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Identifying and improving factors causing peak energy consumption of reefers at container terminals

A quantitative study towards root-cause factors and development of improvements thereof

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TUDelft

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by

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Summary

Reefers are refrigerated containers commonly used for transporting perishable goods such as meat, fish, vegetables, and fruit. Perishable goods require that the temperature within a reefer is controlled throughout transport. The reefer trade shows a significant growth of 3,1% annually from 2012 to 2017 (Dekker, 2014). Growth in reefer usage can be appointed to the containerization trend of cargo transport and the fact that consumers demand availability of seasonal products throughout the year. Together with the growth in reefer usage, the energy consumption of reefers at container terminals grows significantly. Reefers are responsible for the consumption of 40% the total energy consumption of the container terminal (Wilmsmeier et al., 2014). The energy is consumed during the temporary storage of reefers when the reefers are plugged-in to the electricity on shore. However, when reefers are connected to the electricity grid, peaks in energy consumption lead to high costs (de Heij, 2015). The container terminal must purchase the required energy from an energy utility company using a demand-based fee. A specific capacity is reserved for the container terminal, exceeding the reserved capacity will have a significant impact on the total energy costs (ABB, 2017b). Therefore, reducing peak energy consumptions of reefers at container terminals will reduce energy costs and reduce the carbon footprint of reefer transport.

Previous research has taken highly technical views on the problem as mentioned above. By researching refrigeration and insulation techniques (Schmidt et al., 2015) the operation of a reefer has become more efficient, but innovations in this area seem to reduce. However, there are promising results which focus on control systems of reefers. Lukasse et al. (2013); Barzin et al. (2015, 2016) have shown that advanced control systems can reduce the energy consumption of individual reefers and refrigerators significantly. More recent studies focus on the broader picture of multiple reefers connected simultaneously at the container terminal (van Duin et al., 2016). Filina and Filin (2008) have taken a more process-based view on the problem by investigating factors that lead to power-out moments within the supply chain. In the research of Filina and Filin it is assumed that power-out moments lead to an increased energy consumption. Meanwhile, the root-cause of peak energy consumptions remains un-researched leading to the research question of this study. *How can the peak energy consumption of reefers at container terminals be reduced after identification and improvement of the root-cause factors?* By applying the Six-sigma methodology a process based view is taken, and root-cause factors are identified. The steps of Define, Measure, Analyze, and Improve are followed in this study.

After defining the process and the boundaries of the research, all possible root-cause factors are brainstormed with experts from the field (ABB, 2017a; ECT Delta Terminal, 2017). Using 60% of the dataset supplied by ABB, a sequential multiple regression analysis, with backwards feature selection is performed. Using this method the influence of these factors on the total energy consumption is analysed. A model is found in which the number of arriving reefers, dwell time, plug-in temperature, insulation value, and cargo type are found to be significant (R^2=0,829; P<0,001). The model is cross-validated with the remaining 40% of the dataset and is found to be consistent. The developed model shows that the number of arriving reefers explains 76,6 % of the variance, dwell time 4,6%, cargo type 1,1%, thermal insulation 0,3% and the delta plug-in temperature 0,4%.

The final step is to develop an improvement to one of the previously identified root cause factors. It is argued that improvement of the dwell time will produce the most yield. Improving upon the number of arriving reefers is impossible and improving using the cargo type, thermal insulation, and delta plug-in temperature would provide too little yield. It is suggested that long stay reefers can only be targeted if the revenue of the container terminal does not reduce as a result of the implementation of the improvement measure. Therefore two Revenue Management schemes are proposed. Firstly a complex dynamic pricing scheme is proposed. Such a scheme could increase the revenue of the container terminal. However, a dynamic pricing scheme requires (i) an initial fixed capacity (ii) perfect knowledge of the demand (Bitran and Caldentey, 2003), and (iii) price sensitivity of the demand (Elmaghraby and Keskinocak, 2003). A peak pricing scheme is less fine-tuned as it does not require a perfect knowledge of the demand, merely knowledge of when peaks occur. Additionally, price sensitivity is not a requirement when using peak pricing as the peak price is used as an incentive for fast collection of the reefer. It is not attempted to stimulate the customer to keep the reefer at the terminal during off-peak moments. When considering the requirement for perfect knowledge of the demand, it is attempted to predict the energy consumption. With only the data known to the terminal, before the arrival of the ship, the energy consumption is predicted. This enables the model to be applied in the work field. The cargo type, thermal insulation, and delta plug-in temperature are unavailable prior to the arrival of the ship and therefore cannot be used to predict the energy consumption. Using a neural network, it is attempted to predict the dwell time with the purpose of using this in the energy consumption model. The neural network (N=23968) has shown that the dwell time cannot be predicted with the data available prior to the arrival of the ship as it has a relative error 93,9%. Hence, 93,9% of the predictions are inaccurate. The outcome of the neural network reduces the accuracy of the energy consumption model. Additionally, after conversations with Dutch importers of meat, fish, vegetables, and fruit it is shown that the demand is not price-sensitive. Therefore it is advised to apply a peak pricing scheme to provide an incentive to reduce the dwell time. It is calculated that an effective implementation of a peak pricing scheme would provide a 5,5% to 11,6% reduction in energy consumption. This reduction is equal to the consumption of 230 to 480 two-person households. It is estimated that the energy reduction is achieved without reducing the revenue of the container terminal.

Contents

List of Figures

List of Tables

1 Introduction

1.1. Background

With the annual increase of 1,2% of people (from 2010 to 2016 (UNFPA, 2016)) and welfare across the globe, ports become increasingly important for the trade and supply of goods. The increase in population results in a current world population of 7,4 billion, this puts a major strain on the global food availability. The increase in welfare results in a continuous demand for food, despite the current season. To ensure the availability of seasonal food products, or exotic fruits, throughout the year a specialised refrigerated container is used. The usage of refrigerated containers (or reefers) grows together with the world population and global container usage. The reefer trade cumulative annual growth rate is 3.1% from 2012 - 2017. This continuous growth of reefers is primarily driven by the increase in world population. Also, the fact that people want to eat healthier, and weather influences play a role in the increase of global reefer usage (Dekker, 2014). According to Jolly et al. the global cold food supply chain is a critical vain in the global food supply as it accounts for 31% of the global food supply (Jolly et al., 2000). The increase of global trade using containers and reefers logically leads to a net increase in energy consumption. Not only the energy consumption of deep-sea transport increases but also the energy consumption of container terminal increases. Within the container terminals, reefers account for a significant portion of the total energy consumption. Wilmsmeier et al. (2014) found that reefers consumed as much as 40% of the total energy consumption of a container terminal. The other 60% is assigned to ship-to-shore cranes (40%), terminal lightning (12%), and administration and workshops (8%) (Wilmsmeier et al., 2014). The large proportion of electrical energy usage of reefers at container terminals shows the importance of a smart and active energy reduction system.

The increase of global container usage leads to improvements in the efficiency of the global supply chain as increasingly larger ships are being built and used. Ships, such as the MSC Maya, have become large enough to transport 19.224 TEU. This increase in ship size, together with seasonality effects, lead to high peak energy consumption at container terminals. The peak energy seasonality effects are increased by the outside temperature combined with the harvest season of fruit. Also, with the use of larger ships peaks increase in amplitude due to the high volume of simultaneous reefer arrivals. The operational nature of container terminals with large simultaneous reefer arrivals presents significant costs for the container terminal. The container terminal is required to unload, and temporarily store the incoming reefers before they can be transported further. During the temporary storage of reefers, the core temperature must remain within the set bandwidth. Thus the reefer requires continuous electricity when stacked. The container terminal must purchase the required energy at an energy utility company in advance. Often container terminals purchase electricity using a demand-based fee; this is billing based on a specific capacity which is reserved by the utility company for the terminal. Any (temporary) peak above the reserved capacity will have a significant impact on the total energy costs (ABB, 2017b). These costs are high as the energy utility company must ensure the continuous supply of electricity. Therefore, they must supply the exact amount of required energy across their entire network. When sudden peaks occur, the terminal must pay an increased electrical charge applied by the utility company. The exact height of this additional charge varies with each contract and supplier. The measured maximum peak consumption is then billed to the terminal operator for the next 12 months (de Heij, 2015). Currently the container-terminal bills the additional costs to the shipping company. Via the shipping company and importer, the consumer eventually pays for the high electricity costs (ECT Delta terminal, 2017). By billing the higher electricity consumption costs to the customers, the terminal does not notice the added costs. However, in the current sustainable trend companies are always looking to reduce their electricity consumption. Also, if the electricity costs can decrease the operation also can decrease, this leads to a competitive transhipment price for reefers.

In previous research, the peak energy consumption of reefers has been reduced significantly. After an initial simulation of reefer energy simulation, the reefers are simply switched on and off with 15 and 5-minute intervals and by setting a peak power limit. This study has shown a peak energy consumption reduction of as much as 40% (€600.000 - €700.000) and 80% (€1.000.000) annually. Many other studies research the possibilities of reducing the energy consumption of refrigerated containers by taking a technological view on reefers. Meanwhile, no proper research has been performed towards the factors existing at the core of the problem. We know that the peaks exist, and are working hard (and succeeding) towards reducing the peaks. However, why the peaks exist, in this frequency and this form, remains un-researched.

1.2. System description

In this section, the system will be described to get an idea of the size of the problem. The system described in this research is confined to the port of Rotterdam, although it is known that the problem is an issue worldwide.

The port of Rotterdam is the most extensive port of Europe and is in the top 10 of largest ports globally. The port of Rotterdam shipped a total of 461.2 million Ton of cargo in the year 2016. Apart from dry bulk, wet bulk, and break bulk the port of Rotterdam had a throughput of 7,3 million containers in 2016, this is shown in Figures 1.1. 5.9 million of these containers are loaded hence 1.4 million containers are empty. Of the 5.9 million loaded containers a selection is reefer containers are plugged in one of the 18.500 reefer connections divided across the terminals. Each container is plugged in over a period of 3 - 4 days on average. (N.V. Havenbedrijf, 2017) The exact percentage of reefers, compared to the total containers, in the port of Rotterdam is unclear. However, it is estimated that globally the market share of reefers was 16,8% in 2014 (Dekker, 2014).

The 18.500 reefer connections are geographically dispersed across the port. The majority of the electrical connections is operated by the six largest deep-sea container terminals; these are the following. (1) Rotterdam World Gateway, (2) APM Terminals Maasvlakte II, (3) Euromax Terminal Rotterdam, (4) APM terminals, (5) ECT Delta Terminal, and (6) Uniport Multipurpose Terminals. The exact distribution of reefer connections between the container-terminals as mentioned earlier are described below in Table 1.1.

Table 1.1 shows that multiple container terminals have many reefer plugs, indicating that it is likely that

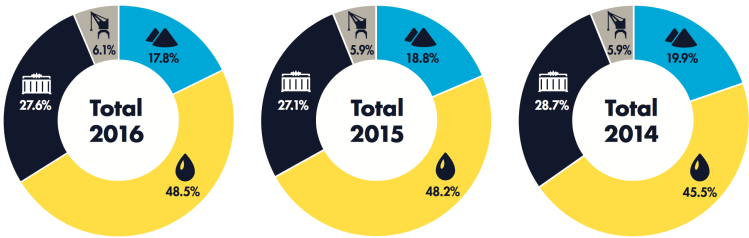


Figure 1.1: Division of cargo in the Port of Rotterdam in 2016 (Port of Rotterdam, 2017)

Table 1.1: Reefer plug distribution (N.V. Havenbedrijf, 2017)

Container terminal	Reefer plugs
Rotterdam world Gateway	1.700
APM Terminals Maasvlakte II	3.600
Euromax Terminal Rotterdam	1.776
APM terminals	2.250
ECT Delta Terminal	3.250
Uniport Multipurpose Terminals	1.648
Other	4.276
Total	**18.500**

numerous container terminals encounter similar high peak energy consumption. Apart from the primary container terminals, there are multiple container depots which also handle and store reefers. However, these facilities have much fewer reefer plugs (10-120) and thus are assumed to experience less peak energy consumption. The same argument is used for the perishable goods facilities. Perishable goods facilities often offer value-adding services (i.e. by (re)packaging the refrigerated cargo), cooled storage of cargo and border inspections. These facilities also handle reefers in lower quantities and using different methods, as it is their core business. (Kloosterboer, 2017)

1.3. Reefer supply chain

The supply chain of refrigerated products using a reefer is a cold chain using multi-modal transport. In this supply chain, the products are refrigerated from the point that it leaves the production plant to the point that it arrives at the final destination. The cold chain is used for perishable goods. These goods are characterised by high sensitivity to their environment. An example of these goods is exotic fruits, meat, fish, and pharmaceutical products. If these products are transported incorrect, the value of the cargo can be reduced, or possibly even vanish completely. Therefore, it is essential that the entire supply chain is organised properly with power supply.

