricity, Water, Fossil fuels						
		Detailed sub-metering on department level and main equipment as a part of the energy audit conducted.						
		Per unit of final product						
		Allocation on a department level based on sub-metering.						
		Not specified						
		Energy conservation projects were conducted based on the results of energy audit.						
		Not specified						
		Yes						
Martin, Muûls, De Preux, Wagner	2012	Both	190	Manufacturing industry	Not specified	Large	Not mentioned	Not mentioned
		Not specified						
		Broad range of measurement practices, from utility bills to detailed sub-metering.						
		Not specified						
		Not specified						
		Cca 66% of the companies from the sample have targets for energy consumption (13% of that have expenditure targets, other quantity targets).						
		Not specified						
		On average payback period of 3-5 years						
		Not specified						
Muller, Marechal, Wolewinski, Roux	2007	Case study	1	Food industry	NEI	Large	Basic	Not mentioned
		Electricity, Fossil fuels						
		Energy is metered monthly, based on invoices from utility companies. In the scope of the energy management project described in the paper, electricity is also metered daily.						
		Not specified						
		Allocation of costs to process and product level based on calculations.						
		Not specified						

		As a part of the study, energy saving improvements were identified and savings and payback periods were calculated.						
		Payback period						
		Not specified						
O'Driscoll, Cusack, O'Donnell	2012	Case study	1	Biomedical industry	EI	Large	Detailed	Not mentioned
		Electricity						
		Implemented detailed metering system where energy is metered at several levels and for all significant processes.						
		Not specified						
		Not specified						
		Not specified						
		Implementation of detailed energy metering strategy described in the paper is a part of investment projects.						
		Not specified						
		Not specified						
Ozturk	2005	Structured questionnaire	4	Textile industry	EI	Diverse	Basic	Not mentioned
		Electricity, Fossil fuels						
		Electricity is metered, coal, fuel oil and LPG consumption is based on invoices.						
		Per kg of final product						
		Calculation how much energy is used at process and product level.						
		Not specified						
		Not specified						
		Not specified						
		Not specified						
Rohdin, Thollander	2006	Both	8	Manufacturing industry	NEI	Diverse	Mixed (in a sample)	Not mentioned
		Not specified						

		Only one company from the sample has sub-metering. It seems that other companies from the sample use only invoice data.						
		Not specified						
		Allocation of energy costs is done per square meter, per machine group or not at all.						
		Three companies have clearly stated long-term energy strategy, but no further details are provided.						
		Large companies in the sample have more strict criteria with short payback times for investment projects. Two companies in the sample have payback period of 3+ years, and other have shorter.						
		Payback period						
		Yes, conducted energy audits during the previous 5 years.						
Rudberg, Waldemarsson, Lidestam	2013	Case study	1	Chemical industry	EI	Large	Not mentioned	Not mentioned
		Not specified						
		It seems that metering is conducted on a more detailed level than just based on utility invoice, but no further information is provided.						
		Per ton of final product						
		Not specified						
		The company does not have formalized process of optimization of energy system.						
		Implemented energy saving programs in the past and decreased energy use by 13%.						
		Payback period, risk factor						
		Not specified						
Sa, Paramonova, Thollander, Cagno	2015	Case study	1	Iron and steel industry	EI	Large	Both	Not mentioned
		Electricity, Water, Other						
		Regular sub-metering is conducted on a department level, which also serves as a base for regular reporting system.						
		Not specified						
		Energy reports on a department level based on detailed sub-metering.						
		Yes, detailed strategy and potential areas for improvements identified.						

		Identification and prioritization of investment projects based on energy efficiency and payback period (less than 3 years). The company had already implemented various projects.						
		Payback period (less than 3 years)						
		Not specified						
Sandberg, Söderström	2003	Interviews	9	Multiple	Both	Large	Mixed (in a sample)	Not mentioned
		Not specified						
		Energy intensive company (EIC): In some EICs measuring energy is hard because of high temperatures, so the consumption is calculated instead. Non-energy intensive company (NEIC): NEICs meter energy usage to a small extent.						
		Not specified						
		Not specified						
		Not specified						
		Some of the companies in the sample are conducting investment projects, but there is no detailed information about those.						
		EIC: For smaller investments payback period and common sense are used, and with large investments calculations are very important. NEIC: Low priority of energy investments because energy costs are small part of total costs, they mostly use payback period.						
		EIC: Some of the companies in the sample are conducting energy audits. NEIC: Some are conducting energy audits, but they rarely lead to energy-related investments.						
Sathitbun-anan, Fungtammasan, Barz, Sajjakulnukit, Pathumsawad	2015	Structured questionnaire	9	Food industry	NEI	Diverse	Not mentioned	Not mentioned
		Electricity, Steam						
		It seems that electricity and steam are measured, but there is no detailed data provided.						
		Per ton of final product						
		Not specified						
		Not specified						

		Not specified						
		Not specified						
		Not specified						
Shrouf, Gong, Ordieres-Meré	2017	Case study	1	Automotive industry	NEI	SME	Both	Yes
		Electricity						
		Smart meters with detailed and frequent metering used as a part of the pilot study, but only for selected machines. Not specified what usual practice with metering is.						
		Not specified						
		First stage: Calculation how much energy is used at the process level Second stage: As a part of the pilot study, energy consumption per part, product and order are calculated						
		Not specified						
		Not specified						
		Not specified						
		Not specified						
Sivill, Manninen, Hippinen, Ahtila	2013	Both	6	Multiple	EI	Large	Basic	Not mentioned
		Electricity, Fossil fuels, Other						
		Companies monitor monthly and annual data at the level of production departments.						
		Per ton of final product						
		Not specified						
		Not specified						
		Not specified						
		Not specified						
		Not specified						
Sucic, Al-Mansour, Pusnik, Vuk	2015	Case study	1	Cement industry	EI	Large	Both	Not mentioned
		Electricity, Fossil fuels, Gas						

		In the scope of new energy management system, sub-metering is performed on energy cost center level on hourly basis.						
		Per ton of final product						
		Not specified						
		Not specified						
		This paper describes an implementation of the new energy management system.						
		Payback period of 2 years						
		Not specified						
Thollander, Backlund, Trianni, Cagno	2013	Both	65	Iron and steel industry	EI	Diverse	Not mentioned	Not mentioned
		Not specified						
		Not specified						
		Not specified						
		Not specified						
		47% of the observed companies do not have a long term energy strategy. (About one-third of the small, half of the medium-sized, and two-thirds of the large foundries had conducted an energy audit.)						
		Not specified						
		Not specified						
		Around 40% of the studied companies conducted energy audit. (About half of the small, three out of five of the medium-sized, and two-thirds of the large foundries had conducted an energy audit.)						
Thollander, Karlsson, Söderström, Creutz	2005	Case study	1	Iron and steel industry	EI	SME	Basic	Not mentioned
		Electricity, Fossil fuels, Other						
		Sub-metering is conducted on the production and support process level.						
		Per ton of final product						
		Not specified						
		Not specified						
		This paper describes the energy audit conducted at the company. Measures for investment projects are proposed as a result of the audit.						

		Not specified						
		Yes, the paper describes energy audit.						
Thollander, Ottosson	2010	Structured questionnaire	55	Multiple	EI	Diverse	Mixed (in a sample)	Not mentioned
		Not specified						
		65% f (foundaries) and 66% p&p (pulp and paper companies) use sub-metering, no further details provided.						
		Not specified						
		Sub-metering: 65% f and 66% p&p, per square meter: 5% f and 8% p&p, per number of employees: 0% f and 5% p&p, not at all: 30% f and 21% p&p						
		No long term energy strategy: 53% f and 22% p&p. Energy strategy between 1-5 years: 37% f and 62% p&p. 5+ years strategy: 11% f and 16% p&p.						
		Not specified						
		Most of the companies use payback period of 3 years and less: 65% f and 85% p&p. Payback period of 3+ years: 10% f and 8% p&p. No criteria: 25% f and 8% p&p.						
		Not specified						
Trianni, Cagno, Thollander, Backlund	2013	Both	65	Iron and steel industry	EI	Diverse	Not mentioned	Not mentioned
		Not specified						
		Not specified						
		Not specified						
		Not specified						
		Not specified						
		Not specified						
		Not specified						
		58% of the studied companies conducted energy audit, 42% did not.						
Tunc, Kaplan, Sisbot, Camdali	2016	Case study	1	Textile industry	EI	SME	Detailed	Not mentioned
		Electricity, Water, Fossil fuels, Gas						

		Metering of energy consumption is conducted monthly, on a department level.						
		Not specified						
		Allocations of energy costs to department level are based on metered data.						
		Not specified						
		Better pipe insulation is done as a result of improving energy management. Other potential improvements are identified, but not yet conducted.						
		Calculation of energy loss and payback period						
		Not specified						
Venmans	2014	Both	16	Multiple	EI	Diverse	Mixed (in a sample)	Not mentioned
		Not specified						
		Energy sub-metering is widely used in 14 companies, and 2 plants have only one gas meter.						
		Not specified						
		Not specified						
		Not specified						
		Not specified						
		NPV, IRR and Payback period, and the latter was the most important criterion. However, the calculation typically did not include some main effects of the investments.						
		Not specified						
Virtanen, Tuomaala, & Pentti	2013	Case study	1	Petrochemical industry	EI	Large	Detailed	Not mentioned
		Electricity, Fossil fuels, Steam						
		Sub-metering is used on a plant and production unit level.						
		Per ton of final product. Two types of SEC are calculated: SEC of the production unit level and SEC on the plant-wide level.						
		Not specified						
		Yes, no further details provided.						
		Not specified						
		Not specified						

		Not specified						
Wu, Li, Liu, Zhang, Zhou, Zhao	2012	Case study	1	Pulp and paper industry	EI	Large	Both	Not mentioned
		Electricity, Water, Fossil fuels, Steam						
		Very detailed utility and smart meters metering data every minute, which is the basis for real time energy calculation.						
		Per ton of final product						
		Not specified						
		Not specified						
		Implementation of real time online monitoring system described in the paper.						
		Not specified						
		Not specified						
Yacout, El-Kawi, Hassouna	2014	Case study	1	Textile industry	EI	Large	Both	Not mentioned
		Electricity, Steam						
		As a part of energy management system (EMS), metering was performed daily on a department and plant level. Steam was metered on the plant level. It seems that usual practice before implementing EMS was measuring energy monthly on the basis of utility invoices.						
		Per ton of final product						
		Not specified						
		Not specified						
		Based on the implementation of energy management, the possible improvements were identified and some of them implemented, monthly reduction in power consumption was 3.9%.						
		Not specified						
		Internal audits done weekly to identify leakages, and external auditing performed once during the study.						
Zolkowski, Nichols	2013	Case study	1	Textile industry	EI	Large	Frequent	Not mentioned
		Not specified						

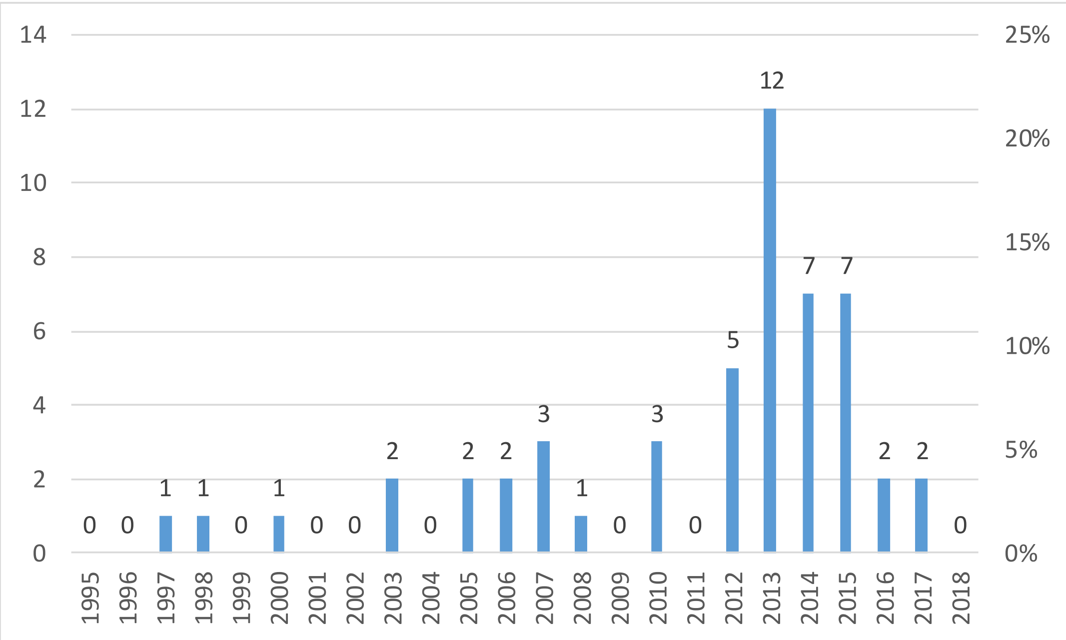
As a part of measurement and verification data loggers were used.
Not specified
Not specified
Not specified
Not specified
The company is focusing on low-risk projects in order to meet their savings targets.
Not specified

2.3. Results

2.3.1. Descriptive analysis

Three journals have clearly published the largest number of papers in our sample: *Journal of Cleaner Production*, *Applied Energy*, and *Energy*, collectively almost half (49%) of all studies in our sample (see Table 1). Figure 2 illustrates the publication years, showing that most of the papers in the sample have been published from 2012 onward. This shows the increasing importance of this research topic.

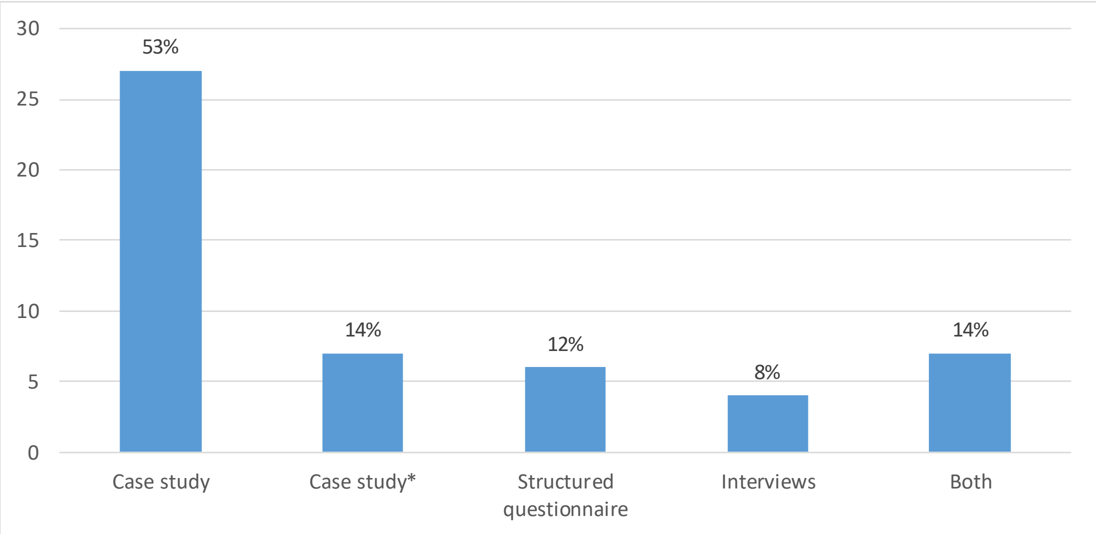
Figure 2 – Distribution of the 51 studies in the sample by the year of publication



Next, we consider the research method applied in the studies in our sample, referring to Field A in Table 2. We define "case study" as in-depth investigation of practices and procedures within one or a small number of companies, whereby the *in-depth* nature is apparent in that diverse kinds of data have been collected and/or the research has been conducted longitudinally. We define "structured questionnaire" as a method whereby the large majority of questions have closed answer possibilities, such as multiple-choice or Likert-scale questions (also called "survey" in some of the papers). The questionnaire yields mainly *quantitative* data, although there may also be a few open questions that generate qualitative data. We define "interviews" as consisting of basically open questions, collecting *qualitative* data, guided by an interview guide (that is usually flexibly applied). There may also be a few questions to which a quantitative answer is likely, such as the answer to a question on the amount of energy usage. We used the label “both” if significant quantitative as well as qualitative data have been gathered and reported in the paper, using both methods mentioned above. Furthermore, we needed to differentiate between two kinds of case studies. The findings presented in some papers suggested that the research method had been a case study, but the paper did not provide sufficient explicit information about the breadth of data gathered or about the longitudinal character of the research. For those papers, we used the label “case study*” as a separate column in Figure 3. As shown in Figure 3, the vast majority of papers (67%) is based on case studies.[7]

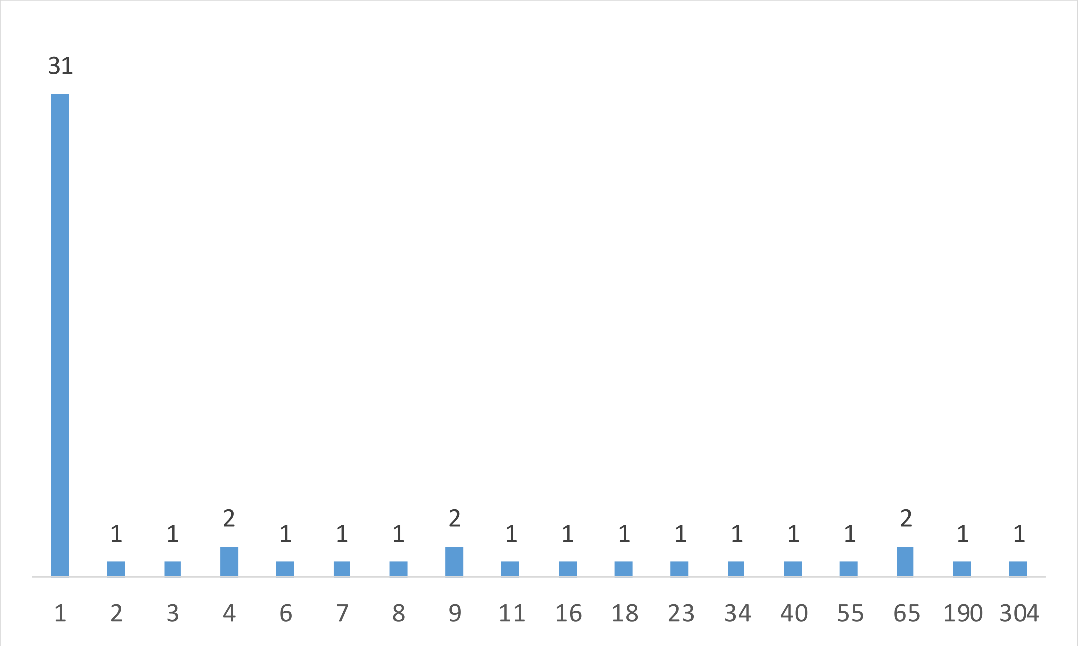
Related to the research method is the number of companies that a paper has studied (Field B in Table 2), which ranges from 1 to 304, as shown in Figure 4. However, the vast majority of studies are based on one organization (31 studies).

Figure 3 – Research methods used in the sample of the 51 papers



[7] Note that Thollander and Ottosson (2010) used the term “multiple case study” but we labelled their research method as a structured questionnaire, based on the definitions provided above.

Figure 4 – Number of companies studied in each of the 51 papers



We also considered for each paper the industry the investigated companies were in (Figure 5 based on Field C in Table 2) and whether these were energy intensive (EI) and non-energy intensive companies (NEI) (Field D in Table 2). In most cases, the energy intensity level of the company was mentioned in the paper and we used that information. When such information was not provided, we labelled it as energy intensive or not, based on the industry the company was in and the categorization of industries according to the US Energy information association (Association, 2016). As shown in Figure 6, the majority of papers in our sample (71%) studied energy intensive companies.

Figure 5 – Industry sector focus in the sample of papers

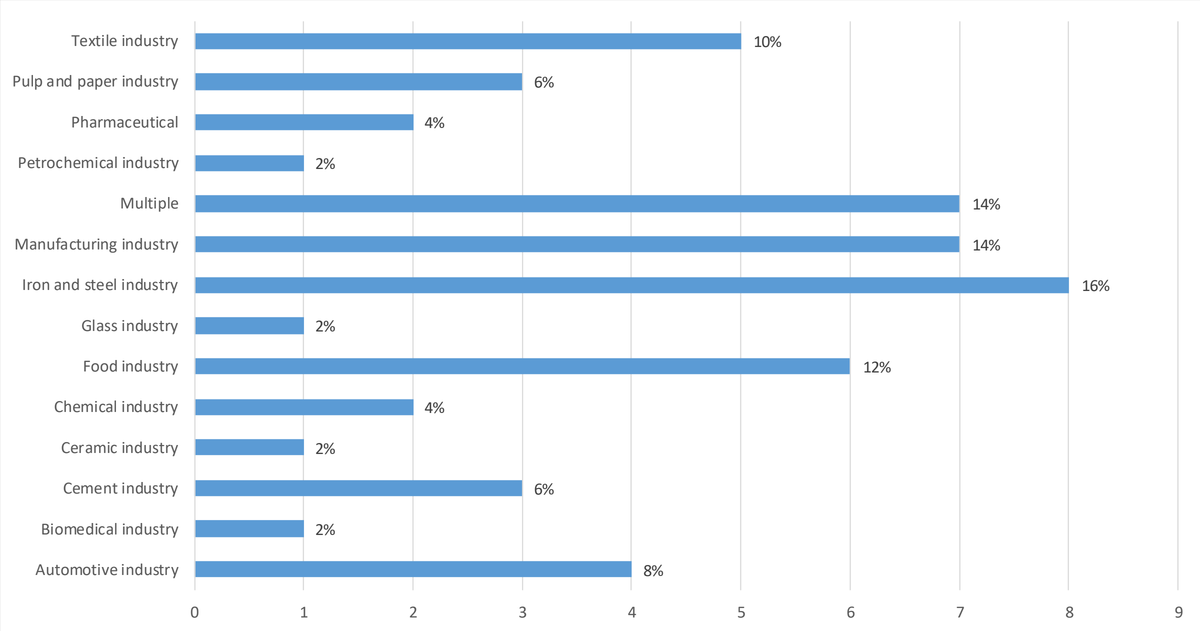


Figure 6 – Energy intensity levels in the sample of papers

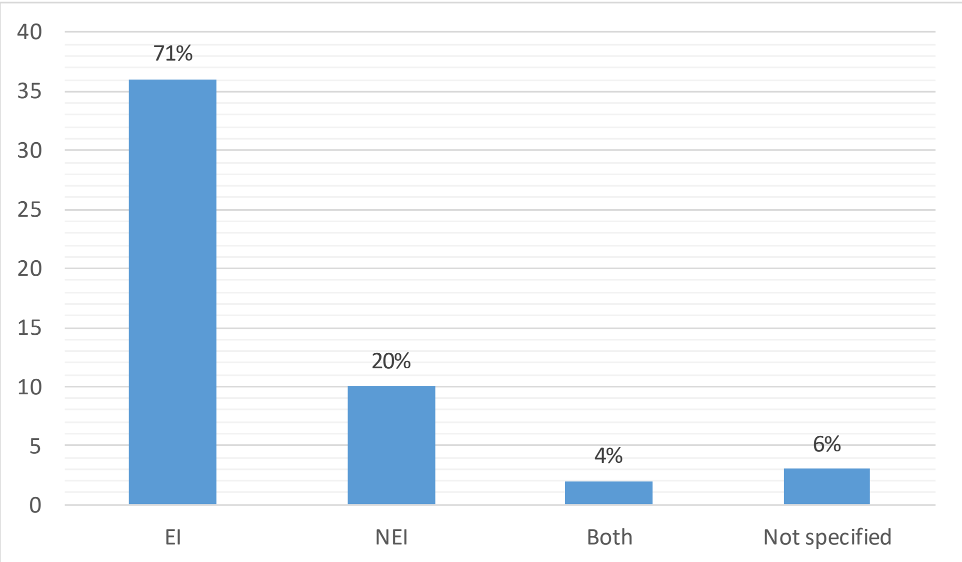


Figure 7 shows the distribution regarding company size, referring to Field E in Table 2. We used the European Commission's definition of SMEs mentioned above, if there was enough information in a paper to do so, otherwise we assumed the categories mentioned in the paper itself. We used "diverse" to indicate that a study included both SMEs and large companies. Our sample includes 26 papers (51%) with the focus on large companies and only 9 papers (18%)

with focus on SMEs. These findings corroborate an earlier literature review (Schulze et al., 2016) showing that empirical papers in the field of energy management focus more on large companies then on SMEs.

Figure 7 – Distribution of company sizes in the sample of papers

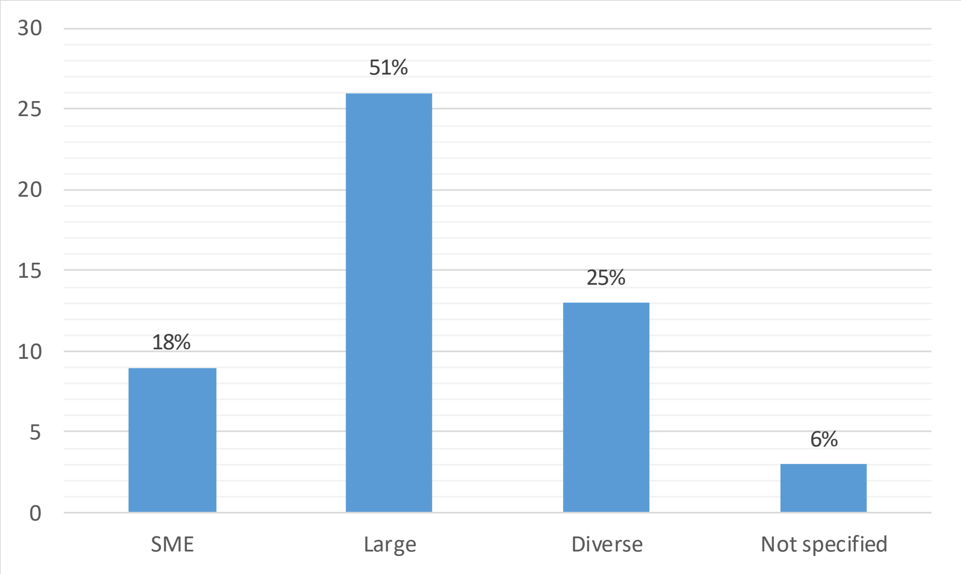


Table 3 shows the detailed distribution of companies according to both dimensions of energy intensity and company size. This emphasizes the results mentioned above: most research focused on energy intensive companies, and in so far as non-energy intensive companies were investigated, these were large companies.

Table 3 – Energy intensity levels and company sizes in the sample of papers

	Large	**SME**	**Diverse**	**Not specified**	Total
EI	17	8	8	3	36
NEI	7	0	3	0	10
Both	1	0	1	0	2
Not specified	1	1	1	0	3
Total	26	9	13	3	51

2.3.2. Energy metering

We are interested in the level of detail of energy metering. We assume that a "basic" level of energy metering will usually be done by a utilities company and other suppliers, as the basis for invoicing the energy resources a company receives. Such metering concerns energy consumption at the level of the entire purchasing organization, and the frequency of measuring depends on the pricing structure (for example, an invoice for a delivery of a quantity of fuel, or periodic invoicing for consumption of gas from an on-site consignment stock). For electricity, it would be sufficient to measure only total consumption for a period over which the price of electricity is constant. As electricity prices are more dynamic (i.e., the intervals during which a price is fixed become shorter), more frequent measuring is required for invoicing. Still, more detailed information will typically be required for supporting energy management. Energy metering could be conducted within a company to get more detailed information on energy consumption by separate departments and processes, or during smaller time intervals, for example specifically for the time interval during which a batch of a particular type of product is processed. Moreover, it could be relevant to conduct measurement on energy transfers from one system to another, such as residual heat.[8]

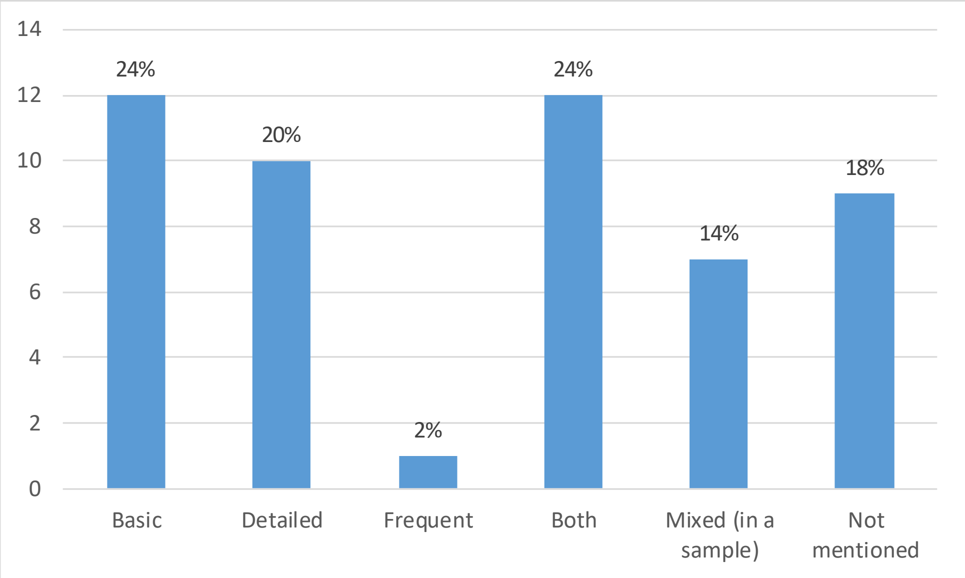
Field F in Table 2 provides information on the level of detail of metering. We discern the following categories:

- Basic: energy measurement is conducted at the level needed for invoicing purposes and there are no indications in the paper that more detailed measurement information is available.
- Detailed: the paper provides explicit information or indications that information on energy consumption is available for more detailed parts of the company, such as departments or production processes.
- Frequent: the paper provides explicit information or indications that information on energy consumption is available for smaller time intervals than needed for invoicing purposes.
- Both: detailed and frequent.
- Mixed (in a sample): the data in the paper concern a sample of several companies and collectively they apply several methods.
- Not mentioned: the paper does not provide any indications to assess the level of measurement detail.

[8] Invoicing could also require more detailed measurements than only for the entire purchasing organization, if the purchasing organization has multiple sites and/or sites have multiple connections to the grid. The point is that energy management may require more detailed data than what is are needed and available for invoicing purposes.

As shown in Figure 8, in about half of the papers (23 papers) it is reported that companies conduct measurement that is more detailed and/or more frequent than the basic level.

Figure 8 – Information about energy measurement in the sample of papers



Differentiating some of these numbers between energy intensive and non-energy intensive companies does not reveal large differences: of the 36 papers focusing on energy intensive companies, 22% report Basic measurement, 22% report Detailed, and 25% report Both; of the 10 papers focusing on non-energy intensive companies, these percentages are 30%, 20%, and 30%, respectively.

Field G in Table 2, provides information on the kinds of energy carrier measured. Thirteen papers do not provide any information on this. For 38 papers, we could discern the following categories, including their combinations (in parentheses the number of papers that mention the energy carrier being measured, whereby one paper often mentions measurements of multiple energy carriers, so that is why the total count below exceeds 38):

- Electricity (36, so almost all of the 38 papers)
- Water (often treated water) (13)
- Fossil fuels (e.g., oil, gasoline, coal, kerosene) (19)
- Gas (e.g., natural gas, propane) (11)
- Biomass (2)
- Hot water (3)
- Steam (11)

- Other (5)

The summaries in Field H of Table 2 provide some more information on energy measurement. Noticeable, though, is that the papers in our sample hardly provide information that goes into much more descriptive detail on measurement of energy usage. In particular, it would have been useful to also have more information on measurement methods that are used, for example on the basis of the Best Available Techniques (BAT). This reference document issued by the Joint Research Centre of the European Commission describes several techniques that can be used to measure, calculate and monitor energy properties of activities in companies (European Commission, 2009). *Estimations* and *calculations* are one of the possible energy measuring techniques, besides *sub-metering* and *ultrasonic metering*, which are more advanced and more accurate techniques. Calculations are often based on an easily measured parameter in combination with other parameters that are given by the equipment manufacturer. An example of that could be an industrial oven with number of hours in use as an easily measured parameter, and other information used to calculate energy consumption provided by the manufacturer. Similarly, estimations are based on specifications given by the manufacturer. In cases where energy consumption of an activity is relatively small comparing to the whole system, estimations and calculations could validly be used. Sub-metering can be conducted with traditional or advanced meters. Traditional utility meters are usually manually read and measure the amount of energy used by a system. More advanced metering systems collect energy data online and in more granular time intervals. Ultrasonic metering can be used in measuring liquids, but these kinds of meters can be rather expensive, so they are often introduced only at new installations or during significant upgrades (European Comission, 2009). The BAT reference document also describes several data sets that should be recorded for every energy source.[9]

In the following, we describe some of the studies that include more fine-grained information about energy metering practices in more detail. An analysis of the Swedish iron and steel industry found that when it comes to the kind of energy carrier being measured, all of the

[9] For electrically powered devices, the data on rated power, efficiency, load factor and working hours per year should be gathered. For equipment consuming fuel, the data on type of fuel supplied in a specific time period, kind of thermal carrier entering the boiler: flowrate, temperature, pressure; condensate: percentage of recovery, temperature and pressure; boiler body: manufacturer, model, installation year, thermal power, rated efficiency, exchange surface area, number of working hours in a year, body temperature and average load factor; burner: manufacturer, model, installation year; thermal power exhaust: flowrate, temperature, average carbon dioxide content; kind of thermal carrier leaving the boiler: temperature and pressure should be recorded. And also for every item of equipment using thermal energy: type of thermal carrier used, hours/years of thermal demand, load factor at which thermal energy is used, rated thermal power.

observed companies metered electricity and about 70% metered fuel, steam and hot water (Brunke et al., 2014). SMEs usually purchased energy from the grid, while self-generation such as with combined heat and power was more widespread within larger companies (Aflaki et al., 2013) and energy intensive companies (Johansson & Söderström, 2011; Kong et al., 2013; Li et al., 2010; Sathitbun-anan & Fungtammasan, 2015).

Sub-metering was used in a majority of energy intensive companies (Thollander & Ottosson, 2010) and was less distributed in non-energy intensive companies (Rohdin & Thollander, 2006). Especially in SMEs, sub-metering was lacking (Apeaning & Thollander, 2013; Bunse, Vodicka, Schönsleben, Brülhart, & Ernst, 2011; Christoffersen et al., 2006; Thollander et al., 2015). Interviews in the Belgian ceramic, cement and lime sector, which is an energy intensive sector, revealed that sub-metering seemed to have become common practice among the sample companies and was considered as a useful tool for finding energy efficiency opportunities and assessing the energy efficiency of new equipment ex post (Venmans, 2014). A survey of 304 Danish manufacturing companies showed that 61% of these companies measured energy consumption in detail regularly (Christoffersen et al., 2006). Practical circumstances complicated information gathering, for example in developing countries (Apeaning & Thollander, 2013). Some energy flows were also very difficult to measure, for example, because of extreme temperatures as in some energy intensive companies, such as in a steel company (Sandberg & Söderström, 2003).

Furthermore, decisions on measuring involved a cost-benefit tradeoff. Costs such as transaction cost could be considered, implying that a rational decision maker would determine the level of information gathering on energy consumption based on the tradeoff between extra cost and the additional benefit of information gathering (Sorrell et al., 2011). For example, O'Driscoll et al. (2012) briefly describe a case study of the introduction of energy metering in a manufacturing plant in the Irish biomedical industry. The decision to equip certain machines with metering devices was made depending on the respective machine's total or average power consumption and consumption profile (i.e., whether consumption was dynamic or static).

If measurement is difficult or too expensive, several alternative ways to determine energy usage information were mentioned. For instance, regression based methods can be a suitable way to obtain a clearer picture of the drivers underlying energy consumption patterns, as described in a case study of a ceramic manufacturer (Quinteiro, Araújo, Dias, Oliveira, & Arroja, 2012). Moreover, simulation based approaches can be used to determine the impact of different influence factors on machines’ energy consumption (Larek, Brinksmeier, Meyer, Pawletta, & Hagendorf, 2011).

Some of the studies reported how introducing some new measurement methods made energy metering more efficient. For example, a case study described the implementation of a new energy management system (STRUCTese) in the energy intensive chemical industry. The system allowed for detailed and daily measurement and tracking of energy efficiency, which helped producing an extensive list with suggestions for the reduction of energy consumption (Drumm et al., 2013). In another case study, a company captured additional data when it installed sub-meters, monitored exterior climatic conditions, the temperature, and humidity of the interior of the building. Based on the data gathered over the course of six months, a list of around twenty energy-saving options and feasible measures was created. Some of the measures were soon implemented and accounted for over 10% reduction of the total energy costs (Dobes, 2013).

2.3.3. Allocation of energy costs

Allocation of energy costs for homogeneous products can be done in a straightforward way by using Specific Energy Consumption (SEC). This indicator is often used for energy management and is a physical indicator, in contrast to energy intensity, which is an economic indicator (Phylipsen, Blok, & Worrell, 1997). For both indicators, the numerator measures energy use; the denominator in SEC is expressed in units (e.g., products produced) or weight (e.g., kg or ton) of final product, whereas the denominator for energy intensity is measured in economic terms. Information on SEC is in Field I of Table 2, showing that 26 papers (51%) reported on the use of SEC. The SEC can be used to allocate energy costs to products. For example, if the SEC is expressed in kWh/kg of processed flour (Kannan & Boie, 2003), then the energy required for a particular product, which requires processing Y kg of flour, can be calculated as $Y \times$ SEC. This can be multiplied with the average cost of energy to get the energy cost for that particular product. However, this is only a valid method for homogeneous products. For other situations, cost allocation needs to be done more elaborately to achieve an accurate measurement of the energy costs of different products.

We differentiate between first-stage and second-stage allocation. First-stage allocation concerns the allocation of costs to departments, work centers, or processes—more generally to production cost pools. These are parts of the entire company, and since the company incurs energy costs in total, the question arises which parts of its total energy costs belongs to each production cost pool. This allocation is not only relevant for measuring energy costs to support decisions, but is also important for accountability. The split incentive problem arises, meaning that department managers could be less motivated to save energy if department's costs are allocated based on imprecise measures, as per square meter or per number of employees, instead on actual energy consumption (Thollander & Ottosson, 2010). Second-stage allocation is the next step: dividing the costs of the production cost pools to products produced at those production cost pools.

Field J in Table 2 contains information on the first-stage allocation. We summarized the information on the allocation basis (such as per meter square, number of employees, or sub-metering) and to which kinds of production cost pools the energy costs were allocated (such as departments, work centers, or processes) if such information was provided. Field K specifies whether the paper contains information about the second-stage allocation, and if so, we included information about the second-stage allocation also in the summary Field J. We find that only 16 papers (31%) provide information on allocation of energy costs, of which only four papers provide information on the second-stage allocation. Of these, two papers basically describe the use of SECs for second-stage allocation (Askounis & Psarras, 1998; Kannan & Boie, 2003) and only two other papers provide more interesting facets of second-stage cost allocation (Fernandes et al., 1997; Shrouf et al., 2017).

Zooming-in on company size and energy intensity does not reveal much difference about the provision of information on cost allocations in the papers. Of the 16 papers providing information on the allocation of energy costs, 11 papers concerned energy intensive companies (which represents 31% of all 36 papers that concerned energy intensive companies) and 4 papers focused on non-energy intensive companies (representing 40% of 10 papers focusing on non-energy intensive companies). Similarly, 6 papers concerned large companies (representing 23% of all 26 papers that concerned large companies) and 5 focused on SMEs (representing 56% of all 9 papers that concerned SMEs). Surprisingly, papers in our sample focusing on non-energy intensive companies or SMEs seemed to offer cost allocation information more often.

We now describe some of the studies in more detail that include more fine-grained information about allocation of energy costs. First-stage allocation is most accurately possible based on sub-metering, and various studies show quite diverse descriptive information about how this allocation is actually done. A study about energy management practices among 18 Swedish companies found that more than 60% did not allocate energy costs at all, and the rest allocated these per square meters, per product, per department, or on the basis of sub-metering (Backlund et al., 2012). Similar results were reported in a study of non-energy intensive companies, which allocated energy cost per square meter, per machine group, or not at all (and only one company used sub-metering) (Rohdin & Thollander, 2006). In a study among 23 companies in iron and steel industry, 65% of these companies allocated their energy costs on the basis of production per ton and 26% used sub-metering, while none of the participating companies allocated the energy costs per square meter or per employee (Brunke et al., 2014). However, another study reported that the majority of the studied energy intensive companies used sub-metering as a method of allocating energy costs, while others allocated their energy costs per employee or per square meter, or not at all (Thollander & Ottosson, 2010).

Two studies describe the allocation of energy costs in some more detail, by allocating energy costs to energy cost centers (ECC) (Dobes, 2013; Sucic, Al-Mansour, Pusnik, & Vuk, 2015). An ECC can be any department, section, or machine that uses energy; all consumption related to these ECCs is allocated and performance indicators are defined for each cost center. Those cost centers are precisely defined, based on the variables that are driving their energy usage. This way, their energy consumption can be measured accurately. Usually, there is also a person responsible for each of the ECC units and its energy usage (Dobes, 2013). The data gathered from monitoring of ECCs can be then further used for various purposes, such as for identification of inefficiencies, performance improvements, cost reduction, fulfilment of government reporting requirements, etc. (Sucic et al., 2015). Similarly to activity-based costing, this also helps to identify where exactly energy was spent. Implementing accounting methods such as ECCs or activity-based costing would be the logical next step after the implementation of sub-metering, to allocate and monitor energy costs on a regular basis.

The first paper that addresses second-stage allocation (Fernandes et al., 1997) provides an example of a small and non-energy intensive manufacturing company where activity-based costing was examined in detail with supporting measurements and calculations. The authors argue that traditional costing methods often allocated energy costs together with overhead costs inaccurately to products. Activity-based costing identifies specific cost drivers and then allocates costs based on the details of the facility's equipment, operation, and product mix. The paper describes in detail how a company calculated energy costs on the resource and activity level, and subsequently distributed these costs in order to identify the total energy costs per product. The authors use a two-stage activity-based costing model. In the first stage, costs are allocated from resource to activity cost pools by using first-stage cost drivers. This is done based on the kWh consumed by each of the activity cost pools. In the second stage, the costs are allocated from activity cost pools to cost objects with the help of second-stage cost drivers, specifically: the number of machine hours, product volume, and number of orders or transactions processed by the department. If the information about an empirically determined cost driver was not available, it was necessary to rely on estimations, calculations and simplifications (Fernandes et al., 1997). The other paper is also a case study (Shrouf et al., 2017), where smart meters were used to measure electricity in detail, the level of operations (i.e., activities) and products. In addition to the energy consumption, data on the moment of energy usage and historical prices of the energy were also recorded. This enabled the company to calculate the exact energy costs used by each operation and for each product this energy was used.