The supply chain of reefers is as follows: At the production plant, the cargo is pre-cooled to the required transport temperature, guaranteeing the product quality. In the production plant, the reefer is packed to ensure airflow around the product as best as possible. From the production plant, the reefers are transported (by truck/train/barge) to a harbour, where reefers are loaded off the truck/train/barge, temporarily stacked until possible to load onto the deep-sea cargo ship. During the dwell time, the reefers are connected to the power net of the container terminal. The deep-sea ship then departs for another port where the reefer is unloaded and temporarily stacked (and plugged in) before it can be loaded onto another truck/train/barge for transport to the distribution centre. From here the cargo is distributed further. During the complete transport cycle, the reefers receive the required power from the respective vehicle with which it is transported. This entire process is shown in Figure 1.2. (Hamburg Sud, 2016) However, in practice the fruits and vegetables from Latin America are often not pre-cooled at the production plant, this results in an increase of reefer power consumption at the departing port as the temperature of the cargo must be brought down. (Groente en Fruithuis, 2017)

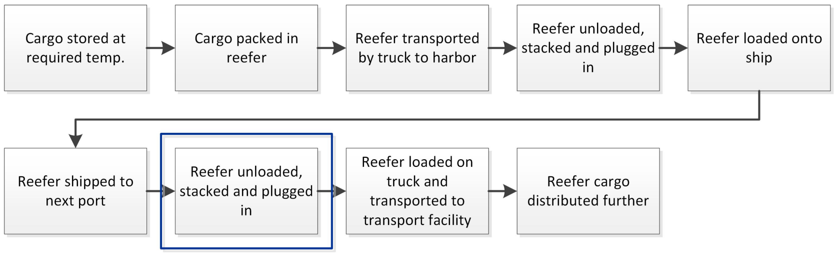


Figure 1.2: Cold chain of reefer transport

When the reefers are disconnected on the arrived ship (1), they are transported to the shore (2) using the previously mentioned ship-to-shore (quay) cranes and loaded onto automated guided vehicles (AGV's). Next, an automated stacking crane (ASC) picks up the reefer from the AGV (3) and the reefers are transported to reefer stacks (4) where the reefers can be stacked (5). Before stacking the reefer, it is possible that customs select the reefer for a random check. Once the reefers are stacked, it must be plugged in manually again. During the power-out phase, the temperature of the reefer cannot be controlled and subsequently the temperature will rise. Thus after the reefers are plugged-in, the reefer will control the temperature automatically (6). After a certain period, the reefers are unplugged again (7) and loaded unto the next modality (8a and 8b) from which they are transported further (9a and 9b) (Hamburg Sud, 2016). This sub-process is of interest for this research and is shown in Figure 1.3. It is during the 6th step of the process illustrated in Figure 1.3 that the peak energy consumption of reefers occurs.

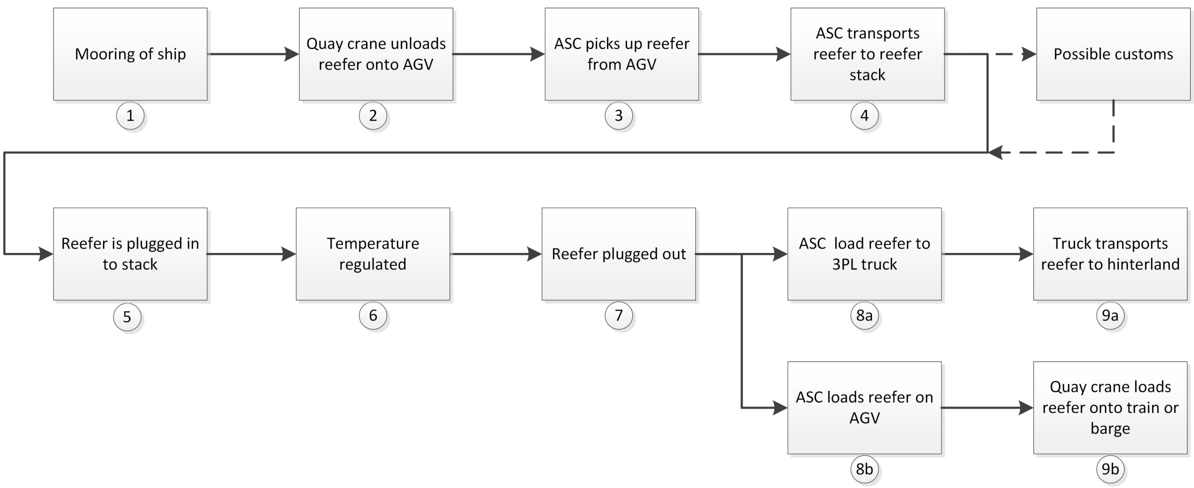


Figure 1.3: Sub-process of interest for this research

1.4. Research design

After the background introduction and system description, this section will describe the research design. After the problem statement the research objective is formulated. The research questions follow directly from the research objective, after which the project scope and relevance of this research are discussed.

1.4.1. Problem statement

As discussed above, the energy consumption of reefers at container terminals are a large portion of the total costs of container terminals (40%). Also, current trends require companies to reduce its carbon footprint, not only due to public scrutiny but also due to international political pressure from governments. I.e. the international treaty of Paris of 2015 on climate change states that global warming cannot exceed 1,5°C above pre-industrial levels. Thus additional measures are required to stop global warming.

Previous research has taken a highly technical view on the problem, often by simulating the peak energy consumption and combining these with new methods of control. Previous research is also focused on the improving of refrigerating efficiency. Although these approaches are a logical steps, when research aims to reduce energy consumption and peak energy consumption, these approaches can also be considered to be symptom controlling. However, up to date, no research has been found that attempts to explain and break-down the energy consumption into the causal factors. Hence the underlying causal factors of peak energy consumption remains unclear. In this research it will be attempted to break down the energy consumption into multiple contributing factors. Such a breakdown allows for improvements upon the root causes; the solutions are then aimed at reducing the peak energy consumption. Firstly, the research is focused on analysing the energy consumption. Secondly, if the causal factors of the total consumption are known, then peak energy consumption also can be explained by the identified factors. Hence, the peaks can be reduced by improving upon these factors.

Therefore the problem is stated as the following:

> *The power consumption of reefers in 2014 shows multiple peaks of well over 100.000 kWh, while the average power consumption is 31.000 kWh, resulting in high electricity costs for the terminal operator. Meanwhile, the underlying causal factors, to (peak)energy consumption, remain unclear.*

1.4.2. Research objective

With any topic, there is a risk that the research will be too broadly defined and that research will be performed less rigorous. Therefore, a research objective is defined to steer the research in the right direction. The research objective follows from the problem statement as mentioned in section 1.4.1. The main research objective of this research is:

> *To decrease the peak energy consumption of reefer containers at container terminals by identifying and improving the root-cause factors leading to high power consumption peaks*

In the research objective the "root-cause" refers to the deeper underlying cause that can be considered to be at the origin of the problem. The objective can be further sub-divided into sub-goals to achieve the main research objective. These sub-goals are derived from the standard DMAIC Six-sigma approach (Eckes, 2001). DMAIC stands for Define, Measure, Analyze, Improve, and Control. However, determining the market possibilities of the improvement is the last step as the control phase is not possible during this research. In short, the sub-goals are described below:

1. Define the problem, objectives and benefits.
   To define clear boundaries of what is required and expected after improvement of the process, defining the actors involved, and their needs and requirements.
2. Measure key process characteristics
   To determine what customers want and calculate the current process capabilities.
3. Analyze collected data
   To provide insights into the power consumption of reefers by analysing the collected data.
4. Suggest improvements to reefers
   Based on insights provided by the previously performed analysis improvements to the identified root-cause factors are suggested.
5. Market possibilities
   To perform a market analysis and give recommendations regarding market possibilities and strategies.

Following these sub-goals will result in the completing the research objective. The research objective and sub-goals are translated into research questions and sub-questions in the following section 1.4.3.

1.4.3. Research questions

The research questions addressed in this research follow from the research objective mentioned in section 1.4.2. The research question addressed in this research is as follows:

> *How can the peak energy consumption of reefers at container terminals be reduced after identification and improvement of the root-cause factors?*

Multiple sub-questions must be answered to answer this main research question. The first subquestion will help in the identification of the root-cause of the total energy consumption. The identification of the root-cause factors lets us explain the total energy consumption. Hence, with identifying root cause factors the peak energy consumption also can be explained. After this, the second sub-question shows the magnitude and direction of the factors. To answer the third sub-question cross-validation is used to verify that the factors identified in sub-question 1 are present in different situations. Next, a solution is researched to lift the constraint causing the factor. The market potential of the proposed solution is determined by answering the 5th sub-question. Finally, the application of the Six-sigma methodology in this research is reviewed.

The sub-questions are:

1. What factors can be considered to be the root-cause of energy consumption?
2. How does the root-cause effect the energy consumption?
3. Can the found root-cause factors be used to predict the energy consumption?
4. What are possible improvements on the root-cause that will improve peak energy consumption?
5. What is the market potential for the possible improvements?
6. Is Six-sigma suitable to be applied in a broader context?

Answering the research-questions mentioned above will structure the research towards finding a suitable solution for the peak energy consumption.

1.4.4. Project scope

A cause of failure of many projects is an under-defined project scope. An under-defined scope may lead to research which is too broad to be meaningful and value adding. Therefore, in this section, the project scope will be defined. As Table 1.2 shows, the focus of the project scope will be on the on-shore process of reefers in the port of Rotterdam. This process will be analysed, and the peak stimulating factors identified and validated. After which, a solution is generated and validated. The scope of this research is not on the processes of getting the reefer onshore and towards the hinterland, but on what happens between the two events. Also, a cost reduction calculation will not be made as this would be too speculative, an estimation of the energy reduction of the proposed solution will be performed.

Table 1.2: Project scope

In	Out
On-shore reefer process	Foreign ports
Import	Export
Process analysis	Small container terminals
Factor analysis in energy consumption	Hinterland transportation
Factor validation	Ship-to-shore transport
Solution generation	
Market-potential validation of solutions	
Reduction estimation	

1.5. Relevance of the research

This section describes the knowledge gap that is addressed in this study together with the scientific and practical relevance of this study.

1.5.1. Knowledge gap

The problem of peak energy consumption of reefers at container terminals is shown to be a significant international problem. Hence, much research is performed in this field. Previous researchers have provided us with much insight in the field and have proposed many solutions to reduce energy consumption. After the development of equations that approach the thermal behaviour of reefers (Equation 2.4 and 2.5), these formulas were used in simulations. However, the previous research is focused on searching for highly technical solutions. The extensive research into advanced and smart control systems which regulate cooling of reefers based on weather, energy price (Barzin et al., 2015, 2016), shows the technology-focused view. Alternatively, control systems that throttle the fans such as QUEST II (Lukasse et al., 2013). Other researchers take a broader perspective and view not a single reefer, but an entire reefer system on-shore (Nafde, 2015; van Duin et al., 2016). This latter research is essential to reduce the peak energy levels, and have shown to deliver promising results. However, these research methods can be considered to be symptom controlling. By researching the root-cause underlying the peaks, solutions can be sought to avoid the peak energy.

It is in the technical thinking of previous researchers that the knowledge gap can be identified. Up-to-date, researchers have always taken a highly technological view towards the problem. Researchers have yet to take a process based view. Therefore, I argue that taking a process based view, towards the problem of peak energy levels, will identify the underlying factors causing the high peak amplitudes.

1.5.2. Scientific relevance

Many studies regarding the power consumptions of reefers have been performed over the years. However, the focus of these studies has mostly been on the saving potentials of individual reefers (i.e. Lukasse et al. (2013) (2013), and Sørensen et al. (2015) (2015)). The complete reefer system, as a whole at the container terminal, has been investigated in previous research of van Duin et al. However, the previous research of van Duin et al. can be considered to be (not less important!) symptom controlling. I argue that, when the energy consumption of reefers is viewed from a process-based perspective, the root-cause can be identified. With a process-based perspective it is meant that the problem is not viewed in a technical manner but the process in which the problem occurs is analysed. By applying this view, the problem can be avoided. This different perspective can extend the toolbox of scientists in reducing peak electricity consumption of reefers at container terminals. The proposed research adds to the existing literature as it opens a discussion about the most effective approach to this problem.

1.5.3. Practical relevance

The practical significance of this research project is evident. Currently, reefers consume an estimated 40% of the total electrical energy consumption of the container terminal operator (Wilmsmeier et al., 2014). Therefore, reducing factors causing high energy consumption will result in a cost saving for the terminal operator. On top of this, a combination of high peak energy pricing by the electrical utility company and the sudden peak loading due to the arrival of large container ships with a high number of reefers, drive up the costs and energy consumption even further. Hence, when the root-cause of high energy peaks can be identified, this will help to reduce energy costs and the carbon footprint of the container terminal. Also, the design and development of a sophisticated control system for the temperature of many containers is a costly process. Applying a process based view shows the root-cause of the peaks and searches for solutions with low investment.