2.3.4. Energy strategy

Having a long-term energy strategy is seen as an important step for ensuring the implementation of energy efficiency measures (Gordic et al., 2010; Rudberg et al., 2013; Thollander & Ottosson, 2010). Such a strategy includes the formulation of targets for energy efficiency improvements and setting directions of energy management for the future; having an energy strategy stimulates the identification and implementation of energy efficiency measures (Brunke et al., 2014; Rohdin et al., 2007; Thollander et al., 2007; Thollander & Ottosson, 2008). On the other hand and perhaps surprisingly, many companies, even in industries with particularly high energy consumptions, such as Sweden's iron and steel (Brunke et al., 2014), pulp and paper, and foundry industries (Thollander & Ottosson, 2010), seem to have no (long-term) strategy for energy-related topics.

Findings in our overview in Table 2 (Field L) show that only 15 papers included some, although often limited, information on the energy strategies of companies. Zooming-in, we see that 11 of these are among the 36 papers that investigate energy intensive companies (31%), whereas of the 10 papers that focus on non-energy intensive companies, only 2 papers (20%) have very brief information on energy strategy (Hildreth & Oh, 2014; Rohdin & Thollander, 2006).[10] Of eight studied companies by Rohdin and Thollander (2006), only three claim to have a long-term energy strategy regarding energy-related issues, but the paper does not provide any further details on this matter. The study of Hildreth and Oh (2014) also provides very limited

[10] The remaining two papers were related to companies for which the energy intensity was "Not specified" or in the category "Both."

information on energy strategy of the studied company, and only mentions its 10-year goals for energy and carbon intensity reduction.

Regarding energy intensive companies, a study conducted with 23 companies in the iron and steel sector in Sweden found that 32% of these had an energy policy with a long-term strategy of more than three years. Same companies had an energy strategy between one and three years and others had no energy strategy or only unwritten sets of goals (Brunke et al., 2014). A survey on energy intensive companies in Turkey found that only 40% of the surveyed companies had a formal energy policy and the rest of the companies stated that energy-related goals and principles were communicated orally (Ates & Durakbasa, 2012). In yet another study, 5 of the observed 11 energy intensive companies had an energy policy with a long term energy strategy of more than three years (Johansson, 2015). Another study differentiated between companies that had participated in a program for improving energy efficiency in energy intensive industries or in an energy audit in the last three years versus companies who had not done this (Backlund et al., 2012). Of the former group, most had an energy strategy, whilst of the latter group, most companies lacked a strategy or did not know if they had a strategy with regard to energy.

2.3.5. Energy investments

Some of the papers in the sample describe investments that companies have made and the criteria for implementing these investments. Given the scope of our literature review, many of these investment projects were specifically related to improving energy efficiency but did not need to be limited to that, for example because an investment had many consequences among which energy efficiency was one. Field M in Table 2 summarizes information about investment projects and Field N about the criteria for investments, if such information was available. We find that 37 papers (73%) of all papers provide information on investment projects and 30 papers (59%) on investment criteria. Splitting this for investment projects, information is provided in 72% and 70% of the papers for energy intensive and non-energy intensive, respectively, and in 85% and 67% of the papers for large companies versus SMEs. Splitting the overall results for investment criteria, information is provided in 53% and 70% of the papers for energy intensive and non-energy intensive companies, respectively, and in 69% and 56% of the papers for large companies versus SMEs. In other words, in our sample information on investments is about equally often provided for energy intensive companies as for non-energy intensive companies and for large companies as for SMEs, sometimes more for one category, sometimes more for the other category.

Many measures to reduce energy consumption require zero or low cost investments (Aflaki et al., 2013; Dobes, 2013; Thollander et al., 2015) and result in direct monetary savings. This has a particularly high relevance for SMEs, where investment budgets are smaller and investment planning is conducted for a shorter time period (Apeaning & Thollander, 2013). In large companies, investments that require significant amounts of capital were more often implemented (Aflaki et al., 2013; Dobes, 2013; Klugman et al., 2007). Differences can also be found between non-energy intensive companies and energy intensive companies. The latter made more long-range investments, such as power plants or furnaces, with payback times up to 30 years. Non-energy intensive companies had more changes in their production (e.g., new products lines, shout down, move) and therefore needed more flexibility and shorter payback times (Sandberg & Söderström, 2003).

Payback time is most often mentioned in our sample of papers as a key criterion for energy investment projects (Brunke et al., 2014; DeCanio & Watkins, 1998). Strict investment criteria and short payback times were often applied in large companies, whereas in medium sized enterprises, the investment criteria were less formalized (Rohdin & Thollander, 2006; Sucic et al., 2015). The criteria may also depend on the size of the investments, whereby payback was the criterion for smaller investments, and for larger investments, complementary methods were also used (such as net present value (NPV) and internal rate of return (IRR)) (Sandberg & Söderström, 2003). Some studies report the specific requirements, such as payback periods or hurdle rates, demanded by their sample companies for an energy efficiency project to be accepted. Some companies in the Swedish iron and steel industry applied a payback threshold of three years or less—some even required payback periods of less than one year (Brunke et al., 2014). Similar requirements were found for pulp and paper producers and foundries in Sweden (Thollander & Ottosson, 2010).

Many energy investments are not implemented because they either extended defined payback times (which was on average three years in most of companies) (Venmans, 2014) or internal rate of return, with high minimum return rates that were used as criteria for investments (Brunke et al., 2014). For example, the companies in Thollander et al. (2015) only considered investments with an IRR of more than 15%. Too long payback period was mentioned as one of the main reasons for not accepting and implementing energy efficiency measures in the study about 11 iron and steel companies in Sweden (Johansson, 2015). Uncertainty about the future also lead to tighter investment criteria, i.e., shorter payback times (Venmans, 2014).

More energy investments were considered, if net present value was used as investment evaluation (Bunse et al., 2011). The advantage of NPV in terms of energy investments is that discount rates are considered, as well as the total lifetime of the investment (Sandberg & Söderström, 2003). Short payback requirements lead to safe investments, neglecting profitable energy investments. Energy audits were therefore important in order to constantly review the recent status and to identify energy saving potential. Another aspect of strict investment criteria, which hampered the implementation of energy investments, was that other benefits of energy efficiency investments, such as better working conditions, greater staff motivation, raw material savings, and reduced emissions were often not considered, because they were more difficult to quantify (Sandberg & Söderström, 2003). Sivill et al. (2013) recommend companies to determine their energy performance objectives on economic, environmental, and social levels, and turn these into quantifiable and accessible objectives.

Data requirements may be difficult for supporting energy investments. Lacking information on energy usage may complicate identification of energy improvement opportunities and estimation of energy savings (Rohdin et al., 2007). A survey and interview with eight non-energy intensive Swedish manufacturers revealed that a lack of sub-metering and proper allocation of energy cost could be especially disadvantageous when explicit investment criteria were applied, as the lack of sufficient data may aggravate valuation of investment opportunities and thus lead to their rejection (Rohdin & Thollander, 2006). However, not all studies support this problem for investments due to lack of sub-metering or data more generally. For example, a survey of Swedish pulp and paper producers revealed that "lack of sub-metering" was not considered very important as a barrier to energy-efficiency investments (Thollander & Ottosson, 2008). Similarly, iron and steel companies in another study did not consider missing information on energy consumptions to be of major concern, even though the allocation of energy costs was mostly done on a production-volume basis instead of based on sub-metering (Brunke et al., 2014). A study of companies in Ghana also did not find missing sub-metering to be considered a major barrier to increased energy-efficiency (Apeaning & Thollander, 2013).

2.3.6. Energy audit

Energy audits can be defined as "a systematic procedure to obtain adequate knowledge of the existing energy consumption profile of a building or group of buildings, of an industrial operation and/or installation or of a private or public service, identify and quantify cost-effective energy savings opportunities, and report the findings" (European Parliament, 2006, p. 68). Energy audits provide a good starting point to gain information about internal energy flows, energy consumption and losses within their processes in order to understand the energy use within a company (Rohdin & Thollander, 2006; Sandberg & Söderström, 2003).

Field O in Table 2 provides information on energy audits for 23 papers in the sample, although for seven of these papers, the information is extremely limited (for example, only that "yes" an audit is done, but without providing further information). Looking in more detail, 16 of the papers concerned energy intensive companies (of 36 in total, so for 44% of energy intensive companies some information on energy audits was provided), and 4 of the papers concerned non-energy intensive companies (of 10 in total, so for 40% of the non-energy intensive companies some information on energy audits was provided).

Energy audits served various purposes. In an energy intensive company in Norway, a technical environmental audit was scheduled every third year to identify new improvement measures, determine new targets and suggest further actions (Amundsen, 2000). Another study (Apeaning & Thollander, 2013) identified that in their sample, only 5 out of 34 observed companies conducted energy audits within the last 10 years. From the remaining companies, six of them used monitoring and targeting schemes to manage their electricity use, and four companies used benchmarks to compare their energy use against. Interestingly, Thollander et al. (2013) compared their findings in relation to company size and found that about half of the small, three out of five of medium-sized, and two-thirds of the large foundries had conducted an energy audit. They also found that foundries that had conducted an energy audit had higher energy use on average than the foundries that had not conducted an energy audit. Altogether, around 40% of the observed companies had conducted an energy audit.

An example of a study of non-energy intensive company concerns a large Serbian car producer (Gordic et al., 2010). An energy audit was conducted as a part of the implementation of a new energy management system in this company. Before the energy audit, there was no proper monitoring of energy consumption. For the energy audit, a detailed analysis of energy consumption was made and with portable measuring equipment, which allowed identifying several improvement possibilities. Several energy saving measures were implemented and an overall reduction of 25% of total energy consumption was achieved.

2.4. Discussion and conclusion

The overall question for this literature review was to find out what is known about energy costs information that is available in companies. To what extent do companies have the necessary information on energy costs for energy management, for example, for identifying opportunities for improving energy efficiency, for evaluating the financial benefits and costs of energy efficiency improvement investments, and for holding managers accountable for energy efficiency? The purpose of the review was to provide a comprehensive overview of practices, with attention for differences between energy intensive vs. non-energy intensive, and small and medium enterprises vs. large companies. Our search process yielded 51 papers in 22 journals. Three journals published more than half of all studies: *Journal of Cleaner Production, Applied Energy* and *Energy*. The majority of the papers in our sample had energy intensive companies in main focus (36 papers, so 71%). Only 10 papers (so 20%) focused on non-energy intensive companies. Five other papers either addressed both energy intensive and non-energy intensive companies or companies for which the energy intensity was unknown. Furthermore, many papers focused on large companies (26, so 51%), SMEs (9, so 18%) or of companies of diverse sizes (13, so 25%). In three other papers, company size was unknown.

The common idea among the papers in our sample is that better monitoring of energy consumption and energy audits are necessary to reduce energy costs and improve energy efficiency of the company (Sandberg & Söderström, 2003). Case studies in energy intensive companies showed that these could reach a high energy efficiency level after the conducted improvements and following investments (Klugman et al., 2007; Kong et al., 2013; Rudberg et al., 2013; Sucic et al., 2015; Thollander et al., 2005), but only a few were already on a high efficiency level before the case studies were conducted (Li et al., 2010; Siitonen & Holmberg, 2012). Although it seems to make sense to focus on energy intensive companies, there is considerable energy saving potential in non-energy intensive companies (Brunke et al., 2014) and these should therefore deserve greater attention from researchers and policy makers (Trianni et al., 2013). SMEs tend to lack information regarding their energy costs and underestimate the monetary potential of energy efficiency investments (Christoffersen et al., 2006; Kannan & Boie, 2003; Li et al., 2010; Thollander & Palm, 2015).

Regarding the first two research questions, the main conclusion is that the papers in the sample identified for this study did not provide very detailed information on what energy costs information companies have and how that information is constructed. Several papers do provide some more detailed information on these matters (Backlund et al., 2012; Brunke et al., 2014;

Fernandes et al., 1997; Thollander & Ottosson, 2010) but these are exceptions and more research going in that direction would be needed. Many important aspects of energy costing were not reported in the sample of papers, and we will discuss several lacunas in the literature.

Firstly, information on metering of energy usage left out some important aspects that are quite specific to energy. Some studies report sub-metering practices, but we would like to know more specifically for which kinds of departments, processes, or other levels within the organization sub-metering is being conducted. Also, we would like to know for which types of energy sub-metering is carried out, which measurement methods are being used, and which data are gathered. Furthermore, we would like to know more about how frequently energy usage is measured within companies. Is this frequently enough to capture the effect of the dynamics of purchase prices (i.e., how frequently and how much these change)? For example, if for invoicing purposes the basic measurement is done on a daily basis, is more detailed information also updated at least daily? Moreover, how much is measured regarding energy flows between departments, processes, machines etc.? This is especially relevant to capture energy transfers. For example, excess heat from one production process may, by design, be used in another production process. Or, heat coming from one machine may increase the room temperature and subsequently also the process temperature of another machine (so the energy transfer is "by accident"). Are such energy flows measured? Without measurement, actual energy usage would be estimated too high for the first process and too low for the second process. Measuring energy usage is the basis for producing energy costs information and little is known about how this basic information is being produced and what is the quality of it.

Secondly, information on allocation was very limited and important aspects of energy costs were not explored in our sample of studies. Regarding the first-stage allocation, several studies described to what extent sub-metering was used and which allocation bases are applied, but we are very much in the dark about how second-stage allocation is done. How are companies allocating costs from departments and processes to products and services? What would be meaningful bases for this allocation? What data are actually available for this? How satisfied are companies with energy costs information at the level of products and services? Which problems do they perceive? For which purposes are they using (or would they like to use) energy costs information at the level or products and services?

Several other specific issues that are quite specific to energy costs would also have deserved more specific investigation, such as: How do companies model substitution possibilities in their costing systems, such as switching between different fuels? How are they dealing with the allocation of fixed costs? Many energy costs will be external and variable, but there is always a fixed cost, for the company's connection to the grid, its internal infrastructure and possibly for generation, either conventional or renewable (for example, own wind turbines or photovoltaic installations, in which case variable costs are negligible). How are companies dealing with issues of joint costing, such as in combined electricity and heat? Cogeneration creates a difficult problem for the allocation of joint costs. Cogeneration "usually refers to the simultaneous production of two energy forms (electricity, and heat in the form of steam and/or hot water) from one energy source (normally a fossil fuel)" (Rosen, 2008). There are several methods for splitting the cost of fuel for producing steam and electricity produced in a combined heat and power (CHP) system: according to energy or exergy content of the two energy products, according to costs that would be caused by independent production of each product, by defining one product as the main output and allocating to the other the incremental fuel consumption caused by cogeneration, splitting it based on economic values (such as market prices), or via arrangements among parties within the company (Rosen, 2008). Selection of the method can have a significant impact on energy efficiency investments, as demonstrated in illustrative case study (Siitonen & Holmberg, 2012).

Thirdly, not much is known about how energy costs information is used for making energy-related investments. How are energy costs data helping to identify in which areas energy efficiency needs attention? How is such information helping to develop energy efficiency improvements and related investment projects? How is information on energy costs used for conducting an economic evaluation of such energy-related investments? How are financial and other criteria combined when making decisions on energy-related investments? Of particular interest is how companies are dealing with uncertainty surrounding these investments and to what extent are they using, for example, real option models that draw on commodity pricing data for modelling such uncertainty? Also, we would like to know more about how companies determine the priority of energy-related investments, as these are often not "core business."

The third research question addressed what is known about differences between energy intensive companies and non-energy intensive companies, as well as between large companies and SMEs regarding measuring and allocating energy costs. We note that the most papers from our literature review sample are focused on energy intensive companies, and in so far as non-energy intensive companies were investigated, these were large companies. Regarding measuring of energy costs, we see that about half of the papers reported that companies conduct measurement that is more detailed and/or more frequent than the basic level. Further analysis of these numbers does not reveal large differences between energy intensive and non-energy intensive companies. While analyzing the allocation of energy costs in reported companies, we note that more papers provided information on the allocation of energy costs in energy intensive companies than in non-energy intensive companies. However, within the respective samples, we did not find much differences about the provision of the information on cost allocation. We also note that approximately the same amount of papers on large companies and SMEs are reporting the data on cost allocation.

Interestingly, in so far as papers provided qualitative information about measurement, cost allocation, investments, and audits, we did not find that such information was less often provided for non-energy intensive companies or SMEs.

This review suggests several directions for future research (the fourth research question). The main suggestion would be to look at several specific questions around energy costs information in much more detail than most studies have done so far. We discussed several such questions above. In addition, empirical research could explicitly address the adoption of more advanced costing systems that focus on energy more specifically, such as Material Flow Cost Accounting (MFCA) (Schmidt, Götze, & Sygulla, 2015; Wagner, 2015). Which factors are explaining the adoption of such systems and which were barriers and enablers for implementation? Similar questions are also posed by a recent study of Christ and Burritt (2015), where they review previous research on MFCA and present an agenda for future research. Further research could also investigate how companies, which have implemented advanced energy costs methods, have profited from the measured data during a longer period of time and how the measured data has influenced their decisions. What were the experienced benefits (and possibly also the disadvantages)? Finally, future research could explicitly focus on non-energy intensive companies. These may have fewer financial reasons to focus managerial attention on improving energy efficiency and less expertise in this area, including no advanced energy costs information. Both quantitative studies and qualitative research could aim to better understand how non-energy intensive companies could be enabled to have the information and expertise and implement energy efficiency improvements.

A limitation of this chapter is the sample of papers we drew on. These are based on a careful process for identifying and selecting papers but have all been published in peer-reviewed academic journals. Other kinds of sources may have provided more detailed empirical information about energy costs systems in companies. Another limitation of the current research in our sample is the strong regional research emphases on Scandinavia, China and Europe, but case studies in different regions are lacking. To gain information about energy measurement in other regions is as important as to get more information from less developed countries, since case studies were mostly conducted in developed economies.

To conclude, we could identify only limited information in the literature about the current state of energy cost information that is available in companies. The overall impression is that only a small share of companies is applying more refined methods for measuring their energy costs accurately. For example, energy measurement methods vary from inefficient measurement methods to detailed sub-metering in real time. Nonetheless even in some large and energy intensive companies, sub-metering is often lacking and cost saving potential is left unexploited. This points to an even larger unexploited cost saving potential in SMEs and non-energy intensive industries. However, this is only a coarse picture, as there are almost no studies that provide a more nuanced description of measuring and allocating energy costs, for example, by investigating specific cost allocation bases, the accuracy of cost allocations, and differentiating between first-stage and second-stage allocation.

3. The effect of activity cost pool interdependency on the accuracy of energy costing information – a simulation study

Abstract

The objective of this chapter is to investigate factors that determine the size of errors in energy costing systems. Specifically, we model simplifications that occur as a result of interdependencies between activity cost pools and cause errors in energy costing systems. To model the influences of these energy specific factors on accuracy we use numerical simulations. Such simulations can help with providing guidelines for the conditions under which energy costing errors are likely to be small or large, and also in assessing the accuracy of a particular company's costing system. The results of this study show that simplifying energy costing systems and ignoring the influences of interdependencies between cost pools would result in large errors. We also report how the errors of costing systems, caused by ignoring interdependencies, are changing with different properties and manufacturing environments. We conclude that the overall error of the costing systems increase in an environment where more cost pools are affected by interdependency, and also where the density of cost drivers matrix is lower.

Keywords

Costing system errors, energy costs, energy costing systems, numerical simulation, activity-based costing, interdependency

3.1. Introduction

This chapter investigates costing system errors regarding energy costs. This concerns energy costs as part of the costs of products and services the company sells to its customers but also the energy costs as part of the costs of departments, activities, and other relevant cost objects. Many non-energy intensive companies use inaccurate methods for measuring and allocating energy costs (Sandberg & Söderström, 2003), and so their energy cost information could be inaccurate. As a result, they may lack much of the information necessary for energy management, for example, for identifying opportunities for improving energy efficiency, for evaluating the financial benefits and costs of energy efficiency improvement investments, and for holding managers accountable for energy efficiency (Martin et al., 2012; Schleich, 2009; Schleich & Gruber, 2008).

However, getting more accurate energy cost information is not free. It requires investments in sub-metering and more advanced IT systems for capturing and managing data, such as manufacturing execution systems, and involves ongoing expenses for staff to analyze the data and prepare reports (Capehart, Turner, & Kennedy, 2003; European Commission, 2009). Thus, a company needs to make a cost-benefit tradeoff between the cost of generating more accurate energy cost information and the benefits of having that information (Sorrell et al., 2011).

The benefits of having more accurate energy cost information will depend on how inaccurate a company's current energy cost information already is. Pragmatically, the inaccuracy of the current cost information could be established by developing and implementing another costing system that is supposed to generate more accurate information and, subsequently, comparing it to the company's current information: Does the new system generate different information, is this believed to be more accurate? However, that may not be the outcome, but significant resources for developing and implementing another costing system would already have been invested. Because of that, it is important to evaluate the information in other ways, such as numerical or computer models, or qualitative evaluation. In this chapter, we develop a numerical simulation to investigate the accuracy of energy costing systems. This will allow us to compare the gain in accuracy (the benefit of having the new information) against the expenses of generating the new energy cost information. Under particular conditions, even simple methods may in some situations still provide accurate information. For example, suppose a company allocates its electricity costs to departments based on their material costs, and these costs are subsequently allocated to products based on direct product costs consisting of material costs and machine costs. The latter are calculated based on machines hours and machine hour rates. Technical information makes it clear that energy usage is largely driven by machining times, which completely depend on the amount of material processed, and the different types of materials all have about the same purchase prices. Thus, it can be inferred that there is a high correlation between energy cost and material cost and between energy cost and machine hours. So, simply looking at the material and machining cost of a product is informative about the energy cost of that product. For this company, the expenses needed for generating more accurate energy cost information would likely exceed the benefits of having that information.

However, in other situations energy cost information allocated in the same way will be inaccurate. For example, when energy usage of the activity depends also on technical characteristics of products (so some types of products require more energy per unit than others), the energy usage for a setup depends on the order of production (for example, because of processing temperatures of subsequent production batches), and energy usage depends on other conditions (for example, outside temperature and the particular batch of material that is used). Obviously, allocation of energy costs based on something straightforward as direct product costs will not be very accurate.

Being able to assess that inaccuracy is an important input for the cost-benefit tradeoff between the cost of generating more accurate energy cost information and the benefits of having that information. We focus on types of characteristics in costing systems that are specific to energy costs, namely interdependencies between cost pools regarding energy usage. This would mean that energy usage in one cost pool is affecting the energy usage of another cost pool, either positively or negatively, and either intentionally or unintentionally. For example, having an industrial oven in the production department, which is causing a lot of excess heat, could lower the heating costs of heating in another, adjacent department. This would be an example of a situation where another department most likely needs less heating in winter months, but also more cooling in the summer months, so this effect is both positive and negative, depending on the time of the year. Since such interdependency is difficult to observe and measure in detail, we model and compare systems that account for such interdependencies and simplified systems where this is not included.

Previous research has focused on general errors of costing systems and divided these into measurement, aggregation and specification errors. Measurement errors occur as a result of practical difficulties in associating costs with a particular cost pool or in measuring the specific units of the resources used by various activities (Datar & Gupta, 1994). Measurement error that is caused by misclassifications or incorrect estimates can occur at three different points in the two-stage activity-based costing system: on resource cost pool level, on resource driver level, and on activity driver level (Labro & Vanhoucke, 2007). We continue on this research and focus on energy specific errors that are the result of interdependencies. The interdependency error can be seen as a special type of measurement error, which is occurring on the activity cost pool level, and that has not been investigated in prior research.

We use numerical simulations in this chapter. We calculate accurate costs (benchmark or true costs) with a costing system that models interdependencies, as well as the costs when we introduce simplifications into the costing system by not modelling the interdependencies. We then simulate those simplifications in different settings to see how results change in different manufacturing environments. Outcomes of the simulations can also help a particular company in assessing the accuracy of its energy costing system. In order to come up with guidelines for the conditions under which energy costing errors are likely to be small or large, we develop specific simulation environments to actually conduct experiments and analyze the results. Overall, the results indicate that an increase in the level of interdependency always causes the overall error of energy costing system to rise.

The remainder of this chapter is organized as follows. The second section provides the theoretical background on energy measurement and costing errors. The third section explains the formulation of the objective of the simulation experiment and hypotheses motivation. The fourth section describes the research method, first by introducing the variables used in the simulation and by defining the simulation environment, and then by developing the underlying mathematical background and algorithm. The fifth section presents the results of the numerical simulation. We end this study with a brief conclusion.

3.2. Theoretical background

In this section, we will first review the literature on measurement of energy costs, which provides some of the motivation for looking at simplifications in costing systems. We also review the literature on numerical simulations in costing systems, showing some of the complexities that are specific to energy costs and have not been investigated thus far.

3.2.1. Energy measurement

One area of the literature that is relevant for this chapter consists of empirical studies on practices of energy cost measurement. These provide mixed findings. For example, interviews in the Belgian ceramic, cement and lime sector, which is an energy intensive sector, revealed that sub-metering seems to be a common practice among sample companies (Venmans, 2014). A survey of energy intensive companies in Sweden showed that roughly two thirds of the responding companies allocate the cost of energy consumption via sub-metering, while about one fifth of the studied mills and about one third of the studied foundries do not allocate energy costs at all, and in about one tenth of the studied industries, energy costs are allocated per square meter and per number of employees (Thollander & Ottosson, 2010). A survey of Danish manufacturing companies found that 61% of companies in the sample measured energy consumption in detail and regularly (Christoffersen et al., 2006). Yet a survey and interview-based study of Swedish iron and steel companies reports that only about a fourth used sub-metering to track energy consumption within the company, while allocation based on production volume was applied most commonly (Brunke et al., 2014). It also depends on the kind of energy: the same authors found that all of the observed companies meter electricity, and only about 70% meter fuel, steam and hot water. Similar conclusions are reported in Apeaning and Thollander (2013), O'Driscoll, Cusack and O'Donnell (2012), Rohdin and Thollander (2006), Rohdin, Thollander and Solding (2007) and Stenqvist and Nilsson (2012). In conclusion, these results suggest that there are very diverse energy measurement practices, and it appears unlikely that all choices about energy measurement are based on perfect information about the benefits and costs of measurement practices.

Another area of the literature that is relevant for this research project consists of studies on methods for measurement of energy costs as part of energy management systems. Schulze, Nehler, Ottosson, & Thollander (2016) review studies on energy management in the industry and present the following definition: "Energy management comprises the systematic activities, procedures and routines within an industrial company including the elements strategy/planning, implementation/operation, controlling, organization and culture and involving both production and support processes, which aim to continuously reduce the company's energy consumption and its related energy costs" (Schulze et al., 2016, p. 3704).

One of the costing techniques that focusses on energy costs is called "material flow cost accounting" (Schmidt et al., 2015; Ronny Sygulla, Götze, & Bierer, 2014). Its objective is to provide transparency of material flows and energy consumption for supporting decisions and enhancing material- and energy-related coordination and communication within organizations. Whereas traditional cost accounting only considers useable outputs as cost carriers, material flow cost accounting uses both desired and undesired outputs of a production process as cost carriers (Bierer, Götze, Meynerts, & Sygulla, 2015). Key steps of this costing technique are modelling of the material and energy flows, along with quantification and cost appraisal of these flows. Sygulla et al. (2011) divide the procedure of MFCA in the following three steps: modeling the flow structure, quantification of the flows, and monetary evaluation of the flows. The first two steps model and quantify the material and energy flows of the system within a certain time period, and in the final step costs are allocated and assigned to cost objects. Measurement of energy costs and efficiency is also often seen in the wider context of environmental management accounting (Bennet, Bouwma, & Wolters, 2002; Bennett, Rikhardsson, & Schaltegger, 2003). In conclusion, this literature shows that there are various approaches to measuring energy costs, but in any case these are informationally demanding. Having more comprehensive energy measurement systems will require considerable efforts and most likely, the information that is actually available will not be "perfect."

3.2.2. Costing errors

This brings us to the accounting literature which has looked at different kinds of costing errors. The theoretical management accounting literature has established that costing systems are unlikely to be error-free (Datar & Gupta, 1994; Labro & Vanhoucke, 2007). A large proportion of that work is based on activity-based costing (ABC) analysis, where costs are allocated in two stages, from resource cost pools to activity cost pools in the first stage, and from activity cost pools to cost objects in the second stage. Datar and Gupta (1994) identified three types of errors in product costing: specification, aggregation and measurement errors. Specification errors are the result of using the wrong cost driver, aggregation errors appear as a result of adding heterogeneous resources together into cost pools, and measurement errors occur as a result of practical difficulties in associating costs with a particular cost pool or in measuring the specific units of the resources used by various activities (Cardinaels & Labro, 2008; Datar & Gupta, 1994). Reductions in specification and aggregation errors from more disaggregated (i.e., more cost pools) and better specified costing systems (i.e., better cost drivers) may increase measurement errors and hence errors in product costs (Cardinaels & Labro, 2008; Datar & Gupta, 1994). Recent papers have started to use numerical simulations to investigate costing errors. These simulations in management accounting are usually based on the following principle: authors construct a number of true cost benchmarks and then simulate a wide variety of imprecise costing systems with different types and sizes of variations (Balakrishnan, Hansen, & Labro, 2011b; Hocke, Meyer, & Lorscheid, 2015; Labro & Vanhoucke, 2007, 2008; Leitner, 2014). In this section, we review in more detail some of the most important papers that use simulation models in analysis of the accuracy of costing systems. Datar and Gupta (1994) concluded that partially improving specification of cost allocation bases and increasing the number of cost pools in a costing system can actually increase specification and aggregation errors.

To review papers on numerical simulations conducted in the field of management accounting, and specifically on the accuracy of costing systems, we conducted a comprehensive literature search. The main goal of this review is to identify the parameters used in determining the accuracy of costing systems in the previous literature. We used the following keywords: "simulation," "management accounting," and "cost accounting," and focused our search on articles published in English, in business and economics literature.[11] After conducting the initial search in Scopus, we obtained 278 results. Reading the title, abstract and keywords of those papers revealed that most of those papers would not be suitable for this review. Many of the papers that we excluded were focused on the topic of simulations in areas other than costing systems, like inventory planning, price and supply chain simulations, or financial reporting in different industries, such as tourism, health, telecommunications or financial markets. The papers that we decided to include were focused on numerical simulations in costing systems. This analysis resulted in 31 papers, which we then further analyzed. We analyzed in detail those selected papers, and after that also conducted further backward and forward analysis. This led to a final number of eight papers. Details of those papers are summarized in the Table 4. For each of the papers, we report the type of model (activity-based costing, two-stage activity-based costing, full costing, service cost allocation and traditional costing system) and goal of the study. Since it is important to see what factors are crucial to determine how accurate costing systems are, we also summarize details of the parameters used in the simulations, dividing them in three different categories. The first category describes parameters that stay fixed throughout the simulation process, the second category are parameters that are used for construction of different manufacturing settings, and the third category are parameters varied for the

[11] (TITLE-ABS-KEY(simulation) AND TITLE-ABS-KEY(management accounting) OR TITLE-ABS-KEY(cost accounting)) AND (LIMIT-TO(SUBJAREA,"BUSI") OR LIMIT-TO(SUBJAREA,"ECON")) AND (LIMIT-TO(DOCTYPE,"ar")) AND (LIMIT-TO(LANGUAGE,"English"))

construction of noisy systems or for estimating the errors of the systems. We also report the type of calculation used in order to measure errors of the systems. The most common error measure is Euclidean distance measure, which is used in most of the papers in our analysis, namely in the 75% of the observed papers. Some papers also use other error measures, like mean percentage error (38%) or "materiality" measure (13%). The final column in the Table 4 reports the type of statistical analysis used to evaluate costing system inaccuracies, and the way the results are represented in the paper. Papers mostly include descriptive statistics and regression results, and present tabular and graphical representation of the results.

Table 4 – Summarized data for the literature review on simulations of costing systems in management accounting research

Authors	**Year**	**Type of costing system**	**Goal of the study**	**Parameters fixed throughout the whole simulation process**	**Parameters used for constructing different manufacturing settings (benchmark costing systems)**	**Parameters varied for the costing system simplifications ("noisy systems") (or other parameters used in the simulations)**	**How are errors defined and measured?**	**Analysis of the simulation results**
Balakrishnan, Hansen, Labro	2011	Activity-based costing	Evaluating design options (heuristics) in ABC systems - grouping resources into cost pools, selecting cost drivers and characteristics of the production environment	1. Total resource cost 2. Number of resources 3. Number of products	1. Vector of resource costs 2. Consumption matrix These are constructed based on: 3. Variance of resource costs 4. Density of consumption matrix 5. Correlation between resources	1. Number of activity cost pools Heuristics for generation of activity consumption matrix: 2. Heuristics for assigning resources to activity pools (random size based and correlation based rules), 3. Rule by which a cost driver is selected (used for allocating the costs of the activity cost pool to products)	Euclidean distance, percentage accurate measure, mean percentage error	Descriptive statistics, tabular and graphical representation of results, ANOVA

Coller, Collini	2015	Full-costing	Evaluating the accuracy of full-cost pricing decisions by measuring the change in the profit when a bias is introduced to its cost accounting system	1. Number of products 2. Total costs	1. Vector of resource costs 2. Resource consumption matrix 3. Demand curve (slope and parameters that define the curve) 4. Variable costs for each product	1. Bias of resource cost vector, 2. Bias of resource consumption pattern, 3. Markup ratio	Euclidean distance	Tabular and graphical representation of results
Hocke, Meyer, Lorscheid	2015	Service cost allocation	Evaluating different methods for the allocation of service department costs to production departments (direct, step, reciprocal method)	1. Total amount of costs 2. Number of runs for each setting	1. Vector of service department costs 2. Consumption matrix (Constructed based on: 3. Number of service departments, 4. Number of production departments, 5. Variation of supplied services, 6. Degree of variety (number of relations between service departments))	No comparison between benchmark and noisy system, but between different kinds of methods, so no noisy system	Euclidean distance	Effect matrix, tabular representation of results

Homburg, Nasev, Plank	2018	Activity-based costing	Impact of cost allocation errors on pricing and product-mix decisions	1. Total resource cost 2. Number of resources 3. Number of products	1. Vector of resource costs 2. Consumption matrix These are constructed based on: 3. Variance of resource costs 4. Density of consumption matrix 5. Correlation between resources Market parameters: 1. Price elasticity 2. Market size	1. Number of activity cost pools Heuristics for generation of activity consumption matrix: 2. Heuristics for assigning resources to activity pools (random size based and correlation based rules), 3. Rule by which a cost driver is selected, used for allocating the costs of the activity cost pool to products	Ratio of noisy and benchmark system profit	Regression analysis
Jacobs, Marshall	1999	Service cost allocation	Numerically comparing different support service cost allocation methods (direct, 2 versions of step, reciprocal method)	1. Total amount of costs 2. Number of runs for each setting	1. Number of service activities 2. Average service usage 3. Service cost variation (variability of the size of service cost pools)	No comparison between benchmark and noisy system, but between different kinds of methods, so no noisy system	Average and maximum error	Tabular representation of results, graphical comparison

Labro, Vanhoucke	2008	Two-stage activity-based costing	Robustness of two-stage ABC system to errors	1. Number of resource cost pools 2. Number of activity cost pools 3. Number of cost objects	1. Consumption matrices for both stages (Based on: 2. Number of cost drivers, 3. Density of consumption matrix) 4. Size of cost drivers 5. Size of cost pools	1. Aggregation error 2. Measurement error 3. Specification error (in both stages of ABC system)	Euclidean distance	Descriptive statistics, tabular and graphical representation of results, ANOVA
Labro, Vanhoucke	2007	Two-stage activity-based costing	Simulation analysis of interaction effects of errors in two-stage ABC systems	1. Total resource costs 2. Number of cost objects	1. Number of resource cost pools 2. Number of activity cost pools 3. Number of cost objects 4. Density of cost driver links and percentages allocated by those links	1. Aggregation error 2. Measurement error (in both stages of ABC system)	Euclidean distance, mean percentage error, materiality measure	Descriptive statistics, tabular and graphical representation of results, ANOVA

Leitner	2014	Traditional costing systems	Analysis of traditional costing systems by investigating how single and multiple biases in raw accounting data influence the final information's accuracy	1. Total amount of costs 2. Number of runs for each setting	1. Cost centers (direct, indirect) 2. Cost objects 3. Cost drivers 4. Cost categories (direct, indirect)	1. Input biases 2. Biases of allocation	Euclidean distance, mean percentage error	Tabular and graphical representation of effects of biases and interaction effects, sensitivity analysis

Jacobs and Marshall (1999) did a simulation of multiple cost pool allocation systems. They observed how the use of direct, step and reciprocal methods, which are commonly used to allocate service activity costs to production services, are influencing the size of allocation errors. In their analysis, Jacobs and Marshall are using three quantifiable measures for constructing benchmark costing systems: number of service activities, average service usage (amount of service used by service activities) and service cost variation (relates to the variability of the size of the service cost pools) (Jacobs & Marshall, 1999, p. 48).

Labro and Vanhoucke (2007) provide a simulation study of two-stage cost allocation systems to observe and analyze the interactions among errors in costing systems. In their simulation experiments, they are using the following variables in order to construct benchmark costing systems. A number of resource cost pools, activity cost pools and cost objects, and also the density of cost drivers in both stages. Furthermore, they simulate a wide variety of true costing systems to cover the range of potential true cost benchmarks. For each benchmark costing system, they also simulate a large variety of false costing system approximations, by varying several aggregation, specification and measurement errors that could arise in developing and implementing the costing system (Labro & Vanhoucke, 2007).

Balakrishnan et al. (2011b) use the vector of resource costs and consumption matrix in constructing benchmark costing systems. The consumption matrix is constructed based on the variance of resource costs, density of the matrix, and the correlation between resources whose consumption varies with production volume and with number of batches. Similar as Labro and Vanhoucke (2007), they too simulate a number of benchmark costing systems with abovementioned parameters. Furthermore, they vary three parameters that reflect potential heuristics that a system designer could use. Those are the number of activity cost pools, the heuristics to assign resources to activity pools and the rule by which they select a cost driver (Balakrishnan et al., 2011b).

To some extent, energy costs are "just another cost" and the existing knowledge about cost system accuracy also applies to energy costs. For example, "firms can group a large portion of their costs into a 'miscellaneous' pool without significantly degrading system accuracy" (Balakrishnan et al., 2011b, p. 533), which suggests that energy costs might in some situations be included in such a cost pool. Also since, "even marginal improvements in specification have the potential to reduce error considerably in a wide range of environments" (Balakrishnan et al., 2011b, p. 539) using available data in contemporary manufacturing execution systems for better specified cost drivers of energy costs is often worthwhile. Interestingly, it is also found that "the impact of Stage II costing errors on overall accuracy is stronger than that of Stage I errors" (Labro & Vanhoucke, 2007, p. 939), so it may be more beneficial to focus on reducing errors in the second stage of the allocation of energy costs. Yet, although this literature on errors in costing systems provides a useful starting point, there are also important lacunas in the literature when it comes to the investigation of costing system errors regarding energy costs.

Energy costs have some specific errors that have not yet been investigated in the literature. Therefore, we continue on this research of measurement, aggregation and specification errors, but we focus on energy specific errors that occur as the result of interdependencies. This interdependency error cannot be classified as any of the categories mentioned above, but can be observed as a special type of measurement error which is occurring on the activity cost pool level, and which consequences are not apparent from previous research.

3.3. Hypotheses motivation

This section presents the motivation of several hypotheses regarding the impact of the simplifications on the accuracy of energy costing systems.

A specific role for energy costs concerns interdependencies between the energy usages of different activities and the resulting costing errors. For example, heat generated by an oven or air compressor also helps to heat a space in winter, but it requires extra cooling in summer (Capehart et al., 2003). More generally, energy usage in one cost pool may increase or decrease energy usage in another cost pool. Thus, energy usage caused by a cost pool extends beyond the boundaries of that cost pool. Importantly, even sub-metering would not solve this problem, because it would accurately capture energy usage of cost pools, but it would not identify how much of a pool's usage has actually been caused by another cost pool.

While other authors use the term "error" when describing measurement, aggregation and specification errors, in our example of interdependency we prefer the term "simplification" of the benchmark system. We decide to use the term simplification, as we assume that it is possible that simplifications do not increase the overall error of the system in some specific settings. We also expect that the interdependency error would cause cancelling off or offsetting effects of the overall error of the costing system for certain manufacturing environments. We specifically focus on the following research questions and formulate our hypotheses.

How are energy specific costing system simplifications, caused by ignoring interdependencies, influencing the accuracy of energy costing systems?

How are errors of costing systems, caused by ignoring interdependencies, changing with different properties and manufacturing environments?

We focus on two cost pools whose energy usage is interdependent. This can be unintentional, for example as mentioned above, when excess heat from equipment used in one production department increases the temperature in a building that is jointly used with other departments, and as a result the facility management department needs less energy for heating the building (and perhaps more energy for cooling it). The interdependency can also exist by design, for example, when cooling water from the equipment of one department is used for heating purposes in the production process of another department. In such examples it could be hard to measure precisely how much energy is used by each department separately. As a result, the data obtained in such a system could be inaccurate or completely missing. The costing system would be simplified in comparison to the system in which all the data on the energy transfer between the cost pools would be available and correct, which we then call the benchmark or true costing system. In a benchmark costing system, all the interactions would also be perfectly measured and accounted for.

Let us consider two activity cost centers, A and B, whereby energy is spilt over from cost pool A to cost pool B. From both cost pools, costs are allocated to products on the basis of different cost allocation drivers. As the amount of energy that actually flows from A to B increases, the cost allocation from cost pool A to products should include more energy costs and, reversely, the cost allocation from B to products should include less energy costs. If this effect is ignored due to a simplification in the costing system, the costing errors regarding the cost of products increases. Furthermore, we would expect this effect to be greater as the interdependency is larger, so if a larger part of the cost of cost pool A flows to B. Formally stated, this leads to Hypotheses 1 and 2.

Hypothesis 1:

As the amount of true activity cost pool increases, the overall error of the energy costing system caused by ignoring interdependency (i.e., having a simplification in the costing system) also increases.

Hypothesis 2:

Increasing the level of interdependency between two activity cost pools causes the overall error of the energy costing system to increase, i.e. reduces accuracy of the system.