1.6. Methodology

During this research, the process in which the reefer operates is analysed. Indicating that improvements are sought in the improvement of elements of the process rather than improving the technology. By a sound analysis of the process, possible constraints leading to high power consumption can be identified and improved. Applying the *Six-sigma* methodology structures the research. The six sigma methodology provides a methodological, profound, and field tested method of identifying root-causes of a problem within a process. Six-sigma is a method of improving processes originally from the business industry and is not yet widely applied to research focused on a broader perspective. Knowles et al. (2005) and Dasgupta (2003) argue that the application of six-sigma to a broader context is "a structured methodology, with which the performance of a supply chain and its entities can be effectively measured" (Dasgupta, 2003). Also, in the paper of Yang et al. (2007) it is mentioned that the application of six-sigma is suitable for a broader context due to the project discipline and qualitative strength characteristics. The project discipline refers to the usage of the structured DMAIC process which steers the research towards resolving the root cause. Due to this project discipline, the Six-sigma method adds valuable tools and handholds for the improvement of a process. These tools present added value for using the Six-sigma method in this context. The qualitative strengths of Six-sigma refers to the application of standard scientific statistic methods such as regression analysis and Design of Experiments (DOE).

1.6.1. Six-sigma methodology

Six-sigma is a statistical approach and aims to minimise variation in a process; the method focuses on improving the critical-to-quality requirements of the customer. The Six-sigma process is traditionally performed from the perspective of a company. By measuring and analysing the process, the variation of that process can be shown. During the analysis, the root-cause of the variation will be identified after which it can be improved, resulting in a process with lower variation and higher customer satisfaction. The standard method of achieving the higher customer satisfaction follows the DMAIC procedure. DMAIC stands for *Define, Measure, Analyze, Improve,* and *Control.* The DMAIC process is defined by George Eckes (Eckes, 2001) and Yahia Zare Mehrjerdi (Zare Mehrjerdi, 2011) as:

1. *Define*: Define the customers, their critical to quality (CTQ) requirements, and the key process that affects that customer. In this phase, the project boundaries and goals are set.

2. *Measure*: In this phase, the key measures are identified, and information regarding the current situation is collected. During this phase, the current process performance is displayed.

3. *Analyze*: In the analyse phase the collected data is statistically analysed using the IBM SPSS package, using the analysis the root-causes, which prevents the system to perform as desired, are determined. The data is analysed using a sequential multiple regression analysis.

4. *Improve*: During this phase potential solutions to the identified root-cause factor are generated. Arguments for implementation of the proposed solutions are presented in this section.

5. *Control*: Develop, document, and implement a plan to ensure that performance improvement remains at the desired level. For this project, this step of the DMAIC sequence is impossible to perform as it is impossible to implement solutions.

Each part of the DMAIC process supplies different tools to gain insight into the process and its performance. The implemented improvements must be evaluated and monitored.

1.6.2. Six-sigma application outside the business context

A mentioned above the Six-sigma methodology originated inside a business environment. This means that the method is focused on the customer of the company and in a business environment new data is generated continuously. Outside the business environment, the Six-sigma methodology is not widely used. However, the methodology provides us with a tool-set which provide clear insight into the process, its capability, root-cause analysis, and improvement generation. Also, in the wider context, multiple actors must be acknowledged where the Six-sigma methodology is customer focused and only takes the critical to quality requirements of the customer into consideration. Besides the customers of the process, other actors and their CTQ requirements must be taken into account during this research; this extends the Six-sigma method. Dasgupta (2003) and Knowles et al. (2005) argue that the application of six-sigma to a broader context outside the business perspective is a structured method which makes it possible to measure and refine the process due to the clear set-up and the qualitative strength of a six-sigma project. The clear set-up of Six-sigma which is referred to, by Dasgupta and Knowles et al., is the DMAIC structure of a standard Six-sigma approach.

The application of the Six-sigma method provides additional challenges but, most importantly, also provides a leitmotif throughout the research.

1.6.3. Validation

Throughout the research many validation moments are essential. Therefore the first important validation moment is after the define phase. During the define phase the process, the customers, and the critical to quality requirements are defined. To move correctly forward in the project, the defined characteristics must be validated with experts from the field and possibly with customers of the process. When the define phase is validated, it is safe to move on to the measure-phase without the risk for a wrong focus throughout the project.

The second validation moment is after the analysis phase. The outcome of the analysis is validated using cross-validation. The cross-validation method means that the dataset is split into two sections. Namely the *training*- and *test-section*. The training regression analysis is performed on 60% of the dataset after which the found model is applied to the remaining 40% of the dataset.

1.7. Layout of the report

After an extensive literature review and background research in Chapter 2, the report follows the Define, Measure, Analyze, Improve, and Control structure of the Six-sigma methodology. In Chapter 3 the process, customers, and needs & requirements are defined. Next, in Chapter 4, the process is measured, and the current process capabilities are identified. Chapter 5 provides the multiple regression analysis that leads us to the root-cause factors of high energy consumption. In Chapter 6 improvements to the identified root-cause factors will be discussed. Finally, in Chapter 7 the conclusions and recommendations will be given.

2

Reefer operation - Literature review

The usage of reefer containers is essential for the transportation of perishable goods across the globe. These highly sensitive goods require continuous electricity supply or the value of the cargo can decrease, or be lost entirely. Transporting a reefer across the globe requires a significant amount of energy to ensure a continuous and stable temperature. Research of Fitzgerald et al. (2011) have shown how much energy this is and the associated impact on the carbon footprint. Fitzgerald et al. found that the impact of cooling reefers during transport is approximately 19% of the total energy associated with the transportation of a refrigerated container. The residual 81% is appointed to the actual transport of the reefer to another location. In his research Fitzgerald et al. took New Zealand for a case study and showed that the refrigeration of goods expelled approximately 190kt of CO_2 during transport. This study shows the high carbon footprint associated with the cooled transport of goods and the urgency required to reduce the energy consumption of reefers. Wilmsmeier et al. (2014) demonstrated that reefer containers are not only accountable for a significant share of the consumed energy during transport, but are also responsible for a large section of energy consumption at port container terminals. He found that reefers are accountable for 40% of the total energy consumption across container terminals responsible for 70% of all container handling in South America. With the increase of containerization and global container trade, the energy consumption will continue to grow unless action is taken. Hence, in the recent years, much research is performed toward reducing the electrical energy consumption of and reefers.

This chapter describes previous research performed towards energy reductions concerning reefers. However, to get a complete picture of the reefer transportation and operation, first, a short description of these subjects is given. Hereafter,previous research in this field is discussed.

2.1. Short description of reefer and operation at the terminal

The operational basics of reefers will be discussed, it is discussed how reefers work and how reefers operate at the terminal. Also electrical operational characteristics are discussed.

2.1.1. Operation of the temperature controlled container

When the reefers are plugged in, the refrigeration mechanism will kick in to get the core temperature of the reefer within the contracted bandwidth. The refrigeration mechanism is shown in figure 2.1. Figure 2.1 shows the flow of cooled air throughout the reefer schematically.In the cooling unit of the reefer, the evaporator fan blows cooled air through the evaporator coil. Subsequently, the refrigerated air enters the cargo area of the reefer from the bottom through a specially designed "T-bar" floor (Hamburg Sud, 2016) (number 3 in Figure 2.1). While moving up past the cargo, the air exchanges heat with the cargo and leave the reefer at the top to get re-cooled by the cooling unit. For efficient operation, it is required that the cargo is packed in a specific manner to ensure proper airflow over the cargo. Per cargo type, this depends due to temperature and humidity requirements. In an example, palletised bananas can be packed fully close, but require special boxes with strong corners and holes in the top and bottom (number 5 in Figure 2.1), hence the characteristic banana boxes. Number 1 in Figure 2.1 shows the location of the cooling unit at the rear of the reefer. Number 2 is the maximum load line, above which no cargo must be stacked to ensure proper air circulation. Number 4 in the figure are the location of the doors.

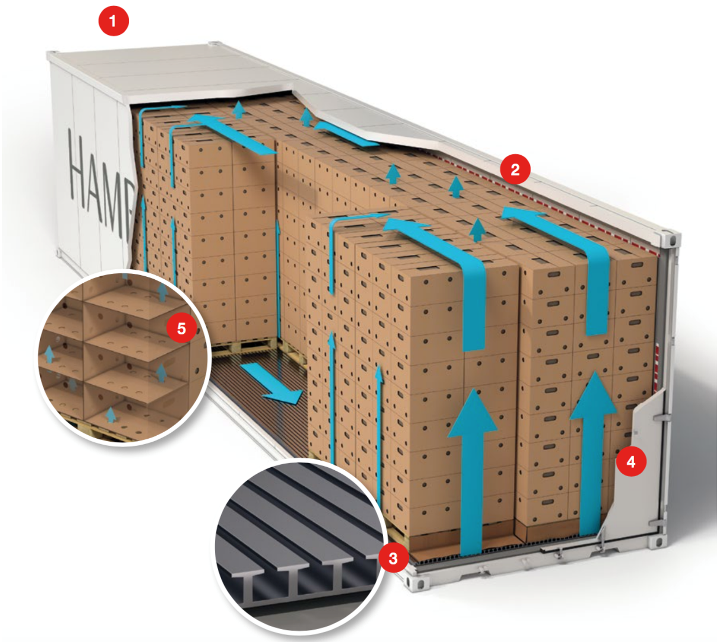


Figure 2.1: Cooling mechanism (Hamburg Sud, 2016)

The temperature range of reefers depends per model type, the standard reefer model can reach a set-point of any value between -30°C and +30°C. There are exceptions with *super-freezers* which are capable of achieving a temperature of -60°C. The required temperature depends on the cargo type which is transported. The cargo type also requires a certain temperature accuracy. The temperature settings have been standardised, however, any set-point can be requested by the customer. Table 2.1 shows the standard temperature ranges, the typical cargo transported in that range, and the allowed temperature fluctuation. Pharmaceuticals are a particular category which is rarely transported using reefers, due to the high value of the cargo these are often airlifted to their destination.

Table 2.1: Temperature ranges (Rodrigue, 2014)

Standard	Cargo type	Temperature range	Fluctuation
Deep frozen	Shrimp, and ice cream	-25°C to -30°C	±2°C
Frozen	Meat and bread	-10°C to -20°C	±2°C
Chilled	fruits and vegetables	2°C to 4°C	±1 °C
Pharmaceutical	medicines and vaccines	2°C to 8°C	high sensitivity
Banana	tropical fruits	12°C to 14°C	±0,5°C

2.1.2. Reefer operation at container terminal

As mentioned before the reefers are unloaded by quay cranes and placed on an AGV, the AGV transports the reefer to the ASC. Next, the ASC transports the reefer to the correct reefer stack where the reefers are manually plugged into electricity. The location of the reefer stacks differs per terminal. Some terminals have a few reefer stacks in each container row, while other terminals appointed one or multiple container rows completely to reefers. The layout of the terminal depends on design choices made by each terminal prior to construction. When the reefers are connected, they start to consume electricity from the net, leading to peak power consumption. Reefers are inductive machines [1], an inductive machine causes a phase change in the power supply. A phase change in the power supply eventually results in an increase of power consumption.