Furthermore, we encounter a similar problem when we include a third activity cost center C. Energy is then spilt from cost pool A to two other cost pools, B and C. If the amount of energy that actually flows from pool A to pools B and C increases, cost allocation from cost pool A to products should include more energy costs and the cost allocation from B and C to products should now both include less energy costs. As this interaction would be ignored in a simplified system, the overall costing errors would also increase. This leads to the second part of Hypothesis 3. In this hypothesis, the change in one cost pool is spilling over to two other cost pools, as opposed to Hypotheses 1 and 2, where only one other cost pool was affected. Since more cost pools are influenced by the effect of interdependency, this means that more cost drivers will be influenced, too. Because of that, we expect that the effect of interdependency will disperse over multiple cost drivers to multiple cost objects, and this would absorb the magnitude of the effect of the error. This would potentially lead to a cancelling off effect on the overall error of the costing system. As a consequence of that, we expect the overall error of the costing system to be smaller in Hypothesis 3 than in the Hypotheses 1 and 2.

Hypothesis 3a:

In a case where an increase in one activity cost pool causes a decrease in two other pools, if the amount of true activity cost pool increases, the overall error of the energy costing system caused by ignoring interdependency also increases.

Hypothesis 3b:

The overall error of the energy costing system would be smaller in the case of one cost pool influencing two other cost pools, than in the case of one cost pool influencing only one other cost pool. (The error would be smaller in Hypothesis 3 in comparison to Hypotheses 1 and 2.)

In the second-stage allocation, energy costs are allocated from cost centers A and B to products on the basis of several cost allocation drivers (which are combined in a cost drivers matrix). If the matrix is more dense, i.e., has more non-zero elements, then the costs are allocated to a greater number of different products and so the erroneous costs of the cost pools end up with a greater number of products, with the error being smaller for each product. Reversely, if the matrix is sparse, then the errors would be concentrated to fewer number of products, each having a larger error. The overall error of the costing system would be smaller in case of many small errors compared to a few large ones, thus we expect that a more sparse matrix results in a larger overall error.

Therefore, we construct Hypothesis 4.

Hypothesis 4:

Increasing the number of cost allocation drivers (increasing the density of cost drivers matrix) in a case with interdependencies would result in a reduction of the overall error of the energy costing system.

3.4. Research method

3.4.1. Defining simulation environment and variables

As we have shown in the Section 3.2.2., numerical simulations are not often used in management accounting as a research method, even though the advantages are numerous. A simulation model is always an approximation of an actual complex system, and can only be an abstraction and simplification of reality (Law, 2008). It is especially useful in cases where data is not available or for complex analytical models that could not be managed otherwise (Harrison, Carroll, & Carley, 2007). Another positive side of conducting numerical simulations in management accounting is that it allows us to observe certain effects in extreme situations. It is likely that those situations will not occur in real life settings, but they still provide insight. Labro (2015) reports also some downsides, referring to the great amount of data that can be manipulated in simulations, which can lead to difficulties in identifying the most important results. In such cases, it is also hard to conclude what are the possible mechanisms that lead to such effects, being challenging as "seeing the forest for the trees" (Labro, 2015, p. 101).

Conducting simulation experiments usually includes several steps. Here, we present a modification of a model given by Balakrishnan and Sivaramakrishnan (2008). We develop and extend that model with a special focus on energy and related simplifications of energy costing systems that occur as a result of ignoring interdependencies.

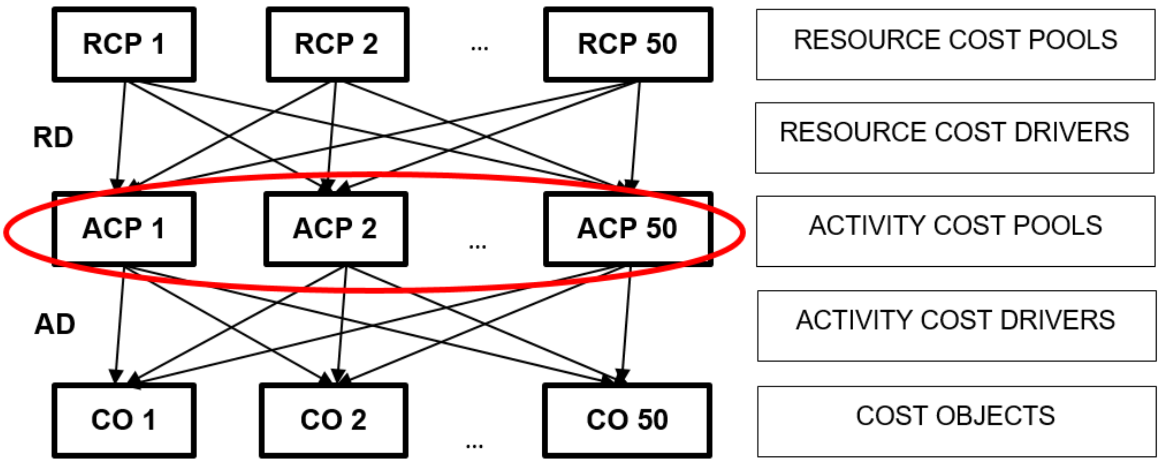
a) Define the manufacturing environment that will remain constant across experimental conditions. This includes the following parameters: the amount of total resource costs, the number of resource and activity cost pools, and the number of cost drivers. These parameters stay fixed throughout the simulations to ensure comparability across the iterations.
b) Define the first part of the experimental conditions for the simulation study, namely the conditions of the manufacturing environment that will be manipulated (the independent variables). The independent variables that are going to be modelled in order to establish

different benchmark systems are the level of interdependency and the density of cost driver matrix.

c) Select deterministic parameter values or probability distributions for these conditions, based on empirical studies (Capehart et al., 2003; European Commission, 2009; Thollander & Ottosson, 2010) and on field work with companies. A costing system with a particular set of parameter values is called a benchmark system.
d) Calculate the true costs of each benchmark system, using numerical simulation. This is also called a solution.
e) Define the second part of the experimental conditions, namely the simplifications (also called inaccuracies or heuristics) that are built into the costing system. These are also independent variables. In this chapter, the simplification occurs as a result of ignoring different levels of interdependencies in the costing system.
f) Select parameter values for these conditions. A costing system with a particular set of parameter values that reflect one or several inaccuracies is called a simplified system. Each simplified system is related to one benchmark system that includes none of the inaccuracies.
g) Calculate the costs of each simplified system, using numerical simulations.
h) For each benchmark system, compare its true costs of the benchmark system with the observed costs of the related simplified systems. The difference between the actual cost of the benchmark system and the observed cost of a simplified system is the accuracy of the costing system under those specific experimental conditions. This accuracy is the dependent variable, and we use Euclidean distance measure to assess it.
i) Analyze the results to understand the impact of independent variables (conditions of the manufacturing environment, cost system simplifications, and their interactions) on the accuracy of energy costing systems (the dependent variable).

Figure 9 also represents an illustration of the simulated energy costing system, which is based on a model of activity-based costing, where costs are divided and allocated in two stages. In the first stage, we allocate costs from energy resources or resource cost pools (RCP) through resource cost drivers (RD) to departments or activity cost pools (ACP), and in the second stage from activity cost pools with activity cost drivers (AD) to products or cost objects (CO). The interdependency simplification that occurs in such a system is affecting the costs at the level of activity cost pools.

Figure 9 – Two-stage activity-based costing scheme used in the numerical simulation



3.4.2. Detailed algorithm and mathematical notation

We conduct numerical simulations by using Matlab software.[12]

Creating resource cost pools (RCP):

First, we create a vector RC of resource cost pools with dimension [1,50] (where 50 is a number of resource cost pools) with non-zero elements only. Throughout the whole simulation, we set the number of resource cost pools, activity cost pools and cost objects to be fixed (50). We also fix the monetary amount of total resource costs ($1.000.000). Using a fixed amount of total costs in the simulations allows us to compare the accuracy of the systems across all simulation runs. All the elements from the resource cost vector are selected randomly from uniform distribution.

$$RCP_{1,\dots,50} \in [1{,}1000000] : \sum_{i=1}^{50} RCP_i = 1000000$$

Creating resource cost drivers (RD):

Density of cost drivers matrix is set at 70% in the simulation for Hypothesis 1, Hypothesis 2 and Hypothesis 3, and 30% for Hypothesis 4. We define density as a percentage of cost drivers that are non-zero.

We then construct the matrix of resource cost drivers where every column consists of $i_{1,\dots,50}$ elements from uniform distribution.

[12] Matlab R2015b (Version 8.6.0.267246)

$\forall i_{1,\dots,50} \in [\max(RCP, ACP)\,, RCP \cdot ACP]$ where $RD_{1,\dots,50}$ is vector of $i_{1,\dots,50}$ elements from uniform distribution.

Creating activity cost pools (ACP):

In this step, we calculate values of activity cost pools by multiplying resource cost pools and resource cost drivers.

$$ACP = RD_1 \cdot RCP_1 + RD_2 \cdot RCP_2 + \cdots + RD_{50} \cdot RCP_{50} = ACP_1 + ACP_2 + \cdots + ACP_{50}$$

Interdependency at activity cost pool level:

In this step, we introduce a simplification of energy costing system, where interdependencies are not modelled, at the activity cost pool level. We choose a random activity cost pool and allocate percentage of interdependency to another randomly chosen activity cost pool.

$$\exists!\, ACP_x \in (ACP_1, \dots, ACP_{50}) \Rightarrow ACP' = ACP_x + ACP_x \cdot p$$

$$\exists!\, ACP_y \in (ACP_1, \dots, ACP_{50}) \backslash \{ACP_x\} \Rightarrow ACP'' = ACP_y - ACP_y \cdot p$$

where $p \in [0\%, 10\%, \dots, 100\%]$, and p is the percentage that describes the amount of interdependency in the energy costing system.

For H3, we observe three activity cost pools affected by interdependency:

$$\exists!\, ACP_x \in (ACP_1, \dots, ACP_{50}) \Rightarrow ACP' = ACP_x + ACP_x \cdot p$$

$$\exists!\, ACP_y \in (ACP_1, \dots, ACP_{50}) \backslash \{ACP_x\} \Rightarrow ACP'' = ACP_y - ACP_y \cdot p_1$$

$$\exists!\, ACP_z \in (ACP_1, \dots, ACP_{50}) \backslash \{ACP_x, ACP_y\} \Rightarrow ACP''' = ACP_z - ACP_z \cdot p_2$$

where $p \in [0\%, 10\%, \dots, 100\%] : p = p_1 + p_2$

Creating activity cost drivers (AD):

Similar as creating resource cost drivers, we also construct activity cost drivers. The density of cost driver at this stage is also set to be 70% in the simulation for H1, H2 and H3 hypothesis, and 30% for H4 hypothesis. We then construct a matrix of activity cost drivers where every column consists of $j_{1,\dots,50}$ elements from uniform distribution.

$\forall j_{1,\dots,50} \in [\max(ACP, CO)\,, ACP \cdot CO]$ where $AD_{1,\dots,50}$ is a vector of $j_{1,\dots,50}$ elements from a uniform distribution.

Creating cost objects (CO):

Finally, we calculate the values of cost objects by multiplying activity cost pools and activity cost drivers.

For a simplified system that does not include any interdependency, we use:

$CO = AD_1 \cdot ACP_1 + AD_2 \cdot ACP_2 + \cdots + AD_{50} \cdot ACP_{50} = CO_1 + CO_2 + \cdots + CO_{50}$

For a true system with interdependencies ACP' and ACP'':

$CO_t = AD_1 \cdot ACP_1 + AD_x \cdot ACP'_x + AD_y \cdot ACP''_y + \cdots + AD_{50} \cdot ACP_{50}$

$= CO_{t1} + CO_{t2} + \cdots + CO_{t50}$

For a true system with interdependencies ACP', ACP'' and ACP'''::

$CO_t = AD_1 \cdot ACP_1 + AD_x \cdot ACP'_x + AD_y \cdot ACP''_y + AD_z \cdot ACP'''_z + \cdots + AD_{50} \cdot ACP_{50}$

$= CO_{t1} + CO_{t2} + \cdots + CO_{t50}$

Euclidean distance:

We then evaluate the results obtained in the simulations. Similar to other papers in the field of management accounting who are observing costing system errors (Babad & Balachandran, 1993; Balakrishnan et al., 2011b; Homburg, 2001; Hwang, Evans, John H., & Hegde, 1993; Labro & Vanhoucke, 2007, 2008), we also use Euclidian distance (*EUCD*) for measuring the overall error of the costing system.

$$EUCD = d(CO, CO_t) = \sqrt{\sum_{i=1}^{n} (CO - CO_t)^2}$$

We repeat the simulation 500 times for every percentage of interdependency: $500 \cdot 11 = 5500$ simulations for every hypothesis.

For each hypothesis, we show graphical representations of 2D and 3D plots, which depict the relationship between dependent (Euclidean distance measure) and independent variables (true activity cost pools, percentages of interdependency). In both plots the dependent variable (EUCD) is presented on the y-axis. We also report descriptive statistics. Furthermore, we conduct multiple linear regression analysis and provide a summary of results.

A general expression for a multiple linear regression equation involving a multiplicative interaction is:

$$EUCD = \beta_0 + \beta_1 p + \beta_2 ACP_t + \beta_3 \cdot p \cdot ACP_t + \varepsilon$$

where β's represent regression weights or coefficients. Euclidean distance of the overall error in energy costing systems is used as response (or dependent) variable, while percentages of interdependencies (p) and true values of activity cost pools (ACP_t) are observed as predictors of the multiple linear regression model. Variables are also standardized to their respective means (Aiken & West, 1991). Standardization rescales data, which removes multicollinearity and allows comparability of the results.

3.5. Results

3.5.1. Hypothesis 1 and 2

In Hypothesis 1, we hypothesize that the overall error of the costing system caused by ignoring interdependency would increase as the amount of true cost of the activity cost pool increases.

In Hypothesis 2, we hypothesize that increasing the level of interdependency between activity cost pools would cause the overall error of the costing system to increase. As the 3D plot shows (Figure 10), if the interdependency between two activities is increasing and the correct (true) value of the activity cost pool is bigger, then the simplified system contains a larger error. That effect is even more visible in the 2D plot (Figure 11), where moving from a low level of true activity cost pool to high level increases the overall error, for each percentage of interdependency.

Multiple linear regression analysis for the simulation output (Table 5) shows that both parameters, true activity cost pool and percentage of interdependency, as well as their interaction term, are significant on a 1% level. The parameter "true ACP" allows for testing of the Hypothesis 1, and parameter "percentage" for the testing of Hypothesis 2. The plot of the interaction effects for this regression (Figure 22 in Appendix) shows that an increase in both predictors causes the overall error of the costing system to increase. From the interaction effects plot, we can also conclude that the effect of the change in percentage of interdependency has a larger impact on the overall accuracy than the change in true activity cost pool. This means that changing the percentage of interdependency from 0% to 100% increases the Euclidean distance error, given that the true activity cost pool is held constant. Similarly, changing the true activity cost pools from lower to higher, while keeping the percentage of interdependency constant, will cause the overall error of the energy costing system to increase.

Overall, we can conclude that an increase in true activity cost pool would cause the overall error of the energy costing system (EUCD) also to increase, in the setting where the effect of interdependencies is ignored. This is supporting Hypothesis 1.

Furthermore, increasing the level of interdependency between activity cost pools would cause the overall error of the costing system to increase, which is supporting Hypothesis 2.

Figure 10 – Hypotheses 1 and 2: 3D plot of the effect of change in true activity cost pool and percentage on the Euclidean distance measure

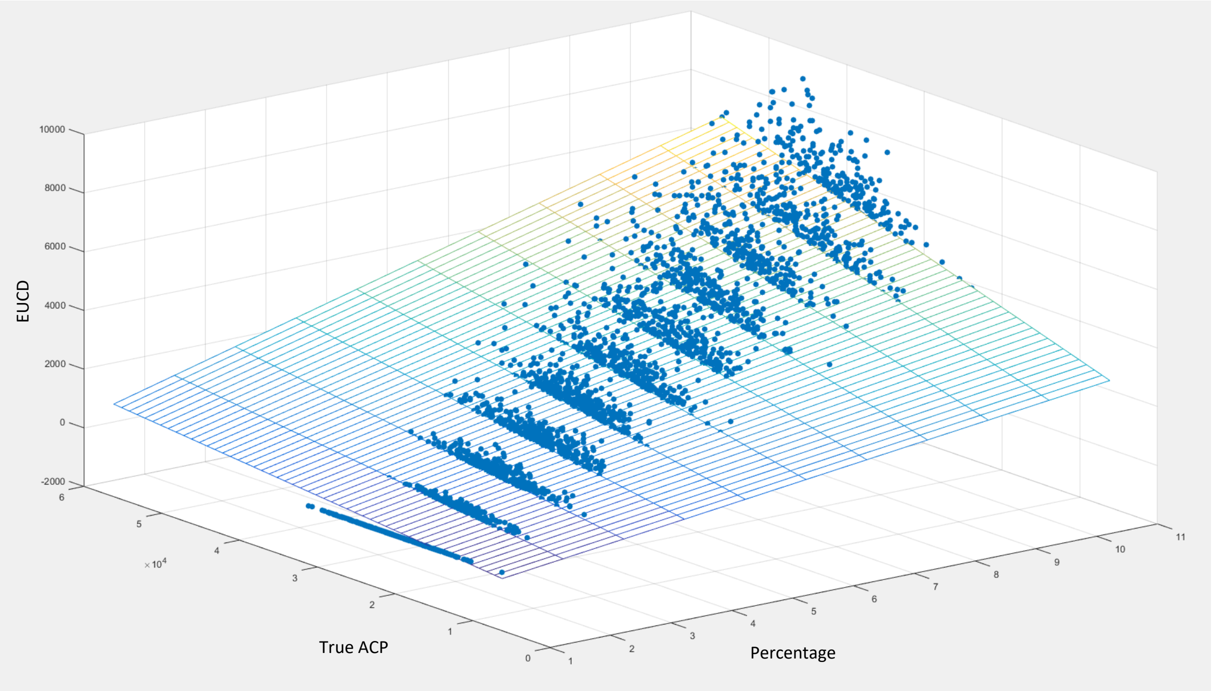


Figure 11 – Hypotheses 1 and 2: 2D plot of the effect of change in true activity cost pool on the Euclidean distance measure for 11 observed percentage levels

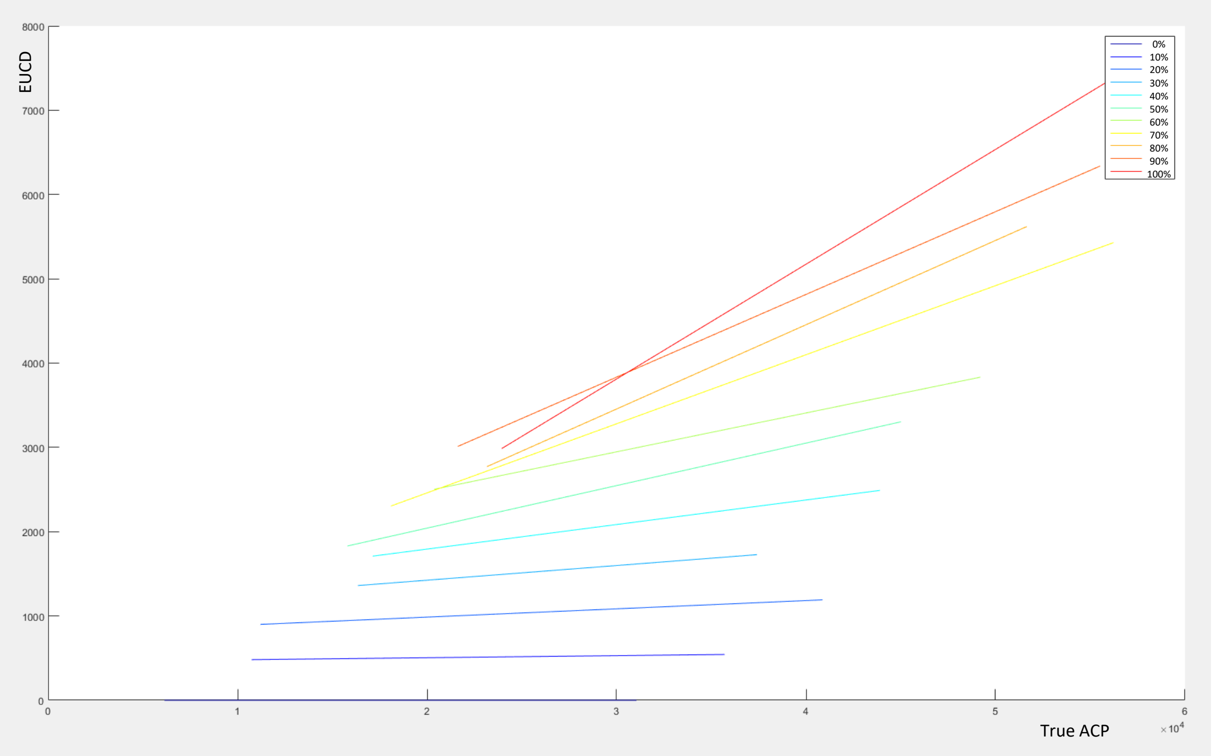


Table 5 – Hypotheses 1 and 2: Statistical analysis of the effect of change in true activity cost pool and percentage on the Euclidean distance measure

Output of multiple linear regression analysis with interaction term				
Variable	Coefficient	SE	t-statistics	p-value
Intercept	-0.073205	0.0063703	-11.492	0.000
Percentage	0.69851	0.0079744	87.594	0.000
True ACP	0.27068	0.0080056	33.812	0.000
Percentage x True ACP	0.092341	0.0052491	17.592	0.000

R-squared: 0.872, Adjusted R-Squared 0.872

F-statistic vs. constant model: 12 500, p-value = 0

Descriptive statistics				
Variable	Mean	SD	Minimum	Maximum
EUCD	2 560.90	1 773.10	0.00	9 001.00
True ACP	30 044.00	7 923.50	6 141.30	56 232.00

3.5.2. Hypothesis 3

In Hypothesis 3a, we hypothesize that in a case where an increase in one activity cost pool causes a decrease in two other pools, if the amount of true activity cost pool increases, the overall error of the energy costing system caused by ignoring interdependency also increases.

In Hypothesis 3b, we hypothesize that the overall error of the energy costing system would be smaller in the case of one cost pool influencing two other cost pools, than in the case of one cost pool influencing only one other cost pool. In other words, we expect that the error would be smaller in Hypothesis 3 in comparison to Hypotheses 1 and 2.

The 3D plot (Figure 12) shows that if the interdependency in a case with three activity cost pools is increasing and the true activity cost pool is bigger, then the simplified system contains a larger error comparing to the true system. The 2D plot (Figure 13) shows more clearly what is the relationship between value of true activity cost pools and the overall error of the energy costing system.

Multiple linear regression analysis for the simulation output (Table 6) shows that both parameters, true activity cost pool and percentage of interdependency, as well as their interaction term, are significant on a 1% level. The plot of the interaction effects for this regression (Figure 23 in Appendix) shows that changing the percentage of interdependency from 0% to 100% increases the Euclidean distance error, given that the true activity cost pool is held constant. Changing the true activity cost pools from lower to higher, while keeping the percentage of interdependency constant, will cause the error also to increase. From the interaction effects plot, we can also conclude that the effect of the change in percentage of interdependency has a much larger impact on the overall accuracy than the change in true activity cost pool. It is worth noting that the slope of the lines in Figure 13 are almost horizontal, which also points out that in the setting with more pools affected by interdependency, the increase in the value of true cost pool does not make a big difference.

This leads to the conclusion that Hypothesis 3a can be supported and shows that in a setting where an increase in one activity cost pool causes a decrease in two other pools, the overall error of cost system caused by ignoring interdependency increases if the amount of true cost of an activity cost pool increases. However, the effect of the coefficient "percentage of interdependency" is much larger than the effect of the increase of true activity cost pool.

To test the Hypothesis 3b, we compare the overall error of the costing system in Hypothesis 3 (descriptive statistics in Table 6) with the results of the Hypotheses 1 and 2 (descriptive statistics in Table 5). By comparing the descriptive statistics in both hypotheses, we conclude that the error is indeed larger in Hypotheses 1 and 2. This is supporting the Hypothesis 3b.

Figure 12 – Hypothesis 3: 3D plot of the effect of change in true activity cost pool and percentage on the Euclidean distance measure

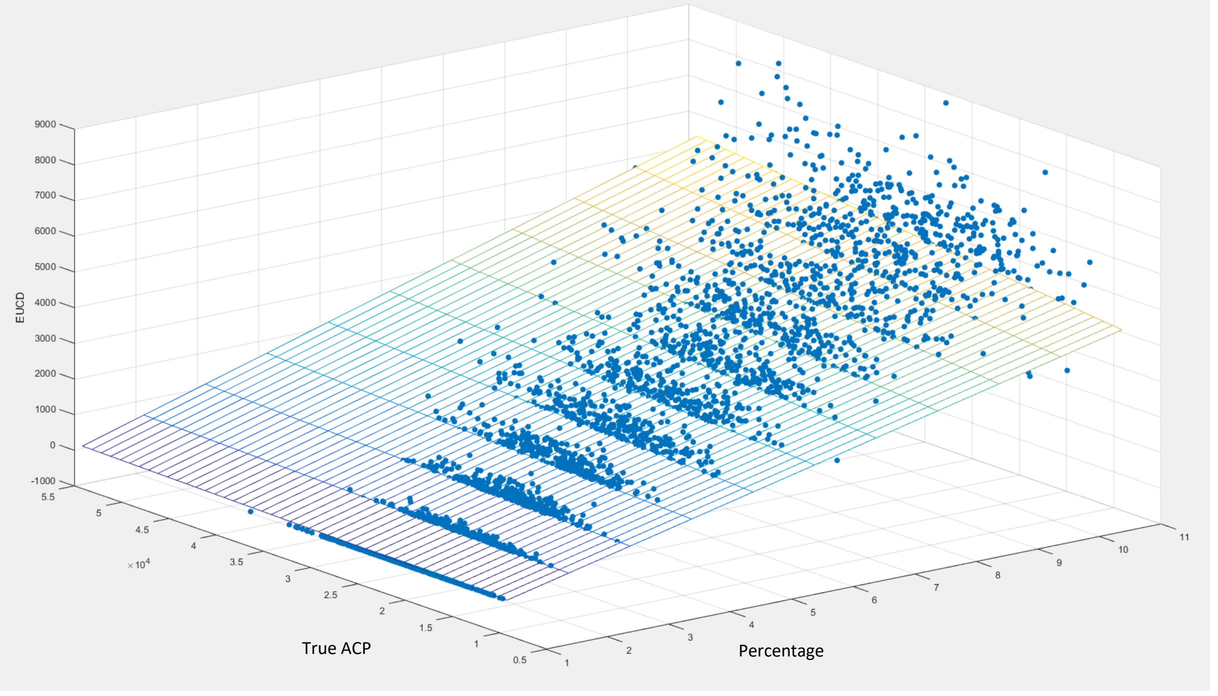


Figure 13 – Hypothesis 3: 2D plot of the effect of change in true activity cost pool on the Euclidean distance measure for 11 observed percentage levels

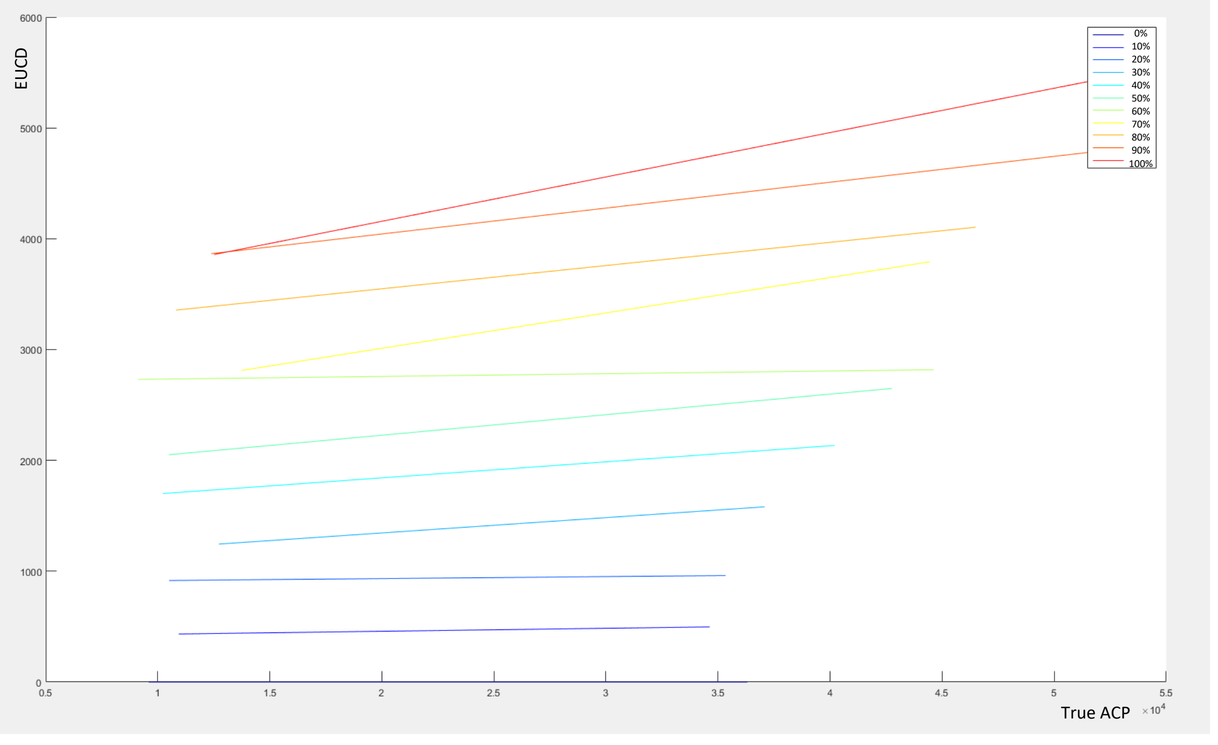


Table 6 – Hypothesis 3: Statistical analysis of the effect of change in true activity cost pool and percentage on the Euclidean distance measure

Output of multiple linear regression analysis with interaction term				
Variable	Coefficient	SE	t-statistics	p-value
Intercept	-0.015484	0.0061444	-2.52	0.012
Percentage	0.87985	0.006348	138.6	0.000
True ACP	0.065137	0.0066439	9.804	0.000
Percentage x True ACP	0.031948	0.0057997	5.5086	0.000

R-squared: 0.836, Adjusted R-Squared 0.836

F-statistic vs. constant model: 9 330, p-value = 0

Descriptive statistics				
Variable	Mean	SD	Minimum	Maximum
EUCD	2 322.30	1 605.90	0.00	8 705.20
True ACP	25 021.00	6 306.30	9 133.30	54 180.00

3.5.3. Hypothesis 4

In Hypothesis 4, we hypothesize that increasing the number of cost allocation drivers (increasing the density of cost drivers matrix) in a setting with interdependencies would result in a reduction of the overall error of the energy costing system.

In this hypothesis, we construct a setting similar to the one for Hypothesis 1, with two activity cost centers A and B, where costs are allocated to products on the basis of different cost allocation drivers. We also assume that the accuracy of the energy costing system would be higher if we use more cost drivers in the system. Because of that we set the level of density (number of non-zero elements in cost drivers matrix) to be 30% and compare obtained results with the results from Hypothesis 1, where we used 70%. Comparing the results obtained from this hypothesis and from Hypothesis 1 will allow us to conclude whether our assumption that an increase in the number of cost drivers would cause a reduction of overall error is correct or not. For 3D plots, we compare Figure 10 and Figure 14, and for 2D plots, we compare Figure 11 and Figure 15. Comparing those figures shows that the overall error of the costing system is higher in Hypothesis 4, i.e., when the density of the cost driver matrix is lower. This effect is especially noticeable at higher levels of true activity cost pools, where the error is much larger with higher sparsity of the cost driver matrix. The descriptive statistics of the Euclidean distance measure in both hypotheses (Table 5 for Hypothesis 1 and Table 7 for Hypothesis 4) are supporting the same finding.

Since the errors in this setting are much larger than in the Hypothesis 1, this is also supporting the hypothesis that increasing the number of cost allocation drivers (increasing the density of cost drivers matrix) in a case with interdependencies would result in a reduction of the overall error.

The effect of the results is similar as in Hypothesis 1. The results from the Table 7 also show that. The multiple linear regression analysis for the simulation output shows that both parameters, true activity cost pool and percentage of interdependency, as well as their interaction term, are significant on a 1% level. The plot of interaction effects for this regression (Figure 24 in Appendix) shows that changing the percentage of interdependency from 0% to 100% increases the Euclidean distance error, given that true activity cost pool is held constant. Changing the true activity cost pools from lower to higher, while keeping the percentage of interdependency constant, will cause the error also to increase. From the interaction effects plot, we can also conclude that the effect of the change in percentage of interdependency has a very similar impact on the overall accuracy as the change in true activity cost pool.

Figure 14 – Hypothesis 4: 3D plot of the effect of change in true activity cost pool and percentage on the Euclidean distance measure

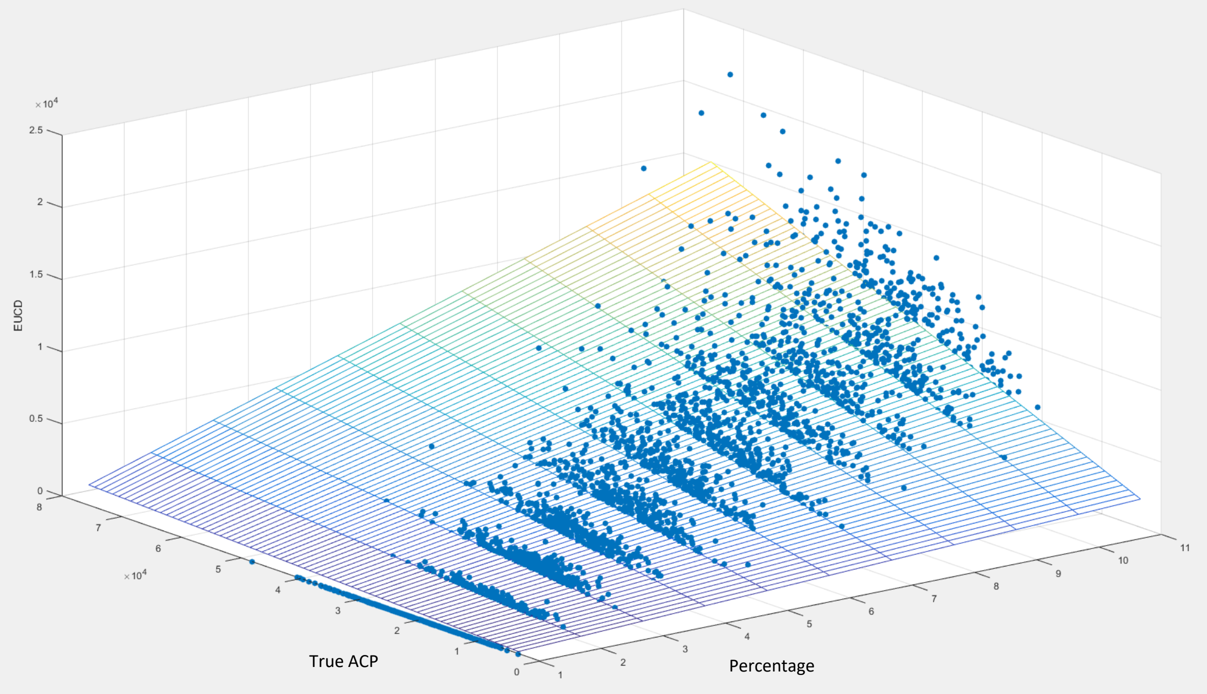


Figure 15 – Hypothesis 4: 2D plot of the effect of change in true activity cost pool on the Euclidean distance measure for 11 observed percentage levels

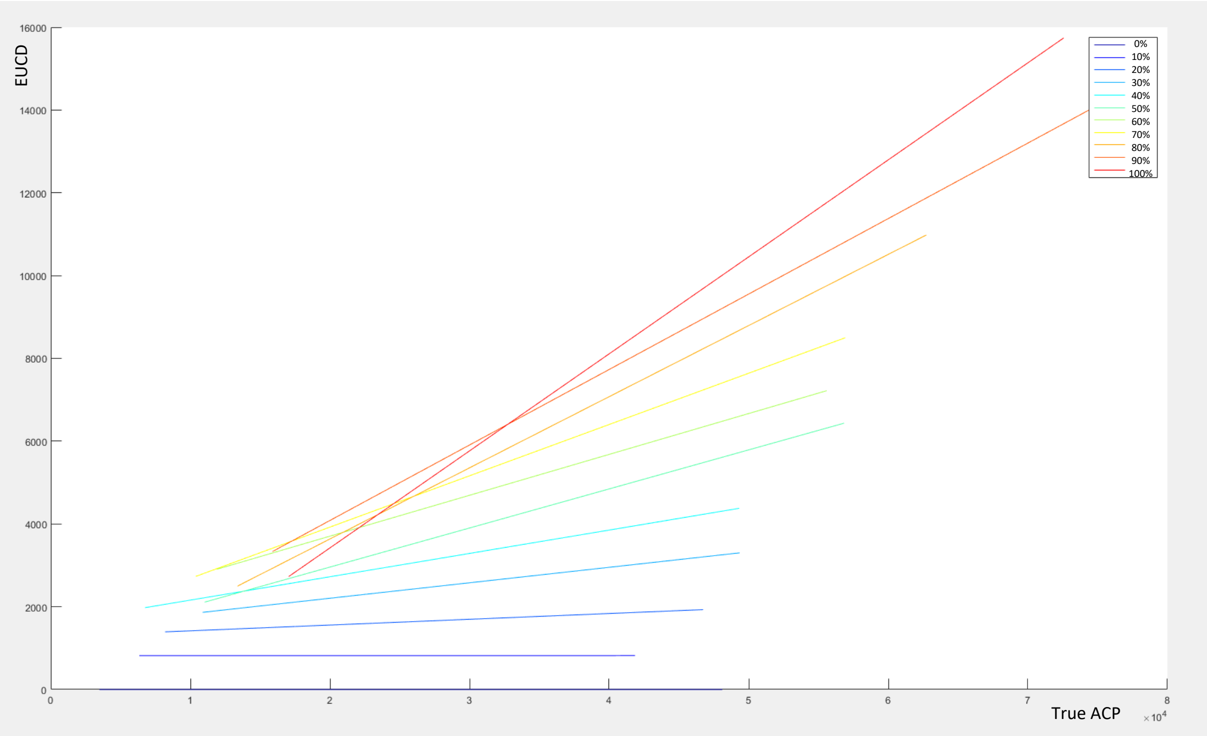


Table 7 – Hypothesis 4: Statistical analysis of the effect of change in true activity cost pool and percentage on the Euclidean distance measure

Output of multiple linear regression analysis with interaction term				
Variable	Coefficient	SE	t-statistics	p-value
Intercept	-0.08812	0.0078538	-11.22	0.000
Percentage	0.63517	0.0085838	73.996	0.000
True ACP	0.30011	0.0086556	34.672	0.000
Percentage x True ACP	0.13645	0.0068031	20.058	0.000

R-squared: 0.767, Adjusted R-Squared 0.767

F-statistic vs. constant model: 6 030, p-value = 0

Descriptive statistics				
Variable	Mean	SD	Minimum	Maximum
EUCD	4 039.30	3 112.40	0.00	23 886.00
True ACP	30 218.00	9 830.10	3 488.50	76 355.00

3.6. Conclusion

The main goal of this chapter is to provide better understanding of the factors that are detrimental for the accuracy of energy costing systems. We show that by using numerical simulations. Unlike specification, aggregation or measurement error, which have been known in management accounting literature, the effect of interdependency on activity cost pool level has not been investigated so far. One example of this is an industrial oven which is used in production of products, but in the same time as heating source for another department. In this case even detailed sub-metering would not capture the exact amount transferred.

In our simulations, we model different settings including interdependencies, such as the amount of interdependency influencing the costing system (Hypotheses 1 and 2), number of cost pools affected by interdependency (Hypothesis 3), and different densities of cost driver matrices included in the systems (Hypothesis 4).

Our results suggest that simplifying energy costing systems and ignoring the influence of such interdependencies would result in large errors. Increasing either the level of interdependency or the value of the true activity cost pool would cause a large overall error of the system, comparing to the system where such error is not ignored, which is the finding of Hypotheses 1 and 2. Hypothesis 3 is testing for the setting where an increase in one activity cost pool causes decrease in two other pools. In this case, the overall error of cost system caused by ignoring interdependency increases if the amount of true cost of an activity cost pool increases. We also note that the overall error of the costing system would be bigger in such setting, where one cost pool is influencing two other cost pools, than in the case of one cost pool influencing only one other cost pool. In Hypothesis 4, we model different densities of cost drivers matrix, and conclude that increasing the density of cost drivers matrix (i.e. increasing the number of cost allocation drivers) is resulting in a reduction of the overall error of the energy costing system. From the interaction effects plots, we can conclude that the effect of the change in percentage of interdependency has a much larger impact on the overall accuracy than the change in true activity cost pool in Hypotheses 1, 2 and 3, and in Hypothesis 4 both variables have a similar effect on the overall accuracy.

The first research question addresses how energy specific costing system simplifications, caused by ignoring interdependencies, are influencing the accuracy of energy costing systems. This is the finding of the Hypotheses 1 and 2, where we conclude that simplifying energy costing systems and ignoring the influences of interdependencies between cost pools would result in large errors. With Hypotheses 3 and 4, we address the second research question, how the errors of costing systems, caused by ignoring interdependencies, are changing with different properties and manufacturing environments. We conclude that the overall error of the costing systems increases in an environment where more cost pools are affected by interdependency, and also where the density of cost drivers matrix is lower.

Future research should investigate how accuracy of energy costing systems changes in different manufacturing conditions. These conditions concern, for example, the kinds of energy used, various costs besides energy, departments/production activities, and products. It is also possible to further develop the simulation as an assessment method, which would consist of an evaluation tool and a flexible simulation. The evaluation tool can be operationalized by using the results of the simulation experiments. The tool would provide a practical way to position a particular company in terms of the experimental conditions of the simulation experiment and to translate the conclusions of the simulation experiment to that company. It would also be useful to make the simulation model more flexible and suitable for company-specific analyses. After all, the conditions or parameter values/probability distributions used in the simulation experiment may be too unrealistic for a particular company. This limits the number of situations for which the results of the simulation experiment in the form of the assessment tool can be applied. Therefore, a flexible simulation model could be calibrated to a particular organization.

4. The impact of input market dynamics on the accuracy of costing systems over time

Abstract

The objective of this chapter is to investigate factors that determine the size of errors in dynamic costing systems. Previous research has focused on measurement, aggregation and specification errors in static simulations. We build on that research and observe how adding a time-component influences the costing systems. Specifically, we focus on costing systems with resources with particularly complex purchase price structure. In order to observe the effect these characteristics have on errors, it is not enough to observe costing systems at one time point. Instead, it is important to take into account their time properties. Because of that, we introduce the term dynamic activity-based costing.

Keywords

Activity-based costing, dynamic simulation, costing system errors, market dynamics, commodity prices

4.1. Introduction

Many companies use imprecise methods for measuring and allocating costs. As a result, their cost information is likely to be inaccurate and they lack the information necessary for cost management. However, getting more accurate cost information requires various investments, such as in more advanced IT systems for capturing and managing data, as well as operational expenses, such as for staff analyzing the data and preparing reports. A cost-benefit tradeoff is required. The benefits of investing in more refined cost information depend on the purposes of the costing information and on how accurate a company's current cost information already is. Therefore, it is useful to know under which conditions even imprecise methods already provide relatively accurate information on costs, and under which other conditions more refined (and more expensive) methods actually provide significantly more accurate information.

Research in management accounting has yielded important insights about errors of costing systems and specifically on measurement, aggregation and specification errors (Balakrishnan, Hansen, & Labro, 2011a; Datar & Gupta, 1994; Labro & Vanhoucke, 2007, 2008). We continue on this research and focus on how accuracy of costing system changes when we also consider dynamic properties of resource prices. Companies often do not have "perfect" (i.e., detailed) data on resource prices as the basis for an accurate costing system, or it is too costly to get those. Instead, they use simplifications within their costing systems of those data and calculate costs based on imprecise inputs on resource prices. We try to model observable parameters which show us when the outcome of a system is likely to be accurate or inaccurate by comparing true costing systems with full information available to the company and simplified system where that information is not known or only limited information is available.

The main goal of this chapter is to better understand which factors determine the accuracy of cost information in a time setting. To observe the influences of these specific factors on accuracy, we formulate dynamic activity-based costing. Specifically, in our hypotheses we model errors that occur as a result of dynamic nature of resource prices and cause errors in costing systems. Electricity is a good example. The prices of electricity can vary considerably over time, at spot markets even every 15 minutes. Also, the consumption of electricity can be dynamic, for example because the production plans shift between batches of a particularly energy intensive products and non-energy intensive products. However, the costing system may not measure such varying prices and consumption in detail. Still, such an error may not always result in large costing inaccuracies. We focus on types of characteristics in costing systems that are specific to time-dependent costs, in order to better understand the conditions under which costing errors are likely to be small or large.

The remainder of this chapter is organized as follows. The second section provides the theoretical background and short descriptions of research on costing errors. In the third section, we postulate our research questions and define the key concepts used in the study. In the fourth section, we formulate our hypotheses. The fifth section explains the research method and defines parameters and simulation environments observed. We continue with the results in the sixth section. The final section presents the potential ideas for future research and potential discussion issues. We end this study with a brief conclusion.

4.2. Literature review

The management accounting literature has looked at different kinds of costing errors. The theoretical management accounting literature has established that costing systems are unlikely to be error-free (Datar & Gupta, 1994; Labro & Vanhoucke, 2007). A large proportion of that work is based on activity-based costing (ABC) analysis, where costs are allocated in two stages: from resource cost pools to activity cost pools in the first stage, and from activity cost pools to cost objects in the second stage. Datar and Gupta (1994) identified three types of errors in product costing: specification, aggregation, and measurement errors. Specification errors are the result of using the wrong cost driver, aggregation errors appear as a result of adding heterogeneous resources together into cost pools, and measurement errors occur as a result of practical difficulties in associating costs with a particular cost pool or in measuring the specific units of the resources used by various activities (Cardinaels & Labro, 2008; Datar & Gupta, 1994). Reductions in specification and aggregation errors from more disaggregated (i.e., more cost pools) and better specified costing systems (i.e., better cost drivers) may, however, increase measurement errors and hence errors in product costs (Cardinaels & Labro, 2008; Datar & Gupta, 1994). More recent papers use numerical simulations to investigate costing errors. These simulations in management accounting are usually based on the following principle: authors construct a number of true cost benchmarks and then simulate a wide variety of imprecise costing systems with different types and sizes of variations (Balakrishnan et al., 2011b; Hocke et al., 2015; Labro & Vanhoucke, 2007, 2008; Leitner, 2014). Next, we review a few of these papers in more detail.

Datar and Gupta (1994) conclude that partially improving specification of cost allocation bases and increasing the number of cost pools in a costing system can actually increase specification and aggregation errors. Secondly, they explain that reductions in specification and aggregation errors from more disaggregated and better specified costing systems may increase measurement errors and hence errors in product costs (Datar & Gupta, 1994).

Jacobs and Marshall (1999) conduct a simulation of multiple cost pool allocation systems. They observe how the use of direct, step and reciprocal methods, which are commonly used to allocate service activity costs to production services, are influencing the size of allocation errors. In their analysis, Jacobs and Marshall are using three quantifiable measures for constructing benchmark costing systems: number of service activities, average service usage (amount of service used by service activities) and service cost variation (relates to the variability of the size of the service cost pools) (Jacobs & Marshall, 1999, p. 48).

Labro and Vanhoucke (2007) provide a simulation study of two-stage cost allocation systems to observe and analyze the interactions among errors in costing systems. In their simulation experiments, they are using the following variables in order to construct benchmark costing systems. A number of resource cost pools, activity cost pools and cost objects, and also the density of cost drivers in both stages. Furthermore, they simulate a wide variety of true costing systems to cover the range of potential true cost benchmarks. For each benchmark costing system, they also simulate a large variety of false costing system approximations, by varying several aggregation, specification and measurement errors that could arise in developing and implementing the costing system (Labro & Vanhoucke, 2007).

Balakrishnan et al. (2011b) use the vector of resource costs and consumption matrix in constructing benchmark costing systems. The consumption matrix is constructed based on the variance of resource costs, density of the matrix, and the correlation between resources whose consumption varies with production volume and with number of batches. Similar as Labro and Vanhoucke (2007), they too simulate a number of benchmark costing systems with abovementioned parameters. Furthermore, they vary three parameters that reflect potential heuristics that a system designer could use. Those are the number of activity cost pools, the heuristics to assign resources to activity pools and the rule by which they select a cost driver (Balakrishnan et al., 2011b).

However, the research so far is based on static simulations and observes costing systems only at one time point. That way, the systems do not capture properties that are changing over time.

A source for measurement errors may be that resource prices and resource consumption changes over time but without the costing system measuring this. Because of that, we investigate what factors determine the size of errors in systems where a time component is taken into consideration. This gives us possibilities to observe how some properties that are changing over time affect the accuracy of costing systems. Previous work on simulations in costing systems was mostly focused on activity-based costing. Therefore, we continue on that research and term the system used in this research as dynamic activity-based costing system.

4.3. Hypotheses motivation

We will focus on the effects of dynamic changes in activity-based costing systems on the overall accuracy of the system. We show why time is an important factor to observe in activity-based costing and formulate research questions based on those observations.

4.3.1. Dynamic activity-based costing

Dynamic changes in this research refer to changes of the resource prices over time. Our motivational example is electricity prices in Germany, since electricity is a widely used commodity in many industries and the data is publicly available. For example, it is possible that a company purchases part of its resources from commodity markets. Electricity is traded in 15 minutes intervals on the market, so the company can bid directly and purchase electricity from the energy market. These are typically large and energy intensive companies that buy (and sell) electricity on the energy exchange market and so market prices are relevant for them. However, the costing system may not measure purchase prices with this level of detail and, for example, use an average price for a longer time interval instead. For example, the company's IT system may not be able to handle such granular price data, or it could be too costly to purchase the data at such detailed level. The purchase price may also be dynamic without the company trading on spot markets. Most companies purchase electricity from energy suppliers, who offer various kinds of purchase price structures. Research shows that typical purchasing strategy in Germany includes about 80% of power being acquired from bilateral contracts and around 20% from the energy market (Fraunhofer-ISI, 2015). If the prices are established as a result of bilateral contract with energy supplier, the volatility could be lower than on spot markets and, for example, be fixed for an agreed time period. Apart from volatility, the pricing structure of energy may have other complexities that can result in measurement errors. For example, the price may be much higher if consumption exceeds a threshold during particular peak hours. Such pricing complexities may also not be fully measured in the firm's costing system.

The same problem may occur for data on resource consumption. Perfect data would require an IT system that measures and records energy consumption frequently (at least as often as energy prices are changing) and at many different places in the company. Such data may be lacking, too, for example, because sub-meters are not installed, or these would have to be read manually and this is not done very frequently. And even if the data would be available in a specialized IT system, the costing system may not be able to handle these amounts of data on dynamic resource consumption.

Such properties of electricity prices are similar for other commodities, such as oil, gas, corn, wheat, silver and others. Purchasing contracts of commodities usually contain dynamic prices and may also otherwise have a pricing structure that is more complex compared to other resources (Capehart et al., 2003; Spees & Lave, 2007). For example, a company can buy a commodity at a certain fixed rate, for the intervals of peak/off-peak hours or daily intervals. However, their costing system might only process monthly, invoice level data. Ignoring input market dynamics, because of inability of the costing system to capture real time data or lack of full information, would lead to measurement error. Where previous research explains measurement error in activity-based costing in a single time period, we continue on that research and show how measurement error influences costing system accuracy over time. To be able to do that, we model activity-based costing system which is developing dynamically under external influences of price changes, and term this **dynamic activity-based costing**. We will model different possibilities of input market dynamics, to observe how using different intervals influences accuracy of costing systems.

The economic relevance of the setting we consider is as follows. We focus only on exogenous changes of input prices, and we model the manufacturing environment from the perspective of a company being a price taker. We decide not to model endogenous influences, which are much more complex regarding the pricing and decision context; an example would be Anand et al. (2017). Furthermore, we also observe a setting in which an outcome of the costing system would help the decision makers to make decisions on the product mix or on the production schedule, but without observing other endogenous influences, such as pricing and marginal costs. Other situations are possible, in which inaccurate costing information would be unproblematic. For example, a company could have inaccurate information and be aware of this, but it has no opportunities to change the product mix or the production schedule.

Furthermore, it should be noted that we focus mostly on direct, variable cost, so purchase price per unit times quantity used. Indirect costs could be also included. For example, in a case where installing additional energy meters could turn the indirect costs into direct variable costs. Fixed costs are not considered, such as fixed network costs a company may have to pay every period for being connected to the grid. Fixed and indirect costs could, in principle, also be allocated parallel to the direct, variable costs considered here to provide a long-term perspective on costs and the profitability of different products.

Regarding the economic relevance, it is also important to note that the applicability of the simulation will largely depend on the resource or commodity that is used the most in the company. Some companies, that use more volatile commodities, could benefit from the information provided from the simulation much more than the companies where such fluctuations are limited. For example, a company which is largely dependent on oil will probably have less accurate costing system information than the company dependent mostly on electricity. Since oil often displays trends and jumps in prices, it is more difficult to estimate and account for those fluctuations in a costing system. On the other hand, electricity often displays mean-reversion effect, i.e., oscillates around certain value, which means that a costing system estimations could potentially be more accurate. Moreover, a company which uses resources for which purchase price fluctuations are limited, or can be (partly) hedged, or for which purchase contracts are available that dampen the influence of spot markets (such as electricity purchased from an energy provider) will have different error rates than the companies that for all their resources use highly volatile resources.

Our overall hypothesis is the following: the level of change in dynamic patterns of resource prices influences accuracy of costing systems. In our simulation, we will model a variety of input price dynamics types with different patterns, such as volatility, trend, and seasonality. We term this **dynamics of commodity input prices**. The few patterns that we will include in our simulations are based on economics and finance literature describing real world commodity price changes. Those patterns include different trends, like an upward trend in commodity prices, that would put a pressure on margins through an exogenous source. In this case, we expect that there will be many cost objects in costing systems that are under-costed. A company would then keep using the same system thinking that they have positive margins, when in reality they are no longer profitable. This would result in making decisions that are negative for the company. For a downward trend, we expect the exact opposite. We also consider different levels of volatility of commodity input prices. We hypothesize that limited price volatility has lower effect on accuracy than significant price volatility (Reichelstein & Rohlfing-Bastian, 2015), and we will model several such variations. Furthermore, we will include time functions of commodity prices with various effects of seasonality. Our expectation is that the accuracy will vary greatly with different patterns, and that some specific cases, such as seasonality, will also display offsetting effects. This would mean that the errors would cancel out partially or completely in a certain time interval.

We specifically focus on the following **research questions:** What are the specific input market dynamics of commodity prices that cause errors in costing systems? How are these errors of costing systems changing with different manufacturing environments?

While other authors use the term "error" when describing measurement, aggregation and specification errors, in our example of dynamic costing system we prefer the term "simplification" of the true or benchmark system. A simplification means that the costing system does not model particular complexities about prices or resource consumption that occur in reality. The question is under which conditions having a simplification of a costing system actually leads to significant inaccuracies. This may not always be the case. That is why we use the term "simplification", as we assume that it is possible that simplifications of the costing system do not necessarily increase the overall error of the system in some specific settings, because of the offsetting effects. Furthermore, having an error in costing system does not necessarily lead to an error in decision making if the decision is unaltered by information for the costing system.

In our manufacturing settings, we model two types of simplifications of measurement, simplification of method and simplification of frequency. Simplification of method means that we will use average or snapshot prices instead of real market prices. As explained before, by using real market prices we would have the perfect information as an input for our costing system. On the other hand, if we use more aggregate data, we will inevitably produce some error as a result of our calculations, since we would not be able to capture all the movements. The other type of simplification is simplification of frequency. By not using the highest frequency (as for example 15 minutes frequency for electricity), we will also lose some level of detail, similar as with simplification of method.

4.3.2. Definitions of key concepts

Before formulating our hypotheses, we first define the following terms.

Real time commodity prices: perfect real time prices of commodities available from the market. For the already mentioned example of electricity, data is available from the energy market for every 15 minutes. Over the course of a year, with the average of 252 trading days, this sums up to 24.192 data points. For each of those points, real price and trading quantity is available.

Method of calculating commodity prices: if real time commodity prices are not available or not included in the costing system, the simplifications are used. We assume the company observes the commodity price once during an interval. We differentiate between the average and the snapshot method. With *the average method* we assume company uses average price during an interval instead of real time commodity price. This number is then used for further calculations. Figure 16, Figure 17 and Figure 18 show an example of real time commodity prices time series (blue line) and the average method of calculating commodity prices (red line). Real time commodity prices are given for 15 minutes intervals over the course of one year in all figures. In Figure 16, the average is calculated over the intervals of one day at the time. In Figure 17, the average is calculated for every month, and in Figure 18 only one average is calculated for the interval of the whole year.

Figure 16 – Plot with real prices and average prices for every day

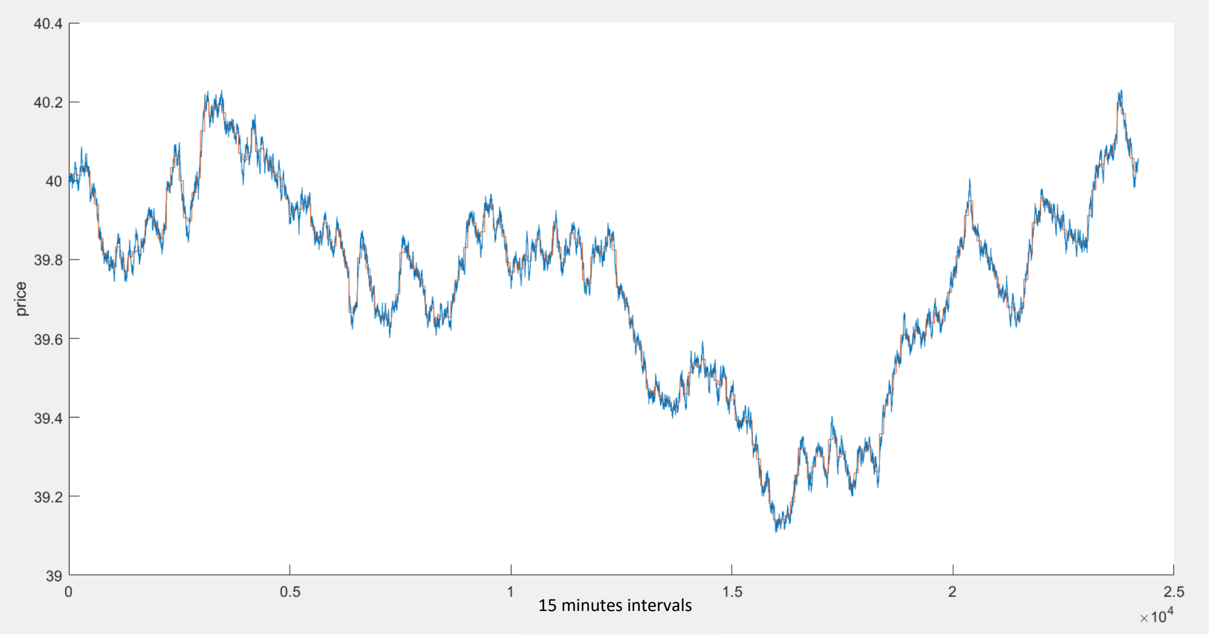


Figure 17 – Plot with real prices and average prices for every month

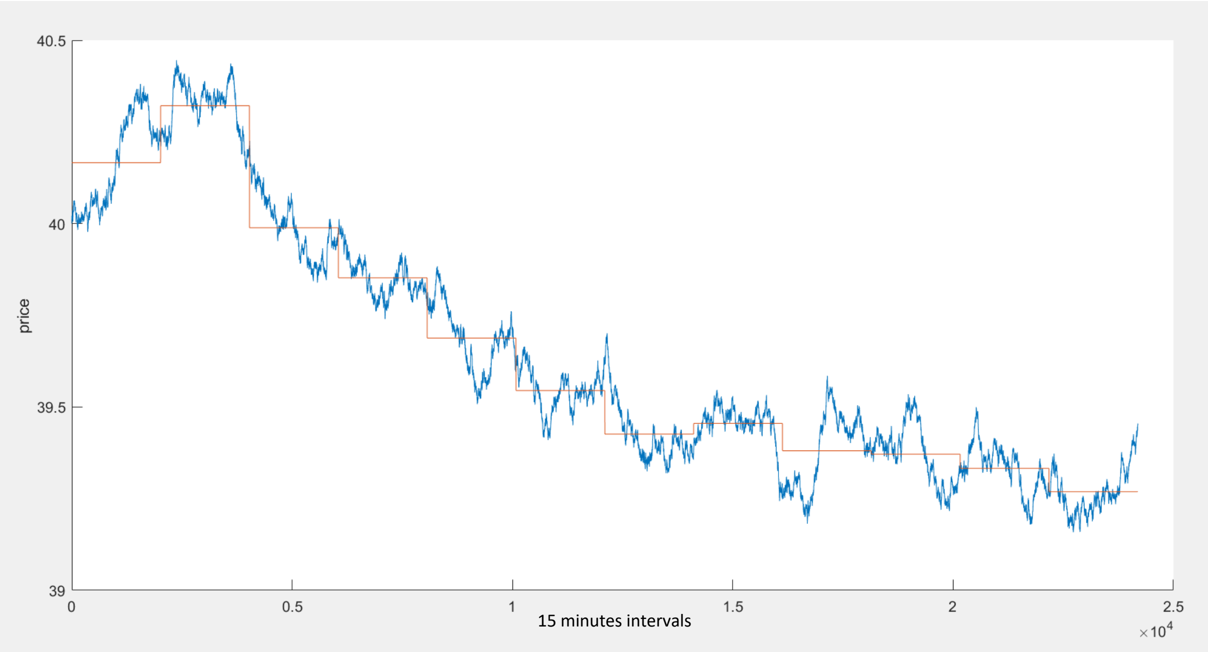
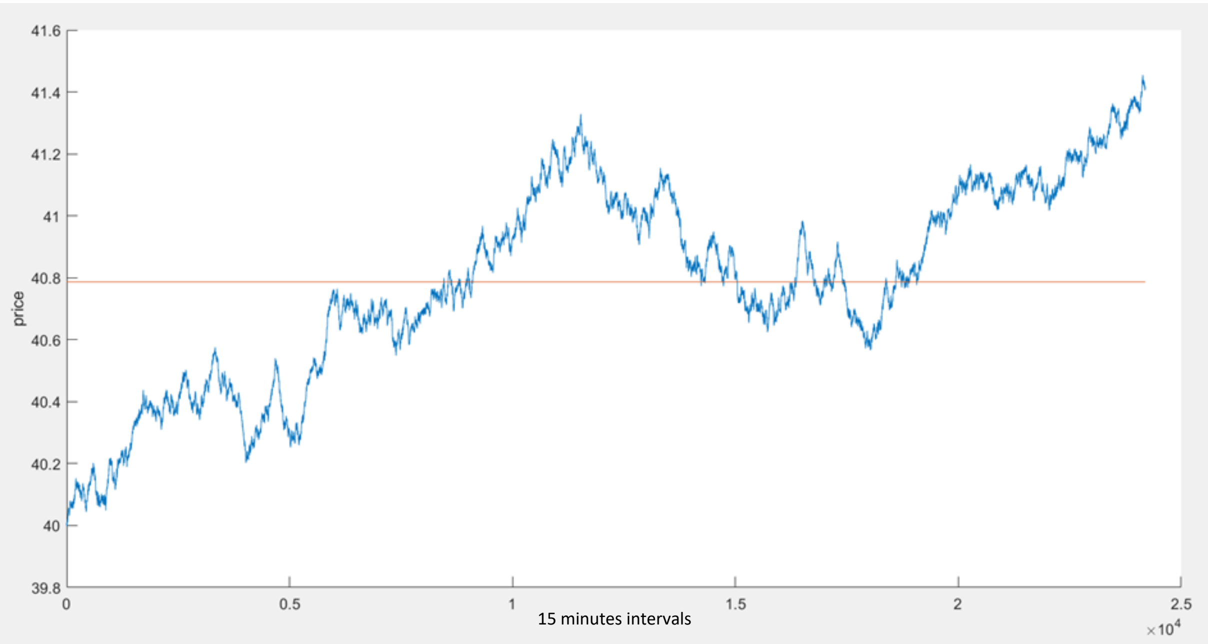


Figure 18 – Plot with real prices and average price for a year



Snapshot method means reading the data at one time point (at the beginning of an interval) and using that data for further calculations. As with the average method, we also observe the snapshot method in three levels of frequency: with daily, monthly and yearly intervals. Figure 19, Figure 20 and Figure 21 show an example of real time commodity prices for 15 minutes intervals (blue line) and the snapshot method of calculating commodity prices (red line). In Figure 19, snapshots prices are taken at the beginning of each day and the same price is used throughout the day. In Figure 20 and Figure 21 snapshot prices are taken at the beginning of month and year, respectively.

Figure 19 – Plot with real prices and snapshot prices for every day

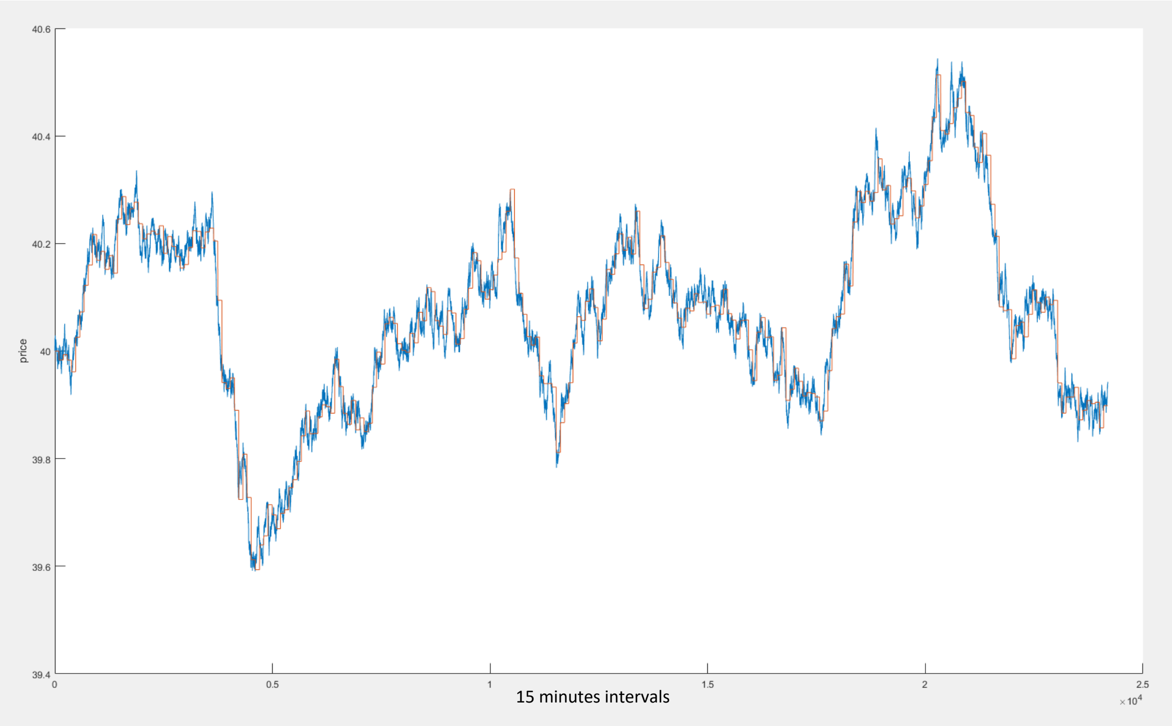


Figure 20 – Plot with real prices and snapshot prices for every month

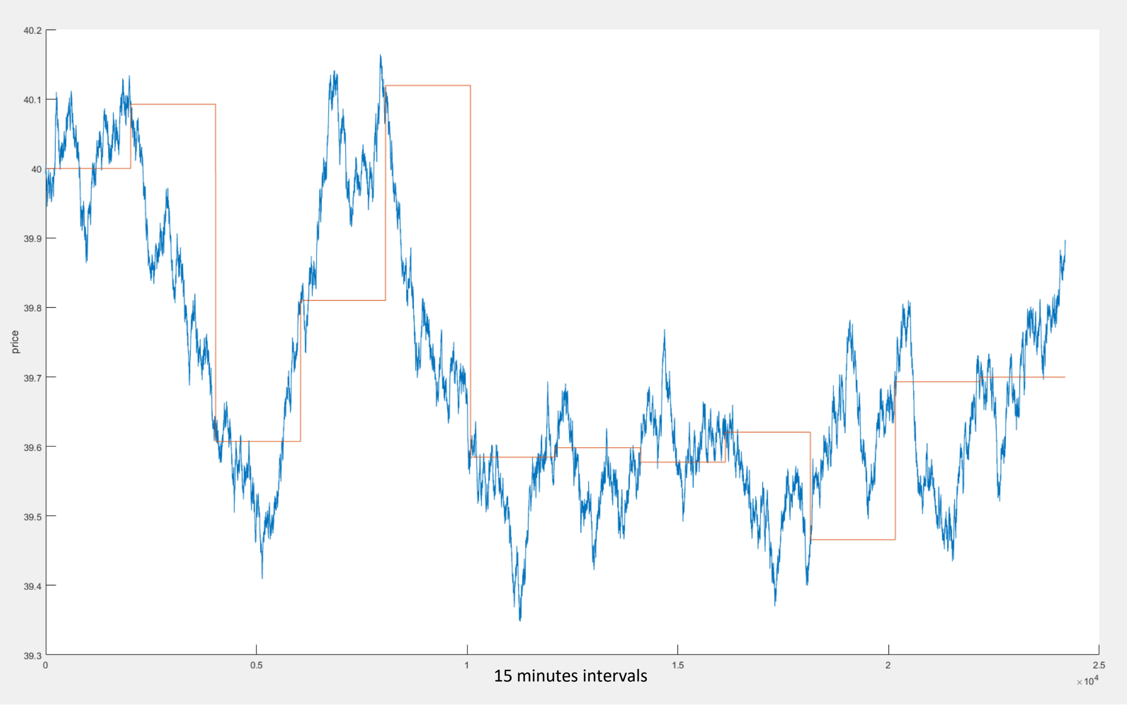
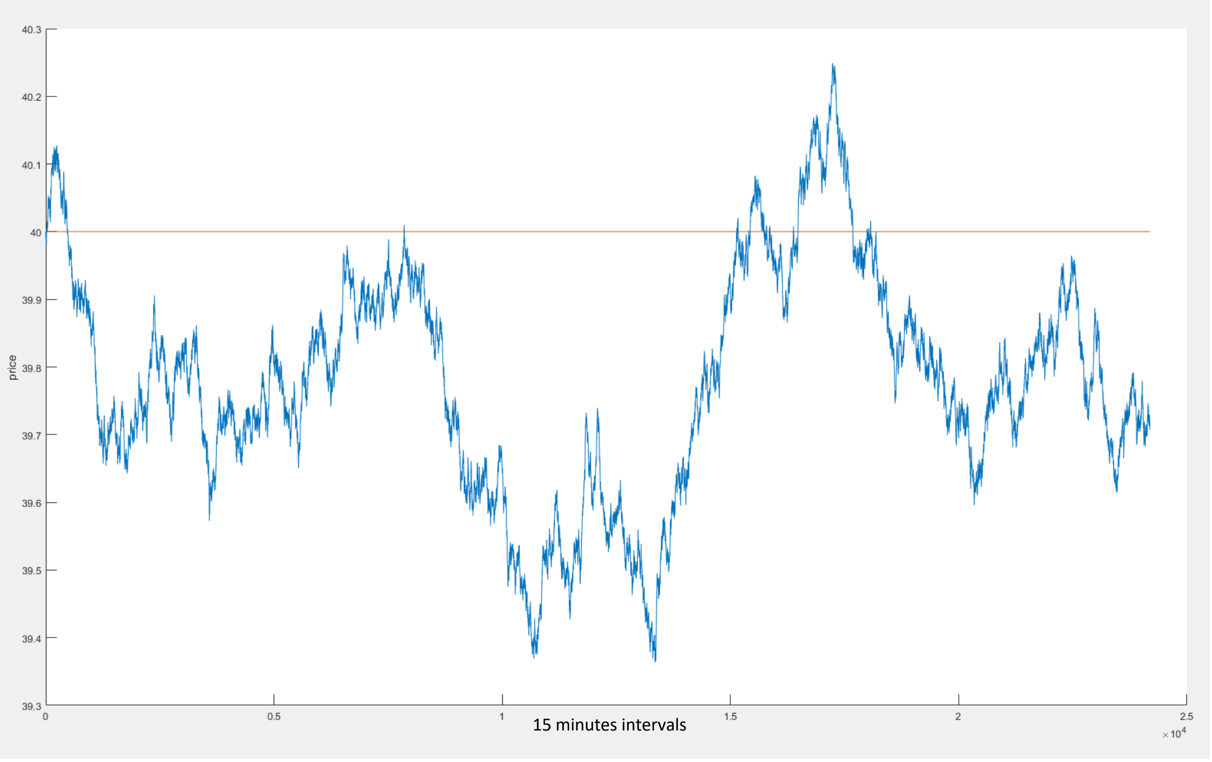


Figure 21 – Plot with real prices and snapshot price for a year



Usage measurement time interval: the length of time for which commodity usage is measured for each resource. For example, the quantity of commodity used on resource level could be measured precisely with sub-meters that provide real time data. On the other hand, it is also possible that this data is not available with such measurement frequency since that would mean the company has online meters and systems that can support processing such a large amount of data. This could mean that the data has to be hand-collected from sub-meters or, that it would be based on utility bills that are provided on monthly or yearly basis. That way, the company would have simplified data about their consumption pattern and would only know the total amount of a commodity that was used in a certain period.

Seasonality of commodity usage: the extent to which commodity usage varies over time. In the simulation, we model three different patterns of the seasonality of commodity usage. First, we model *constant usage* of resource commodity, which means the same amount of commodity is used by a resource in every time point. Second, we model *yearly seasonality* of consumption of a commodity with a peak around July by using sine function and modeling the usage as seasonality. Such an example would be cooling costs that would be the highest in summer and lowest in winter months. Third, we model *daily seasonality* of consumption. The calculations of aggregate consumption in case of yearly and daily peaks are based on averages (similar to the average method from real commodity prices described above). Here, we do not use the snapshot method, since it is more realistic that a company would have aggregate usage data for a certain period, either from sub-meters or from utility invoices.

Density of consumption matrix: number of non-zero elements of this matrix represents the number of cost driver links connecting cost pools and cost objects. The elements of the consumption matrix are percentages that correspond to the level of a resource that is used for a certain cost object. The rows of consumption matrices are summing to 100%, because all the resources are fully used by the cost objects. If density is larger (the number of non-zero elements is bigger), then the number of cost driver links is bigger, which means that more cost objects are using a greater number of different resources.

In the numerical simulation, all the data described is technically available on highest granularity which would provide perfectly accurate results. Since that data is often not available or not used in a company, we will model the simplifications mentioned above that will provide insight when the resulting error of the system is likely to be smaller or larger.

4.4. Hypotheses

Based on our research questions and motivation, we develop following **hypotheses**.

Hypothesis 1: Higher volatility of commodity prices causes the error of the system to rise.

The idea behind this first hypothesis is that increasing the rate of volatility will cause bigger errors, since the price movements are more unpredictable and cannot be captured by infrequent measurements of these prices. When the volatility rate is low, the time series oscillates around certain values, so it is easier to capture price movements.

Simplification of method: We expect that using the average method instead of the snapshot method will provide more accurate results, since the average of the interval aggregates better the pattern of volatile commodity prices in that period.

Simplification of frequency: We expect that more frequent calculation of commodity input prices will result in more accurate costing system data. Using daily calculations instead of larger intervals like monthly or yearly intervals will capture the volatility of the time series of commodity prices better.

Hypothesis 2: Positive or negative trend in commodity prices causes the error of the system to rise. A larger trend will cause a larger error.

For this hypothesis, we consider that commodity prices often display a trend in time series of commodity prices. Not accounting for that trend can cause over-costing or under-costing error in the costing system, depending whether the trend is positive or negative.

Simplification of method: We expect that using the average method will provide more accurate results than the snapshot method. Since the time series of commodity prices will almost constantly rise, averaging the interval should result in higher accuracy than taking the snapshot price at the beginning of the interval. We expect the same results for both directions (for positive and negative trend).

Simplification of frequency: We expect that more frequent calculations of commodity input prices would result in more accurate costing system data, since daily calculations could capture what is happening (the trend) with prices on much smaller periods. We assume the results will be the same also for the negative trend.

Hypothesis 3: Daily seasonality in commodity prices causes larger errors than yearly seasonality.

Commodity prices often contain daily or yearly seasonal patterns. We expect that having a daily seasonality in commodity prices would cause larger errors than yearly seasonality, since it is difficult to capture more frequent price movements. Also, if the amplitude of seasonality of those patterns increases, we expect the error of the system to increase.

Simplification of method: We expect that the average method will provide more accurate results than the snapshot method. We also expect the error for daily seasonality of commodity prices to be quite high for both methods.

Simplification of frequency: Daily seasonality measured with a lower frequency than one day will display high errors, since daily seasonality is more difficult to capture with less granulated measurements.

Hypothesis 4a: Daily seasonality of commodity usage causes larger errors than yearly seasonality.

Hypothesis 4b: Measuring commodity usage more often provides more accurate results.

In the earlier hypotheses, we keep the quantity of commodity usage fixed throughout the simulation. Here, we want to test how changing the quantity of commodity usage, along with volatility of commodity prices, changes the accuracy of the costing system. We model daily and yearly peaks of quantity usage. We assume that companies measure quantity of the consumption daily, monthly or yearly, so we model quantity functions for each of those periods. In modeling those functions, we only use the average method, since it is more realistic that a company would have aggregate data on their consumption from a certain period (i.e., per day, month, or year), either from sub-meters or from utility invoices.

Simplification of method: We expect that the error is going to be higher with the snapshot method (for commodity prices). However, we expect the error to be higher for both the average and the snapshot method in this hypothesis compared to the results of other hypotheses, since the simplification of the costing system is unlikely to capture all the variations that are happening both in quantity of commodity usage and volatility of commodity prices.

Simplification of frequency: We expect that more frequent calculations of commodity input prices will result in more accurate costing system data, since daily calculations could capture what is happening with both variations on much smaller periods than monthly or yearly calculations.

Hypothesis 5: Larger density of consumption matrix causes smaller overall error of the costing system.

In this hypothesis, we show how different levels of density of a consumption matrix affect the accuracy of a costing system. We assume that larger density of the consumption matrix (or more cost driver links) in a setting would result in a smaller overall error of the system. Our assumption is that if the consumption matrix is more dense, i.e., has more non-zero elements, then the costs are allocated to a greater number of different cost objects. That was, the erroneous costs of the cost pools end up with a greater number of cost objects, with the error being smaller, in absolute amount, for each cost object. Reversely, if the consumption matrix is sparse, then the errors would be concentrated to fewer number of cost objects, each having a larger error. The overall error of the costing system would be smaller in a case of many small errors compared to a few large ones, thus we expect that a more sparse consumption matrix results in a larger overall error.

Simplification of method: We expect that using the average method instead of the snapshot method will provide more accurate results. However, because of the dynamic effects, it is difficult to estimate what the effects on accuracy will be.

Simplification of frequency: We expect that more frequent calculation of commodity input prices will result in more accurate costing system data. Using daily calculations instead of larger intervals like monthly or yearly intervals should capture the changes in the data more accurately.

Hypothesis 6: Using the average method causes smaller overall error of the costing system than using the snapshot method.

This hypothesis is a combination of the results obtained in Hypotheses 1-5, focusing on simplification of method. Moreover, we expect that using average prices will result in more accurate costing systems than using the snapshot method. We also expect that this result will be visible in all the hypotheses, since we assume that average of the interval describes better the change in time series in that period than using one measurement at the beginning of the interval. The same effect should be visible by comparing Euclidean distance measures and materiality measures.

Hypothesis 7: Using more frequent calculations of commodity input prices produce more accurate costing systems.

This hypothesis is also a combination of the results obtained in Hypotheses 1-5, focusing on simplification of frequency. This effect should be visible for all the hypotheses, since we assume that using data that are more granular is likely to capture the changes in market dynamics better and would result in a smaller error. We will compare the results from hypotheses for daily, monthly and yearly prices, and expect that using daily prices would result in smaller error than using monthly prices, and that using monthly prices would result in smaller error than using yearly prices.

In order to investigate dynamic factors that determine the size of errors in costing systems over time, we introduce the term dynamic activity-based costing. In our hypotheses, we express our expectations about variations of commodity price dynamics (volatility, trend, seasonality), seasonality of commodity usage and density of consumption matrix, and their effect on the accuracy of costing systems.

4.5. Research method

4.5.1. Defining simulation environment and parameters

As we have shown in Chapter 3, numerical simulations are not often used in management accounting research on costing errors, even though the advantages are numerous. A simulation model is always an approximation of an actual complex system, and can only be an abstraction and simplification of reality (Law, 2008). As Harrison et al. (2007) report, it is especially helpful to use simulations in cases where data is not available or for complex analytical models that could not be analyzed otherwise. Another positive side of conducting numerical simulations in management accounting is that it allows observing certain effects in extreme situations. It is likely that those situations will not occur in real life situations, but they still provide insight. Labro (2015) reports also some downsides, referring to the great amount of data that can be generated in simulations, which can lead to difficulties in identifying the most important results. In such cases, it is also hard to conclude what are the possible mechanisms that lead to such effects, being challenging as “seeing the forest for the trees” (Labro, 2015).

Computer simulation would allow us to calculate accurate costs for a costing system that models time properties, as well as costs after introducing simplifications into the costing system by not modeling those properties. Those simplifications should be modeled in different environments to see how various characteristics of the environment affect the accuracy of the costing system. The computer simulation would provide insights for the conditions under which costing errors are likely to be small or large.

Conducting simulation experiments usually includes several steps. Here, we build on the model from Balakrishnan et al. (2011b) and Balakrishnan and Sivaramakrishnan (2008). We develop and extend that model with a special focus on dynamic properties in costing systems and related costing simplifications. As previous papers on this research, we follow the framework of Anand et al. (2017) and Balakrishnan et al. (2011b). Therefore, we simulate benchmark and simplified systems in a one stage activity-based costing environment. We then compare costing systems with true and simplified information, and calculate Euclidean distance and materiality measure.

1. Define the manufacturing environment that remains constant across experimental conditions. This involves parameters such as: total quantities of each commodity used on a resource cost pool level, number of resource and activity cost pools and number of cost objects (products). These parameters stay fixed throughout the experiments to ensure comparability of the simulation outcomes.
2. Define the first part of the experimental conditions for the simulation study, namely the conditions of the manufacturing environment that are manipulated (the independent variables). The independent variables that we model in order to establish benchmark costing systems are: dynamics of input commodity prices (trend, volatility and seasonality), seasonality of quantity of commodity used and density of consumption matrix.
3. Next, we select parameter values or probability distributions for these independent variables, based on economics and finance literature, and also by modeling real time prices of commodities and simulating several potential price changes in the future. A costing system with a particular set of parameter values or probability distributions is called a benchmark system.
4. Calculate the true costs of each benchmark system, using computer simulation. This is also called a solution.

5. Define the second part of the experimental conditions, namely the simplifications (also called inaccuracies or heuristics) that are built into the costing system. These are also independent variables. We observe the results obtained with the average and the snapshot method instead of real time commodity prices, whereby we observe those methods for different time intervals – daily, monthly and yearly intervals. Furthermore, we observe results for different frequencies for measuring the quantities of resource usage.
6. Select the parameter values for these conditions. A costing system with a particular set of parameter values that reflect one or several simplifications is called a simplified system. Each simplified system is related to one benchmark system that includes none of the simplifications.
7. Calculate the costs of each simplified system, using computer simulation.
8. For each benchmark system, compare its true costs with the observed costs of the related simplified systems. The difference between the actual cost of the benchmark system and the observed cost of a simplified system is the accuracy of the costing system under those specific experimental conditions, which is the dependent variable.
9. Analyze the results to understand the impact of independent variables (conditions of the manufacturing environment, cost system heuristics, and their interactions) on the accuracy of costing systems (the dependent variable). The dependent variables are Euclidean distance measure and a particular materiality measure.

It is not possible to include every single possibility and all parameter variations in a numerical simulation. However, by adjusting parameters in manufacturing settings and changing environments to resemble real companies, it is possible to see what the outcomes would be for specific companies. Our motivation for this chapter is not to cover every single of those possibilities and to generalize the results so that they are applicable for all companies, but our idea is to show how accuracy of costing system changes if the company chooses not to look into the details of input price dynamics.