Alternating Current (AC) power consists of 3 components. There is the Active power, Reactive power, and Apparent power. The active power is the power that actually does the work and which is measured in W. The active power can be calculated using Equation 2.1. Reactive power is a result of the AC system, reactive power is used to build up magnetic fields and is unable to do work. Reactive power is measured in Var (Volt-Amps reactive) and is calculated by equation 2.2. The apparent power is the combination of the active and reactive power (Equation 2.3) in VA; this is the electricity that is available from the utility company. In a phase change occurs as a result of active reefers, the power factor ($cos(\phi)$) increases. The increase in power factor is shown in Figure 2.2a as the angle increases from ϕ' to ϕ. An increase of the power factor increases reactive power and therefore a decrease in real power while the apparent power remains the same (Figure 2.2a). This increase of reactive power can be compensated using capacitors (Matias, 2013; ECT Delta Terminal, 2017).

$$P = S \times cos\phi = U \times I \times cos\phi \tag{2.1}$$

$$Q = S \times sin\phi = U \times I \times sin\phi \tag{2.2}$$

$$S = U \times I \tag{2.3}$$

$Where:$

$P: Active\ power$ $\quad U: Voltage$ $\quad cos\phi: Power\ factor$

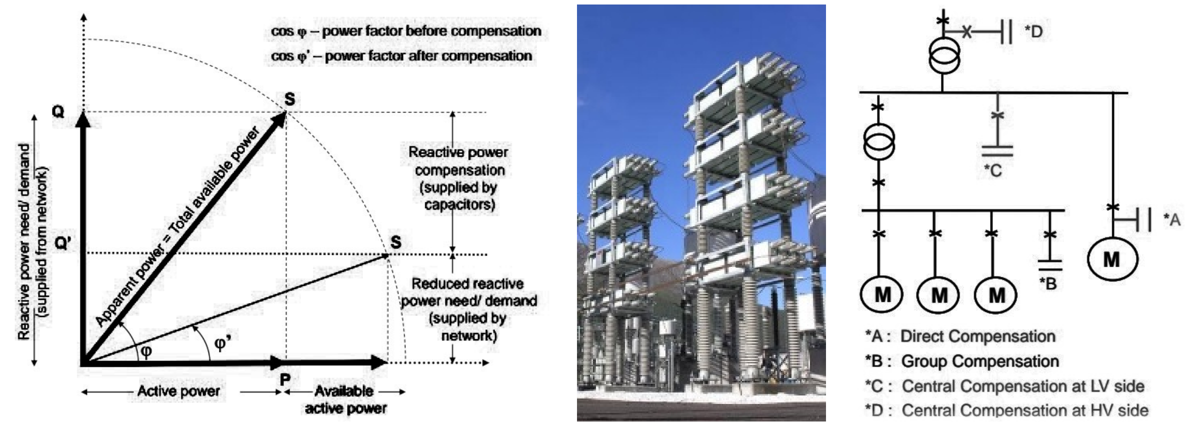
$Q: Reactive\ power$ $\quad I: Amperage$

$S: Apparent\ power$ $\quad \phi: Phase\ change$

The effect of compensation using capacitors is shown in Figure 2.2a. This figure illustrates that the peaks created by many reefers turning on, which are expressed by an increase in reactive power, can be compensated by capacitors as shown in Figure 2.2b. If the reactive power is not compensated the reactive power

[1] An inductive machine is a machine which uses a coil field to operate, this type of machine first builds up voltage before the current starts to flow. This is due to the nature of the coil of the motor within the cool unit, which resists every initial phase change.

absorbs a large section of the apparent power, resulting in an exceeding of the bandwidth agreed with the utility company. Thus, adequate and timely compensation is essential for not exceeding the bandwidth of the utility company. Figure 2.2c shows four forms of compensation for large industrial set-ups. Compensation can occur in a direct, group, and central way. The type compensation method can differ per terminal.



(a) Compensation effect (Matias, 2013) (b) Capacitor bank (c) Compensation forms (Matias, 2013)

Figure 2.2: Effect of compensating reactive power with capacitor bank (Matias, 2013)

2.2. Transport of a sensitive product

The transport of perishable goods is a sensitive logistics chain. To gain insight into the theoretical operation and actual operation of this supply chain a sensitive product is followed throughout the chain. For this, a highly perishable good is chosen: the banana. In Section 1.3 the supply chain of a reefer is described. When considering a banana the supply chain, in theory, can be described as follows: the banana is picked from the banana tree at the plantation. Here the banana is boxed and pre-cooled in an on-site large refrigeration unit. When an empty reefer arrives, the pre-cooled banana boxes are placed inside the reefer, and the reefer is switched on. During transport to the departing port, the reefer is not necessarily cooled. Only when a generator set (genset) is attached to the reefer, it can cool during truck transport. Some reefers are delivered with an integrated genset although these are few in numbers. When the reefer arrives at the departing container terminal, the reefer is connected to the electricity to ensure a correct temperature awaiting its transhipment. The reefer is then unplugged and moved onto the ship by quay crane. Once on the ship, the reefer is plugged into electricity supplied by the ships' engine. During the sea transport, the reefer remains plugged in ensuring the temperature. Once at the destination port the reefers are plugged out of the ships electricity net, offloaded by quay crane and moved to the reefer stack where they are again plugged in. Here they await further transport by truck, train, or barge.

However, in reality, the process is often not precisely as described below. For insurance purposes, importers often place a temperature logger on board the reefer. A temperature logger registers the temperature development of a reefer during transport from the plant to the end-destination. The temperature development of a reefer from the Dominican Republic to the port of Rotterdam is shown in figure 2.3. When reviewing figure 2.3 it shows that the cargo was not pre-cooled before transport; instead the reefers were first plugged in at the departing port. If the cargo were pre-cooled, the cargo would be within the bandwidth from the start of the temperature log. This late plug-in leads to a high energy consumption at the departing terminal. This is a trend often occurring in shipments from South America (Groente en Fruithuis, 2017).

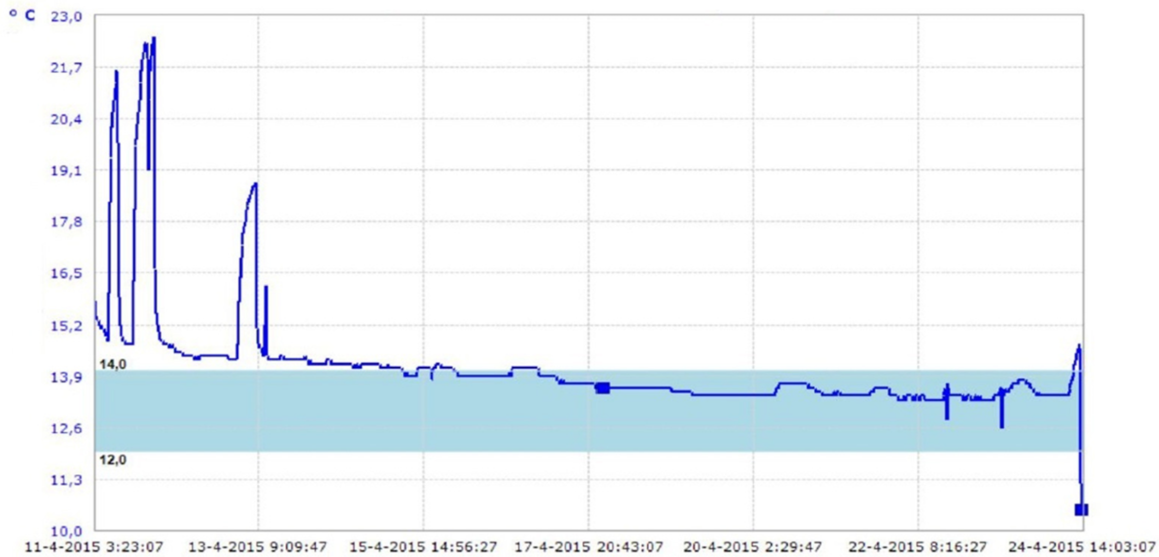


Figure 2.3: Temperature development during transport of bananas (de Geest, 2015)

On the other side of the supply chain, at the destination port, the theoretical supply chain also does not always go as described above. When a ship arrives at the port, a conflict of interests arises among three parties. Firstly, for the owner of the cargo, the temperature requires the reefers to be plugged in as long as possible. Secondly, the container terminal requires the reefers to be plugged out when the ship docks at the terminal, this enables the quay cranes to start offloading immediately. Reefers are always unloaded first so they can be plugged in as quick as possible (ECT Delta terminal, 2017). Thirdly, the container ship is faced with additional costs when sailing in the North-sea (and other emission control areas) due to environmental regulations. This forces the container ship to switch from, much cheaper and more polluting, low-grade bunker fuel to (more expensive) low sulfur fuel (Hapag-Lloyd, 2017). The switch to low sulfur fuel makes the electricity to cool reefers more expensive, which is sometimes avoided. Also, the ship can be confronted with many disembarking reefers which must be disconnected and limited staff . Both these factors add to premature disconnection of the reefers' power. Early disconnection of the reefer onboard the ship lead to added risks in the products' quality and added energy consumption in the destination container terminal. It is not always that reefers are disconnected early, often a few reefers are disconnected prior to docking so that the quay crane immediately can go to work. As the crane is unloading the first reefers, the remaining reefers are unplugged by the crew.

2.3. Energy saving research

Technology based research

When trying to reduce the energy consumption of refrigerators a logical first step is to focus on the refrigeration technology. The energy reduction of consumer refrigerators is a topic that has been researched for centuries as in 1995 refrigerators consumed about 7% of the USA's electricity (Meier, 1995). Thus, first developments of refrigeration were in the efficiency of the large energy consumers such as the heat cycle, insulation improvements, fan efficiency, and compressors. Also, smaller contributions were addressed such as the prevention of frost buildup as this will reduce the efficiency of energy transfer. However, the greatest challenges were in the efficiency of the refrigeration cycle in combination with environment safe refrigerants (Radermacher and Kim, 1996). Developments in refrigeration technique have since not slowed down as it has become increasingly important with the increase in computing technology. Recent developments focus on new solid-state refrigeration methods using the "large latent heats of shape memory alloys (SMA's)" (Schmidt et al., 2015). This technique uses materials that transfer heat when deformed. However, this technique is too avant-garde for the reefer industry (or home appliances) and thus not yet implemented.

Control system based research

Instead of trying to improve little on the efficiency of current compression refrigeration techniques, research has focused on improving control systems. Traditionally, refrigerators can operate in three different ways. Reefers can be in either off, chilled, or frozen operation. In chilled and frozen modes the refrigeration unit will work at full power until the set temperature is achieved, next it will turn off leaving the reefer to warm. This method of refrigeration requires a properly calibrated Proportional–Integral–Derivative (PID) controller, or it can lead to under- or overshoot of the set-point temperature. This phenomenon is shown in Figure 2.4. Advanced control systems based on reducing the impact of energy-intensive parts are currently being researched. This research promise a high energy and cost reduction.

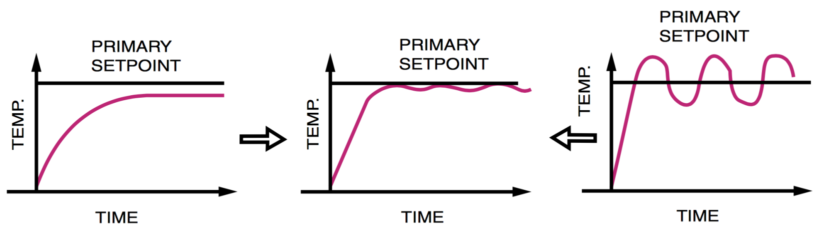


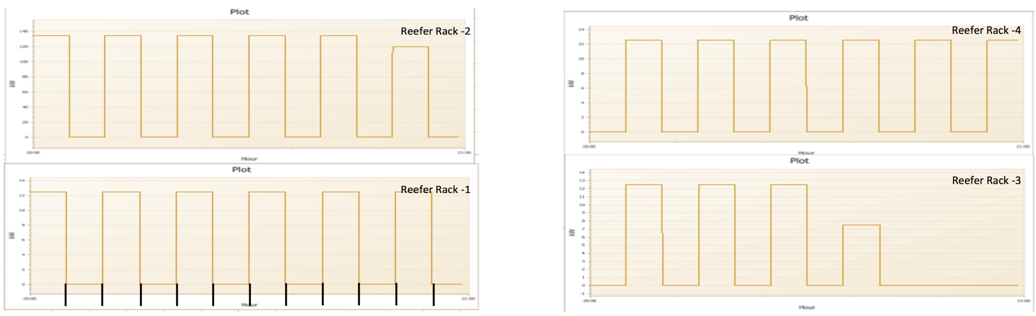
Figure 2.4: Temperature under-, correct, and overshoot resp.

A promising research in control systems of refrigerators is the QUEST II research of the Wageningen University (Lukasse et al., 2013). Lukasse et al. developed a new control algorithm to reduce the energy consumption of reefers. The algorithm is developed to target two essential sources of energy losses, which are the evaporator fan and compressor efficiency. In section 2.3 these two subjects are also identified as an interest for technological research. Lukasse et al. attacks the two problems from a control system perspective. In his article Lukasse et al. argues that evaporator fans are losing efficiency as fans are continuously operating at max speed, regardless of the required heat load. Lukasse et al. also states that the throttling capability of the compressor leads to efficiency losses. The QUEST II algorithm is therefore designed to adjust and reduce the evaporator fan speed when necessary, and avoid part-load compressor operation by operating the compressor as an ON/OFF part. This resulted in an average energy savings of 65% compared to non-QUEST controlled reefers.

Another control system based research is the research of Barzin et al.. In this research Barzin et al. (2015) developed a load shifting model to reduce the electricity costs of a standard freezer. A load shifting model aims to move the electricity consumption from the peaks to the troughs, hence creating an increased continuous operation with a lower average consumption and associated costs. The load shifting model of Barzin et al. was used the electricity price of the utility company as a guideline for the freezer control system. In this control model, a pricing limit for the freezer is set. When the electricity price rises above the pre-set pricing level, the freezer would not cool. An exception is only made when the temperature of the freezer was above the set temperature; this allowed the control system to break the limit rule so the freezer can be cooled and to ensure that the temperature remains within the set bandwidth. This control system resulted in an avoidance of the morning and evening peak-pricing while keeping the freezer within its set bandwidth. Experimentation with this control system in New Zealand and resulted in an energy reduction of 16,5% - 62,64% per day, while keeping the core temperature under the set limit of -10 °C. Later, Barzin et al. (2016) extended the price based model with the integration of weather forecasts. This model used weather predictions integrated into the control system to predict required energy consumption (sunny/not sunny). This time Barzin et al. experimented with the temperature control of small huts instead of refrigerators. Experimentation with this control system reduced the costs of power consumption to 92% on specific days and 40% over an 11 day period (Barzin et al., 2016).