Here we present an overview of the parameters used in the simulation. The following parameters are fixed throughout the whole simulation process:

1. Total quantities of each commodity used (based on kWh, liter, kg or other measurement units). Since prices of commodities and costs calculated with those prices are changing in each time interval, we fix the total quantity of each commodity used throughout the whole period to ensure comparability.
2. Number of resource and activity cost pools, set at five resource and five activity cost pools

3. Number of cost objects (products), set at five cost objects

The independent variables in the simulation concern the manufacturing settings and the errors (simplifications) of the costing system. The following parameters are used for constructing different manufacturing settings (benchmark costing systems):

1. Dynamics of input commodity prices:
   a) Volatility (four levels: small, realistic, high, very high)
   b) Trend/drift (five levels: very negative (downward), negative, neutral, positive, very positive (upward))
   c) Seasonality: daily and yearly (three levels: high, low, no seasonality)
2. Seasonality of commodity quantity used – described with quantity functions (three possibilities: constant usage, daily seasonality, yearly seasonality)
3. Density of consumption matrix (three levels)

The following parameters for the simplified costing systems (inaccuracies or heuristics for simplified systems):

1. Simplification of the method for measuring commodity prices (two levels):
   a) Average method
   b) Snapshot method
2. Simplification of the frequency for measuring commodity prices and quantities used (three levels):
   a) Yearly
   b) Monthly
   c) Daily

We use two dependent variables (these explained in more detail in the next section):

1. Euclidean distance measure
2. Materiality measure (Balakrishnan et al., 2011b; Labro & Vanhoucke, 2007, 2008)

The Euclidean distance measure shows the accuracy of the simplified system comparing to the benchmark system. On the other hand, the materiality measure takes an acceptable range of accuracy into account. By calculating the materiality measure for the results of our simulations, we can conclude how much of the results are within that acceptable range throughout the year.

4.5.2. Detailed algorithm and mathematical notation

In our simulation, we use geometric Brownian motion, which allows us to model the most important patterns that occur in commodity prices, namely volatility, trend and seasonality. Brownian motion is often used to explain the movement of time series variables and of stock prices. The literature and research in finance explains how stock prices exhibit random walk, which is unpredictable path of time series that cannot be mathematically or statistically fully explained without taking certain risk into account. "The geometric Brownian motion model incorporates this idea of random walks in stock prices through its uncertain component, along with the idea that stocks maintain price trends over time as the certain component" (Maruddani & Trimono, 2018, p. 2). The finance and economics literature differentiates between the following patterns that occur in commodity prices: volatility, trend or drift, jumps and seasonality (Cartea & Figueroa, 2005; Mayer, Schmid, & Weber, 2015; Schwartz & Smith, 2003). Even though commodity prices should mostly be stationary, analyses show that many time series are not (Wang & Tomek, 2007). Non-stationarity of the time series can be a consequence of several factors. For example, it may contain a trend (and the average value of the series is not constant), the variance of the series can change over time or the series can contain seasonal and/or cyclic components. One of the most common causes of the non-stationarity of the time series is the presence of a trend (Hamilton, 1994).

First, we gather market data for several commodities from Bloomberg, in order to observe the patterns that occur and the properties of those patterns. We draw on that data and use similar parameters, and also add some variations to cover the wider range of possibilities. We investigate electricity (Epex spot phelix day ahead electricity auction baseload index), crude oil (Bloomberg west texas intermediate (WTI) cushing crude oil spot price, Bloomberg European dated brent forties oseberg ekofisk (BFOE) price – EU crude oil) and natural gas (Germany NCG natural gas forward day ahead – gas index) time series because of their specific properties. In those time series we identify different possibilities for market dynamics. Electricity displays volatility, crude oil shows trend, and natural gas has one high jump with other values mainly stable.

Second, we then conduct numerical simulations by using Matlab software.[13] Costing systems in our simulation are modeled over the course of one year, with data available at the granularity of every 15 minutes. With an average of 252 trading days in one calendar year, this sums up to

[13] Matlab R2015b (Version 8.6.0.267246)

24.192 data points for every simulation setting. Since for each simulation we have to model 24.192 time points, and because of the limited computing power, we simulate 50 runs for each of the settings. We model one stage activity costing system with five resource cost pools or five activity cost pools, and five cost objects. In our simulation we assume Leontief technology, that each product consumes a fixed amount of each input resource, and also that the resources are not substitutable. We will now explain the simulation in more detail:

Resource cost pools (RCP):

In the numerical simulations, we keep the number of resource cost pools, activity cost pools and cost objects to be fixed (five). In order to ensure comparability of results, we also fix the quantity of commodities each resource is using (100.000 units). We then model the dynamics in prices and calculate the resource costs by multiplying quantities and prices. Since we want to isolate the effect that is caused by dynamical changes in the input commodity prices, we model those for only one resource cost pool and observe how it affects the accuracy of the whole system.

We use the following notation for the resource cost pools: $pRCP_1, \dots, pRCP_5$ are prices of input resources, and $qRCP_1, \dots, qRCP_5$ are quantities each resource is using, where $pRCP_2, \dots, pRCP_5$ and $qRCP_2, \dots, qRCP_5$ are kept fixed throughout all settings, and $pRCP_1$ and $qRCP_1$ are modeled with geometric Brownian motion. We model the price of $pRCP_1$ around the same values for all the simulation runs, and we vary its properties (such as volatility). This is also a way of ensuring comparability across simulations and hypotheses.

The volatility of a commodity price is modeled as follows (for Hypothesis 1). Drawing from the electricity pricing data, we calculate intraday volatility of electricity price, which is 0.025 in the year 2017. Taking that as a realistic volatility, we also use some deviations around that value to cover the wider range of possibilities. We use four levels of volatility, 0.01, 0.025, 0.1 and 0.5, and a volatility of value 0, which would mean that there is no volatility throughout the year at all, so the price would be represented as a horizontal line. In all other hypotheses, we use the realistic volatility of 0.025 in price modeling.

In Hypothesis 2 we test the accuracy of the costing system when there is a trend present in the commodity time series. We are interested in both positive and negative trends, so we use five different levels for their modeling: -0.5, -0.25, 0, 0.25, 0.5. These values are representing annual trends; so for example, a trend of 0.5 would mean that there is approximately 50% increase in the price in one year.

In Hypothesis 3 we vary the seasonality of input commodity prices. Since real electricity market data displays yearly and daily seasonality, we decide to model those in our system. We model yearly peak of electricity prices around July, and daily peaks around noon each day. For modeling the seasonality, we combine sine functions with different amplitudes, with the volatility that we model in all simulation settings. We model three levels for both yearly and daily seasonality: no seasonality and low and high seasonality, with a smaller or bigger amplitude.

In Hypothesis 4 we model the commodity usage with quantity functions. Here, we model the seasonality of commodity quantity used in a similar way as the seasonality of input commodity prices described above. In this hypothesis, we want to test how changing the quantity of commodity usage, along with volatility of commodity prices, changes accuracy of the costing systems. We model yearly and daily peaks of consumption with the same amplitude that is around the average value of consumption. Yearly peak of consumption of a commodity is modeled around July by using a sine function. Such an example would be cooling costs that would be the highest in summer and lowest in winter months. We assume that daily peaks reach their highest point around noon. We assume that companies measure quantity of consumption daily, monthly, or yearly, so we model quantity functions for each of those periods. In modeling those functions, we do not use the snapshot method for measuring usage, since it is more realistic that a company would have aggregate data from a certain period, either from sub-meters or from utility invoices. In all other hypotheses, we use constant functions to model the usage of resource commodity, which means the same amount of commodity is used by a resource in every time point.

In Hypothesis 5 we model different densities of consumption matrix. We model the density in three levels, 0.1, 0.5 and 0.9.

To calculate the resource cost pools, we multiply:

$$RCP = pRCP_1 \cdot qRCP_1 + \cdots + pRCP_5 \cdot qRCP_5 = RCP_1 + \cdots + RCP_5$$

Creating resource cost drivers (RD):

Density of the consumption matrix is set to be 70% for all the hypotheses except for the Hypothesis 5, where we test how different densities affect accuracy of costing systems. Density of the consumption matrix is a number of non-zero elements in the matrix. The elements of that matrix represent the number of cost driver links connecting cost pools and cost objects. We simulate three different levels of density in order to test how different manufacturing settings influence the errors of the costing systems. We then construct a matrix of cost drivers where every row consists of $i_{1,\ldots,5}$ elements from a uniform distribution.

$\forall i_{1,\ldots,5} \in [\max(RCP, CO)\,, RCP \cdot CO]$ where $RD_{1,\ldots,5}$ is vector of $i_{1,\ldots,5}$ elements from uniform distribution.

Creating true cost objects (CO_t):

By multiplying resource cost pools with the consumption matrix, we get the values of cost objects. Since all the data used in calculating those cost objects is available at the highest granularity, the results of the costing system would be accurate, or "true". We call that the benchmark system.

$$CO_t = RD_1 \cdot RCP_1 + RD_2 \cdot RCP_2 + \cdots + RD_5 \cdot RCP_5 = CO_{t1} + CO_{t2} + \cdots + CO_{t5}$$

Creating activity cost pools (ACP):

In order to create activity cost pools, we simplify and aggregate the data available in resource cost pools. As previously mentioned, we model two types of simplifications, of method and of frequency. Simplification of method means that we will use the average or snapshot prices instead of real market prices. By using detailed market prices as in forming resource cost pools, we would have the perfect information as an input for our costing system, and therefore the results of the costing system would also be correct. However, if we use simplified data, we will inevitably produce some error as a result of our calculations, since we would not be able to capture all the price movements. With the average method, we assume the company uses average price during an interval instead of real time commodity price. Real time commodity prices are given for every 15 minutes, and we calculate and simulate costs with averages for every day, every month, and whole year. Snapshot method means reading the data at one time point and using that data for further calculations. We also simulate those data on three levels: for daily, monthly and yearly snapshot prices. The other type of simplification, simplification of frequency, considers the time intervals for which we calculate the data. As mentioned above, we are using simplified data on daily, monthly and yearly basis. By not using the highest frequency (as for example 15 minutes frequency for electricity), we will also lose some level of detail, similar as with simplification of method. That way we form $pACP_1, \ldots, pACP_5$, simplified prices of input resources, and $qACP_1, \ldots, qACP_5$ simplified quantities that each cost pool is using.

To calculate the activity cost pools, we multiply:

$ACP = pACP_1 \cdot qACP_1 + \cdots + pACP_5 \cdot qACP_5 = ACP_1 + \cdots + ACP_5$

Creating cost objects of a simplified system (CO):

We keep cost drivers the same as we want to isolate the influence of dynamic changes in prices. By multiplying activity cost pools with cost drives, we get the cost objects of simplified system.

$CO = RD_1 \cdot ACP_1 + RD_2 \cdot ACP_2 + \cdots + RD_5 \cdot ACP_5 = CO_1 + CO_2 + \cdots + CO_5$

By using Euclidean distance and materiality measure, we evaluate the results obtained in the simulations. The results of each benchmark system is compared to the associated simplified system. We repeat the simulation 20 times for every simulation setting and report in the tables in Result section mean values of those simulation runs. Similar to other papers in the field of management accounting who are observing costing system errors (Babad & Balachandran, 1993; Balakrishnan et al., 2011b; Homburg, 2001; Hwang et al., 1993; Labro & Vanhoucke, 2007, 2008), we also measure the accuracy with Euclidian distance. Euclidean distance measure (EUCD) can be used for both static and dynamic simulations.

$$EUCD = d(CO, CO_t) = \sqrt{\sum_{i=1}^{n}(CO - CO_t)^2}$$

We also build on that and use another measure that can be used throughout time. We formulate a materiality band around true costs which allows us to see how much is accuracy changing in time. This band is a percentage of error that would be acceptable in the costing system (in this study, we allow for the error of ±10%). In the simulation, we calculate what percentage of the errors would be outside of this materiality band for specific environments and variables.

In order to statistically evaluate the results, we conduct multiple linear regression analysis. A general expression for a multiple linear regression equation involving a multiplicative interaction is:

$$EUCD = \beta_0 + \beta_1 Dynamics + \beta_2 Frequency + \beta_3 \cdot Dynamics \cdot Frequency + \varepsilon$$

where β's represent regression weights or coefficients, *Dynamics* is the term describing different patterns observed in the chapter (volatility, trend, seasonality), and *Frequency* represents different levels of simplification of frequency (daily, monthly, yearly). Euclidean distance measure of the overall error in costing systems is used as response (or dependent) variable, while percentages of interdependencies and correct (or true) values of activity cost pools are observed as predictors of multiple linear regression model. Variables are also standardized to their respective means (Aiken & West, 1991). Standardization rescales data, which removes multicollinearity and allows comparability of the results. This allows us to compare the regression results across hypotheses. The results of multiple regression analyses are presented in the Results section. Once we determine whether the interactive component of regression analysis is statistically significant, we conduct further analysis to show how are those interactive effects influencing the accuracy of costing systems. Plots that are presenting the analysis of interactive effects are in the Appendix. They display what is the impact of a change in one parameter given that the other parameter is fixed at a certain value.

4.6. Results

4.6.1. Hypothesis 1

In Hypothesis 1 we hypothesize that higher volatility of commodity prices will cause the error of the system to rise.

Table 8 shows how different values of volatility are affecting the accuracy of costing systems when the average method is used. It is visible that the error is lowest when volatility of commodity prices is low. As the volatility rises, the error of the costing systems is increasing, since the price movements are more unpredictable and cannot be captured by infrequent measurements. By simplifying the frequency for the calculation of prices from daily to yearly intervals, the errors are increasing. The materiality measure shows that with low volatility, even when the company is averaging the data daily, the results of the costing system are going to be almost perfect. When the volatility rate is low, the time series oscillates around certain value, so it is easier to capture movements of prices. However, with monthly and yearly averaging, costing systems display much bigger errors. One quite realistic scenario would be a company that calculates its prices according to monthly invoices. With prices that have realistic volatility (0.025), it would mean that the company has only 27.64% of the costs over the year within the bandwidth of 10%. As expected, we observe similar patterns with the snapshot method in Table 10. However, the Euclidean distance measures are slightly lower, which means that the average method can describe the change in time series better than the snapshot method.

Multiple linear regression analysis for simulation with the average method (Table 9) shows that both volatility and frequency are statistically significant at the 1% level, as well as their interaction term. All predictors have positive values, which means that an increase in a predictor will cause the overall error of costing system (EUCD) also to increase. The plot of interaction effects for this regression (Figure 25 in Appendix) shows that changing volatility from 0.01 to 0.5 increases the Euclidean distance error, given that frequency is held constant. Increasing volatility for each level of frequency will increase the overall error of the system. Changing frequency from daily to yearly, while keeping volatility constant, will cause the error also to increase. From the interaction effects plot, we can also conclude that the effect of the change in volatility has a larger impact on the overall accuracy than the change in frequency. The results of linear regression with the snapshot method (Table 11) are similar and all the predictors are also statistically significant at the 1% level. The plot of interaction effects for this regression (Figure 26 in Appendix) shows that changing volatility from 0.01 to 0.5 increases the Euclidean distance error, given that frequency is held constant. Increasing volatility for each level of frequency will increase the overall error of the system. Changing frequency from daily to yearly, while keeping volatility constant, will cause the error to increase. From the interaction effects plot, we can also conclude that the effect of the change in volatility has a larger impact on the overall accuracy than the change in frequency. This means that the effect of volatility is stronger than the effect of frequency both with average and with snapshot method.

The findings above are supporting our hypothesis that higher volatility of commodity prices will cause the error of the system to rise.

Table 8 – Hypothesis 1: Simplification of method – average

Variable	*Simplification of frequency*		
Volatility	Daily	Monthly	Yearly
0.01	0.0201 (99.77%)	0.0897 (64.36%)	0.3249 (20.69%)
0.025	0.0515 (87.29%)	0.2376 (27.64%)	0.7553 (9.27%)
0.1	0.2111 (32.05%)	0.9495 (7.5%)	2.7356 (2.14%)
0.5	1.0106 (7.07%)	4.3729 (1.68%)	16.1556 (0.46%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 9 – Hypothesis 1: Simplification of method – average: Statistical analysis

Output of multiple linear regression analysis with interaction term

Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.024709	0.000	1.000
Volatility	0.54128	0.02473	21.888	0.000
Frequency	0.3651	0.02473	14.764	0.000
Volatility x Frequency	0.45779	0.02475	18.496	0.000

R-squared: 0.636, Adjusted R-Squared 0.634

F-statistic vs. constant model: 346, p-value = 0

Descriptive statistics

Variable	25^{th} percentile	Median	75^{th} percentile
EUCD	0.1383	0.4769	1.8600
Materiality measure	4.08%	11.11%	42.52%

Table 10 – Hypothesis 1: Simplification of method – snapshots

Variable	*Simplification of frequency*		
Volatility	Daily	Monthly	Yearly
0.01	0.0338 (95.96%)	0.1621 (42.48%)	0.5536 (13.57%)
0.025	0.0917 (64.84%)	0.3561 (21.93%)	1.1929 (6.57%)
0.1	0.3550 (22.94%)	1.6560 (5.31%)	5.2375 (1.55%)
0.5	1.7388 (6.35%)	7.4333 (1.17%)	26.3080 (0.34%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 11 – Hypothesis 1: Simplification of method – snapshots: Statistical analysis

Output of multiple linear regression analysis with interaction term

Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.023904	0.000	1.000
Volatility	0.53456	0.023924	22.344	0.000
Frequency	0.38099	0.023924	15.925	0.000
Volatility x Frequency	0.47787	0.023944	19.958	0.000

R-squared: 0.659, Adjusted R-Squared 0.657

F-statistic vs. constant model: 384, p-value = 0

Descriptive statistics

Variable	25th percentile	Median	75th percentile
EUCD	0.2255	0.7735	2.7930
Materiality measure	3.21%	6.99%	31.33%

4.6.2. Hypothesis 2

In Hypothesis 2 we hypothesize that positive or negative trend in commodity prices would cause the error of the system to rise. Moreover, we expect that a stronger trend would cause a larger error.

Table 12 analyzes the changes in trend under the average method. Overall costing system error is the smallest in the situation with no trend, with an exception for daily frequency for 0 and

-0.25 values of trend, where the difference between errors is negligible. We also see that error increases as the trend increases, which is true for both positive and negative trend. Since having a drift in time series means that the values are constantly rising or falling, we expected that this will mean that the error is smaller with the average method than with the snapshot method. Comparing Table 12, which contains the results of the average method, with Table 14, which contains the snapshot method, is consistent with that prediction. Interestingly, in both tables we observe the effect that errors are larger for positive than for negative trends, even though the slopes of the trends are the same in the positive and in negative directions. The positive trend results in higher values of commodity prices in absolute terms than negative trend, so the same level of volatility would influence bigger values more than smaller, which also means that the Euclidean distance measure is going to be larger in the presence of a positive trend. Conversely, the accuracy measured by materiality measure is larger when the drift is negative than when the drift is positive. Ignoring the trend in resource costs can result in over-costing or under-costing error of the costing system.

Multiple linear regression analysis for the average method (Table 13) shows that both trend and frequency are statistically significant at the 1% level, as well as their interaction term. All predictors have positive value, which means that an increase in a predictor will cause the overall error of costing system also to increase. The plot of interaction effects for this regression (Figure 27 in Appendix) shows that changing trend from -0.5 to 0.5 increases the Euclidean distance error, given that frequency is held constant. Increasing trend for each level of frequency will increase the overall error of the system. Changing frequency from daily to yearly, while keeping trend constant, will cause the error also to increase. From the interaction effects plot, we can also conclude that the effect of the change in frequency has a much larger impact on the overall accuracy than the change in trend. The results of linear regression with the snapshot method (Table 15) are similar and all the predictors are also statistically significant at the 1% level. The plot of interaction effects for this regression (Figure 28 in Appendix) shows that changing trend from -0.5 to 0.5 increases the Euclidean distance error, given that frequency is held constant. Increasing trend for each level of frequency will increase the overall error of the system. Changing frequency from daily to yearly, while keeping trend constant, will cause the error to increase. From the interaction effects plot, we can also conclude that the effect of the change in frequency has a much larger impact on the overall accuracy than the change in trend. This effect is visible both for snapshot and for average method.

This is supporting our hypothesis that having a positive or negative trend in commodity prices will cause the error of the system to rise. The expectation that bigger trend is causing larger error is also supported.

Table 12 – Hypothesis 2: Simplification of method - average

Variable	*Simplification of frequency*		
Trend	Daily	Monthly	Yearly
-0.5	0.0564 (83.75%)	0.8255 (7.03%)	9.8136 (0.53%)
-0.25	0.0488 (88.75%)	0.5158 (11.28%)	5.7621 (0.85%)
0	0.0499 (88.35%)	0.2318 (28.24%)	0.8454 (7.5%)
0.25	0.0670 (77.84%)	0.6393 (10.58%)	7.0148 (0.72%)
0.5	0.0913 (64.63%)	1.4594 (3.87%)	18.3186 (0.34%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 13 – Hypothesis 2: Simplification of method - average: Statistical analysis

Output of multiple linear regression analysis with interaction term				
Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.02298	0.000	1.000
Trend	0.13817	0.022995	6.0087	0.000
Frequency	0.7473	0.022995	32.498	0.000
Trend x Frequency	0.16736	0.023011	7.273	0.000

R-squared: 0.606, Adjusted R-Squared 0.604

F-statistic vs. constant model: 382, p-value = 0

Descriptive statistics			
Variable	25th percentile	Median	75th percentile
EUCD	0.0779	0.6250	5.1197
Materiality measure	1.32%	10.50%	69.43%

Table 14 – Hypothesis 2: Simplification of method - snapshots

Variable	*Simplification of frequency*		
Trend	Daily	Monthly	Yearly
-0.5	0.0947 (63.11%)	1.6019 (4.58%)	23.9079 (0.2%)
-0.25	0.0831 (68.77%)	1.0006 (7.84%)	11.8494 (0.45%)
0	0.0867 (67.09%)	0.3805 (21.18%)	1.0639 (8.62%)
0.25	0.1094 (57.71%)	1.2403 (7.21%)	13.7641 (0.88%)
0.5	0.1525 (46.32%)	2.9315 (2.84%)	29.2812 (0.31%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 15 – Hypothesis 2: Simplification of method - snapshots: Statistical analysis

Output of multiple linear regression analysis with interaction term

Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.022975	0.000	1.000
Trend	0.1135	0.02299	4.9369	0.000
Frequency	0.75815	0.02299	32.977	0.000
Trend x Frequency	0.13437	0.023005	5.8409	0.000

R-squared: 0.606, Adjusted R-Squared 0.604

F-statistic vs. constant model: 382, p-value = 0

Descriptive statistics

Variable	25th percentile	Median	75th percentile
EUCD	0.1327	1.1197	10.1777
Materiality measure	0.88%	6.43%	50.88%

4.6.3. Hypothesis 3

In Hypothesis 3 we hypothesize that daily seasonality in commodity prices causes larger errors in costing systems than yearly seasonality.

Table 16 and Table 18 present the results of the calculation with the average method. It can be seen that the accuracy is quite high for the yearly seasonality, even when this seasonality has high amplitudes. On the other hand, daily seasonality shows some interesting deviations. Without daily seasonality, the accuracy is comparable to the results obtained in Hypothesis 1, which was expected since the parameters used are the same. When we include both low and high daily seasonality, the accuracy drops significantly. This is also an important finding, since it is very unlikely that commodities used in companies would not have a daily seasonality at all. Interestingly, when observing the daily seasonality, we notice that the error becomes even smaller when the frequency of measurement is decreasing. This is important to note, since the offsetting effects that are occurring in such situations are providing significant input for understanding the changes in accuracy. This also shows that, in this setting the change in frequency does not seem to have a significant impact on the accuracy. It is also interesting to note that the accuracy is overall very low for daily seasonality. This is because such frequent changes in seasonality are difficult to capture with infrequent measurements.

Table 20 and Table 22 show the results of simulations with the snapshot method. The results show similar patterns as the average method. The accuracy of the systems with yearly seasonality is higher than in the systems with daily seasonality. It is also visible that the accuracy is decreasing as the simplification of frequency is decreasing from high frequency calculations (daily) to low frequency calculations (yearly). By comparing both tables, it is clear that the error for daily seasonality of commodity prices is very high for both methods. However, it is interesting that the accuracy is higher for daily seasonality when we use the snapshot method than when we use the average method. This is a deviation from what we expected, since we assumed that the average method will provide more accurate results than the snapshot method in all simulation settings.

Multiple linear regression analysis for yearly seasonality in commodity prices with the average method (Table 17) shows that both seasonality and frequency are statistically significant at the 1% level, as well as their interaction term. All predictors have a positive value, which means that an increase in a predictor will cause the overall error of costing system (EUCD) also to increase. The plot of interaction effects for this regression (Figure 29 in Appendix) shows that an increase of seasonality also causes an increase of the Euclidean distance error, given that frequency is held constant. Increasing seasonality for each level of frequency will increase the overall error of the system. Changing frequency from daily to yearly, while keeping seasonality constant, will cause the error to increase. From the interaction effects plot, we can also conclude that the effect of the change in frequency has a larger impact on the overall accuracy than the change in seasonality. The results of linear regression for daily seasonality in commodity prices with the average method (Table 19) are also all statistically significant at the 1% level. Seasonality has a large positive value and we could conclude that an increase in daily seasonality will cause the overall error of the costing system to rise. However, frequency and interaction term have small values, of which the coefficient for frequency is positive and for interaction term negative. In order to interpret those effects, we have to conduct further analysis. The plot of interaction effects for this regression (Figure 30 in Appendix) shows that larger daily seasonality increases the Euclidean distance error, given that frequency is held constant. Increasing seasonality for each level of frequency will increase the overall error of the system. Changing frequency from daily to yearly, while keeping seasonality constant, will cause the error to increase. From the interaction effects plot, we can also conclude that the effect of the change in seasonality has a larger impact on the overall accuracy than the change in frequency.

The results of linear regression for yearly seasonality in commodity prices with the snapshot method (Table 21) are similar to yearly seasonality with the average method, and all the predictors are also statistically significant at the 1% level. All predictors have positive value, which means that an increase in a predictor will cause the overall error of costing system also to increase. The plot of interaction effects for this regression (Figure 31 in Appendix) shows that increase of yearly seasonality also causes an increase of the Euclidean distance error, given that frequency is held constant. Increasing seasonality for each level of frequency will increase the overall error of the system. Changing frequency from daily to yearly, while keeping seasonality constant, will cause the error to increase. From the interaction effects plot, we can also conclude that the effect of the change in frequency has a larger impact on the overall accuracy than the change in seasonality. The results of linear regression for daily seasonality in commodity prices with the snapshot method (Table 23) are similar to daily seasonality with the average method, and all the predictors are also statistically significant at the 1% level. Seasonality has large positive value and we could conclude that an increase in daily seasonality will cause the overall error of the costing system to rise. However, frequency and interaction term have small values, of which the coefficient for frequency is positive and for interaction term negative. In order to interpret those effects, we have to conduct further analysis. The plot of interaction effects for this regression (Figure 32 in Appendix) shows that larger daily seasonality increases the Euclidean distance error, given that frequency is held constant. Increasing seasonality for each level of frequency will increase the overall error of the system. Changing frequency from daily to yearly, while keeping seasonality constant, will cause the error to increase. From the interaction effects plot, we can conclude that in the case of yearly seasonality, the effect of frequency is stronger than the effect of seasonality, both for the snapshot and for the average method. On the other hand, this effect is reversed for daily seasonality, where in both cases we observe stronger influence of seasonality on the overall error of the system.

This is supporting our hypothesis that daily seasonality in commodity prices will cause larger error than yearly seasonality. In addition, the assumption that daily seasonality measured on a lower level of frequency than one day will display high errors is supported. Explanation for this is that daily seasonality is more difficult to capture with less granulated measurements.

Table 16 – Hypothesis 3: Simplification of method – average

Variable	*Simplification of frequency*		
Yearly seasonality	Daily	Monthly	Yearly
No seasonality	0.0542 (85.70%)	0.2493 (27.46%)	0.8058 (8.13%)
Low seasonality	0.0556 (84.72%)	0.3279 (22.48%)	1.9212 (2.86%)
High seasonality	0.0632 (79.90%)	0.7093 (10.82%)	5.2039 (0.76%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 17 – Hypothesis 3: Simplification of method – average: Statistical analysis

Output of multiple linear regression analysis with interaction term

Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.012156	0.000	1.000
Seasonality	0.42306	0.01217	34.762	0.000
Frequency	0.70155	0.01217	57.646	0.000
Seasonality x Frequency	0.5132	0.012184	42.123	0.000

R-squared: 0.934, Adjusted R-Squared 0.933

F-statistic vs. constant model: 2100, p-value = 0

Descriptive statistics

Variable	25^{th} percentile	Median	75^{th} percentile
EUCD	0.0641	0.3306	1.0636
Materiality measure	3.73%	19.30%	71.38%

Table 18 – Hypothesis 3: Simplification of method – average

Variable	*Simplification of frequency*		
Daily seasonality	Daily	Monthly	Yearly
No seasonality	0.0566 (84.23%)	0.2584 (26.28%)	0.8347 (7.85%)
Low seasonality	1.7334 (2.38%)	1.8620 (2.29%)	1.8718 (2.73%)
High seasonality	5.2739 (1.8%)	5.3583 (0.77%)	5.2587 (0.8%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 19 – Hypothesis 3: Simplification of method – average: Statistical analysis

Output of multiple linear regression analysis with interaction term

Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.012624	0.000	1.000
Seasonality	0.96038	0.012638	0.96038	0.000
Frequency	0.052571	0.012638	4.1597	0.000
Seasonality x Frequency	-0.06063	0.012652	4.7921	0.000

R-squared: 0.929, Adjusted R-Squared 0.928

F-statistic vs. constant model: 1940, p-value = 0

Descriptive statistics

Variable	25th percentile	Median	75th percentile
EUCD	0.5559	1.7668	4.6587
Materiality measure	1.51%	2.46%	8.32%

Table 20 – Hypothesis 3: Simplification of method – snapshots

Variable	*Simplification of frequency*		
Yearly seasonality	Daily	Monthly	Yearly
No seasonality	0.0959 (62.98%)	0.4204 (19.1%)	1.3738 (5.33%)
Low seasonality	0.0943 (63.66%)	0.6069 (14.54%)	2.9871 (3.77%)
High seasonality	0.1120 (57.56%)	1.3704 (8.14%)	8.3640 (1.98%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 21 – Hypothesis 3: Simplification of method – snapshots: Statistical analysis

Output of multiple linear regression analysis with interaction term

Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.01617	0.000	1.000
Seasonality	0.42426	0.016188	26.207	0.000
Frequency	0.67826	0.016188	41.897	0.000
Seasonality x Frequency	0.4936	0.016206	30.457	0.000

R-squared: 0.883, Adjusted R-Squared 0.882

F-statistic vs. constant model: 1120, p-value = 0

Descriptive statistics

Variable	25th percentile	Median	75th percentile
EUCD	0.1098	0.5617	1.7041
Materiality measure	4.91%	14.52%	57.10%

Table 22 – Hypothesis 3: Simplification of method – snapshots

Variable	*Simplification of frequency*		
Daily seasonality	Daily	Monthly	Yearly
No seasonality	0.0895 (65.5%)	0.4196 (19.94%)	1.2289 (5.87%)
Low seasonality	2.8223 (7.35%)	2.8871 (3.6%)	3.5611 (2.11%)
High seasonality	8.4100 (4.4%)	8.5282 (2.06%)	8.5705 (1.01%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 23 – Hypothesis 3: Simplification of method – snapshots: Statistical analysis

Output of multiple linear regression analysis with interaction term				
Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.016735	0.000	1.000
Seasonality	0.9306	0.016753	55.547	0.000
Frequency	0.080038	0.016753	4.7774	0.000
Seasonality x Frequency	-0.048943	0.016772	2.9181	0.004

R-squared: 0.875, Adjusted R-Squared 0.874

F-statistic vs. constant model: 1040, p-value = 0

Descriptive statistics			
Variable	25th percentile	Median	75th percentile
EUCD	0.8364	2.8565	7.3187
Materiality measure	2.52%	4.34%	10.66%

4.6.4. Hypothesis 4

In Hypothesis 4a we hypothesize that daily seasonality of commodity usage will cause larger errors than yearly seasonality. We also hypothesize that measuring the commodity usage more often will provide more accurate results (Hypothesis 4b).

For testing Hypothesis 4a we compare Table 24 and Table 26 (and Table 28 and Table 30). In all cells, the EUCD is larger and the materiality measure is lower in Table 26 (and Table 30), which supports Hypothesis 4a. (Note that Table 24 and Table 26 show the results of using the average method for calculation of commodity prices, and Table 28 and Table 30 present the results of the snapshot method.) Furthermore, in all cells of the Table 24 and Table 26, accuracy is extremely low, except for a few cells in the first row of Table 24, where there is a yearly seasonality of consumption and the consumption is measured daily. In other settings, the accuracy of the costing systems is very low. We observe the similar effect for Table 28 and Table 30. Having seasonality on two sides, both in prices and consumption, will make a big distortion in costing systems. This is an important finding since it is realistic that both of those parameters in a company would have dynamic patterns.

The second part of hypothesis was referring to measuring commodity usage. Table 24 and Table 28, which are modeling yearly seasonality of consumption, are supporting our hypothesis that having more frequent usage data would result in more accurate results. But interestingly, Table 26 and Table 30, where we model daily seasonality of consumption, show inconclusive results. Even though the accuracy is quite low, so it is difficult to detect a pattern that is using those deviations, it is clear that despite the intervals of measuring the seasonality of commodity usage changing, the results are the same. Because of that we cannot support our hypothesis that measuring the commodity usage more often would provide more accurate results when there is daily seasonality (Hypothesis 4b).

Multiple linear regression analysis for yearly seasonality of consumption with the average method (Table 25) shows that only seasonality is statistically significant at the 5% level. This predictor also has a large positive value, which means that an increase in a yearly seasonality of consumption will cause the overall error of costing system also to increase. The results of linear regression for daily seasonality of consumption with the average method (Table 27) are not statistically significant at the 5% level. This means that no statistically significant linear dependence of the costing system error on seasonality of consumption or frequency was detected. The results of linear regression for yearly seasonality of consumption with the snapshot method (Table 29) are similar to yearly seasonality with the average method, and show that only seasonality is statistically significant at the 5% level. This predictor also has a large positive value, which means that an increase in a yearly seasonality of consumption will cause the overall error of costing system also to increase. The results of linear regression for daily seasonality of consumption with the snapshot method (Table 31) are not statistically significant at the 5% level. This means that no statistically significant linear dependence of the costing system error on seasonality of consumption or frequency was detected.

Table 24 – Hypothesis 4: Simplification of method – average

Variable	*Simplification of frequency (prices)*		
Yearly seasonality of consumption	Daily	Monthly	Yearly
Quantity measured: daily	0.2199 (33.78%)	0.3003 (22.96%)	0.8687 (8.2%)
Quantity measured: monthly	4.2065 (1.48%)	4.3654 (1.5%)	4.4791 (1.42%)
Quantity measured: yearly	30.6197 (0.12%)	33.7206 (0.11%)	31.1677 (0.13%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 25 – Hypothesis 4: Simplification of method – average: Statistical analysis

Output of multiple linear regression analysis with interaction term

Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.011831	0.000	1.000
Seasonality	0.96778	0.011844	81.708	0.000
Frequency	0.022028	0.011844	1.8598	0.064
Seasonality x Frequency	0.018566	0.011858	1.5657	0.118

R-squared: 0.937, Adjusted R-Squared 0.937

F-statistic vs. constant model: 2230, p-value = 0

Descriptive statistics

Variable	25th percentile	Median	75th percentile
EUCD	0.5733	4.1844	29.3603
Materiality measure	0.13%	1.19%	6.79%

Table 26 – Hypothesis 4: Simplification of method – average

Variable	*Simplification of frequency (prices)*		
Daily seasonality of consumption	Daily	Monthly	Yearly
Quantity measured: daily	31.9406 (1.88%)	31.9352 (0.59%)	31.8044 (0.16%)
Quantity measured: monthly	32.9810 (1.85%)	31.1313 (0.63%)	31.0585 (0.18%)
Quantity measured: yearly	32.0442 (1.88%)	30.9630 (0.6%)	35.0440 (0.17%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 27 – Hypothesis 4: Simplification of method – average: Statistical analysis

Output of multiple linear regression analysis with interaction term

Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.047183	0.000	1.000
Seasonality	0.068204	0.047235	1.4439	0.149
Frequency	0.0025028	0.047235	0.052986	0.958
Seasonality x Frequency	-0.015272	0.047288	-0.32296	0.747

R-squared: 0.00489, Adjusted R-Squared -0.0018

F-statistic vs. constant model: 0.731, p-value = 0.534

Descriptive statistics

Variable	25th percentile	Median	75th percentile
EUCD	29.7162	32.4475	37.2420
Materiality measure	0.28%	0.54%	1.76%

Table 28 – Hypothesis 4: Simplification of method – snapshots

Variable	*Simplification of frequency (prices)*		
Yearly seasonality of consumption	Daily	Monthly	Yearly
Quantity measured: daily	0.2210 (31.18%)	0.4431 (17.88%)	1.6059 (6.09%)
Quantity measured: monthly	4.6170 (1.46%)	4.1268 (1.56%)	4.4661 (1.63%)
Quantity measured: yearly	30.8763 (0.14%)	33.0005 (0.15%)	32.8031 (0.12%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 29 – Hypothesis 4: Simplification of method – snapshots: Statistical analysis

Output of multiple linear regression analysis with interaction term

Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.011759	0.000	1.000
Seasonality	0.96842	0.011772	82.264	0.000
Frequency	0.017726	0.011772	1.5058	0.133
Seasonality x Frequency	-0.0063677	0.011785	0.54031	0.589

R-squared: 0.938, Adjusted R-Squared 0.938

F-statistic vs. constant model: 2260, p-value = 0

Descriptive statistics

Variable	25th percentile	Median	75th percentile
EUCD	0.8334	4.6401	28.4140
Materiality measure	0.16%	1.46%	7.58%

Table 30 – Hypothesis 4: Simplification of method – snapshots

Variable	*Simplification of frequency (prices)*		
Daily seasonality of consumption	Daily	Monthly	Yearly
Quantity measured: daily	30.9055 (1.42%)	30.7623 (0.44%)	31.0914 (0.14%)
Quantity measured: monthly	31.2683 (1.42%)	31.4425 (0.42%)	31.1976 (0.19%)
Quantity measured: yearly	31.8801 (1.41%)	32.9547 (0.4%)	33.7533 (0.15%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 31 – Hypothesis 4: Simplification of method – snapshots: Statistical analysis

Output of multiple linear regression analysis with interaction term

Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.047244	0.000	1.000
Seasonality	-0.018381	0.047297	-0.38862	0.698
Frequency	-0.016913	0.047297	0.35759	0.721
Seasonality x Frequency	0.041066	0.047349	0.8673	0.386

R-squared: 0.00231, Adjusted R-Squared -0.0044

F-statistic vs. constant model: 0.344, p-value = 0.794

Descriptive statistics

Variable	25th percentile	Median	75th percentile
EUCD	29.6404	33.5290	37.4914
Materiality measure	0.17%	0.37%	1.28%

4.6.5. Hypothesis 5

In Hypothesis 5 we hypothesize that larger density of consumption matrix will cause smaller overall error of the costing system.

So far, we used a density of 30%, but the following results are based on a density that varies between 10% and 90%. In Table 32, where we use the average method for calculations of commodity prices, the results have high accuracy in the first column, with daily frequency of calculations. It is interesting to note that all three observations have rather high accuracy in that column. This means that with daily frequency of calculations the results are going to be quite high regardless of the level of density. For monthly and daily frequencies, the accuracy is significantly lower. Here we also see that the accuracy increases for higher levels of density. In Table 34 the pattern of the results is similar, but the overall accuracy level is smaller.

Multiple linear regression analysis with the average method (Table 33) shows that both density and frequency are statistically significant at the 1% level, as well as their interaction term. Frequency has large positive value and we could conclude that an increase in frequency will cause the overall error of the costing system to rise. However, density and interaction term have small negative values, and in order to interpret those effects, we have to conduct further analysis. The plot of interaction effects (Figure 37 in Appendix) for this regression shows that changing density from 0.1 to 0.9 decreases the Euclidean distance error, given that frequency is held constant. Increasing density for each level of frequency will increase the overall error of the system. Changing frequency from daily to yearly, while keeping density constant, will cause the error to increase. From the interaction effects plot, we can also conclude that the effect of the change in frequency has a larger impact on the overall accuracy than the change in density. The results of linear regression with the snapshot method (Table 35) are similar and all the predictors are also statistically significant at the 1% level. Frequency has large positive value and we could conclude that an increase in frequency will cause the overall error of the costing system to rise. However, density and interaction term have small negative values, and in order to interpret those effects, we have to conduct further analysis. The plot of interaction effects for this regression (Figure 38 in Appendix) shows that changing density from 0.1 to 0.9 decreases the Euclidean distance error, given that frequency is held constant. Increasing density for each level of frequency will increase the overall error of the system. Changing frequency from daily to yearly, while keeping density constant, will cause the error to increase. From the interaction effects plot, we can also conclude that the effect of the change in frequency has a larger impact on the overall accuracy than the change in density. This is true for both average and snapshot method.

The results of both tables support our hypothesis that larger density of consumption matrix would result in a smaller overall error of the system. This would mean that in a company where more cost objects are using more resources (and some of those resources have dynamic commodity prices), the simplified system would be more accurate.