Broader perspective of multiple reefers

van Duin et al. took a broader perspective by addressing all refrigerated containers in a terminal rather than single reefer units. Tushar Nafde graduated from the TU Delft under the supervision of van Duin on this topic. In his research, Nafde developed a model to simulate energy consumption with a basic control system. In this control system model, the temperature is allowed to increase to the allowed bandwidth limit, when this is reached the temperature reduced again to within the set. Next, the reefer is switched off until the temperature again as reached the limits of the allowed bandwidth. This control system was simulated in a representation of the energy consumption of 60.000+ reefers over the course of the year 2014. The 60.000+ reefers where simulated to define a base case of the energy consumption of reefers. Next, two different peak energy reduction methods were simulated to investigate their impact on energy consumption. In the first simulated peak reduction method, the power between half of the plugged-in reefers was alternated, as shown in Figures 2.5a and 2.5b.



(a) Rack 1 & 2 ON

(b) Rack 3 & 4 OFF

Figure 2.5: Reefer rack ON and OFF (Nafde, 2015)

This simulation resulted in an expected reduction of energy consumption from 14.831 kW to 2.763 kW using alternate power supplied with 5 and 15 minutes slots. The second simulated peak reduction method was the application of a peak limit at 14.000 kW. This resulted in a simulated max peak of 13.760 kW. The effects of the simulations of Nafde; van Duin et al. are shown in Figure 2.6. This figure shows the significant achieved reduction of peak power consumption after application of alternate power supply (Solution 1).

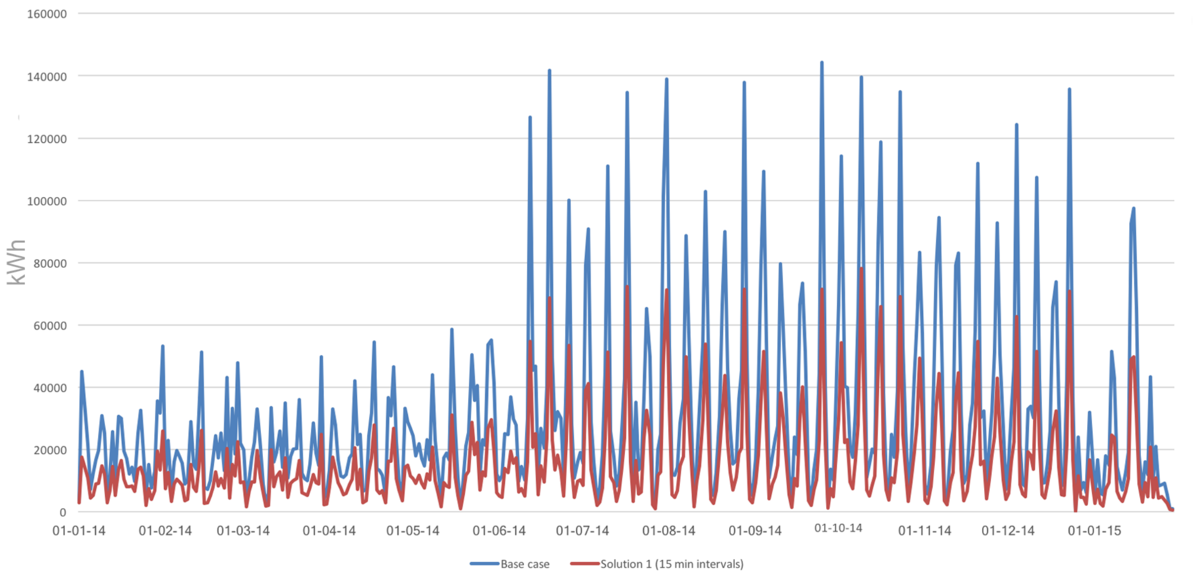


Figure 2.6: Reefer peak energy consumption (Nafde, 2015)

On-shore reefer handling

Other research takes a more process-based view and focuses on the operation of reefers and the risks following reefer handling. A large risk of reefer handling is long periods when no power is supplied to the reefer. It is essential that the temperature inside the reefer be controlled to ensure the quality of the perishable goods inside. Failure can result in a costly loss of cargo. If failure results in loss of cargo, the port is required to compensate the owner of the cargo for its losses. Reefers always are filled with valuable cargo thus compensation can cost the port large sums. Therefore, it is essential that reefers are plugged in as quick as possible after the arrival of the ship. Filina and Filin (2008) has shown that power-out periods of reefers are often 2 - 4 hours, which can climb to 6 - 8 hours due to human factors, technological factors, and environmental factors. These power-outs occur twice when reefers are handled in the port. The first time is when the ship arrives in the port, the reefer is disconnected from the ships power-net to prepare it for ship-to-shore transfer. The reefer may be transported to a customs check ("GPKW" in Figure 2.7) before it is transported further to the reefer stack. The reefer is plugged in again when it arrives at a reefer stack in the container terminal where it can be plugged into the power-net of the terminal. The second time is when the reefer is transported further from the container terminal. The transport moments of a reefer within a typical European port are shown by Filina and Filin (2008). The scheme as presented by Filina and Filin is shown in Figure 2.7.

When the reefer is plugged into the power-net of the container terminal the onboard refrigeration unit can control the temperature of the unit. The container terminal then continuously monitors the correct operation of the reefer. Some reefers can be monitored on distance; other reefers do not have the capability of sending data to the control centre. These reefers are checked manually three times a day (Delta reefer care, 2017).

Filina and Filin states that the temperature control of reefers is compromised on many occasions due to human factors. In an example, the extended plugged-out period can be caused due to early plug-out on the ship before the arrival of the ship. Early plug-out stimulates a quick ship offload but increases the off-line time and power consumption of the terminal. Another common factor is the failure of plugging the reefer in the power net, as it is known that the reefer will be moved within a short time frame.

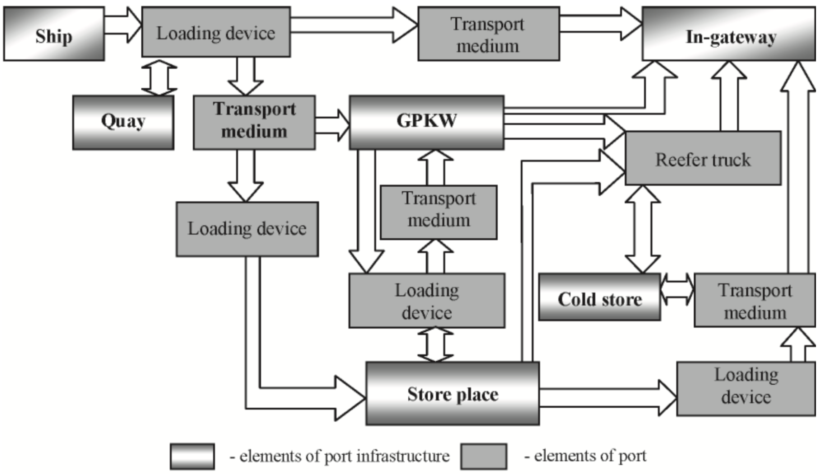


Figure 2.7: On-shore reefer transportation (Filina and Filin, 2008)

2.3.1. Factors influencing reefer energy consumption

Seasonality effects

Due to increased wealth in the western society, consumers expect that all meats, fruits, and vegetables are always available in the supermarkets. These products are the products for which reefers are used for transport. Other products that must be transported using reefers, such as medicines and pharmaceuticals, are less subjective to seasonality. The market requirements of meats, fruits, and vegetables result in seasonality effects of reefer transport, as the products must be imported when they are not locally available (in the right quantity) to fulfil the demand. Total seasonality effects are shown in Figure 2.8 where the number of arriving reefers in 2014 is shown by month. This figure shows that in the second semester of 2014 there is an increase of arriving reefers. Unsurprisingly, this effect shows similarities with the power consumption as shown in Figure 2.6. An explanation for this trend could be that in the first semester of the year the capacity of local food producers is larger; thus there is a lower need for food import. The seasonality effects increase the total power consumption peaks as shown in Figure 2.6.

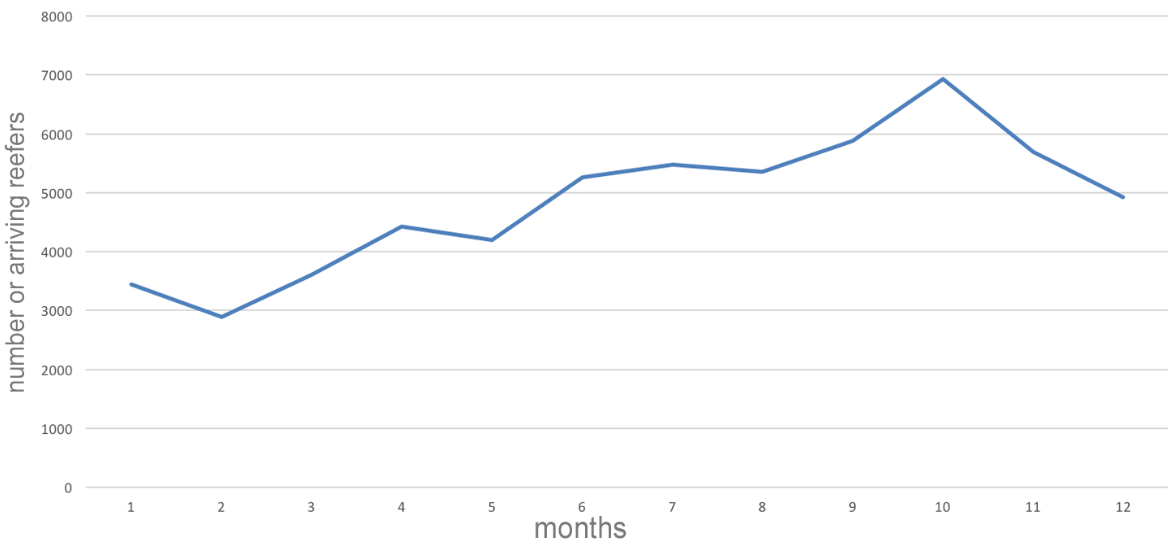


Figure 2.8: Number of monthly arriving reefers

Global reefer usage

Over the past years, the global cargo trade has been characterised by an increase of containers. The market share of container transport increases at a faster pace than the annual cargo growth. This phenomenon is called the "containerization" of cargo transport. The container transport comprises approximately 78% of the cargo market in 2017. The containerization affects the global reefer usage. The global reefer cargo trade grows with approximately 3% - 6% per annum (Dekker, 2014; World Cargo News, 2017). Dekker (2014) states that key drivers for an increase in reefer usage are (among others) the healthy eating trend, increase in population and weather. Due to these trends, the large reefer players (such as Maersk, MSC, CMA CGM, and Hamburg Sud) have an average capacity of approximately 16,8% of their total capacity. This capacity is increasingly divided over the large container vessels with mixed containers. The total number single purpose reefer ships decrease annually. On the other hand, the routes of large container ships (of 8000+ TEU) are increasingly designed around reefer trade flows. (Dekker, 2014)

Largest reefer trade flows are focused on five major trade routes. These are between North Europe - Asia, South Africa - Asia, South Africa - Europe, Brazil - Europe, Brazil - Asia. The largest global reefer trade routes are shown in figure 2.9 In 2013 the two most significant routes were from North Europe to Asia and from Brazil to Europe transported 426.526 TEU, and 307.027 TEU of reefers respectfully. From North Europe to Asia the reefers were mostly filled with seafood and raw fish. On the route from Brazil to Europe the main cargo was citrus and deciduous fruits.