Table 32 – Hypothesis 5: Simplification of method – average

Variable	*Simplification of frequency*		
Density	Daily	Monthly	Yearly
0.1	0.0744 (72.9%)	0.3369 (19.56%)	1.0639 (6.34%)
0.5	0.0567 (84.11%)	0.2639 (26.3%)	1.0849 (6.81%)
0.9	0.0533 (86.19%)	0.2340 (28.46%)	0.7587 (8.27%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 33 – Hypothesis 5: Simplification of method – average: Statistical analysis

Output of multiple linear regression analysis with interaction term				
Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.027902	0.000	1.000
Density	-0.16216	0.027933	-5.8054	0.000
Frequency	0.77601	0.027933	27.782	0.000
Density x Frequency	-0.15355	0.027964	-5.4912	0.000

R-squared: 0.652, Adjusted R-Squared 0.65

F-statistic vs. constant model: 279, p-value = 0

Descriptive statistics			
Variable	25th percentile	Median	75th percentile
EUCD	0.0794	0.2811	0.5933
Materiality measure	9.17%	22.79%	67.95%

Table 34 – Hypothesis 5: Simplification of method – snapshots

Variable	*Simplification of frequency*		
Density	Daily	Monthly	Yearly
0.1	0.1207 (53.65%)	0.5827 (14.38%)	2.0731 (4.37%)
0.5	0.0982 (62.03%)	0.5020 (17.56%)	1.4298 (5.33%)
0.9	0.0867 (66.6%)	0.4131 (19.78%)	1.1409 (6.63%)

Note: reported are values EUCD and materiality measure (in brackets)

Table 35 – Hypothesis 5: Simplification of method – snapshots: Statistical analysis

Output of multiple linear regression analysis with interaction term

Variable	Coefficient	SE	t-statistics	p-value
Intercept	0.000	0.030908	0.000	1.000
Density	-0.12363	0.030942	-3.9956	0.000
Frequency	0.7385	0.030942	23.867	0.000
Density x Frequency	-0.11113	0.030977	-3.5876	0.000

R-squared: 0.573, Adjusted R-Squared 0.57

F-statistic vs. constant model: 199, p-value = 0

Descriptive statistics

Variable	25th percentile	Median	75th percentile
EUCD	0.1293	0.4564	0.9763
Materiality measure	7.40%	19.34%	49.18%

4.6.6. Hypothesis 6

In Hypothesis 6 we hypothesize that using an average method causes smaller costing system error than using the snapshot method. The results for this hypothesis are drawn from the tables in Hypotheses 1-5 and comparing results of using the average and the snapshot method.

In Hypothesis 1 we observe volatility of commodity prices. In order to test the assumption that using an average instead of snapshot prices, we compare Table 8 and Table 10. To test the same assumption in Hypothesis 2, where we analyze the influence of different rates of trends, we compare Table 12 and Table 14. From the same reason, we compare Table 28 and Table 30 from Hypothesis 5, where we model different levels of density of consumption matrix.[14] All of those results clearly show that using an average of real commodity prices causes smaller costing system error than using snapshot prices, which is supporting Hypothesis 6. However, other results are contradictory. In Hypothesis 3, we observe the influence of daily and yearly seasonality in commodity prices on the accuracy of the costing system. The results with yearly seasonality are according to our expectations, and using snapshot prices is resulting in less accurate costing systems than using average data. However, with daily seasonality of commodity prices, the results are opposite. Since the error is bigger for costing systems with daily seasonality of commodity prices when using the average method, we cannot support the Hypothesis 6. To test the same assumption for Hypothesis 4, where we model seasonality of commodity usage, we compare Table 24 and Table 28 (and Table 26 and Table 30). For most of the observations, the assumption that the average method is causing smaller errors than using snapshot prices is proven to be correct. However, few observations are contradictory, and most importantly, for all observations the effect is very small. With such a minimal effect, we can only conclude that the results are inconclusive, so the Hypothesis 6 is not supported.

Our expectation that using an average price instead of snapshot price will cause smaller error of the costing system was supported in most of the hypotheses tested. This is supported in settings with variable volatility of commodity prices (Hypothesis 1), settings including trends (Hypothesis 2) and density of consumption matrix (Hypothesis 5). This is also what we expected, since we assume that the average of the interval describes better the change in time series in that period than using one measurement at the beginning of the interval. However, for settings with seasonality in commodity prices (Hypothesis 3) and settings with seasonality of commodity usage (Hypothesis 4), the hypothesis that using the average method instead of the snapshot method would result in a smaller costing system error cannot be supported.

4.6.7. Hypothesis 7

In Hypothesis 7 we hypothesize that using more frequent calculation of commodity input prices gives more accurate data. The results for this hypothesis are obtained from the tables in

[14] This comparison is not based on statistical analysis. Such analysis would be implausible because of the different independent variables in hypotheses.

Hypotheses 1-5 and by comparing their results of daily, monthly and yearly method. This means comparing columns in each table in those hypotheses.

In Hypothesis 1 we model volatility of commodity prices, in Hypothesis 2 different rates of trend and in Hypothesis 5 different levels of density of consumption matrix. By comparing columns with daily, monthly and yearly data in each of those hypotheses, we can conclude that using more frequent calculation of commodity input prices results in more accurate data.[15] This is supporting the Hypothesis 7. On the other hand, the results obtained from other hypotheses are not that straightforward. In Hypothesis 3 we model the influence of daily and yearly seasonality in commodity prices on the accuracy of the costing system. We present our results in Table 16 and Table 18, for the average method, and Table 20 and Table 22, for the snapshot method. The results from Table 20 and Table 22 are in line with our expectations, and show that the accuracy of the costing systems is improving when more frequent calculations of commodity prices are used. However, in Table 16 and Table 18, the results are mixed. When there is low daily seasonality in commodity prices, the results are more accurate if the calculations are less frequent. So the most accurate result would be obtained through yearly averaging of prices. This means that we cannot support Hypothesis 7. We test the same assumption for Hypothesis 4, where we model seasonality of commodity usage. Table 26 and Table 30, where daily seasonality of consumption is modeled, give the results that are in line with our expectations and Hypothesis 7. Table 24 (average method) and Table 28 (snapshot method), where yearly seasonality of consumption is modeled, give inconclusive data, i.e. it is not true that increasing frequency of price calculations would lead to better results. Even though these numbers are quite low, so the effect is minimal, we clearly see that there is an underlying effect that is causing those deviations. Because of this, we can conclude that in this case, the Hypothesis 7 is rejected.

Our expectation that using more frequent calculation of commodity input prices gives more accurate data was supported in most of the hypotheses. This effect is supported in settings with variable volatility of commodity prices (Hypothesis 1), settings including trends (Hypothesis 2) and density of consumption matrix (Hypothesis 5). This is in line with our expectations, since we assumed that using more granular data is likely to capture the changes in market dynamics better and would result in a smaller error. However, for settings with seasonality in commodity prices (Hypothesis 3) and settings with seasonality of commodity usage (Hypothesis 4), the

[15] This comparison is not based on statistical analysis. Such analysis would be implausible because of the different independent variables in hypotheses.

hypothesis that using more frequent calculation of commodity input prices gives more accurate data cannot be supported.

4.7. Discussion and conclusion

In this chapter, we have conducted an analysis of the impact of input commodity prices on the accuracy of costing systems over time. We show that higher volatility of commodity prices causes errors of costing systems to increase, as does the existence of a stronger trend or more frequent seasonality pattern in time series of commodity prices. We also see how daily seasonality of commodity usage and lower density of consumption matrix negatively influence the accuracy of the costing system. Also, having simplifications in costing systems, such as what method is used for calculation of the prices or what is the frequency of those measurements, will cause inaccuracies of the costing systems. These results were also in line with our hypotheses.

However, there are several interesting results which deviate from our expectations. In Hypothesis 3 we model daily and yearly seasonality of commodity prices. Our results show that daily seasonality causes disproportionally high errors of the costing systems compared to yearly seasonality. Furthermore, using the snapshot method instead of the average method causes less error when there is seasonality in commodity prices, which is opposite to our Hypothesis 6. Another conflicting finding related to Hypothesis 3 is that the results are more accurate if the calculations are done less frequently when there is low daily seasonality in commodity prices and we use average method. In Hypothesis 4 we model seasonality of commodity usage, where we also find some interesting results. Despite the changing frequency of intervals for measuring daily seasonality of commodity usage (Table 24 and Table 28), the results of the systems stay approximately the same, which is not aligned with the results for yearly seasonality of commodity usage. For the same observations, we see that using either the average or the snapshot method results in almost the same error of the systems. Furthermore, changing frequency for the calculation of commodity prices results in approximately the same error. We note that most of the unexpected results come from Hypotheses 3 and 4, which explore two types of seasonality, seasonality in commodity prices and seasonality of commodity usage. It is interesting that those results are also the results with lowest accuracy of costing systems, since such a setting is very realistic in a company that uses commodities as resources. This points out that the problem of input price dynamics and dynamic activity-based costing is very important for management accounting.

We use two dependent variables for measuring accuracy, which we expect to provide the same qualitative results. In most of the observations, these two measures provide consistent results. But in some observations, the numbers are contradictory. Let us observe Table 18 and Table 22, and specifically the values of data that describe high daily seasonality of commodity prices, for which the accuracy is calculated on a daily level. With the average method, these measures are: 4.8695 (1.85%), and for the snapshot method 7.3351 (4.66%), which is inconsistent to our expectations. A possible explanation would be that the accuracy calculated with the snapshot method is more volatile, but still more observations are staying within the given accuracy bandwidth. This finding is interesting since it demonstrates that future research should also analyze in more detail the process behind the error calculations. For example, it would be relevant to observe how is the accuracy of the costing system declining over time, so after how much time will the error of the system be larger than acceptable range of 10%. Another possibility is observing under which conditions the overall error of the costing systems stays the same or within the materiality band (steadiness of accuracy).

In this research, we use geometric Brownian motion to model volatility, trend and seasonality of commodity prices. Future research could also include models with unexpected jumps in time series, which are common for commodity prices. There are several possibilities of modeling a jump in a time series. The jump can be either in positive or in negative direction; its absolute value can be quite low, medium or extremely high; and it could be that jumps are occurring regularly, occasionally or only once in observed period. Since jumps in commodity prices could influence the accuracy of costing systems, it would be interesting to see their interactions with the parameters observed in this research.

Continuing on the previous research in management accounting literature, this chapter models the influence of measurement error in dynamic activity-based costing. One possibility of extending this research is including other, already researched errors, like aggregation and specification error, and see how they affect accuracy in a dynamic setting. We expect that the dynamic properties of prices cause large errors in settings where also aggregation and specification errors are present. This inaccurate cost information is then presumably also causing errors in decision making.

An inevitable limitation is that in our hypotheses and simulation, we simplify some variables and hold them constant throughout the model. One reason for this is computational time, which would not be manageable if we included all the possibilities for variations of parameters. But the other reason is already mentioned problem of "seeing the forest for the trees" (Labro, 2015) referring to the great amount of data that can be manipulated in simulations, which in dynamic simulations becomes an even larger problem. However, the "ceteris paribus" assumption is probably very rare in practice. To illustrate the complexity of dynamic simulation, we may consider the possibility of including variations on cost driver level, which could be considered in future research. One option is to keep resource cost drivers fixed throughout the whole simulation because of simplicity and comparability of results, even though there are much more precise possibilities. This is the option that we choose for this chapter. A second option would be to model the elements of the consumption matrix, i.e., resource cost drivers, randomly within the uniform distribution from 0%-100%, keeping in mind that the sum of cost drivers going from one resource cost pool should be exactly 100%. If we would model each cost driver in the percentage step of 10% (from 0%-100%), that would sum up to 1.001 different possibilities, which is already computationally demanding for dynamic simulations. The third, most complex (and most precise) option would be to model cost drivers with functions that represent change of cost drivers in time. This would be very computationally intensive and even impossible if we would try to include every possible variation of those functions.

In our research, we assume Leontief technology, i.e., that each product consumes a fixed amount of each input resource and the resources are not substitutable. However, a firm may have the flexibility to switch between different resources, such as different energy carriers with different prices. Examples would be switching between own generation of electricity and external power, or between different fuels for own generation. Suppose inexpensive, self-generated electricity would be used in a production of one product, and more expensive electricity from an external supplier used for another product. These cases include substitutability in the production process, but have not yet not been investigated in current studies on costing errors.

It is also possible to further develop the simulation as an assessment method, which would consist of an evaluation tool and a flexible simulation. Based on the results of the simulation experiments, it could be operationalized as an evaluation tool. The tool would provide a practical way to position a particular company in terms of the experimental conditions of the simulation experiment and to translate the conclusions of the simulation experiment to that company. It would also be useful to make the simulation model more flexible and suitable for company-specific analyses. After all, the conditions or parameter values and probability distributions used in the simulation experiment may be too unrealistic for a particular company. This limits the number of situations for which the results of the simulation experiment in the form of the assessment tool can be applied. Therefore, a flexible simulation model could be calibrated to a particular organization.

To conclude, the objective of this chapter was to investigate dynamic factors that determine the size of errors in costing systems and how this error changes over time. Our focus was on commodity prices because of the complexity of their purchase price structure. Purchasing contracts of companies may contain dynamic prices for commodities that change throughout the day and week, depend on usage within certain bandwidths, or are affected by spot prices on the market. From the perspective of management accounting, there is also another interesting aspect when observing dynamic commodity prices. Typically, when we meter, we think about direct costs, and hence tracing of costs, which makes allocation of costs unnecessary. However, the setting of commodities brings an interesting complexity, because even with metering of quantity of commodity use, the complex pricing structure will result in calculations of a rate per quantity used that may vary or be different.

While previous research has focused on measurement, aggregation and specification errors in static simulations, we build on that framework and introduce the term dynamic activity-based costing. In this study, we developed seven hypotheses where we explained our expectations and possible influences of changes in commodity prices on the accuracy of costing systems in time. We modeled several variations of commodity prices, namely volatility, trend and seasonality, along with seasonality of commodity usage and density of consumption matrix. We then conducted the numerical simulations that we used for exploring how different settings influence costing system errors. In evaluation of the results, we used simplifications of manufacturing settings that are in reality used by companies, like using average or snapshot prices, and daily, monthly or yearly frequency for calculation of those prices. The results of this study indicate that there is a large impact of input market dynamics on the accuracy of costing systems over time.

5. Conclusion

The purpose of this dissertation was to investigate factors that determine costing system accuracy. The research method used was numerical simulations. Three research projects have been conducted to explore the topic from three different perspectives – a systematic literature review on energy cost information in manufacturing companies, a simulation study on the effects of activity cost pool interdependency on the accuracy of energy costing information, and another simulation study on the impact of input market dynamics on the accuracy of costing systems over time. In this conclusion, we briefly summarize our main findings. We then look at limitations and suggest opportunities for future research.

In the second chapter, the systematic literature review, we examined the empirical studies on the availability of energy cost information for energy management in manufacturing companies. The main purpose was to provide an overview of the practices of companies for measurement and allocation of energy costs. We also focused on the type of companies in the sample, and differentiated between large companies and small and medium size enterprises, and energy intensive and non-energy intensive companies.

We could identify only limited number of papers in the sample of observed literature that provide detailed information about the current state of energy cost information that is available in companies. Moreover, we found almost no studies that provide a more nuanced description of measuring and allocating energy costs, for example, by investigating specific cost allocation bases, the accuracy of cost allocations, and differentiating between first-stage and second-stage allocation. The majority of the papers from our literature review were focused on energy intensive companies, and in so far as non-energy intensive companies were investigated, these were large companies. More refined procedures for measuring and allocating energy costs are often lacking even in some large and energy intensive companies, which may suggest an even larger unexploited cost saving potential in SMEs and non-energy intensive companies.

There are also several limitations of the systematic literature review. The most important limitation is the sample of papers that we include in our analysis, which is based on the papers published in academic journals. Other sources, such as practitioner journals, could offer some more detailed information of practices on energy management in companies and these could be included in the future research. This could also investigate in more detail the specific questions regarding the availability, characteristics, and usage of energy cost information.

In the third chapter, we aimed to provide a better understanding of the factors that influence the accuracy of energy costing systems. In order to do that, we used numerical simulations to simulate the effect of interdependency on the activity cost pool level. We modeled different settings regarding interdependencies, such as the amount of interdependency influencing the costing system, the number of cost pools affected by interdependency, and different densities of cost driver matrices included in the costing systems.

The results of the conducted numerical simulations suggest that increasing either the level of interdependency or the value of true activity cost pool would cause the overall error of the system to rise, comparing to the system where such error is not ignored. We show that in a setting where an increase in one activity cost pool causes decrease in two other pools, the overall error of cost system increases if the amount of true cost of an activity cost pool increases. We also note that the overall error of the costing system would be bigger in such setting, where one cost pool is influencing two other cost pools, than in the case of one cost pool influencing only one other cost pool. We also model different densities of the cost driver matrix, and conclude that increasing the density of cost driver matrix (i.e. increasing the number of cost allocation drivers) is resulting in a reduction of the overall error of the energy costing system. Overall, our results suggest that simplifying energy costing systems and ignoring the influence of such interdependencies results would result in large errors.

In the fourth chapter, we investigate the impact of input market dynamics on the accuracy of costing systems over time. In the previous chapters, our focus was mainly on energy costs and energy costing systems. In this chapter, however, we focus more generally on commodity prices. Specifically, we focus on costing systems with resources that have a particularly complex purchase price structure, such as electricity, which have dynamics properties. We investigate those changes in their dynamic properties and how they influence the accuracy of costing system.

The results of this chapter suggest that higher volatility of commodity prices causes the errors of the costing systems to increase, as does the existence of a stronger trend or more frequent seasonality pattern in time series of commodity prices. We also note that daily seasonality of commodity usage and lower density of consumption matrix negatively influence the accuracy of the costing system. Our results also show that having simplifications in costing systems, such as different simplified methods used for calculation of the prices or less frequent measurement of the prices, will cause inaccuracies of costing systems.

We also identify several limitations of our work. In the chapters three and four, we use the same research method of numerical simulations, resulting in some common limitations for those studies. Since simulations are inevitably simplifications of the real world, it is necessary to restrict the number of parameters and parameter variations used. The problem of managing the number of parameters is even larger in the dynamic simulation, where time causes additional changes in variables. Including a large number of parameters would make interpretation of the results difficult, and the computational time would increase.

The possibilities of further extending this research are numerous. It would be interesting to investigate different manufacturing environments, to deepen the understanding when the errors are likely to be small or large, and also to provide further guidance to practitioners. It is also possible to further develop the simulation as an assessment method, which would consist of an evaluation tool and a flexible simulation. Such an evaluation tool would provide a practical way to position a particular company in terms of the experimental conditions of the simulation experiment and to translate the conclusions of the simulation experiment to that company. Such a tool would make the simulation more flexible and suitable for company-specific analyses, since it could also be calibrated to a particular organization.

The accuracy of costing systems is a rather specialized topic in management accounting. At the same time, it is also at the core of it, since the information about costs is a central pillar in management accounting. However, accurate information does not necessarily require a refined and expensive costing system without errors. The cost-benefit tradeoff is also a pillar in management accounting. These two pillars have motivated the current research on costing system accuracy and will hopefully remain an inspiration for much future research.

References

Abolarin, S. M., Shitta, M. B., Gbadegesin, O., Nna, C. D., Eguma, C. A., Onafeso, B., & Adegbenro, O. (2015). An Economic Evaluation of Energy Management Opportunities in a Medium Scale Manufacturing Industry in Lagos. *International Journal of Engineering Research in Africa*, *14*, 97–106. http://doi.org/10.4028/www.scientific.net/JERA.14.97

Afkhami, B., Akbarian, B., Beheshti A., N., Kakaee, A. H., & Shabani, B. (2015). Energy consumption assessment in a cement production plant. *Sustainable Energy Technologies and Assessments*, *10*, 84–89. http://doi.org/10.1016/j.seta.2015.03.003

Aflaki, S., Kleindorfer, P. R., & De Miera Polvorinos, V. S. (2013). Finding and implementing energy efficiency projects in industrial facilities. *Production and Operations Management*, *22*(3), 503–517. http://doi.org/10.1111/j.1937-5956.2012.01377.x

Aiken, L., & West, S. (1991). *Multiple Regression: Testing and Interpreting Interactions*. SAGE Publications.

Alkaya, E., & Demirer, G. N. (2014). Sustainable textile production: A case study from a woven fabric manufacturing mill in Turkey. *Journal of Cleaner Production*, *65*, 595–603. http://doi.org/10.1016/j.jclepro.2013.07.008

Amundsen, A. (2000). Joint management of energy and environment. *Journal of Cleaner Production*, *8*(6), 483–494. http://doi.org/10.1016/S0959-6526(00)00018-4

Anand, V., Balakrishnan, R., & Labro, E. (2017). Obtaining Informationally Consistent Decisions When Computing Costs with Limited Information. *Production and Operations Management*, *26*(2), 211–230. http://doi.org/10.1111/poms.12631

Apeaning, R. W., & Thollander, P. (2013). Barriers to and driving forces for industrial energy efficiency improvements in African industries - A case study of Ghana's largest industrial area. *Journal of Cleaner Production*, *53*, 204–213. http://doi.org/10.1016/j.jclepro.2013.04.003

Askounis, D. T. H., & Psarras, J. (1998). Information system for monitoring and targeting (M&T) of energy consumption in breweries. *Energy*, *23*(5), 5.

Association, U. S. E. I. (2016). International energy outlook 2016. Retrieved June 14, 2017, from http://www.eia.gov/outlooks/ieo/table7-1.cfm

Ates, S. A., & Durakbasa, N. M. (2012). Evaluation of corporate energy management practices of energy intensive industries in Turkey. *Energy*, *45*(1), 81–91. http://doi.org/10.1016/j.energy.2012.03.032

Babad, Y. M., & Balachandran, B. V. (1993). Cost driver optimization in activity-based costing. *The Accounting Review*, *68*(3), 563–575.

Backlund, S., Broberg, S., Ottosson, M., & Thollander, P. (2012). Energy efficiency potentials and energy management practices in Swedish firms. *Summer Study on Energy Efficiency in Industry (Eceee 2012)*, (eceee), 11–14. http://doi.org/http://dx.doi.org/10.1016/j.enpol.2012.08.042

Balakrishnan, R., Hansen, S., & Labro, E. (2011a). Designing an Effective Cost System.

Balakrishnan, R., Hansen, S., & Labro, E. (2011b). Evaluating Heuristics Used When Designing Product Costing Systems. *Management Science, 57*(3), 520–541. http://doi.org/10.1287/mnsc.1100.1293

Balakrishnan, R., & Sivaramakrishnan, K. (2008). A Critical Overview of the Use of Full-Cost Data for Planning and Pricing. *Journal of Management Accounting Research*, *14*(1), 3–31. http://doi.org/10.2308/jmar.2002.14.1.3

Beecroft, H. H. (2007). The value of comparing an energy management program with those in other industries. *Strategic Planning for Energy and the Environment*, *27*(2), 65–80. http://doi.org/10.1080/10485230709509740

Bennet, M., Bouwma, J. J., & Wolters, T. (Eds.). (2002). *Environmental Management Accounting — Informational and Institutional Developments*. Dordrecht: Kluwer Academic Publishers.

Bennett, M., Rikhardsson, P. M., & Schaltegger, S. (Eds.). (2003). *Environmental Management Accounting — Purpose and Progress* (Vol. 12). Dordrecht: Springer Netherlands. http://doi.org/10.1007/978-94-010-0197-7

Bevilacqua, M., Ciarapica, F. E., Diamantini, C., & Potena, D. (2017). Big data analytics methodologies applied at energy management in industrial sector: A case study. *International Journal of RF Technologies, 8*(3), 105–122. http://doi.org/10.3233/RFT-171671

Bierer, A., Götze, U., Meynerts, L., & Sygulla, R. (2015). Integrating life cycle costing and life cycle assessment using extended material flow cost accounting. *Journal of Cleaner Production*, *108*, 1289–1301. http://doi.org/10.1016/j.jclepro.2014.08.036

Boutaghriout, B., Hamouda, C., Smadi, H., & Malek, A. (2016). Auditing of Energy Use and Costs Analysis in the Algerian Agro Food Sector: A Case Study in Three Dairies. *Energy Engineering: Journal of the Association of Energy Engineering*, *113*(2), 48–62. http://doi.org/10.1080/01998595.2016.11668652

Brunke, J. C., Johansson, M., & Thollander, P. (2014). Empirical investigation of barriers and drivers to the adoption of energy conservation measures, energy management practices and energy services in the Swedish iron and steel industry. *Journal of Cleaner Production*, *84*(1), 509–525. http://doi.org/10.1016/j.jclepro.2014.04.078

Bunse, K., Vodicka, M., Schönsleben, P., Brülhart, M., & Ernst, F. O. (2011). Integrating energy efficiency performance in production management - Gap analysis between industrial needs and scientific literature. *Journal of Cleaner Production*, *19*(6–7), 667–679. http://doi.org/10.1016/j.jclepro.2010.11.011

Capehart, B. L., Turner, W. C., & Kennedy, W. J. (2003). *Guide to Energy Management* (Fourth edi). The Fairmont Press.

Cardinaels, E., & Labro, E. (2008). On the determinants of measurement error in time-driven costing. *Accounting Review*, *83*(3), 735–756. http://doi.org/10.2308/accr.2008.83.3.735

Cartea, Á., & Figueroa, M. G. (2005). Pricing in electricity markets: A mean reverting jump diffusion model with seasonality. *Applied Mathematical Finance*, *12*(4), 313–335. http://doi.org/10.1080/13504860500117503

Christ, K. L., & Burritt, R. L. (2015). Material flow cost accounting: A review and agenda for future research. *Journal of Cleaner Production*, *108*, 1378–1389. http://doi.org/10.1016/j.jclepro.2014.09.005

Christoffersen, L. B., Larsen, A., & Togeby, M. (2006). Empirical analysis of energy management in Danish industry. *Journal of Cleaner Production*, *14*(5), 516–526. http://doi.org/10.1016/j.jclepro.2005.03.017

Coller, G., & Collini, P. (2015). The optimality of full-cost pricing: a simulation analysis of the price-adjustment dynamics. *Journal of Management Control*, *26*(2–3), 157–191. http://doi.org/10.1007/s00187-015-0212-3

Datar, S., & Gupta, M. Aggregation, Specification and Measurement Errors in Prodcut Costing, 69 The Accounting Review 567–591 (1994). http://doi.org/10.2307/248432

DeCanio, S. J., & Watkins, W. E. (1998). Investment in Energy Efficiency: Do the Characteristics of Firms Matter? *Review of Economics and Statistics*, *80*, 95–107. http://doi.org/10.1162/003465398557366

Dobes, V. (2013). New tool for promotion of energy management and cleaner production on no cure , no pay basis. *Journal of Cleaner Production*, *39*, 255–264. http://doi.org/10.1016/j.jclepro.2012.08.007

Dongellini, M., Marinosci, C., & Morini, G. L. (2014). Energy audit of an industrial site: A case study. *Energy Procedia*, *45*, 424–433. http://doi.org/10.1016/j.egypro.2014.01.046

Drumm, C., Busch, J., Dietrich, W., Eickmans, J., & Jupke, A. (2013). STRUCTese ® – Energy efficiency management for the process industry. *Chemical Engineering & Processing: Process Intensification*, *67*, 99–110. http://doi.org/10.1016/j.cep.2012.09.009

European Comission. (2009). Reference Document on Best Available Techniques for Energy Efficiency. *European Comission*, (February).

European Commission. (2009). *Reference Document on Best Available Techniques for Energy Efficiency*.

European Commission. (2015). *User guide to the SME Definition*. *Publications Office of the European Union*. http://doi.org/10.2873/782201

European Commission. (2017). *Annual Report on European SMEs 2016/2017: Focus on self employment*. *SME Performance Review*. http://doi.org/10.2873/742338

European Commission. (2018). *Smarter, greener, more inclusive? : indicators to support the Europe 2020 strategy ; 2018 edition*. http://doi.org/10.2785/80156

European Parliament. (2006). Directive 2006/32/EC of the European Parliament and of the Council of 5 April 2006 on energy end-use efficiency and energy services and repealing Council Directive 93/76/EEC. Retrieved March 26, 2019, from http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32006L0032&from=EN

Eurostat. (2016). Consumption of energy. Retrieved June 14, 2017, from http://ec.europa.eu/eurostat/statistics-explained/index.php/Consumption_of_energy

Fernandes, J. M., Capehart, B. L., Capehart, L. C., Fernandes, J. M., Capehart, B. L., & Capehart, L. C. (1997). Allocation of Energy Costs In Manufacturing Using Activity-Based Costing, *8595*(April). http://doi.org/10.1080/01998595.1997.10530381

Gordic, D., Babic, M., Jovicic, N., Sustersic, V., Koncalovic, D., & Jelic, D. (2010). Development of energy management system - Case study of Serbian car manufacturer. *Energy Conversion and Management*, *51*(12), 2783–2790. http://doi.org/10.1016/j.enconman.2010.06.014

Gruber, E., & Brand, M. (1991). Promoting energy conservation in small and medium-sized companies. *Energy Policy*, *19*(3), 279–287.

Hamilton, J. D. (1994). *Time Series Analysis*. Princeton University Press.

Harrison, J. R., Carroll, G. R., & Carley, K. M. (2007). Simulation modeling in organizational and management research. *Academy of Management Review*, *32*(4), 1229–1245.

Hildreth, A. J., & Oh, S.-C. (2014). GM's Robust Energy Management Meets "Challenge For Industry." *Strategic Planning for Energy and the Environment*, *33*(4), 62–80. http://doi.org/10.1080/10485236.2014.10819706

Hocke, S., Meyer, M., & Lorscheid, I. (2015). Improving simulation model analysis and communication via design of experiment principles: an example from the simulation-based design of cost accounting systems. *Journal of Management Control*, *26*(2–3), 131–155. http://doi.org/10.1007/s00187-015-0216-z

Homburg, C. (2001). A note on optimal cost driver selection in ABC. *Management Accounting Research*, *12*(2), 197–205. http://doi.org/10.1006/mare.2000.0150

Homburg, C., Nasev, J., & Plank, P. (2018). The impact of cost allocation errors on price and product-mix decisions. *Review of Quantitative Finance and Accounting*, *51*(2), 497–527. http://doi.org/10.1007/s11156-017-0678-1

Huang, Y., Luo, J., & Xia, B. (2013). Application of cleaner production as an important sustainable strategy in the ceramic tile plant-a case study in Guangzhou, China. *Journal of Cleaner Production*, *43*, 113–121. http://doi.org/10.1016/j.jclepro.2012.12.013

Hwang, Y., Evans, John H., I., & Hegde, V. G. (1993). Product Cost Bias and Selection of an Allocation Base. *Journal of Management Accounting Research*, *5*(3), 213–242. Retrieved from http://libaccess.mcmaster.ca.libaccess.lib.mcmaster.ca/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=9701211559&site=ehost-live&scope=site

Jacobs, F., & Marshall, R. (1999). Accuracy of Service Cost Allocations. *The Journal of Cost Analysis & Management*, *1*(1), 45–57. http://doi.org/10.1080/15411656.1999.10462399

Johansson, M. T. (2015). Improved energy efficiency within the Swedish steel industry — the importance of energy management and networking. *Energy Efficiency*, 713–744. http://doi.org/10.1007/s12053-014-9317-z

Johansson, M. T., & Söderström, M. (2011). Options for the Swedish steel industry - Energy efficiency measures and fuel conversion. *Energy*, *36*(1), 191–198.

http://doi.org/10.1016/j.energy.2010.10.053

Kannan, R., & Boie, W. (2003). Energy management practices in SME—case study of a bakery in Germany. *Energy Conversion and Management*, *44*(6), 945–959. http://doi.org/10.1016/S0196-8904(02)00079-1

Kirabira, J. B., Nalweyiso, A., & Makumbi, T. (2014). Energy Management Practices In Ugandan SME Foundries. *International Journal of Scientific and Technology Research*, *3*(4).

Klugman, S., Karlsson, M., & Moshfegh, B. (2007). A Scandinavian chemical wood pulp mill. Part 1. Energy audit aiming at efficiency measures. *Applied Energy*, *84*(3), 326–339. http://doi.org/10.1016/j.apenergy.2006.07.003

Kong, L., Price, L., Hasanbeigi, A., Liu, H., & Li, J. (2013). Potential for reducing paper mill energy use and carbon dioxide emissions through plant-wide energy audits: A case study in China. *Applied Energy*, *102*(December 2011), 1334–1342. http://doi.org/10.1016/j.apenergy.2012.07.013

Krenn, C., Weichbold, T., Korp, G., Meixner, E., Stockner, H., Berger, D., … Fresner, J. (2015). Qualitative and quantitative modelling to build a conceptual framework to identify energy saving options: Case study of a wire producing company. *Journal of Cleaner Production*, *95*, 212–222. http://doi.org/10.1016/j.jclepro.2015.02.052

Labro, E. (2015). Using simulation methods in accounting research. *Journal of Management Control*, *26*(2–3), 99–104. http://doi.org/10.1007/s00187-015-0203-4

Labro, E., & Vanhoucke, M. (2007). A Simulation Analysis of Interactions among Errors in Costing Systems. *The Accounting Review*, *82*(4), 939–962. http://doi.org/10.2308/accr.2007.82.4.939

Labro, E., & Vanhoucke, M. (2008). Diversity in Resource Consumption Patterns and Robustness of Costing Systems to Errors. *Management Science*, *54*(10), 1715–1730. http://doi.org/10.1287/mnsc.1080.0885

Lampret, M., Bukovec, V., Paternost, A., Krizman, S., Lojk, V., & Golobic, I. (2007). Industrial energy-flow management. *Applied Energy*, *84*(7–8), 781–794. http://doi.org/10.1016/j.apenergy.2007.01.009

Larek, R., Brinksmeier, E., Meyer, D., Pawletta, T., & Hagendorf, O. (2011). A discrete-event simulation approach to predict power consumption in machining processes. *Production Engineering*, *5*(5), 575–579. http://doi.org/10.1007/s11740-011-0333-y

Law, A. M. (2008). How to build valid and credible simulation models. *Proceedings of the 2008 Winter Simulation Conference*, 39–47.

Leitner, S. (2014). A simulation analysis of interactions among intended biases in costing systems and their effects on the accuracy of decision-influencing information. *Central European Journal of Operations Research*, *22*(1), 113–138. http://doi.org/10.1007/s10100-012-0275-2

Li, Y., Li, J., Qiu, Q., & Xu, Y. (2010). Energy auditing and energy conservation potential for glass works. *Applied Energy*, *87*(8), 2438–2446.

http://doi.org/10.1016/j.apenergy.2010.02.029

Martin, R., Muûls, M., De Preux, L. B., & Wagner, U. J. (2012). Anatomy of a paradox: Management practices, organizational structure and energy efficiency. *Journal of Environmental Economics and Management*, *63*(2), 208–223. http://doi.org/10.1016/j.jeem.2011.08.003

Maruddani, & Trimono. (2018). Stock price prediction using geometric Brownian motion Related content Modeling stock prices in a portfolio using multidimensional geometric brownian motion Stock price prediction using geometric Brownian motion. *J. Phys*, 12047. http://doi.org/10.1088/1742-6596/974/1/012047

Mayer, K., Schmid, T., & Weber, F. (2015). Modeling electricity spot prices: combining mean reversion, spikes, and stochastic volatility. *European Journal of Finance*, *21*(4), 292–315. http://doi.org/10.1080/1351847X.2012.716775

Muller, D. C. A., Marechal, F. M. A., Wolewinski, T., & Roux, P. J. (2007). An energy management method for the food industry. *Applied Thermal Engineering*, *27*(16 SPEC. ISS.), 2677–2686. http://doi.org/10.1016/j.applthermaleng.2007.06.005

O’Callaghan, P. W., & Probert, S. D. (1997). Energy management. *Applied Energy*, *3*, 127–138.

O’Driscoll, E., Og Cusack, D., & O’Donnell, G. E. (2012). Implementation of energy metering systems in complex manufacturing facilities-A case study in a biomedical facility. *Procedia CIRP*, *1*(1), 524–529. http://doi.org/10.1016/j.procir.2012.04.093

Ozturk, H. K. (2005). Energy usage and cost in textile industry: A case study for Turkey. *Energy*, *30*(13), 2424–2446. http://doi.org/10.1016/j.energy.2004.11.014

Phylipsen, G. J. M., Blok, K., & Worrell, E. (1997). International comparisons of energy efficiency-Methodologies for the manufacturing industry. *Energy Policy*, *25*(7–9), 715–725. http://doi.org/10.1016/S0301-4215(97)00063-3

Quinteiro, P., Araújo, A., Dias, A. C., Oliveira, B., & Arroja, L. (2012). Allocation of energy consumption and greenhouse gas emissions in the production of earthenware ceramic pieces. *Journal of Cleaner Production*, *31*, 14–21. http://doi.org/10.1016/j.jclepro.2012.02.032

Reichelstein, S., & Rohlfing-Bastian, A. (2015). Levelized Product Cost: Concept and decision relevance. *Accounting Review*, *90*(4), 1653–1682. http://doi.org/10.2308/accr-51009

Rohdin, P., & Thollander, P. (2006). Barriers to and driving forces for energy efficiency in the non-energy intensive manufacturing industry in Sweden. *Energy*, *31*(12), 1836–1844. http://doi.org/10.1016/j.energy.2005.10.010

Rohdin, P., Thollander, P., & Solding, P. (2007). Barriers to and drivers for energy efficiency in the Swedish foundry industry. *Energy Policy*, *35*(1), 672–677. http://doi.org/10.1016/j.enpol.2006.01.010

Rosen, M. A. (2008). Allocating carbon dioxide emissions from cogeneration systems: descriptions of selected output-based methods. *Journal of Cleaner Production*, *16*(2), 171–177. http://doi.org/10.1016/j.jclepro.2006.08.025

Rudberg, M., Waldemarsson, M., & Lidestam, H. (2013). Strategic perspectives on energy management: A case study in the process industry. *Applied Energy*, *104*, 487–496. http://doi.org/10.1016/j.apenergy.2012.11.027

Sa, A., Paramonova, S., Thollander, P., & Cagno, E. (2015). Classification of Industrial Energy Management Practices: A Case Study of a Swedish Foundry. *Energy Procedia*, *75*, 2581–2588. http://doi.org/10.1016/j.egypro.2015.07.311

Sandberg, P., & Söderström, M. (2003). Industrial energy efficiency: The need for investment decision support from a manager perspective. *Energy Policy*, *31*(15), 1623–1634. http://doi.org/10.1016/S0301-4215(02)00228-8

Sathitbun-anan, S., Fungtammasan, B., Barz, M., Sajjakulnukit, B., & Pathumsawad, S. (2015). An analysis of the cost-effectiveness of energy efficiency measures and factors affecting their implementation : a case study of Thai sugar industry. *Energy Efficiency*, *8*, 141–153. http://doi.org/10.1007/s12053-014-9281-7

Schleich, J. (2009). Barriers to energy efficiency: A comparison across the German commercial and services sector. *Ecological Economics*, *68*(7), 2150–2159. http://doi.org/10.1016/j.ecolecon.2009.02.008

Schleich, J., & Gruber, E. (2008). Beyond case studies: Barriers to energy efficiency in commerce and the services sector. *Energy Economics*, *30*(2), 449–464. http://doi.org/10.1016/j.eneco.2006.08.004

Schmidt, A., Götze, U., & Sygulla, R. (2015). Extending the scope of Material Flow Cost Accounting - Methodical refinements and use case. *Journal of Cleaner Production*, *108*, 1320–1332. http://doi.org/10.1016/j.jclepro.2014.10.039

Schulze, M., Nehler, H., Ottosson, M., & Thollander, P. (2016). Energy management in industry - A systematic review of previous findings and an integrative conceptual framework. *Journal of Cleaner Production*, *112*, 3692–3708. http://doi.org/10.1016/j.jclepro.2015.06.060

Schwartz, E., & Smith, J. E. (2003). Short-Term Variations and Long-Term Dynamics in Commodity Prices. *Management Science*, *46*(7), 893–911. http://doi.org/10.1287/mnsc.46.7.893.12034

Shipley, A. M., & Elliot, R. E. (2001). Energy efficiency programs for small and medium sized industry. In *ACEEE summer study* (pp. 183–196).

Shrouf, F., Gong, B., & Ordieres-Meré, J. (2017). Multi-level awareness of energy used in production processes. *Journal of Cleaner Production*, *142*, 2570–2585. http://doi.org/10.1016/j.jclepro.2016.11.019

Siitonen, S., & Holmberg, H. (2012). Estimating the value of energy saving in industry by different cost allocation methods. *International Journal of Energy Research*, *36*(3), 324–334. http://doi.org/10.1002/er.1794

Sivill, L., Manninen, J., Hippinen, I., & Athila, P. (2013). Success factors of energy management in energy- intensive industries: Development priority of energy performance measurement. *International Journal of Energy Research*, *37*, 936–951. http://doi.org/10.1002/er

Sorrell, S., Mallett, A., & Nye, S. (2011). *Barriers to industrial energy efficiency: A literature review*.

Spees, K., & Lave, L. B. (2007). Demand Response and Electricity Market Efficienc. *The Electricity Journal*, *20*(3), 69–85. http://doi.org/10.1016/j.tej.2007.01.006 69

Stenqvist, C., & Nilsson, L. J. (2012). Energy efficiency in energy-intensive industries-an evaluation of the Swedish voluntary agreement PFE. *Energy Efficiency*, *5*(2), 225–241. http://doi.org/10.1007/s12053-011-9131-9

Sucic, B., Al-Mansour, F., Pusnik, M., & Vuk, T. (2015). Context sensitive production planning and energy management approach in energy intensive industries. *Energy*, 1–11. http://doi.org/10.1016/j.energy.2015.10.129

Sygulla, R., Bierer, A., & Götze, U. (2011). Material Flow Cost Accounting–Proposals for Improving the Evaluation of Monetary Effects of Resource Saving Process Designs. *44th CIRP International Conference on Manufacturing Systems*, (June), 1–3.

Sygulla, R., Götze, U., & Bierer, A. (2014). Material Flow Cost Accounting: A Tool for Designing Economically and Ecologically Sustainable Production Processes. In E. Henriques, P. Pecas, & A. Silva (Eds.), *Technology and Manufacturing Process Selection: The Product Life Cycle Perspective* (pp. 105–130). London: Springer London. http://doi.org/10.1007/978-1-4471-5544-7_6

Thollander, P., Backlund, S., Trianni, A., & Cagno, E. (2013). Beyond barriers - A case study on driving forces for improved energy efficiency in the foundry industries in Finland, France, Germany, Italy, Poland, Spain, and Sweden. *Applied Energy*, *111*, 636–643. http://doi.org/10.1016/j.apenergy.2013.05.036

Thollander, P., Danestig, M., & Rohdin, P. (2007). Energy policies for increased industrial energy efficiency: Evaluation of a local energy programme for manufacturing SMEs. *Energy Policy*, *35*(11), 5774–5783. http://doi.org/10.1016/j.enpol.2007.06.013

Thollander, P., Karlsson, M., Söderström, M., & Creutz, D. (2005). Reducing industrial energy costs through energy-efficiency measures in a liberalized European electricity market: Case study of a Swedish iron foundry. *Applied Energy*, *81*(2), 115–126. http://doi.org/10.1016/j.apenergy.2004.07.006

Thollander, P., & Ottosson, M. (2008). An energy efficient Swedish pulp and paper industry - Exploring barriers to and driving forces for cost-effective energy efficiency investments. *Energy Efficiency*, *1*(1), 21–34. http://doi.org/10.1007/s12053-007-9001-7

Thollander, P., & Ottosson, M. (2010). Energy management practices in Swedish energy-intensive industries. *Journal of Cleaner Production*, *18*(12), 1125–1133. http://doi.org/10.1016/j.jclepro.2010.04.011

Thollander, P., & Palm, J. (2015). Industrial Energy Management Decision Making for Improved Energy Efficiency—Strategic System Perspectives and Situated Action in Combination, 5694–5703. http://doi.org/10.3390/en8065694

Thollander, P., Paramonova, S., Cornelis, E., Kimura, O., Trianni, A., Karlsson, M., … Jiménez Navarro, J. P. (2015). International study on energy end-use data among industrial SMEs (small and medium-sized enterprises) and energy end-use efficiency improvement opportunities. *Journal of Cleaner Production*, *104*, 282–296. http://doi.org/10.1016/j.jclepro.2015.04.073

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *British Journal of Management*, *14*(3), 207–222. http://doi.org/10.1111/1467-8551.00375

Trianni, A., Cagno, E., Thollander, P., & Backlund, S. (2013). Barriers to industrial energy efficiency in foundries: A European comparison. *Journal of Cleaner Production*, *40*, 161–176. http://doi.org/10.1016/j.jclepro.2012.08.040

Tunc, M., Kaplan, K., Sisbot, S., & Camdali, U. (2016). Energy management and optimization: case study of a textile plant in Istanbul, Turkey. *World Journal of Engineering*, *13*(4), 348–355. http://doi.org/10.1108/WJE-08-2016-046

Venmans, F. (2014). Triggers and barriers to energy efficiency measures in the ceramic, cement and lime sectors. *Journal of Cleaner Production*, *69*, 133–142. http://doi.org/10.1016/j.jclepro.2014.01.076

Virtanen, T., Tuomaala, M., & Pentti, E. (2013). Energy efficiency complexities: A technical and managerial investigation. *Management Accounting Research*, *24*(4), 401–416. http://doi.org/10.1016/j.mar.2013.06.002

Wagner, B. (2015). A report on the origins of Material Flow Cost Accounting (MFCA) research activities. *Journal of Cleaner Production*, *108*, 1255–1261. http://doi.org/10.1016/j.jclepro.2015.10.020

Wang, D., & Tomek, W. G. (2007). Commodity prices and unit root tests. *American Journal of Agricultural Economics*, *89*(4), 873–889. http://doi.org/10.1111/j.1467-8276.2007.01031.x

Wu, B., Li, J., Liu, H., Zhang, Z., Zhou, Y., & Zhao, N. (2012). Energy information integration based on EMS in paper mill. *Applied Energy*, *93*, 488–495. http://doi.org/10.1016/j.apenergy.2011.12.021

Yacout, D. M. M., El-kawi, M. A. A., & Hassouna, M. S. (2014). Applying Waste Management in Textile Industry : Case Study an Egyptian Plant. *International Energy Journal*, *14*, 87–94.

Zolkowski, J., & Nichols, G. (2013). Building Support for an Energy Management System. *Strategic Planning for Energy and the Environment*, *32*(3), 16–24. http://doi.org/10.1080/10485236.2013.10596284

Appendix

Figures

Figure 22 – Hypotheses 1 and 2: Plot of interaction effects

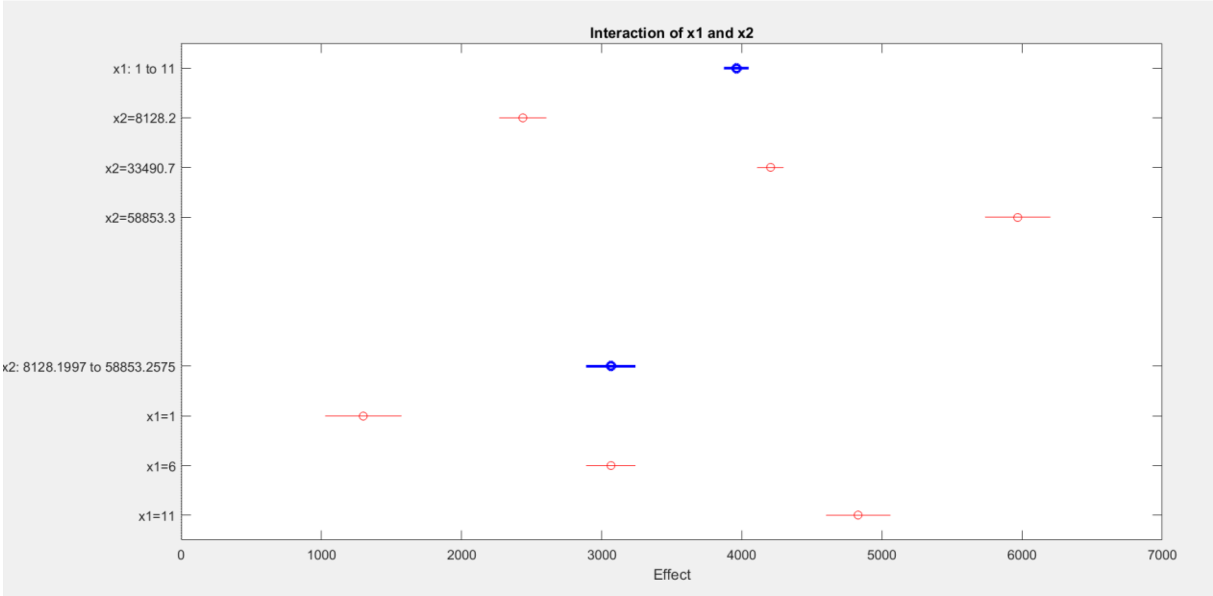


Figure 23 – Hypothesis 3: Plot of interaction effects

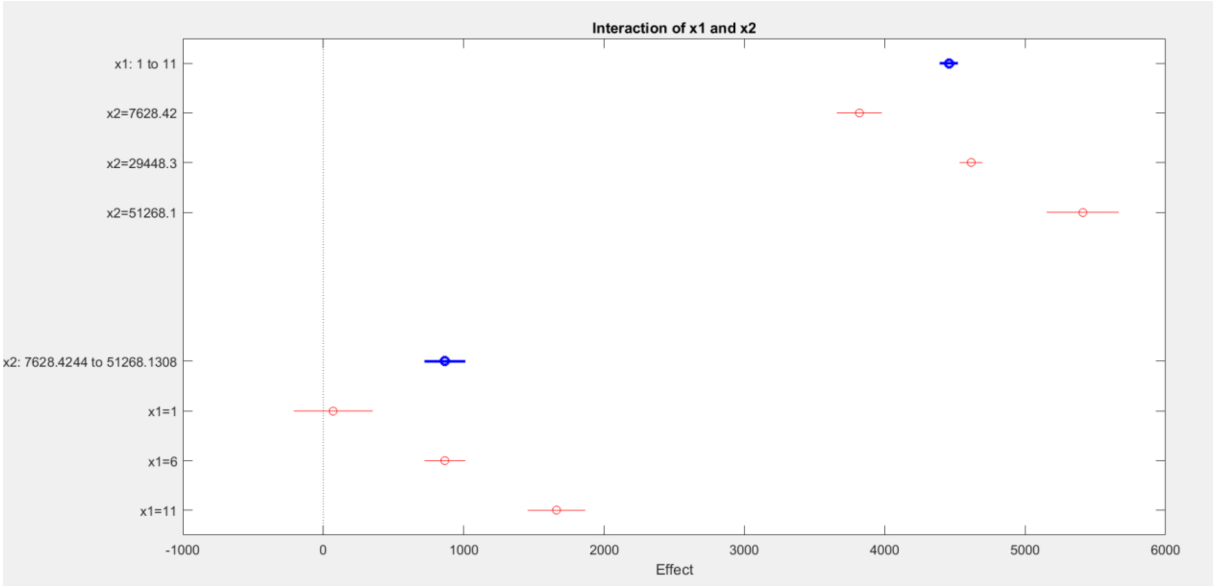


Figure 24 – Hypothesis 4: Plot of interaction effects

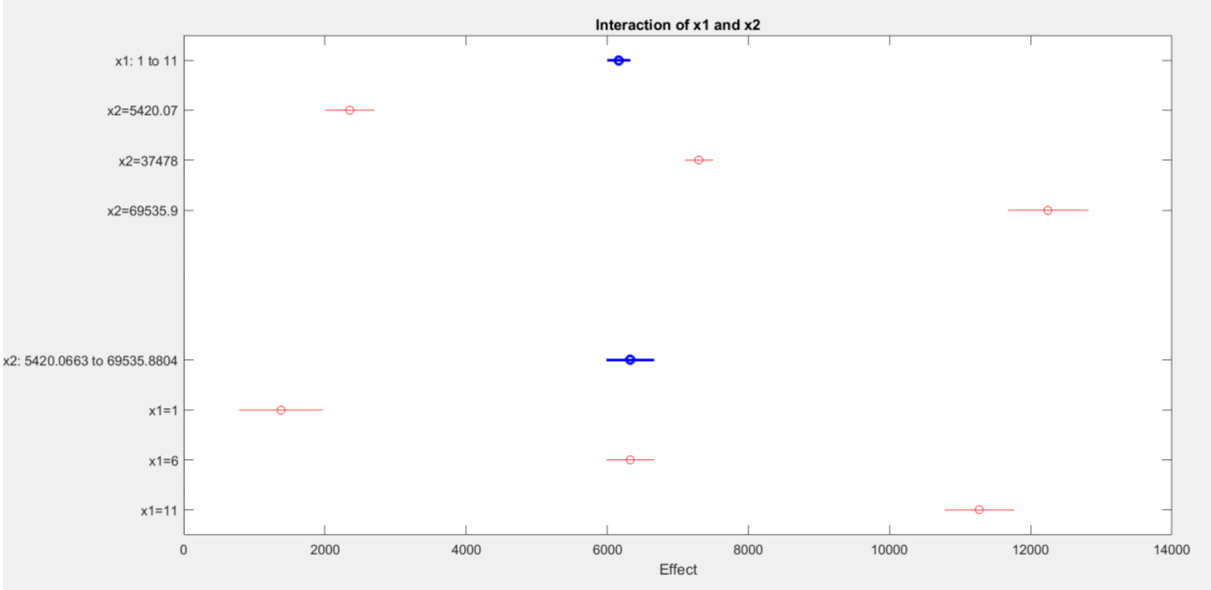


Figure 25 – Hypothesis 1: Plot of interaction effects for average method

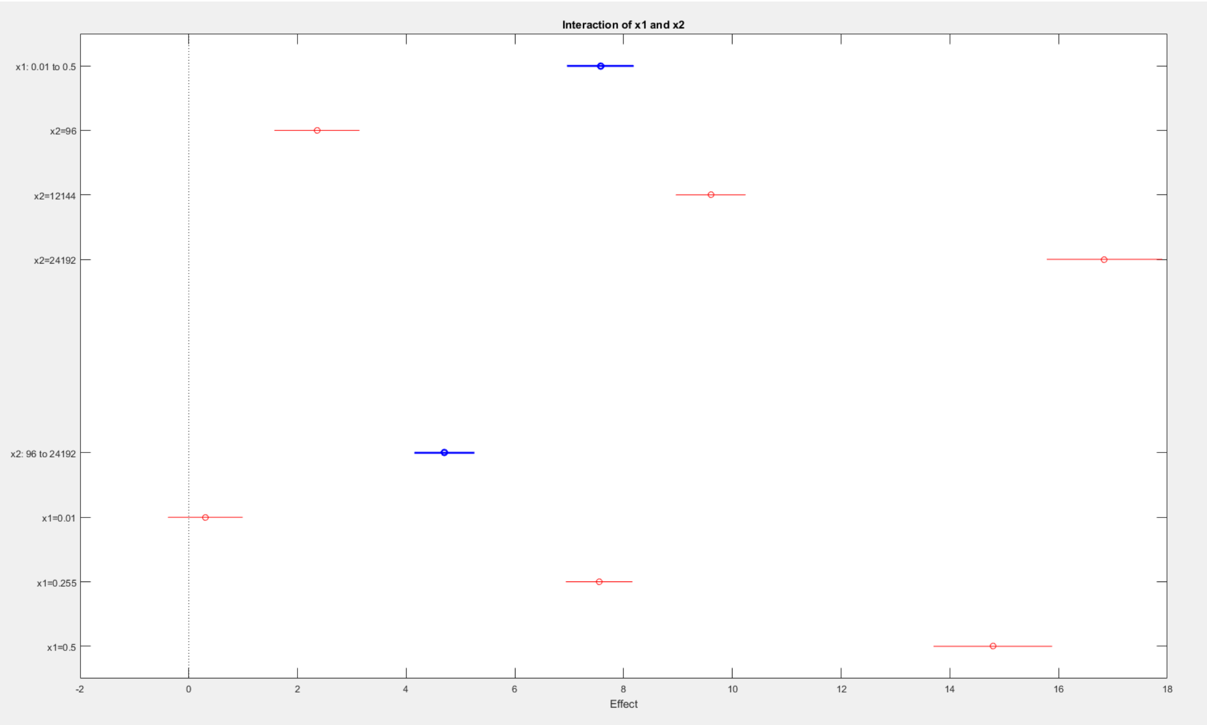


Figure 26 – Hypothesis 1: Plot of interaction effects for snapshot method

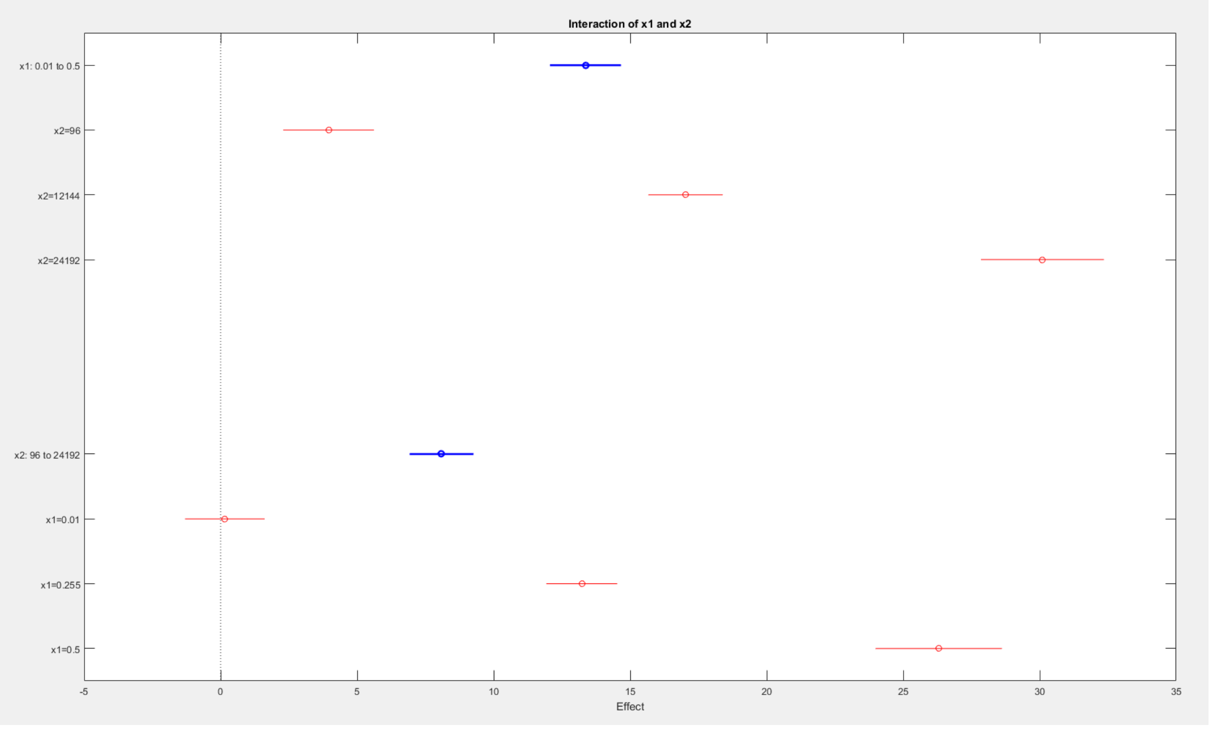


Figure 27 – Hypothesis 2: Plot of interaction effects for average method

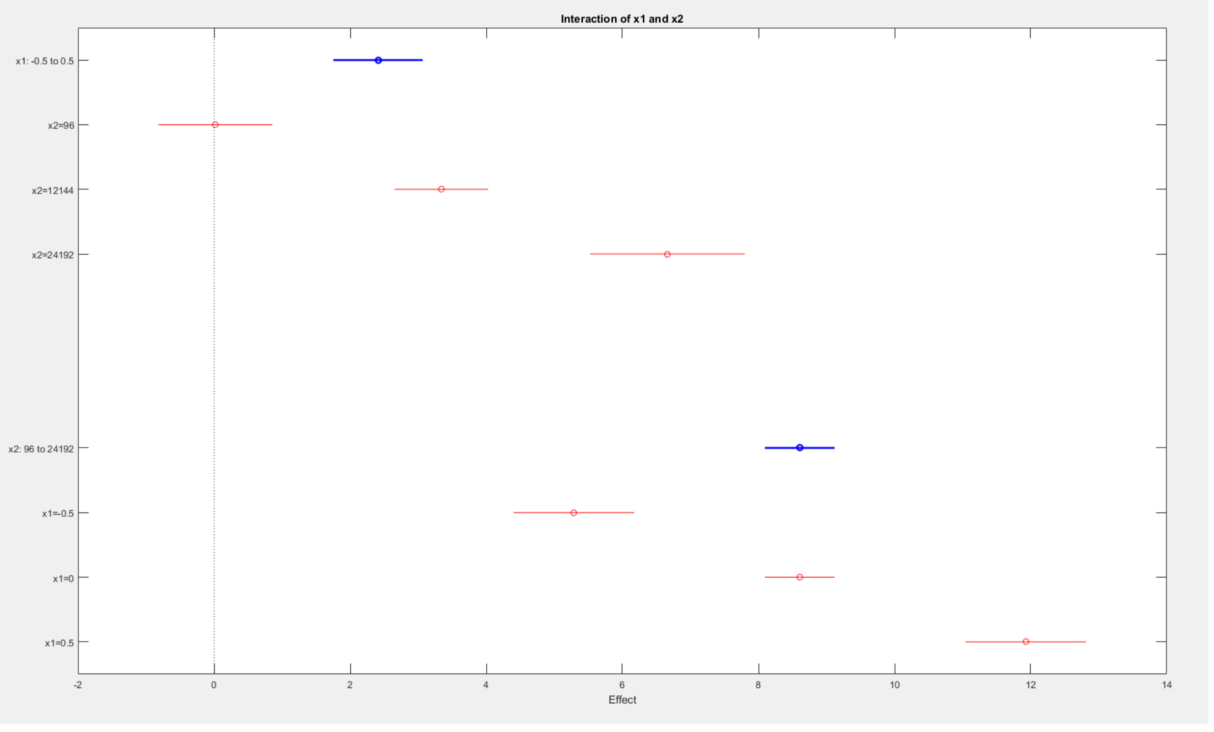


Figure 28 – Hypothesis 2: Plot of interaction effects for snapshot method

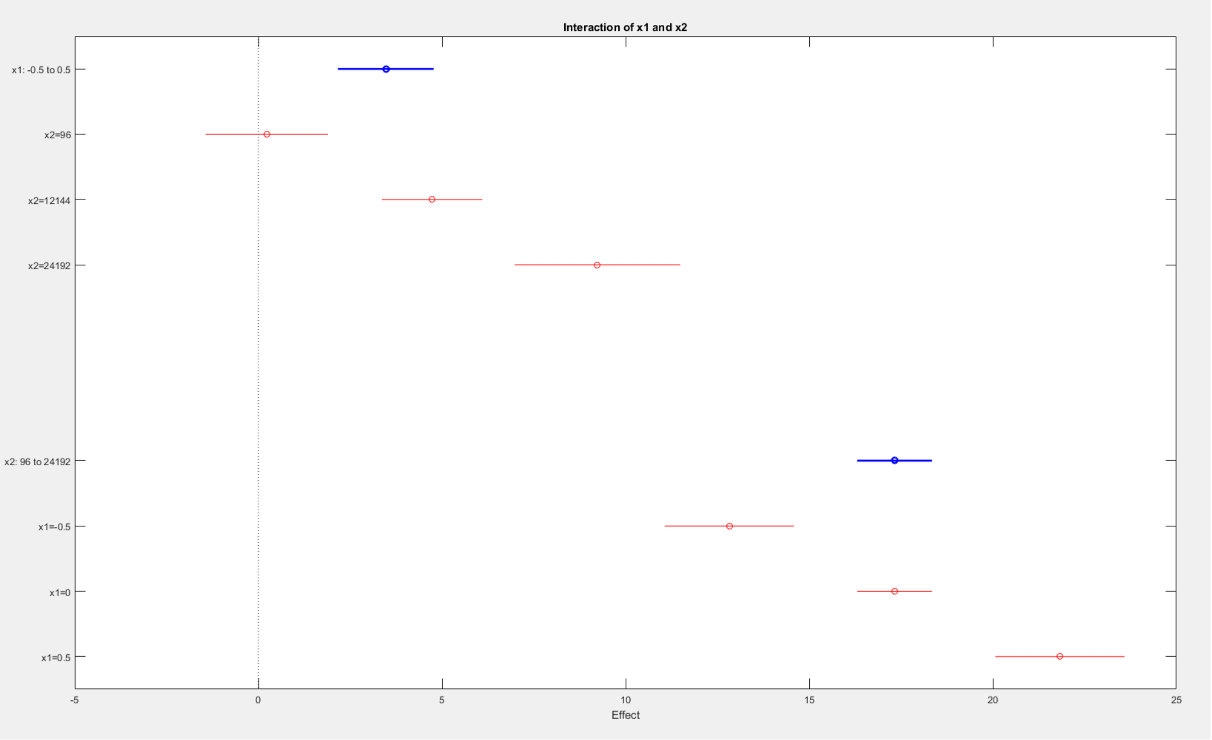


Figure 29 – Hypothesis 3: Plot of interaction effects for average method (yearly seasonality of commodity prices)

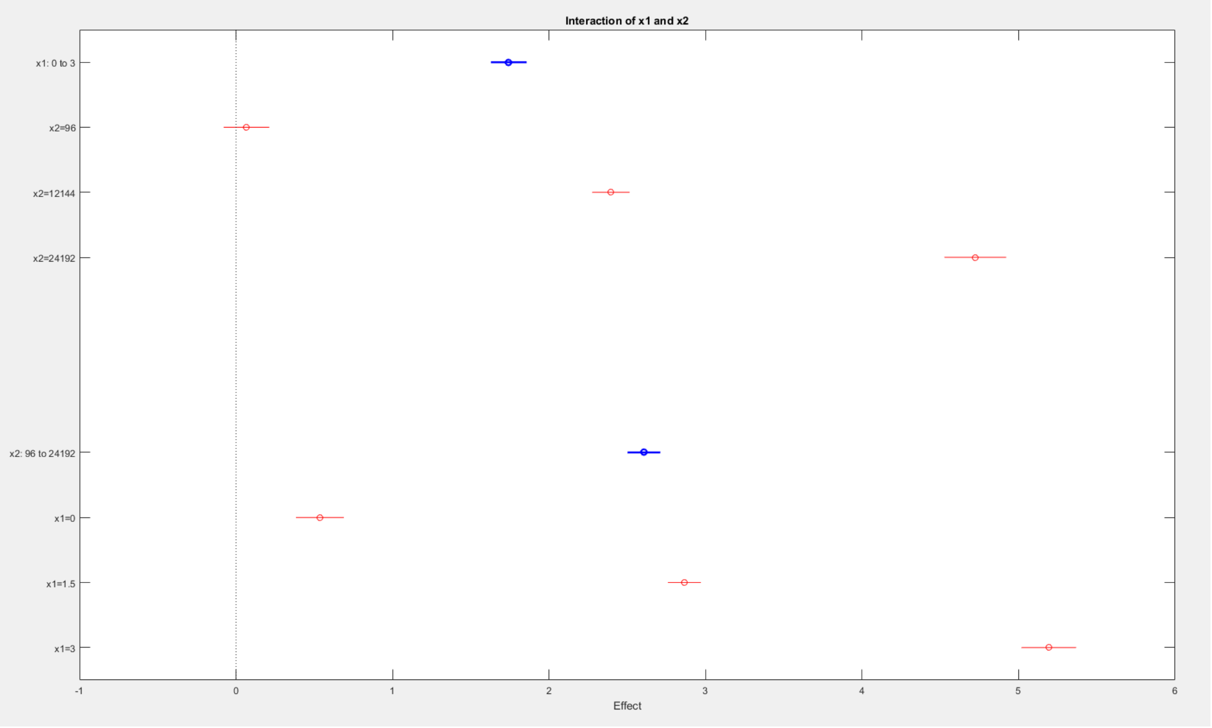


Figure 30 – Hypothesis 3: Plot of interaction effects for average method (daily seasonality of commodity prices)

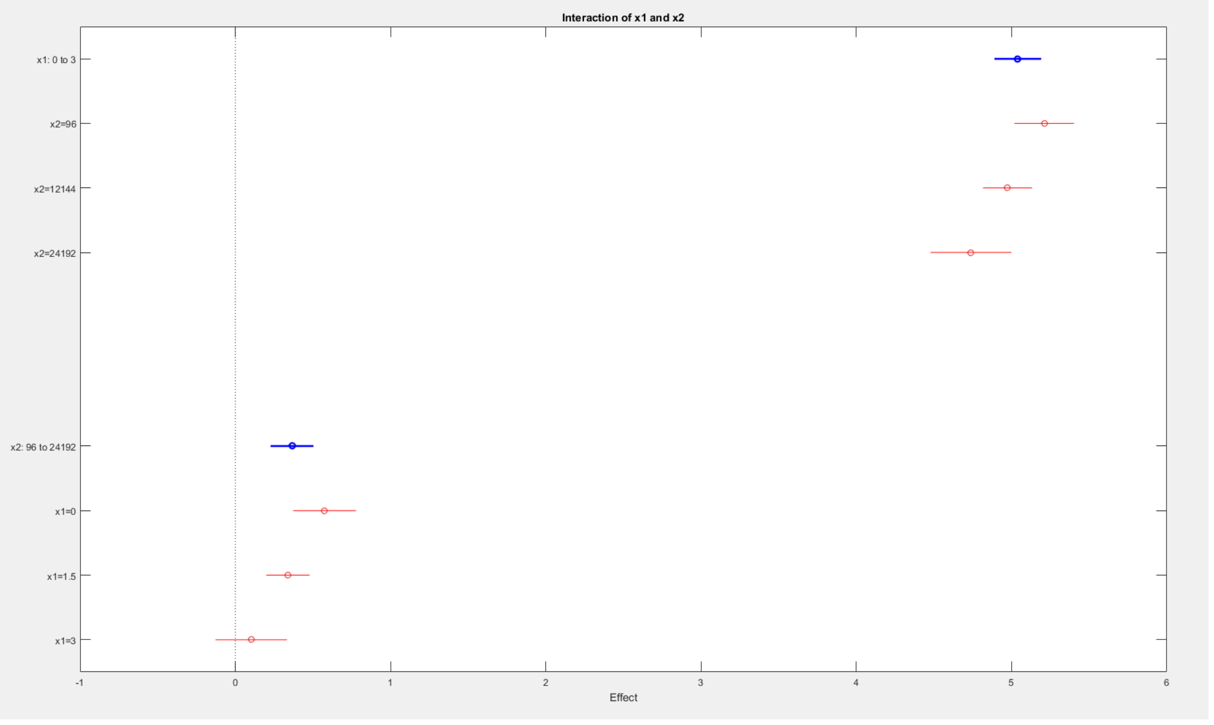


Figure 31 – Hypothesis 3: Plot of interaction effects for snapshot method (yearly seasonality of commodity prices)

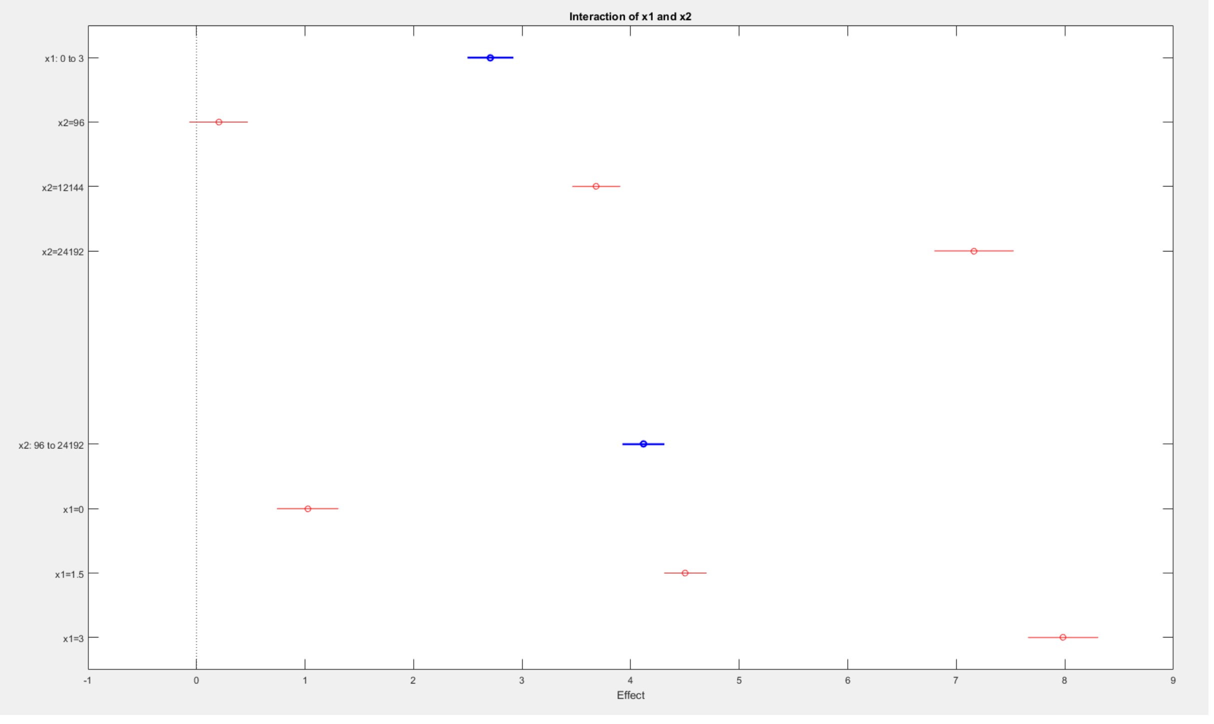


Figure 32 – Hypothesis 3: Plot of interaction effects for snapshot method (daily seasonality of commodity prices)

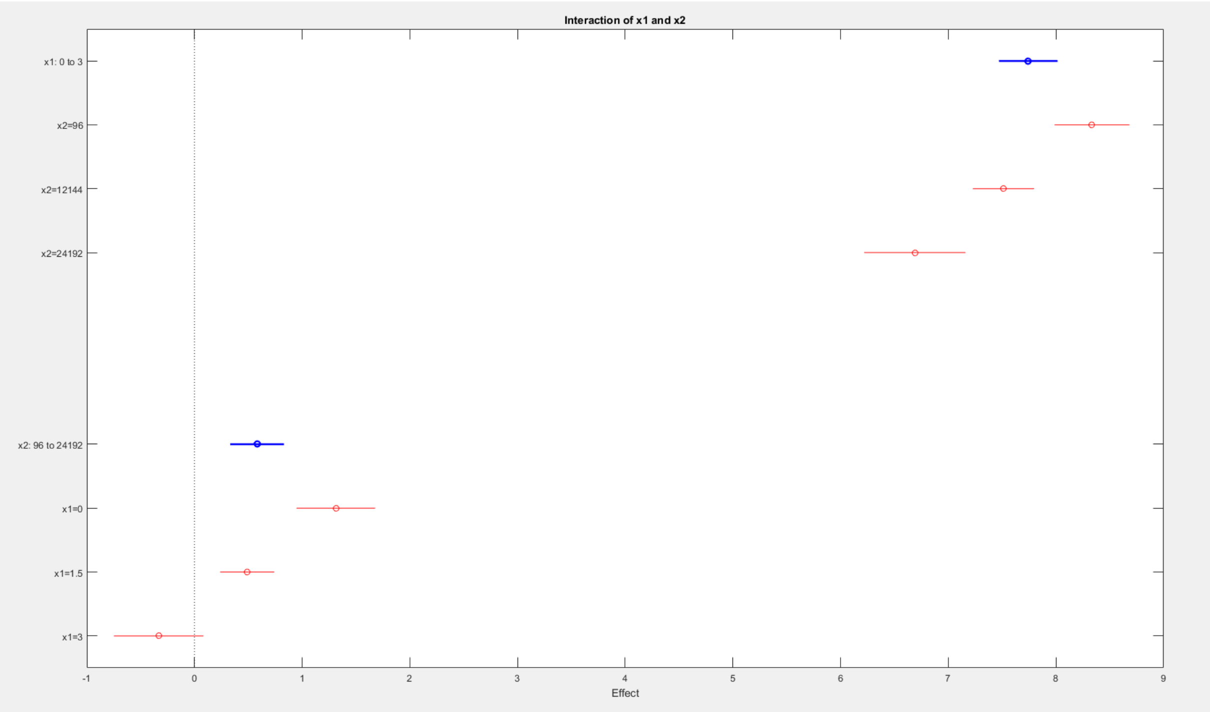


Figure 33 – Hypothesis 4: Plot of interaction effects for average method (yearly seasonality of consumption)

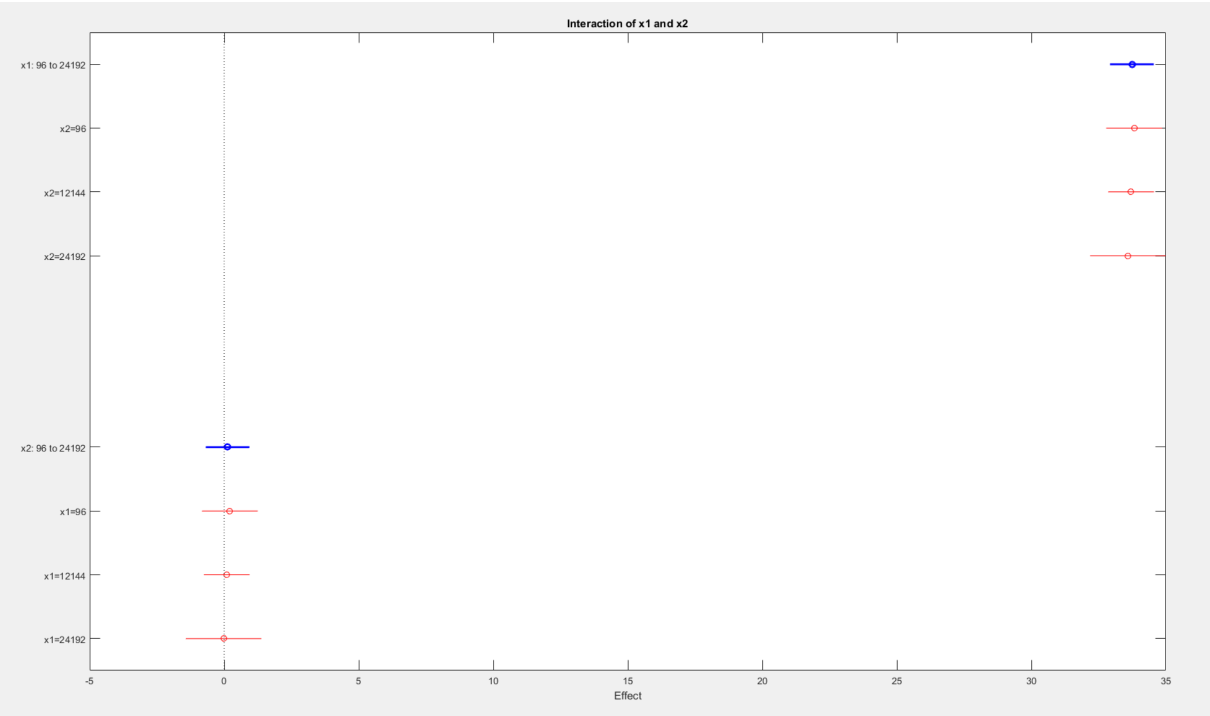


Figure 34 – Hypothesis 4: Plot of interaction effects for average method (daily seasonality of consumption)

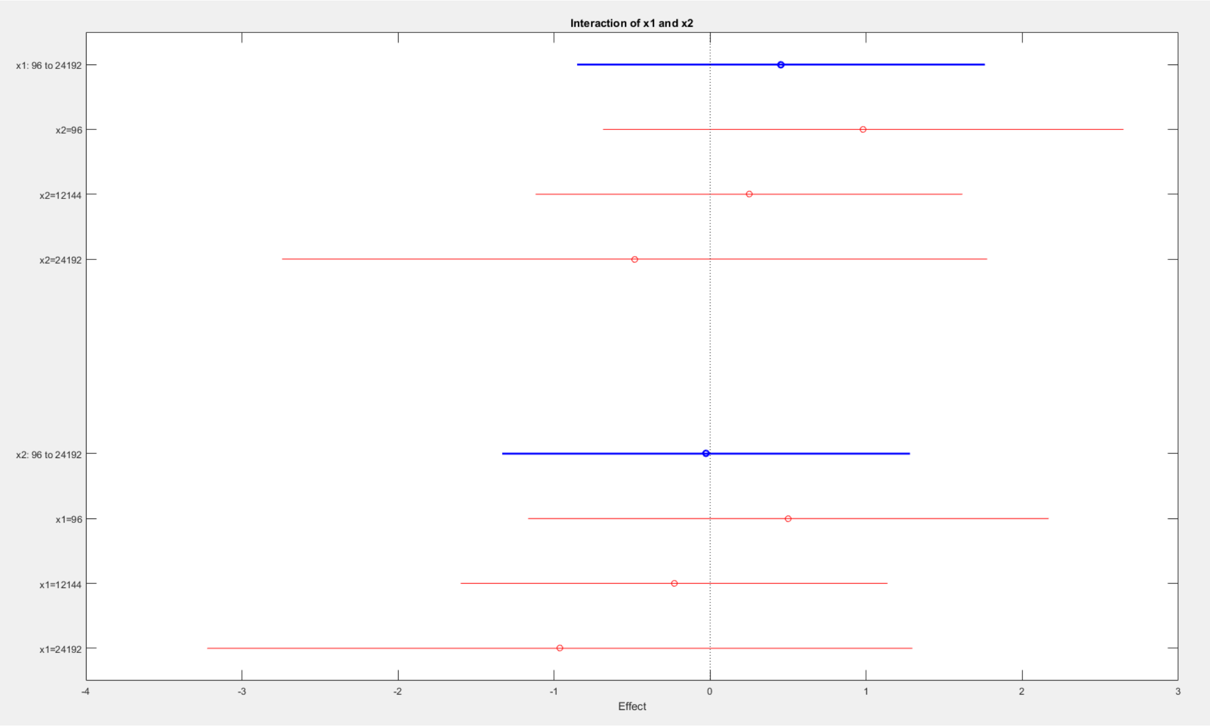


Figure 35 – Hypothesis 4: Plot of interaction effects for snapshot method (yearly seasonality of consumption)

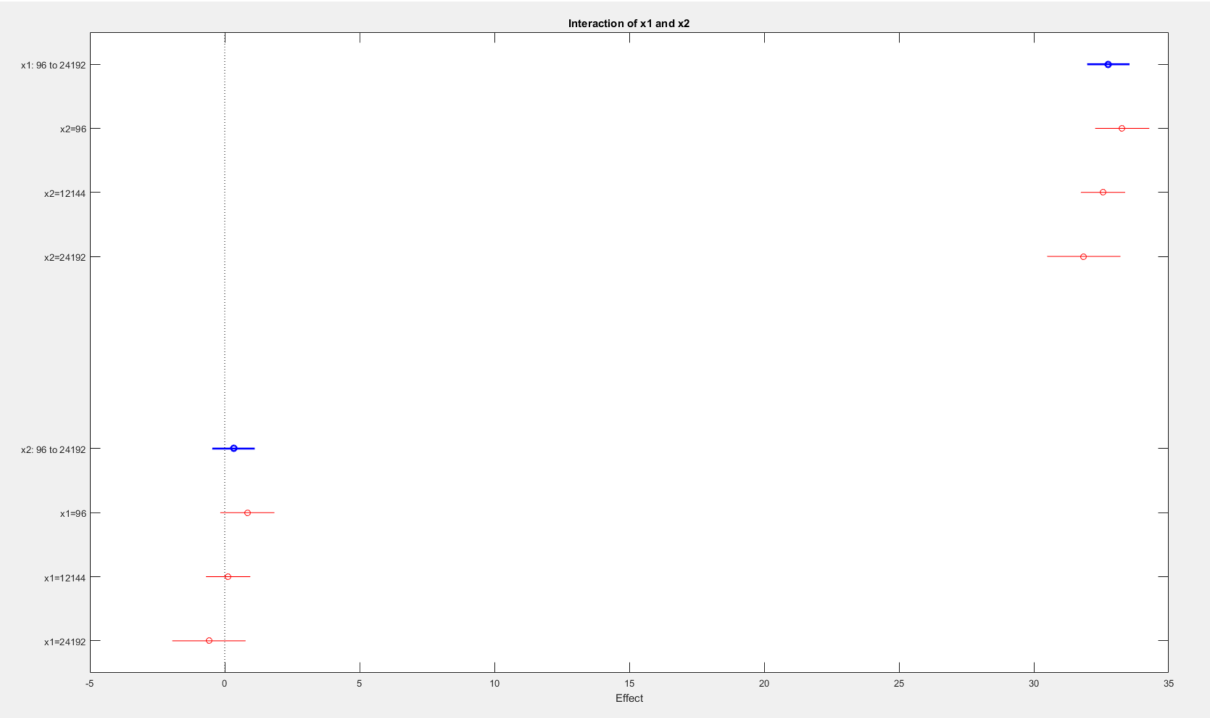


Figure 36 – Hypothesis 4: Plot of interaction effects for snapshot method (daily seasonality of consumption)