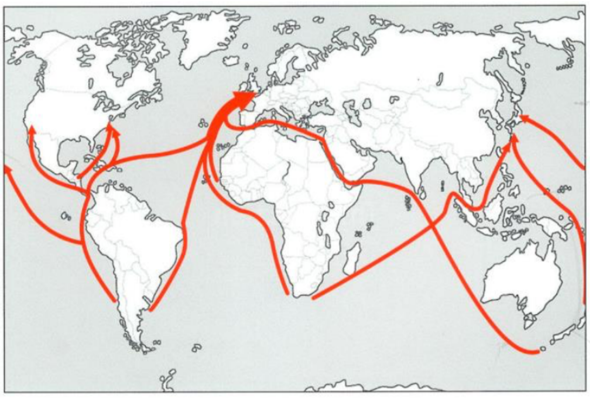


Figure 2.9: Largest global reefer trade routes (ROBLES, 2010)

Calculating the required energy

As shown in previous sections, there is much research performed towards solutions to reduce the energy consumption of reefers. Many of this research used simulation to predict the effect of their proposed solutions. Simulations as such are based on thermodynamic formulas. Analyzing these formulas shows different factors which influence the temperature and thus the required energy to achieve the set temperature. During off-line periods on-shore, the internal temperature of the reefer is subject to uncontrolled change. The quantity of temperature change depends on the ambient temperature and other factors. Previous research of Tran (2012) has shown that the increase of reefer temperature can be calculated with equation (2.4).

$$\Delta T(t) = \Delta T_{ambient} - \Delta T_{ambient} \times e^{\left(-\frac{A\times K}{M\times C_p}t\right)} \tag{2.4}$$

$$\begin{aligned}
&where:\\
\Delta T_{ambient} &: Ambient\ Temperature - Return\ Air\ Temperature\ (°C)\\
A &: Surface\ Area\ of\ Reefer\ (m^2)\\
K &: Thermal\ Insulation\ of\ Reefer\ (W/m^2 \times °C)\\
t &: Time\ before\ plugging\ in\ at\ reefer\ stack\ (Seconds)\\
M &: Mass\ of\ Cargo\ (kg)\\
C_p &: Specific\ heat\ of\ cargo\ (J/kg°C)
\end{aligned}$$

Important factors from equation 2.4 that should be highlighted are the container type, cargo mass, and the difference in temperature between the ambient temperature and inside the reefer. Here the container type covers the K (thermal insulation) and A (surface area). These factors can also be found in equation 2.5. This equation states the required energy (W) to cool the cargo (ΔT) within a specific time (t). However, the theoretical maximum cooling speed based on the maximum refrigeration capacity is usually not achieved. This is due to incorrect packing of the reefer, as discussed in section 2.1. (Tran, 2012; Gesamtverband der Deutschen Versicherungswirtschaft E.V., 2017)

$$Q = M \times C_P \times \frac{\Delta T}{t} \tag{2.5}$$

$$\begin{aligned}
&where:\\
Q &: Cooling/heating\ Power\ (kW)\\
M &: Mass\ of\ cargo\ (kg)\\
C_p &: Specific\ heat\ of\ cargo\ (kJ/kg \times °C)\\
\Delta T &: Temperature\ difference\ (°C)\\
t &: Cooling\ time\ (seconds)
\end{aligned}$$

3

Define

The define phase of the Six-sigma DMAIC process typically starts with the creation of a so-called Team Charter. The team charter states the business case, problem statement, project scope, goals and objectives, milestones, and the roles and responsibilities of the Six-sigma team. The team charter is already discussed in the first chapter of this report. Thus, this will be left out of the Define chapter. All except for the roles and responsibilities of team members was discussed, this is intentional as it is irrelevant for a project executed individually. First the customers of the process and other involved actors will be determined. Secondly, the needs and requirements of the customers are mapped using a critical-to-quality tree, giving an insight in what are important factors for the process to be successful. The findings of these two sections are then summarized using a high-level process map. Hereafter the findings are verified by discussing it with customers.

3.1. Definition of customers

At the beginning of every project, it is required to determine the project goal is. Goal determination is done in the define phase using the team charter. When the boundaries and goals of a project are clear (as discussed in Chapter 1), the focus is changed to the customers of the process. Therefore, the first step is to define the customers of the process and other involved actors.

3.1.1. Customer of the process

The Six-sigma methodology defines the customers of a process as *"recipients of the product or service"* (Eckes, 2001). Therefore the customer is the agent which is at the receiving end of the process and requires the output of the process as an input for its own process. Hence, the customer is not necessarily the external entity that pays the bill. Therefore, the owner of the cargo is not necessarily the customer. Figure 3.1 shows the essence of the process discussed above in section 1.3. Figure 3.1 shows that the process comes down to three steps of unloading the container from the ship, storing and cooling the container while it awaits its further transport to the hinterland, and lastly, the placing the container on the hinterland modality. From Figure 3.1 it can be concluded that the essential recipient of the service is the entity which transports the reefer into the hinterland in case of import, and the deep-sea shipping company in case of export. The hinterland transporter can be either the owner of the cargo who has arranged its own hinterland transport or a third party logistics service (3PL) responsible for further distribution of the cargo.

Thus the customer can be one of three agents:

- Owner of the cargo
- Hinterland transporter or third party logistics (3PL)
- Deep-sea ship

The container terminal often considers the deep-sea shipper to be the customer (ECT Delta terminal, 2017). The shipping company is the entity that decides which container terminal is used for transhipment, meaning that the 3PL has no choice in the terminal and its services. Thus, from the perspective of the terminal, services are designed and focused on the shipping company and not the 3PL.

The owner of the cargo will not be considered the customer of the process. Even though the owner is the entity that pays the final bill and has specific requirements, the owner is not always at the end of the process at the container terminal. The owner of the cargo has the possibility to arrange not its own transport to the hinterland, but to use a 3PL. Therefore, the cargo owner is not always the entity at the end of the process. The hinterland transporter will always be at the end of the process (this can either be the cargo owner or a 3PL), together with the deep-sea shipping company. As the hinterland transporter and the deep-sea ship are always at the end of the process, these are considered to be the customers of the process.

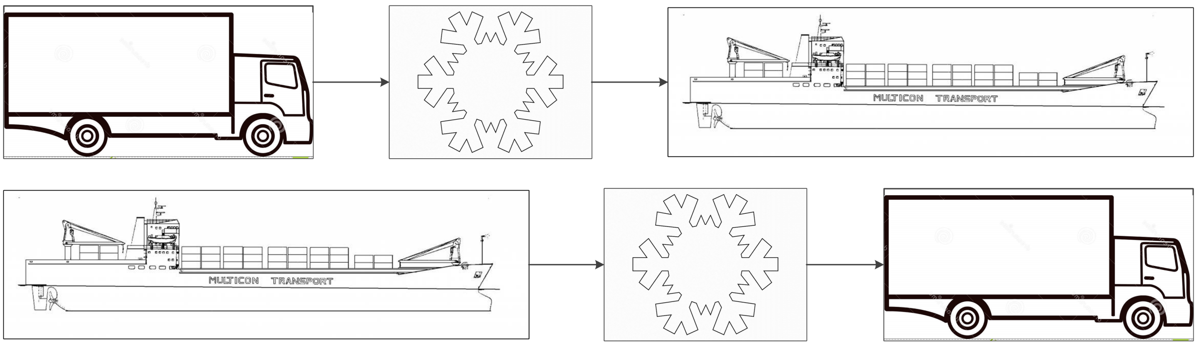


Figure 3.1: Essential process

3.1.2. process owner

The nature of Six-sigma is based on a business perspective. However, in this research a broader view must be applied, meaning that other entities, rather than the customer, must be considered. Apart from the customers, another important entity is the process owner. The process owner cannot be considered a customer as it is not at the end of the process. However, the process owner does benefit from a proper process. Thus, the process owner imposes its requirements on the process which are essential and must not be forgotten. The process owner of the process shown in Figure 3.1 can be considered to be the container terminal. This entity is chosen as it is the company that plans and executes the process with its own staff and equipment. Due to the vital role of the container terminal, the needs and requirements of the terminal must be considered.

3.1.3. Other actors

When the actors from the supply chain are discussed there is another important actor that has an important role. The energy utility company must also be considered in the total picture. The energy utility company must serve electrical power to many customers (industrial and consumer) connected to its power grid. The energy utility company must ensure that it produces enough energy for all consumers. Therefore it agrees on a capacity with large industrial consumers such as a container terminal. If the container terminal suddenly exceeds the agreed capacity the energy utility company must be able to catch this blow to their network. Thus, the energy utility company also benefits from an energy consumption with fewer peaks and must be considered.

3.1.4. Problem owner

The problem addressed during this research is not a problem of the (in section 3.1.1, 3.1.2. and 3.1.3) identified actors. The problem can be considered to be a societal issue as each actor does not have a problem with high peak energy consumption. Currently, every actor calculates the additional costs to their customer. The energy utility company charges additional costs for peak consumption to the container terminal. Subsequently, the added costs are charged to the shipping company and the cargo owner. Eventually, the costs are billed to the consumer. Additionally, the society pressures corporations to reduce their total energy consumption.

3.2. Customers' needs and requirements

After identification of the customer of the process and the process owner, the needs and requirements of the customer and process owner must be defined. Defining the needs and requirements of customers is helpful for two reasons. Firstly, it will help separating critical to quality steps and no added value steps in the process. In other words, what steps does the customer need, for the customer to be able to work with the final product? Secondly, it will indicate what the requirements are for the customer and the process owner. This further defines the need of the customer into requirements that give how, and in what way, the customer needs the final product.

The needs and requirements of the customer will be mapped using a critical-to-quality (CTQ) tree. This tool helps to identify the basic need of a customer and further identifies the requirements of the customers to a more specific level. The CTQ-tree is developed in five steps, leading to multiple levels of customer requirements divided into the basic requirements (Eckes, 2001). Firstly, the customer is identified (which has already been done in section 3.1). Secondly, the need of the customer is defined. The need is what the customer ultimately requires from the process. The need is considered to be level 1 in the CTQ tree. Thirdly, the first set of requirements for the customer, to achieve the level 1 need, are identified. The requirements are considered to be level 2 of the CTQ-tree. Fourthly, where possible, the identified level 2 requirements are further brought back to more specific requirements. If the 3^{rd} level requirement can best be considered in the measurement section, the requirement is too specific and will not be considered in the CTQ-tree. In this case, the CTQ-tree will end at the level 2 requirement. This ensures that the CTQ-tree remains at an overview level of the process. The fifth and final step is the validation of the previously identified steps. This is most effectively done by discussing the identified needs and requirements with the customer.

Figure 3.2 shows the CTQ diagram of this process. In this CTQ-tree all actors as mentioned above are considered. To establish the CTQ-tree of Figure 3.2, the websites of seven large container terminals at Rotterdam, Hamburg, and Antwerp were researched. It is assumed that the terminals know what customers need and require, and thus advertise with these services on their websites. The results can be found in Table A.1 of Appendix A. When looking at the keywords that are found on their websites it can be seen that a few terms are repeatedly mentioned, these are Fast (5/7), Reliability (4/7), and Safety (4/7). The often mentioning of

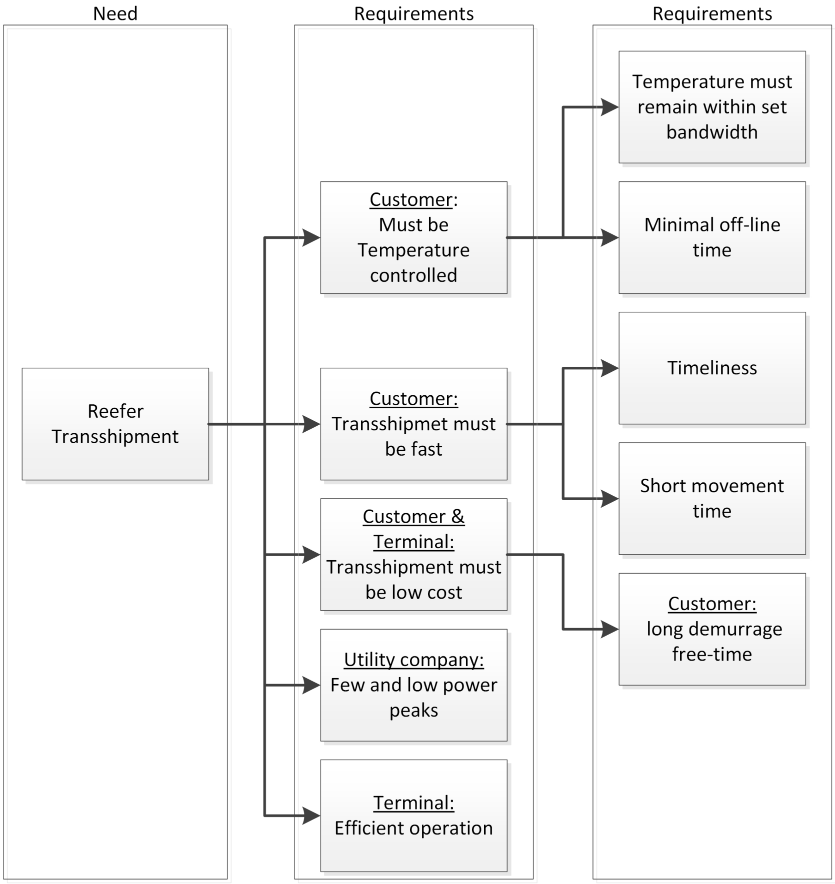


Figure 3.2: Customer Critical-to-Quality tree

Fast translates into the "transhipment must be fast" requirement. Another defined requirement is that the temperature of the reefer must be controlled. This requirement follows from the reliability term found on the websites and shows in the usage of a reefer, by the cargo owner. If temperature control were not a requirement, a regular container would suffice as a non-thermal controlled container is much less costly. This could be considered to be mostly a requirement of the cargo owner which is communicated through the hinterland transporter and to the deep-sea shipping company. Therefore, the cargo owner requirement also becomes a requirement for the process customers. The third level-1 requirement "Transshipment must be low-cost" is only mentioned once on the websites of container terminals. On the other websites, there is generally nothing to be found on costs. This is a requirement as the entire industry is money driven. However, the gap between service and low-cost must be high for a shipping company to choose for a low-cost container terminal (ECT Delta terminal, 2017).