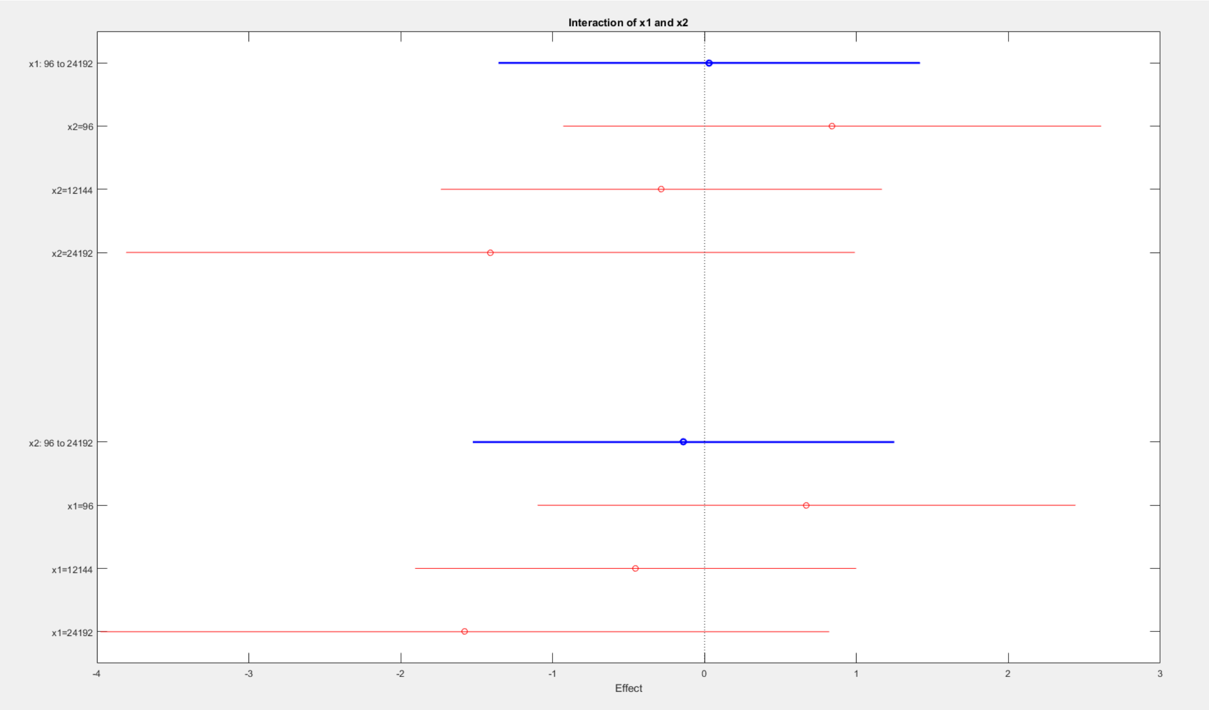


Figure 37 – Hypothesis 5: Plot of interaction effects for average method

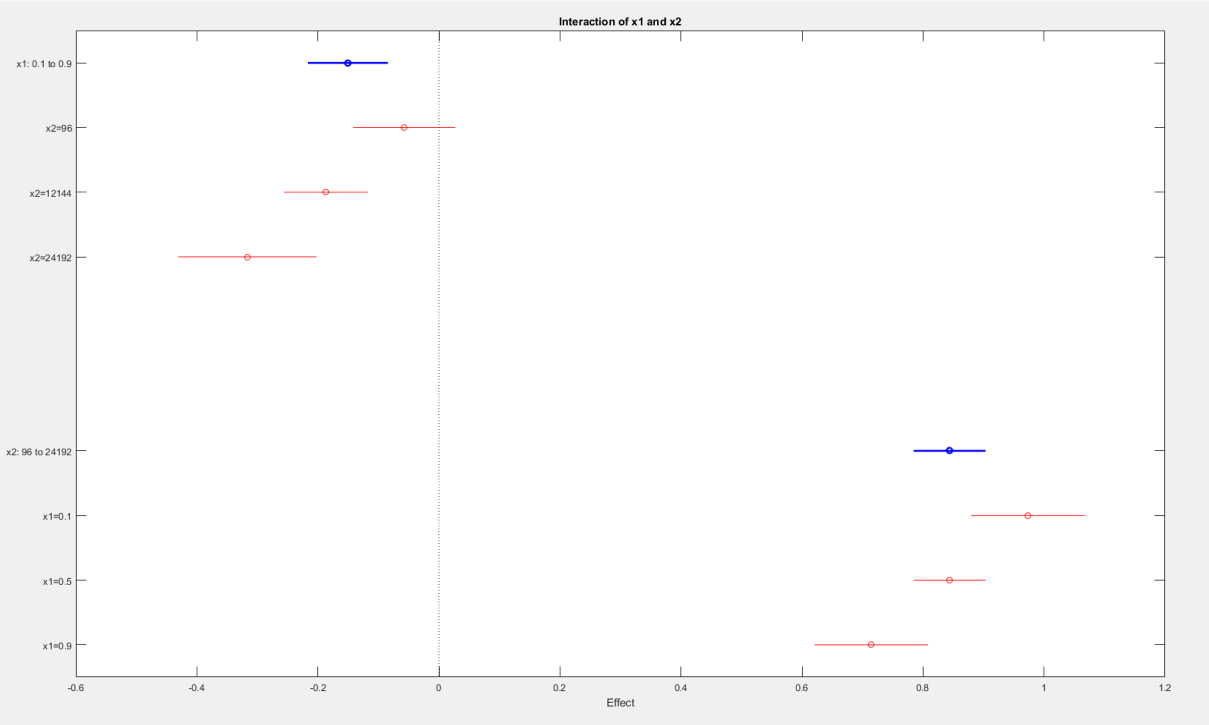
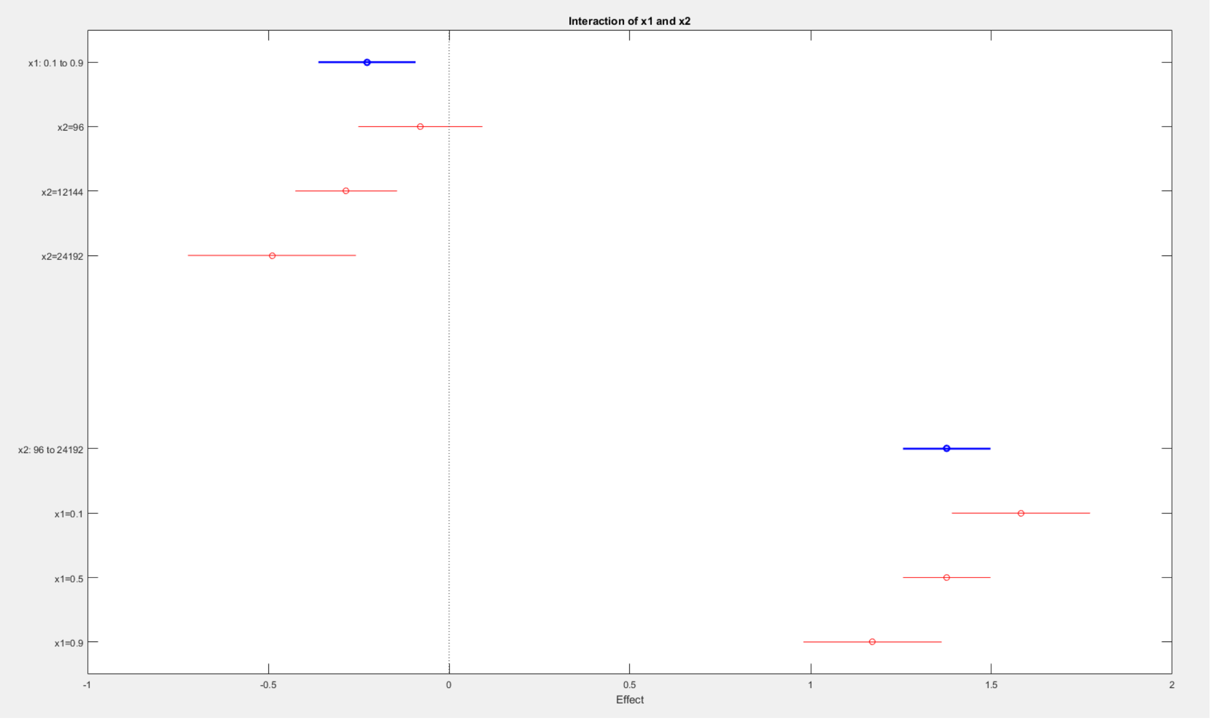


Figure 38 – Hypothesis 5: Plot of interaction effects for snapshot method



Code

Code for H1 and H2 (Chapter 3)

```
%% correlation.m – H1, with 50 resources/products and 500 loops

tic
%% initialization of variables
totalCosts = 1000000;
productCount = 50;
loopCount = 500;
density = 0.7;

%% big simulation
resultsMatrixEuclidean = zeros (500,1);
resultsMatrixEuclidean_big = zeros (11,500);
resultsMatrix_big = zeros (0,200);
percentage = 0;
for ii = 1:11
for jj = 1:500
   ii;
   jj;

%% matrix of resource cost pools
resourceCostPool_s = 0 + (0.5-0)*rand (1,productCount);
sum_resourceCostPool_s = sum (resourceCostPool_s);
resourceCostPool = resourceCostPool_s *(totalCosts/ sum_resourceCostPool_s);

%% check (should be equal to totalCosts)
sum_resourceCostPool = sum (resourceCostPool, 2);
sprintf('%10.0f', sum_resourceCostPool);

%% matrix of resource cost drivers with density 0.7
resourceCostDrivers =zeros(productCount);
resourceCostDrivers (sub2ind([productCount productCount],randperm(productCount),1:
productCount))=rand(productCount,1);
ind = randi([1 productCount * productCount], 1, ceil(density* productCount * productCount));
resourceCostDrivers (ind)=rand(1,length(ind));
length_resourceCostDrivers = length (resourceCostDrivers);
sum_rows_resourceCostDrivers = sum (resourceCostDrivers,2);
resourceCostDrivers_normed = bsxfun (@rdivide, resourceCostDrivers, sum_rows_resourceCostDrivers);
test_sum_rows_resourceCostDrivers_normed = sum (resourceCostDrivers_normed, 2);

%% matrix of activity cost pools
activityCostPools = resourceCostPool * resourceCostDrivers_normed;

%% check (should be equal to TC)
sum_activityCostPools = sum (activityCostPools, 2);
sprintf('%10.0f', sum_activityCostPools);

%% matrix of activity cost drivers with density 0.7
activityCostDrivers =zeros(productCount);
activityCostDrivers (sub2ind([productCount productCount],randperm(productCount),1:
productCount))=rand(productCount,1);
ind = randi([1 productCount * productCount], 1, ceil(density* productCount * productCount));
activityCostDrivers (ind)=rand(1,length(ind));
```

```
length_activityCostDrivers = length (activityCostDrivers);
sum_rows_activityCostDrivers = sum (activityCostDrivers,2);
activityCostDrivers_normed = bsxfun (@rdivide, activityCostDrivers, sum_rows_activityCostDrivers);
test_sum_rows_activityCostDrivers_normed = sum (activityCostDrivers_normed, 2);

%% matrix of cost objects
costObjects = activityCostPools * activityCostDrivers_normed;

%% check (should be equal to TC)
sum_costObjects = sum (costObjects, 2);
sprintf('%10.0f',sum_costObjects);

%% pick 2 random pools and its positions from activity cost pools
d = length (activityCostPools);
x = 2;
j = randperm(d,x);
firstPool = activityCostPools (1,j(1));
secondPool = activityCostPools (1,j(2));
position_firstPool = [1, j(1)];
position_secondPool = [1, j(2)];

%% for loop for true costing system
firstPool_true = firstPool + (secondPool*percentage);
secondPool_true = secondPool - (secondPool*percentage);
activityCostPools_true = activityCostPools;
activityCostPools_true (1,j(1)) = firstPool_true;
activityCostPools_true (1,j(2)) = secondPool_true;
costObjects_true = activityCostPools_true * activityCostDrivers_normed;

Euclidean = norm (costObjects_true - costObjects);

resultsMatrix_small (jj, :) = [ii jj resourceCostPool activityCostPools costObjects costObjects_true Euclidean
firstPool_true];
sortedMatrix_small = sortrows(resultsMatrix_small,204);

end

%% part of code for 2D plot
coefficients = polyfit(sortedMatrix_small(:,204),sortedMatrix_small(:,203),1);
Y = polyval(coefficients, sortedMatrix_small(:,204));
hold on
clr = jet(11);
plot(sortedMatrix_small(:,204),Y,'Color',clr(ii,:))
percentage = percentage + 0.1;
resultsMatrix_big = [resultsMatrix_big; sortedMatrix_small];

end

hold off
str = cellstr(num2str((1:11)','Run%d'));
legend (str);
toc


%% part of code for 3D plot with interaction term
x1 = resultsMatrix_big(:,1);
x2 = resultsMatrix_big(:,204);
y = resultsMatrix_big(:,203);
X = [ones(size(x1)) x1 x2 x1.*x2];
b = regress(y,X)
```

```
scatter3(x1,x2,y,'filled')
hold on
x1fit = min(x1):1:max(x1);
x2fit = min(x2):1000:max(x2);
 [X1FIT,X2FIT] = meshgrid(x1fit,x2fit);
YFIT = b(1) + b(2)*X1FIT + b(3)*X2FIT + b(4)*X1FIT.*X2FIT;
mesh(X1FIT,X2FIT,YFIT)
xlabel('Percentage')
ylabel('Value of true ACP')
zlabel('EUCD')
view(3)

%% part of code for descriptive statistics of EUCD (column 203)
grouped = resultsMatrix_big(:,203);
[stat1,stat2,stat3,stat4,stat5,stat6,stat7] = grpstats(grouped,[],{'mean','min','max','sem','numel','std','range'})

%% part of code for descriptive statistics of ACPt (column 204)
grouped = resultsMatrix_big(:,204);
[stat1,stat2,stat3,stat4,stat5,stat6,stat7] = grpstats(grouped,[],{'mean','min','max','sem','numel','std','range'})

%% standardized coefficients: Free element, x1, x2, x1*x2, multiple linear regression with interaction term
x1 = resultsMatrix_big(:,1);
zx1 = zscore(x1);
x2 = resultsMatrix_big(:,204);
zx2 = zscore (x2);
y = resultsMatrix_big(:,203);
zy = zscore (y);
X = [ones(size(x1)) zx1 zx2 zx1.*zx2];
b = regress(zy,X)
lm = fitlm (X, zy, 'linear')
```

Code for H3 (Chapter 3)

```
%% correlation.m – H2, with 50 resources/products and 500 loops, 3 pools interdependent (1+2)

tic
%% initialization of variables
totalCosts = 1000000;
productCount = 50;
loopCount = 500;
density = 0.7;

%% big simulation
resultsMatrixEuclidean = zeros (500,1);
resultsMatrixEuclidean_big = zeros (11,500);
resultsMatrix_big = zeros (0,200);
percentage = 0;
for ii = 1:11
for jj = 1:500
   ii;
   jj;

%% matrix of resource cost pools
resourceCostPool_s = 0 + (0.5-0)*rand (1,productCount);
sum_resourceCostPool_s = sum (resourceCostPool_s);
resourceCostPool = resourceCostPool_s *(totalCosts/ sum_resourceCostPool_s);

%% check (should be equal to totalCosts)
sum_resourceCostPool = sum (resourceCostPool, 2);
sprintf('%10.0f', sum_resourceCostPool);

%% matrix of resource cost drivers with density 0.7
resourceCostDrivers =zeros(productCount);
resourceCostDrivers (sub2ind([productCount productCount],randperm(productCount),1:
productCount))=rand(productCount,1);
ind = randi([1 productCount * productCount], 1, ceil(density* productCount * productCount));
resourceCostDrivers (ind)=rand(1,length(ind));
length_resourceCostDrivers = length (resourceCostDrivers);
sum_rows_resourceCostDrivers = sum (resourceCostDrivers,2);
resourceCostDrivers_normed = bsxfun (@rdivide, resourceCostDrivers, sum_rows_resourceCostDrivers);
test_sum_rows_resourceCostDrivers_normed = sum (resourceCostDrivers_normed, 2);

%% matrix of activity cost pools
activityCostPools = resourceCostPool * resourceCostDrivers_normed;

%% check (should be equal to TC)
sum_activityCostPools = sum (activityCostPools, 2);
sprintf('%10.0f', sum_activityCostPools);

%% matrix of activity cost drivers with density 0.7
activityCostDrivers =zeros(productCount);
activityCostDrivers (sub2ind([productCount productCount],randperm(productCount),1:
productCount))=rand(productCount,1);
ind = randi([1 productCount * productCount], 1, ceil(density* productCount * productCount));
activityCostDrivers (ind)=rand(1,length(ind));
length_activityCostDrivers = length (activityCostDrivers);
sum_rows_activityCostDrivers = sum (activityCostDrivers,2);
activityCostDrivers_normed = bsxfun (@rdivide, activityCostDrivers, sum_rows_activityCostDrivers);
test_sum_rows_activityCostDrivers_normed = sum (activityCostDrivers_normed, 2);
```

```
%% matrix of cost objects
costObjects = activityCostPools * activityCostDrivers_normed;

%% check (should be equal to TC)
sum_costObjects = sum (costObjects, 2);
sprintf('%10.0f',sum_costObjects);

%% pick 3 random pools and its positions from activity cost pools
d = length (activityCostPools);
x = 3;
j = randperm(d,x);
firstPool = activityCostPools (1,j(1));
secondPool = activityCostPools (1,j(2));
thirdPool = activityCostPools (1,j(3));
position_firstPool = [1, j(1)];
position_secondPool = [1, j(2)];
position_thirdPool = [1, j(3)];

%% for loop for true costing system
percentage2 = 0 + (percentage-0).*rand(1,1);
firstPool_true = firstPool + (secondPool*percentage2);
percentage3 = percentage - percentage2;
thirdPool_true = thirdPool + (secondPool*percentage3);
secondPool_true = secondPool - (secondPool*percentage);
activityCostPools_true = activityCostPools;
activityCostPools_true (1,j(1)) = firstPool_true;
activityCostPools_true (1,j(2)) = secondPool_true;
activityCostPools_true (1,j(3)) = thirdPool_true;
costObjects_true = activityCostPools_true * activityCostDrivers_normed;

Euclidean = norm (costObjects_true - costObjects);

resultsMatrix_small (jj, :) = [ii jj resourceCostPool activityCostPools costObjects costObjects_true Euclidean
firstPool_true];
sortedMatrix_small = sortrows(resultsMatrix_small,204);

end

%% part of code for 2D plot
coefficients = polyfit(sortedMatrix_small(:,204),sortedMatrix_small(:,203),1);
Y = polyval(coefficients, sortedMatrix_small(:,204));
hold on
clr = jet(11);
plot(sortedMatrix_small(:,204),Y,'Color',clr(ii,:))
percentage = percentage + 0.1;
resultsMatrix_big = [resultsMatrix_big; sortedMatrix_small];

end

hold off
str = cellstr(num2str((1:11)','Run%d'));
legend (str);
toc
```

```
%% part of code for 3D plot with interaction term
x1 = resultsMatrix_big(:,1);
x2 = resultsMatrix_big(:,204);
y = resultsMatrix_big(:,203);
X = [ones(size(x1)) x1 x2 x1.*x2];
b = regress(y,X)
scatter3(x1,x2,y,'filled')
hold on
x1fit = min(x1):1:max(x1);
x2fit = min(x2):1000:max(x2);
 [X1FIT,X2FIT] = meshgrid(x1fit,x2fit);
YFIT = b(1) + b(2)*X1FIT + b(3)*X2FIT + b(4)*X1FIT.*X2FIT;
mesh(X1FIT,X2FIT,YFIT)
xlabel('Percentage')
ylabel('Value of true ACP')
zlabel('EUCD')
view(3)

%% part of code for descriptive statistics of EUCD (column 203)
grouped = resultsMatrix_big(:,203);
[stat1,stat2,stat3,stat4,stat5,stat6,stat7] = grpstats(grouped,[],{'mean','min','max','sem','numel','std','range'})

%% part of code for descriptive statistics of ACPt (column 204)
grouped = resultsMatrix_big(:,204);
[stat1,stat2,stat3,stat4,stat5,stat6,stat7] = grpstats(grouped,[],{'mean','min','max','sem','numel','std','range'})

%% standardized coefficients: Free element, x1, x2, x1*x2, multiple linear regression with interaction term
x1 = resultsMatrix_big(:,1);
zx1 = zscore(x1);
x2 = resultsMatrix_big(:,204);
zx2 = zscore (x2);
y = resultsMatrix_big(:,203);
zy = zscore (y);
X = [ones(size(x1)) zx1 zx2 zx1.*zx2];
b = regress(zy,X)
lm = fitlm (X, zy, 'linear')
```

Code for H4 (Chapter 3)

```
%% correlation.m – H3, with 50 resources/products and 500 loops, density = 0.3

tic
%% initialization of variables
totalCosts = 1000000;
productCount = 50;
loopCount = 500;
density = 0.3;

%% big simulation
resultsMatrixEuclidean = zeros (500,1);
resultsMatrixEuclidean_big = zeros (11,500);
resultsMatrix_big = zeros (0,200);
percentage = 0;
for ii = 1:11
for jj = 1:500
    ii;
    jj;

%% matrix of resource cost pools
resourceCostPool_s = 0 + (0.5-0)*rand (1,productCount);
sum_resourceCostPool_s = sum (resourceCostPool_s);
resourceCostPool = resourceCostPool_s *(totalCosts/ sum_resourceCostPool_s);

%% check (should be equal to totalCosts)
sum_resourceCostPool = sum (resourceCostPool, 2);
sprintf('%10.0f', sum_resourceCostPool);

%% matrix of resource cost drivers with density 0.3
resourceCostDrivers =zeros(productCount);
resourceCostDrivers (sub2ind([productCount productCount],randperm(productCount),1:
productCount))=rand(productCount,1);
ind = randi([1 productCount * productCount], 1, ceil(density* productCount * productCount));
resourceCostDrivers (ind)=rand(1,length(ind));
length_resourceCostDrivers = length (resourceCostDrivers);
sum_rows_resourceCostDrivers = sum (resourceCostDrivers,2);
resourceCostDrivers_normed = bsxfun (@rdivide, resourceCostDrivers, sum_rows_resourceCostDrivers);
test_sum_rows_resourceCostDrivers_normed = sum (resourceCostDrivers_normed, 2);

%% matrix of activity cost pools
activityCostPools = resourceCostPool * resourceCostDrivers_normed;

%% check (should be equal to TC)
sum_activityCostPools = sum (activityCostPools, 2);
sprintf('%10.0f', sum_activityCostPools);

%% matrix of activity cost drivers with density 0.3
activityCostDrivers =zeros(productCount);
activityCostDrivers (sub2ind([productCount productCount],randperm(productCount),1:
productCount))=rand(productCount,1);
ind = randi([1 productCount * productCount], 1, ceil(density* productCount * productCount));
activityCostDrivers (ind)=rand(1,length(ind));
length_activityCostDrivers = length (activityCostDrivers);
sum_rows_activityCostDrivers = sum (activityCostDrivers,2);
activityCostDrivers_normed = bsxfun (@rdivide, activityCostDrivers, sum_rows_activityCostDrivers);
test_sum_rows_activityCostDrivers_normed = sum (activityCostDrivers_normed, 2);
```

```
%% matrix of cost objects
costObjects = activityCostPools * activityCostDrivers_normed;

%% check (should be equal to TC)
sum_costObjects = sum (costObjects, 2);
sprintf('%10.0f',sum_costObjects);

%% pick 2 random pools and its positions from activity cost pools
d = length (activityCostPools);
x = 2;
j = randperm(d,x);
firstPool = activityCostPools (1,j(1));
secondPool = activityCostPools (1,j(2));
position_firstPool = [1, j(1)];
position_secondPool = [1, j(2)];

%% for loop for true costing system
firstPool_true = firstPool + (secondPool*percentage);
secondPool_true = secondPool - (secondPool*percentage);
activityCostPools_true = activityCostPools;
activityCostPools_true (1,j(1)) = firstPool_true;
activityCostPools_true (1,j(2)) = secondPool_true;
costObjects_true = activityCostPools_true * activityCostDrivers_normed;

Euclidean = norm (costObjects_true - costObjects);

resultsMatrix_small (jj, :) = [ii jj resourceCostPool activityCostPools costObjects costObjects_true Euclidean
firstPool_true];
sortedMatrix_small = sortrows(resultsMatrix_small,204);

end

%% part of code for 2D plot
coefficients = polyfit(sortedMatrix_small(:,204),sortedMatrix_small(:,203),1);
Y = polyval(coefficients, sortedMatrix_small(:,204));
hold on
clr = jet(11);
plot(sortedMatrix_small(:,204),Y,'Color',clr(ii,:))
percentage = percentage + 0.1;
resultsMatrix_big = [resultsMatrix_big; sortedMatrix_small];

end

hold off
str = cellstr(num2str((1:11)','Run%d'));
legend (str);
toc
```

```
%% part of code for 3D plot with interaction term
x1 = resultsMatrix_big(:,1);
x2 = resultsMatrix_big(:,204);
y = resultsMatrix_big(:,203);
X = [ones(size(x1)) x1 x2 x1.*x2];
b = regress(y,X)
scatter3(x1,x2,y,'filled')
hold on
x1fit = min(x1):1:max(x1);
x2fit = min(x2):1000:max(x2);
 [X1FIT,X2FIT] = meshgrid(x1fit,x2fit);
YFIT = b(1) + b(2)*X1FIT + b(3)*X2FIT + b(4)*X1FIT.*X2FIT;
mesh(X1FIT,X2FIT,YFIT)
xlabel('Percentage')
ylabel('Value of true ACP')
zlabel('EUCD')
view(3)

%% part of code for descriptive statistics of EUCD (column 203)
grouped = resultsMatrix_big(:,203);
[stat1,stat2,stat3,stat4,stat5,stat6,stat7] = grpstats(grouped,[],{'mean','min','max','sem','numel','std','range'})

%% part of code for descriptive statistics of ACPt (column 204)
grouped = resultsMatrix_big(:,204);
[stat1,stat2,stat3,stat4,stat5,stat6,stat7] = grpstats(grouped,[],{'mean','min','max','sem','numel','std','range'})

%% standardized coefficients: Free element, x1, x2, x1*x2, multiple linear regression with interaction term
x1 = resultsMatrix_big(:,1);
zx1 = zscore(x1);
x2 = resultsMatrix_big(:,204);
zx2 = zscore (x2);
y = resultsMatrix_big(:,203);
zy = zscore (y);
X = [ones(size(x1)) zx1 zx2 zx1.*zx2];
b = regress(zy,X)
lm = fitlm (X, zy, 'linear')
```

Code for H1, H2 and H3 (Chapter 4)

```
%% calculating euclidean distance with gbm average function for day/month/year

tic

for i = [96, 2016, 24192]
    for j = 1:20

%% initialization of variables
productCount = 5;
[pRCP1, pACP1] = gbmf_avg (40,0,0.025,i);
%[pRCP1, pACP1] = gbmf_snapshot (40,0,0.025,i);
%[pRCP1, pACP1] = sinef_priceAvg (24192, i, 0); % price sine function avg (1. either daily peaks with 96, or yearly with 24192, 3. volatility no 0, low 1, high 3)
%[pRCP1, pACP1] = sinef_priceSs (24192, i, 0); % price sine function snapshots (1. either daily peaks with 96, or yearly with 24192, 3. volatility no 0, low 1, high 3))

pRCP2 (1:24192, 1)= 40;
pRCP3 (1:24192, 1)= 40;
pRCP4 (1:24192, 1)= 40;
pRCP5 (1:24192, 1)= 40;

pACP2 (1:24192, 1)= 40;
pACP3 (1:24192, 1)= 40;
pACP4 (1:24192, 1)= 40;
pACP5 (1:24192, 1)= 40;

%[qRCP1, qACP1] = sinef_quantityAvg (24192, 96); % quantity sine function (1. either daily peaks with 96, or yearly 24192, 2. how often the consumption is measured: daily 96, monthly 2016, yearly 24192)

qRCP1 (1:24192, 1)= 100000/24192;
qRCP2 (1:24192, 1)= 100000/24192;
qRCP3 (1:24192, 1)= 100000/24192;
qRCP4 (1:24192, 1)= 100000/24192;
qRCP5 (1:24192, 1)= 100000/24192;

qACP1 (1:24192, 1)= 100000/24192;
qACP2 (1:24192, 1)= 100000/24192;
qACP3 (1:24192, 1)= 100000/24192;
qACP4 (1:24192, 1)= 100000/24192;
qACP5 (1:24192, 1)= 100000/24192;

sp = density (0.7);
costObjects_true = zeros (24192,5);
costObjects = zeros (24192,5);
Euclidean = zeros (24192, 1);
for ii = 1:24192
for jj = 1:5
   resourceCostPool = [pRCP1(ii)*qRCP1(ii) pRCP2(ii)*qRCP2(ii) pRCP3(ii)*qRCP3(ii) pRCP4(ii)*qRCP4(ii) pRCP5(ii)*qRCP5(ii)];
   RCP (ii, :) = [pRCP1(ii)*qRCP1(ii) pRCP2(ii)*qRCP2(ii) pRCP3(ii)*qRCP3(ii) pRCP4(ii)*qRCP4(ii) pRCP5(ii)*qRCP5(ii)];
   activityCostPool = [pACP1(ii)*qACP1(ii) pACP2(ii)*qACP2(ii) pACP3(ii)*qACP3(ii) pACP4(ii)*qACP4(ii) pACP5(ii)*qACP5(ii)];
   ACP (ii, :) = [pACP1(ii)*qACP1(ii) pACP2(ii)*qACP2(ii) pACP3(ii)*qACP3(ii) pACP4(ii)*qACP4(ii) pACP5(ii)*qACP5(ii)];
   costObjects_true (ii, :)= resourceCostPool * sp;
   costObjects (ii, :)= activityCostPool * sp;
```

```
    Euclidean(ii, :)  = norm (costObjects_true(ii,:) - costObjects(ii,:));
end
end

% figure;
% hold on;
% plot(Euclidean, 'blue');
% hold off;
% title('Euclidean distance plot');
% xlabel('Date');
% ylabel('Euclidean distance');
%
% figure;
% hold on;
% plot(pRCP1, 'blue');
% plot(pACP1, 'red');
% hold off;
% title('RCP true and average');
% xlabel('Date');
% ylabel('RCP');
% legend('true', 'average');
%
% figure;
% hold on;
% plot(qRCP1, 'blue');
% plot(qACP1, 'red');
% hold off;

eucd_runMean = mean(Euclidean);
eucd_column (j,:) = [eucd_runMean];
numberOfElements = sum(Euclidean >0.1);
matMeasure = (100-numberOfElements/24192*100);
matMeasure_column (j,:) = [matMeasure];

      end

eucd_all = mean(eucd_column)
matMeasure_all = mean(matMeasure_column)

sortedEucd_column = sortrows(eucd_column);
% w = (1:j(length(j)))';
% coefficients = polyfit(w,sortedEucd_column,1);
% Y = polyval(coefficients, sortedEucd_column);
% hold on
% plot(sortedEucd_column,Y)
% title('Euclidean distance plot');
% legend('daily', 'monthly', 'yearly');

%part of code for descriptive statistics of EUCD
grouped = sortedEucd_column;
[stat1,stat2,stat3,stat4,stat5,stat6,stat7] = grpstats(grouped,[],{'mean','min','max','sem','numel','std','range'});
cv = stat6/stat1;
end

% hold off

toc
```

Code for H4 (Chapter 4)

```
%% calculating Euclidean distance with gbm average function for day/month/year

tic

for i = [96, 2016, 24192]
    for j = 1:20

%% initialization of variables
productCount = 5;
[pRCP1, pACP1] = gbmf_avg (40,0,0.025,i);
%[pRCP1, pACP1] = gbmf_snapshot (40,0,0.025,i);
%[pRCP1, pACP1] = sinef_priceAvg (24192, i, 0); % price sine function avg (1. either daily peaks with 96, or yearly with 24192, 3. volatility no 0, low 1, high 3)
%[pRCP1, pACP1] = sinef_priceSs (24192, i, 0); % price sine function snapshots (1. either daily peaks with 96, or yearly with 24192, 3. volatility no 0, low 1, high 3))

pRCP2 (1:24192, 1)= 40;
pRCP3 (1:24192, 1)= 40;
pRCP4 (1:24192, 1)= 40;
pRCP5 (1:24192, 1)= 40;

pACP2 (1:24192, 1)= 40;
pACP3 (1:24192, 1)= 40;
pACP4 (1:24192, 1)= 40;
pACP5 (1:24192, 1)= 40;

[qRCP1, qACP1] = sinef_quantityAvg (24192, 96); % quantity sine function (1. either daily peaks with 96, or yearly 24192, 2. how often the consumption is measured: daily 96, monthly 2016, yearly 24192)

%qRCP1 (1:24192, 1)= 100000/24192;
qRCP2 (1:24192, 1)= 100000/24192;
qRCP3 (1:24192, 1)= 100000/24192;
qRCP4 (1:24192, 1)= 100000/24192;
qRCP5 (1:24192, 1)= 100000/24192;

%qACP1 (1:24192, 1)= 100000/24192;
qACP2 (1:24192, 1)= 100000/24192;
qACP3 (1:24192, 1)= 100000/24192;
qACP4 (1:24192, 1)= 100000/24192;
qACP5 (1:24192, 1)= 100000/24192;

sp = density (0.7);
costObjects_true = zeros (24192,5);
costObjects = zeros (24192,5);
Euclidean = zeros (24192, 1);
for ii = 1:24192
for jj = 1:5
  resourceCostPool = [pRCP1(ii)*qRCP1(ii) pRCP2(ii)*qRCP2(ii) pRCP3(ii)*qRCP3(ii) pRCP4(ii)*qRCP4(ii) pRCP5(ii)*qRCP5(ii)];
  RCP (ii, :) = [pRCP1(ii)*qRCP1(ii) pRCP2(ii)*qRCP2(ii) pRCP3(ii)*qRCP3(ii) pRCP4(ii)*qRCP4(ii) pRCP5(ii)*qRCP5(ii)];
  activityCostPool = [pACP1(ii)*qACP1(ii) pACP2(ii)*qACP2(ii) pACP3(ii)*qACP3(ii) pACP4(ii)*qACP4(ii) pACP5(ii)*qACP5(ii)];
  ACP (ii, :) = [pACP1(ii)*qACP1(ii) pACP2(ii)*qACP2(ii) pACP3(ii)*qACP3(ii) pACP4(ii)*qACP4(ii) pACP5(ii)*qACP5(ii)];
  costObjects_true (ii, :)= resourceCostPool * sp;
  costObjects (ii, :)= activityCostPool * sp;
```

```
    Euclidean(ii, :)  = norm (costObjects_true(ii,:) - costObjects(ii,:));
end
end

% figure;
% hold on;
% plot(Euclidean, 'blue');
% hold off;
% title('Euclidean distance plot');
% xlabel('Date');
% ylabel('Euclidean distance');
%
% figure;
% hold on;
% plot(pRCP1, 'blue');
% plot(pACP1, 'red');
% hold off;
% title('RCP true and average');
% xlabel('Date');
% ylabel('RCP');
% legend('true', 'average');
%
% figure;
% hold on;
% plot(qRCP1, 'blue');
% plot(qACP1, 'red');
% hold off;

eucd_runMean = mean(Euclidean);
eucd_column (j,:) = [eucd_runMean];
numberOfElements = sum(Euclidean >0.1);
matMeasure = (100-numberOfElements/24192*100);
matMeasure_column (j,:) = [matMeasure];

       end

eucd_all = mean(eucd_column)
matMeasure_all = mean(matMeasure_column)

sortedEucd_column = sortrows(eucd_column);
% w = (1:j(length(j)))';
% coefficients = polyfit(w,sortedEucd_column,1);
% Y = polyval(coefficients, sortedEucd_column);
% hold on
% plot(sortedEucd_column,Y)
% title('Euclidean distance plot');
% legend('daily', 'monthly', 'yearly');

%part of code for descriptive statistics of EUCD
grouped = sortedEucd_column;
[stat1,stat2,stat3,stat4,stat5,stat6,stat7] = grpstats(grouped,[],{'mean','min','max','sem','numel','std','range'});
cv = stat6/stat1;
end

% hold off

toc
```

Code: Functions (Chapter 4)

```
% gbmf_avg

function [S,u] = gbmf_avg (s0, mu, sig, ii)

n=24192;
dt=1/n;
S(1)=s0;
t(1)=0;
for j=1:1:n-1       % for loop for making gbm on a yearly basis
S(j+1)=S(j)*exp((mu-sig^2/2)*dt+sig*sqrt(dt)*randn );
t(j+1)=j;
end;
b = arrayfun(@(i) mean(S(i:i+ii-1)),1:ii:length(S)-ii+1)';
u = repelem(b,ii);
S = S';
% hold on;
% plot(t,S);
% plot(t,u);
% xlabel('day')
% ylabel('price')
% hold off;
% Euclidean distance: d = sum((S-u').^2).^0.5;

% gbmf_snapshot

function [S,u] = gbmf_snapshot (s0, mu, sig, ii)

n=24192;
dt=1/n;
S(1)=s0;
t(1)=0;
for j=1:1:n-1
   S(j+1)=S(j)*exp((mu-sig^2/2)*dt+sig*sqrt(dt)*randn ); % +sin(j*pi); (for seasonaltiy)
   t(j+1)=j;
end;
b = S(1:ii:end);
u = repelem(b,ii);
S = S';
u = u';
% hold on;
% plot(t,S);
% plot(t,u);
% xlabel('day')
% ylabel('price')
% hold off;
% d = sum((S-u).^2).^0.5


% density

function resourceCostDrivers_normed = density (s)

productCount = 5;
resourceCostDrivers =zeros(productCount);
resourceCostDrivers (sub2ind([productCount productCount],randperm(productCount),1:
productCount))=rand(productCount,1);
ind = randi([1 productCount * productCount], 1, ceil(s* productCount * productCount));
```

```
resourceCostDrivers (ind)=rand(1,length(ind));
length_resourceCostDrivers = length (resourceCostDrivers);
sum_rows_resourceCostDrivers = sum (resourceCostDrivers,2);
resourceCostDrivers_normed = bsxfun (@rdivide, resourceCostDrivers, sum_rows_resourceCostDrivers);
test_sum_rows_resourceCostDrivers_normed = sum (resourceCostDrivers_normed, 2);

% sinef_quantityAvg

% sine function daily consumption peak around noon, around 4kWh, sum =
% 96768
% generate discrete sine wave on the interval t and sums up values in the array x
% jj 96, 24192 (daily peaks 96, yearly peaks 24192)
% ss snapshots 96, 2016, 24192

function [u,u_avg] = sinef_quantityAvg (jj)

t  = [ 0 : 1 : 24192];
x = (2)*sin(2*pi*t/jj-pi/2)+(4);
% figure(1);
% stem(t,x,'r');
x_sum = sum(x);
sprintf('%10.0f', x_sum);
% check peaks: [pks,locs] = findpeaks(x)

ii=1;
d=x;
d(24193)=[]; % deleting the final element of array, because there are 24193 observations and only 24192 15mins
intervals in a year
u = repelem(d',ii); % adding elements for every month until we have the data for a year
c = [0:1:24191];
% hold on;
% stem(t,x,'r');
% plot(c,u);
% hold off;
u_sum = sum(u);
sprintf('%10.0f', u_sum);

b = arrayfun(@(i) mean(u(i:i+jj-1)),1:jj:length(u)-jj+1)';
u_avg = repelem(b,jj);
% hold on
% plot(c,u_avg);
% plot(c,u);
% hold off

% sinef_priceAvg

% sine function daily consumption peak around noon, around 4kWh, sum =
% 96768
% generate discrete sine wave on the interval t and sums up values in the array x
% jj 96, 24192 (daily peaks 96, yearly peaks 24192)
% ss snapshots 96, 2016, 24192

function [price_avg,u2] = sinef_priceAvg (jj, ss)

% combination of gbm and seasonality
% generate discrete sine wave on the interval t and sums up values in the array x
m  = [ 0 : 1 : 24192 ];
x = (3)*sin(2*pi*m/jj-pi/2)+(0);
%figure(1);
% stem(t,x,'r');
```

```
x_sum = sum(x);
sprintf('%10.0f', x_sum);

ii=1;
d=x;
d(24193)=[]; % deleting the final element of array, because there are 24193 observations and only 24192 15mins
intervals in a year
u = repelem(d',ii); % adding elements for every month until we have the data for a year
c = [0:1:24191];
% hold on;
% stem(m,x,'r');
% plot(c,u);
% hold off;
u_sum = sum(u);
sprintf('%10.0f', u_sum);

s0=40;
mu=0;
sig=0.02;
n=252*24*4;
h=252*24*4;
dt=1/h;
S(1)=s0;
t(1)=0;
for j=1:1:(n-1) % The following value of the stock is evaluated
S(j+1)=S(j)*exp((mu-sig^2/2)*dt+sig*sqrt(dt)*randn);           % +sin(j*pi); (for seasonaltiy)
t(j+1)=j;
end;
price_avg = S+u';
% plot(t,S+u');
% hold on;
% xlabel('day')
% ylabel('price')
% hold off;

b = arrayfun(@(i) mean(price_avg(i:i+ss-1)),1:ss:length(price_avg)-ss+1)';
u2 = repelem(b,ss);
hold on;
plot(t,price_avg);
plot(t,u2);
xlabel('day')
ylabel('price')
hold off;

% sinef_priceSs

% sine function daily consumption peak around noon, around 4kWh, sum =
% 96768
% generate discrete sine wave on the interval t and sums up values in the array x
% jj 96, 24192 (daily peaks 96, yearly peaks 24192)
% ss snapshots 96, 2016, 24192

function [price_avg,u2] = sinef_priceSs (jj, ss)

% combination of gbm and seasonality
% generate discrete sine wave on the interval t and sums up values in the array x
m  = [ 0 : 1 : 24192 ];
x = (3)*sin(2*pi*m/jj-pi/2)+(0);
%figure(1);
% stem(t,x,'r');
```

```
x_sum = sum(x);
sprintf('%10.0f', x_sum);

ii=1;
d=x;
d(24193)=[]; % deleting the final element of array, because there are 24193 observations and only 24192 15mins
intervals in a year
u = repelem(d',ii); % adding elements for every month until we have the data for a year
c = [0:1:24191];
% hold on;
% stem(m,x,'r');
% plot(c,u);
% hold off;
u_sum = sum(u);
sprintf('%10.0f', u_sum);

s0=40;
mu=0;
sig=0.025;
n=252*24*4;
h=252*24*4;
dt=1/h;
S(1)=s0;
t(1)=0;
for j=1:1:(n-1) % The following value of the stock is evaluated
S(j+1)=S(j)*exp((mu-sig^2/2)*dt+sig*sqrt(dt)*randn);          % +sin(j*pi); (for seasonaltiy)
t(j+1)=j;
end;
price_avg = S+u';
% plot(t,S+u');
% hold on;
% xlabel('day')
% ylabel('price')
% hold off;

b = price_avg(1:jj:end);
u2 = repelem(b,jj);
% hold on;
% plot(t,price_avg);
% plot(t,u2);
% xlabel('day')
% ylabel('price')
% hold off;
```