Apart from the customer needs and requirements the owner of the process and other actors impose their requirements on the process. These requirements are additional to the customer requirements and are critical to this research in answering the main research question. Requirements of the terminal company are shown in Figure 3.2. These requirements can be considered to be the drivers for the process owner and additional to the requirements of the customer.

For the energy utility company, as well as the container terminal, it is critical that peak power consumption is kept to a minimum. Both actors have different argumentation for such a requirement. E.g. the container terminal attempts to keep the process sustainable and low-cost. Meanwhile, the container terminal has an agreed capacity with the energy utility company for an agreed price. If the container terminal exceeds the agreed capacity, the price of a kW can reach 27 $€/kW$ (Nafde, 2015) as the utility company must handle such a high peak load in the energy grid. Thus even if the peak occurs for one second, the cost increase significantly. Normally the costs are approximately 0,08 $€/kWh$ during the day and 0,05 $€/kWh$ at night (Nafde, 2015). The energy utility company benefits from lower peaks as it then has a more stable electricity demand pattern. Meaning that it is more predictable to generate electricity.

3.3. High-level process map

A High-level process map is made to create an overview of how the current process operates. An often used mnemonic to create the High-level process map is "SIPOC". This mnemonic is used as the high-level process map states the Suppliers, Inputs, Process, Outputs, Customers, requirements, and measurables. The latter two are not always included in the high-level process map. Additionally, a final column is added with the Six-sigma scores of the process. The Six-sigma score can traditionally be used later during the control phase in the feedback loop. This tool is developed to create an overview of the process and to consider all actors with their inputs and outputs. By taking a birds-eye-view, it groups all the work previously performed and schedules it in a clear table. When the project is performed within a company the high-level-process map is also used as a bench mark during the next iteration of the process improvement. During this research the high-level process map cannot fulfill this purpose as the improvement cannot be implemented.

The creation of a high-level process map is done by following seven steps which are built upon previous work in the design phase. The first step is the identification of the process to be mapped. The process has been identified in section 1.3 as the process of offloading, connecting, and further transported. Secondly, the start and stop points of the process are established. This process starts when the reefer arrives at the container terminal and stops when the reefer leaves the terminal with a different modality. The third step is to determine the output of the process. The output of the process is considered to be a transhiped reefer, a by-product of the output is the energy usage during the process. In the fourth step, the customer is determined, which has been done in section 3.1. In this section the customers are determined to be the 3PL, shipping company, and the cargo owner. The terminal operator is considered to be the process owner and the energy utility company is also considered to be an actor. Then, during the fifth step, the requirements of the customers are defined, this has been done in section 3.2.The most important requirements are the temperature control, transshipment time, sustainable operations, and low and few peaks in the energy consumption. In step six, the suppliers to the process are identified and their subsequent inputs to the process. These are considered to be the shipping company, terminal operator, and the utility company who supply reefers, manpower, and electricity respectively. The seventh and final step in the creation of the high-level process map is to determine 5 to 7 high-level steps that occur between the start and stop points of the process. (Eckes, 2001) The high-level process map of the reefer process is shown in Figure B.1 in Appendix B.

3.4. Verification of findings

To verify the identified customers, their needs and requirements, and the process owner they are discussed with experts from the field. This is called the Voice of Customer, by discussing with customers their needs and requirements the previously identified needs and requirements are verified. These subjects were discussed with the deputy-director of the Groente en Fruithuis (Groente en Fruithuis, 2017), who is in charge of the supply chain and ICT. The Groente en Fruithuis is an industry representative for companies trading and growing fruit and vegetables in the Netherlands. An interview is also held with a Six-sigma black-belt and Consultant Business Development from the ECT Delta terminal in the port of Rotterdam (ECT Delta terminal, 2017). The discussion with the deputy-director of the Groente en Fruithuis gave many insights into the process and customer requirements from the customer point of view. During the discussion, it became clear that the quality of the process is most important for customers, with the quality it is meant that the temperature must be controlled sufficiently, as this guarantees the product quality, and the speed of the transport is important to the customer. This is due to the perishable nature of reefer cargo and high value associated with it. When transport is fast, the shelf-life of the product on the end of the supply chain is increased. The Groente en Fruithuis also stated that the price often is not an important factor for the importer of the goods, this is because the exporter mostly arranges the oversea transport and due to the high value of the cargo. During the interview, it became clear that other factors such as sustainability and energy consumption of the transport are not currently a driving factor for customers in the Netherlands. However, sustainability and energy consumption become increasingly important, fruit and vegetable tailors growers do not select transport based on their energy consumption.

During a visit to the ECT Delta Terminal in the Port of Rotterdam with the Consultant Business Development of ECT, a different perspective on the process was taken. This time the point of view from the terminal was taken. The previously identified customers in section 3.1 where verified. However, it must be stated that the ECT Delta Terminal views the shipping company as their primary customer and not the 3PL. This is because the terminal has contracts with the shipping company and not the 3PL. As mentioned above the definition of customer is not the entity that pays the bill, but the entity that is the recipient of the process. So with that definition, the shipping company and 3PL are considered to be the customer. The needs and requirements of the customers can also be considered to be correct with some comments. As was also mentioned by the Groente en Fruithuis, the transhipment time is the essential requirement for customers. The on-time behaviour of reefers is not a requirement. The customer can collect the reefer any time they wish after unloading from the ship; hence the offloading speed is the key driver for the customer. Also, the costs associated with the transhipment of the reefer are not considered a fundamental requirement. The transhipment costs are a minor factor in the total costs of the transport of the high-value cargo. The low percentage of costs combined with the high value of the cargo make that transhipment costs are not essential. A longer transhipment time is even beneficial for the container terminal as the customer must pay an additional fee if the demurrage free time is exceeded. These costs are billed to the shipping company, which bills it to the 3PL up to the cargo owner. Thus, the terminal makes a higher profit if the container is collected late. The terminal does not mind if reefers are stored temporarily up to the point when the max capacity of the reefer stacks is achieved. Considering the additional profits for the container terminal, the process owner does not consider the high energy usage as a critical requirement to the process. However, energy savings are always an essential requirement of the terminal. Therefore, the sustainability of the process is considered to be a requirement for the process owner. The efficient and low-cost operation is also a requirement of the process owner, however, for this research, these requirements are too complex and thus not considered.

These findings are used as input in the next phase of this research. In the measurement phase, the requirements identified and verified in this section are quantified.

4

Measuring the process

To be able to say anything relevant about the process and to perform a root-cause analysis, the current process capacity must be measured. During this chapter insight is gained in the current operation of the process with respect to the CTQ requirements. Doing this, potential root causes are exposed. Therefore, after the first step, in which the needs and requirements of the customer were defined, these must be quantified. Thus what a good and bad process is, is defined. In the third section of this chapter, the available dataset from ABB is described. In this section the made assumptions for the capability and regression analysis are described and explained. Following the definition of a good and bad process, the current capability of the process is established.

4.1. Performance standards

To give any performance indication of a process, a standard must be set for the process. The CTQ requirements of the customer must be translated to performance standards so that current performances can be measured against this benchmark. For each of the CTQ requirements it is asked what specifications the customer has. In section 4.3 the current process operation is then compared to these specifications.

4.1.1. What does the customer want?

In the previous chapter the requirements of the customer and process owner are determined (see section 3.2). Hereafter, the requirement specification imposed by the customer must be established.In Section 3.2 it is found that the customers view two process characteristics as critical-to-quality. These are the temperature control and fast transhipment of the reefer. The price tag associated with the transhipment and the timeliness of the transhipment where found not to be a CTQ requirement. For each of the identified CTQ requirements, the baseline of the customer is determined. Next to the customers CTQ requirements the requirements of the process owner are defined.

The requirement and allowed deviation for the temperature control are deducted from the set-point temperature of the reefer. Reefers can be set to maintain any temperature between -30°C and +30°C (Hamburg Sud, 2016), thus for all reefers, the exact specification of the temperature requirement can be different. There are some reefers capable of maintaining a temperature of -60°C. However, these reefers are not standard practice and not often used. Table 4.1 shows the allowed temperatures for standard temperature ranges.

The maximal offline time can be calculated using Equation 2.4 (see section 2.3.1) as defined by Tran (2012). Using Equation 2.4 temperature increase per second ($\Delta T(t)$) is calculated per reefer. The temperature bandwidth per reefer is known; thus the $\Delta T(t)$ between the set-point temperature and bandwidth limit is used to calculate the time the reefer takes to warm up to the bandwidth limit. Using this information the maximum offline time is calculated for each reefer using formula 4.2, which follows from the formula shown in equation 4.1. These equations assume that the temperature increase follows a linear pattern and that the reefer is at its set-point temperature when the reefer is plugged out. The value of the maximum offline time can differ for each reefer and is dependent on (among others) the $\Delta T_{ambient}$

$$T_{max} = \Delta T(t) \times t + T_{set} \tag{4.1}$$

$$t_{max} = \frac{T_{max} - T_{set}}{\Delta T(t)} \tag{4.2}$$

$$\begin{aligned}
&where: \\
T_{max} &: Maximum\ allowed\ temperature\ increase/decrease\ (°C) \\
T_{set} &: Set-point\ temperature\ (°C) \\
\Delta T(t) &: Temperature\ increase\ per\ second\ (°C/s) \\
t_{max} &: Maximum\ offline\ time\ without\ exceeding\ bandwidth (s)
\end{aligned}$$

Short transhipment time criteria are measured by the dwell time per reefer. If the dwell time is short, then the entire transhipment period is short, and the customer can transport the reefer to the hinterland quicker. Also, if the dwell time exceeds the "demurrage free time", the customer is required to pay an additional fee. For reefers, the additional cost can be up to €120 for the first three days above the free time and €180 for four or more days above the free time, as illustrated in Figure 4.1 (MOL, 2017; ZIM, 2017; APL, 2016; CMA CGM, 2017; OOCL, 2016). Plus the additional electricity costs which are billed to the customer (LLC Maher Terminals, 2016). Typically the free time can vary between different terminals and different customer contracts. However, larger terminals often handle a free time period of 3 - 5 days (LLC Maher Terminals, 2016; APM terminals, 2016). Therefore, the transhipment time is specified at one day with an allowed deviation of 2 days. This time limit ensures that the customer does not have to pay additional fees.

The peak energy bandwidth of the container terminal differs for each terminal due to individual contracts of the container terminals with the energy utility company. Therefore a maximum allowed peak load is assumed. The maximum allowed peak consumption is assumed to be 80.000 kWh.

Figure 4.1: Demurrage costs

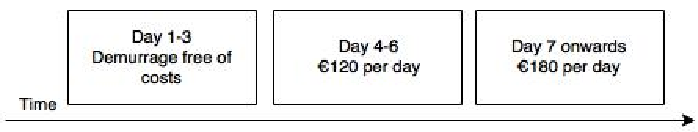


Table 4.1: Performance standards

Requirement		Customer specification	Allowed deviation
Temperature control			
	Deep frozen	-29°C	±2°C
	Frozen	-18°C	±2°C
	Chilled	2°C	±1°C
	Banana	13°C	±0,5°C
maximal Offline time			
	Offline time	4 hours	+1 hour
Short transshipment time			
	Dwell time	1 day	2 days
Energy peak load			
	Peak power	80.000 kWh	0

4.2. Description of dataset

The dataset used for this research is provided by ABB. The data is measured and collected from an unknown container terminal over the course of 1 year and 1 month. It is known that the container terminal is a large terminal in the Netherlands. The terminal where the data is collected is only known to the supervisors of this research. The data collection occurred before this research.

4.2.1. Inputs and assumptions

The inputs of the original dataset as supplied by ABB states a *fictive container number*, *container size*, *plug-in time*, *plug-out time*, *set-point temperature*, and *weight*. These inputs are measured over the course of 01-01-2014 to 23-01-2015. During this period 65732 measurements are collected, each measurement is a single container. The dataset was previously used by Nafde for his graduation thesis (Nafde, 2015). In his thesis, Nafde created a model which represented the energy consumption of reefers. The developed model of Nafde used the equations developed by Tran (2012) as showed in Equation 2.4 and Equation 2.5 to calculate the energy consumption. These equations require inputs which are not supplied by the original dataset of ABB and thus must be assumed. Other inputs can be logically deduced from the supplied dataset.

Logically deducted inputs: Some inputs are not supplied directly thus are deducted from the original dataset. The inputs that can be deducted are: *Dwell time*, *Upper bandwidth limit*, *Lower bandwidth limit*, *Average ambient temperature*, *Sun-hours*, *surface area*, *Cooling capacity*, and *Offline time*.

- The *Dwell time* of the reefer is calculated from the plug-in time and the plug-out time. The difference between these ($t_{plugin} - t_{plugout}$) is considered to be the dwell time.
- *Upper bandwidth limit* and *Lower bandwidth limit* are determined using to the categories described in Table 4.1. The Deep frozen and Frozen reefers have an allowed bandwidth of ±2°C. Reefers with a higher set-point temperature require a closer bandwidth. Therefore, chilled reefers are considered to have a bandwidth of ±1°C and Banana reefers a bandwidth of ±0,5°C is adopted.

- The *Average ambient temperature* is collected using historical data collected by the Royal Dutch Meteorological Institute (KNMI). This institute collects meteorological data since 1901 using weather stations across the Netherlands. In their databases, the temperature recorded in Rotterdam for each day of each year (since 1901) is publicly available. Together with the ambient temperature, the *Sun-hours* is obtained using the same database. In the research of Nafde (2015) an average ambient temperature was assumed, it is not clear where this assumption is based on. However, using the average temperature data from the KNMI the difference in energy consumption is not significant, as is shown in Appendix C.1

- The *Cooling capacity* can be deducted from the set-point temperature of the reefer. When the set-point temperature is high, the reefer requires less energy capacity to overcome the difference with the ambient temperature. This lower used capacity results in a higher capacity available for cooling. (Thermoking, 2013) The cooling capacity is the remaining capacity available for cooling of the cargo after the heat that entered through the isolation is removed. (Gesamtverband der Deutschen Versicherungswirtschaft E.V., 2017)

- *Offline time* is calculated using Equation 2.4 developed by Tran (2012). This formula returns the temperature change of a reefer per time unit ($\Delta T/sec$). Hereof, the total offline time before the plug-in is calculated. From the calculated offline time, it is calculated when a reefer was plugged out onboard the ship. A possible long offline period can point to an early disconnection of the reefer onboard the ship.

Assumptions: Apart from the above described logically deducted inputs, there are assumptions made. Assumption are made regarding the *Thermal insulation*, *Specific heat*, *Reefer size*, and *Linearity*.

- The *Thermal insulation* of reefers refers to the heat transition coefficient (k in Equation 2.4) is assumed to be between 0,4 (W/m^2K) and 0,9 (W/m^2K). According to the UNECE ATP treaty are, reefers with a heat transition coefficient exceeding 0,7 (W/m^2K), not allowed to be shipped internationally. For reefers with a set-point exceeding 0°C the thermal insulation requirement is stricter. Reefers in this category are required to have an insulation factor of <0,4 (W/m^2K) in accordance with ATP treaty of the UNECE which is ratified by The Netherlands (UNCE, 2016). Reefers will be tested before the first usage, after which it is assumed that the insulation value decreases with 5% annually. This means that after x years the reefer has an insulation value of >0,4 (W/m^2K) and thus is not allowed to transport goods with a set-point <0°C. In example, if a reefer is approved for a k-value of 0,35 after 6 years (when the certificate is invalid) the k-value is assumed to be ($0,35 * 1.05^6$) 0.47 thus falls in a different category where it is only allowed to transport goods with a temperature >0°C. For transport of goods <0°C the reefer is required to be re-certified. However, the responsible body for insulation tests in the Netherlands (Wageningen University) explained that they never re-test reefers. (Wageningen University, 2017) The higher values (of between 0,4 and 0,9) are assumed as the state of the reefers are never perfect. Also, a higher value compensates for the poor sealing of the doors and occasional opening. Higher values are also assumed by Nafde (2015) in his calculations for total energy consumptions and thus adopting these in this research enables the ability to compare results. The insulation values are spread evenly throughout the dataset.

- As the container terminal has no knowledge regarding the cargo type inside the reefer the specific heat must be assumed. This assumption is made based on the set-point temperature of the reefer and on the fact that frozen food typically has a specific heat of 1,7 (kJ/kgK) while the heat capacity of unfrozen food is approximately twice as high. (Gesamtverband der Deutschen Versicherungswirtschaft E.V., 2017) The specific heat is spread evenly throughout the dataset.

- Of the reefers in the dataset 94% are 40' containers, and the remaining 6% are 20' reefers. Therefore, the surface area of the reefers is assumed to be based on 40' reefers. The low percentage of 20' containers is considered to be a low impact on the total energy consumption since 20' containers consume less energy compared to 40' containers.

- When using the equations of Tran (2012) it is assumed that the temperature development for cooling and warming of the reefer occurs in a linear pattern.

- It is assumed that the reefer was at its set-point temperature when plugged out onboard the ship. This is essential for the calculation of the offline period.

The above-mentioned deductions and assumptions are essential for the data exploration and analysis. Using the data above the influence of each of these factors can be tested on the peak energy consumption of reefers.

4.3. Current process capability

Following the specifications of the customers' requirements, the current process capability is calculated. The capability is calculated by applying the discrete Six-sigma calculation method using Microsoft Excel. The data is divided into sections based on the temperature set-point of the reefer. This allows us to compare the groups between the different groups and with the total. The used dataset is described in the previous Section 4.2. The analysis on the current process capability gives an insight into the operation of the process and an indication of what parts CTQ requirements are out of control.

Temperature control capability No accurate bandwidth data is available as specific bandwidth is different per reefer. Therefore the bandwidth for the specific temperatures as mentioned by Rodrigue (2014) is assumed for four categories. The data is split up into four categories: deep-frozen (-66°C to -29°C), frozen (-28°to -10°C), chilled (-9°C to 10°C), and banana (11°C to 27°C). The corresponding bandwidth is assumed to be ± 2°C, ± 2°C, ± 1°C, and ± 0,5°C respectively. The result of the analysis is shown below in Table 4.2. In this table *defects* stands for the number of "defects" in the specific category. A defect is defined when the temperature of the reefer exceeds the allowed bandwidth. *Dpu* is the average number of defects per unit, the *FTY* is the First Time Yield (equal to e^{-DPU}), *P(d)* is the probability of a defect (equal to $1-FTY$). The *Z factor* is an important indicator for the process capability, this indicates the sigma score of the process. The standard deviation is given by *S*, the *median* is the center of each category.

Table 4.2 shows that the temperature control of all reefers in every category is rarely out of the allowed bandwidths. In almost all cases 99% of the reefers stays within the allowed temperature range. The deep-frozen reefers score lower with 93% of the reefers that stay within the allowed specification. The high performance of the the temperature control is confirmed by multiple Dutch importers of meat, fish, fruit, and vegetables who indicated that their temperature loggers rarely show that the temperature has been outside the bandwidth.

Table 4.2: Temperature control performance

	Deep frozen	Frozen	Chilled	Banana	Total
defects	2	5	5	43	55
dpu	0,065	0,001	0,001	0,001	0,001
FTY	93,8%	99,9%	99,9%	99,9%	99,9%
P(d)	6,3%	0,1%	0,1%	0,1%	0,1%
Z	1,534	3,708	3,319	2,331	3,132
s	11,03	2,276	3,801	3,064	12,342
median	-59,316	-19,823	4,049	14,959	-19,432

Minimal offline time To guarantee continuous temperature control, the offline time per reefer must be minimal. Hence, the reefer must be plugged out as late as possible, then offloaded, stacked, and plugged in as quick as possible. In this process, the terminal attempts to unload the reefers, as soon as the ship is docked, within 1 - 2 hours (ECT Delta terminal, 2017). However, according to the terminal, it often occurs that the reefers are unplugged at sea due to lack of personnel or to save money by not using more expensive fuel to power the reefers. (a higher quality of fuel is required when the ship enters European waters). In the ideal situation, the reefer would be plugged out when the ship is docked and plugged in 1 hour later on the shore. However, modern large container ships only have a crew capability of approximately 13 people (Maersk Emma, 2017). This means that it takes a smaller crew longer to unplug all reefers. According to the N.V. Havenbedrijf (2017) the time it takes to get from the north-sea to dock the ship at the terminal is 1 hour. When it is assumed that all crew must be available to dock the ship, the reefers must be unplugged before entering the port. Furthermore, when assumed that 500 reefers must be unloaded off a ship (10% of container unloading record in the PoR in 2014), the quay cranes are capable of unloading these in 3,1 hours. (Port of rotterdam, 2014, 2015) Thus, the reefers must be plugged in after approximately 5,5 hours. This is the sum of the time it takes for the ship to dock (1 hour), the offloading period of 3,1 hours, and a deviation of 1,4 hours. The deviation is allowed as the 3,1 hour as mentioned above is a record time and not a standard operation performance and the sea to dock time can be longer. With this specification limit, the capability of the offline time is calculated and is shown in Table 4.3. Table 4.3 shows that 58% of the reefers is plugged in at the reefer stack within 5,5 hours. As expected, there is no large difference between the different categories. This was expected since the terminal is not able to select which reefer types are unloaded first. It must be noted that the low Z-score of the offline time performance has no apparent influence on the temperature control. As shown in Table 4.2, the temperature of the reefers is rarely out of the selected bandwidth at plug-in. Hence the poor offline time performance has little risk of damaging the value of the perishable goods. However, the high average offline time can influence the energy consumption at the terminal. This will be researched in the analysis of the next chapter.

Table 4.3: Offline time performance

	Deep fozen	Frozen	Chilled	Banana	Total
defects	16	25692	5508	1900	33116
dpu	0,516	0,560	0,498	0,439	0,540
FTY	59,7%	57,1%	60,8%	64,5%	58,3%
P(d)	40,3%	42,9%	39,2%	35,5%	41,7%
Z	0,245	0,180	0,274	0,371	0,209
s	4,415	4,501	8,333	18,129	7,052
median	5,765	6,255	5,845	4,836	6,109

Transshipment time For the determination of the transhipment time capability an limit of 1 day with an allowed deviation of 2 days is used. Thus it is considered to be a defect when the transhipment time exceeds three days. This specification is chosen as large container terminal often have a so-called "demurrage free time" of 2 days (APM terminals, 2016; LLC Maher Terminals, 2016) thus when the reefer remains in the terminal for a more extended period of 2 days they are exceeding the agreement. Large customers can negotiate longer free times with the terminal using contracts which are not publicly available. Therfore, during this research a general maximum demurrage free time of 3 days will be considered to be a defect.

Table 4.4 shows that the transhipment time has a 43% chance to exceed the free time period of 2 days. This concludes with a low Z-score of 0,17. This high transhipment time could add to a high energy consumption.

Table 4.4: Transshipment time performance

	Deep Frozen	Frozen	Chilled	Banana	Total
defects	15	28.476	4.317	1.694	34.502
dpu	0,484	0,620	0,390	0,391	0,563
FTY	61,6%	53,8%	67,7%	67,6%	57,0%
P(d)	38,4%	46,2%	32,3%	32,4%	43,0%
Z	0,296	0,095	0,459	0,457	0,176
s	1,364	2,058	2,171	2,202	2,132
median	2,888	3,510	2,213	2,446	3,290

Peak energy The same analysis is performed towards the peak energy performance of the process. For this analysis, it is considered to be a defect when the peak energy consumption exceeds 80.000 kWh. The value of 80.000 kWh is chosen as this is a clear cutoff value, every peak over 80.000 kWh is clearly a high peak consumption. The exact value of the limit is highly dependent on the contract between the container terminal and the energy utility company. Considered this upper limit there are 19 moments when the power consumption exceeds 100.000 kWh. This results in a Z-value of 1,64. For the individual reefer categories, it is considered to be a defect when the energy consumption exceeds the proportional limit. I.e. Frozen reefers account for $\frac{45896}{61320} \times 100 = 74,85\%$ thus the combination of frozen reefers is not allowed to exceed 59.877 kWh. Hence the total number of defects is not the sum of each category, a defect in the frozen category does not directly lead to a defect in total. The results show in the table below (Table 4.5)

Table 4.5: Peak energy performance

	Deep frozen	Frozen	Chilled	Banana	Total
defects	25	25	0	0	29
dpu	0,893	0,064	0,000	0,000	0,080
FTY	41,0%	93,8%	100,0%	100,0%	92,4%
P(d)	59,1%	6,2%	0,0%	0,0%	7,6%
Z	-0,229	1,541	6,2	6,2	1,430
s	24,679	19041,787	1604,419	267,407	28554,872
mean	0,0	12031,317	443,637	179,901	21246,5

4.4. Chapter conclusion

In this chapter, the previously identified customers and their coinciding needs and requirements are quantified. Next, the current process capability was determined by calculating the Z-score. When considering the current performance of the temperatre control, transhipment time, and the peak energy performance it can be said that the current process rarely exceeds the allowed temperature bandwidth. However, it occurs regularly that the offline time is longer than 5 hours. The exceeding offline time was expected as reefers are often unplugged at sea. Also, the complete transhipment process often takes longer than the customer specifications of 3 days. Finally, the amplitude of the peaks also often exceeds the required maximum. It is especially remarkable that frozen reefers often exceed the allowed peak consumption.

After this initial data exploration, the data will be analysed systematically in the next chapter. The regression analysis of Chapter 5 will show if the found capability limitations of the dwell time and the offline time performance add to the energy consumption. Thus in the next chapter possible factors their influence on the behaviour of critical-to-quality factors will be investigated. Hereafter, the vital root-cause factors will be selected for further improvement.

5
Process analysis

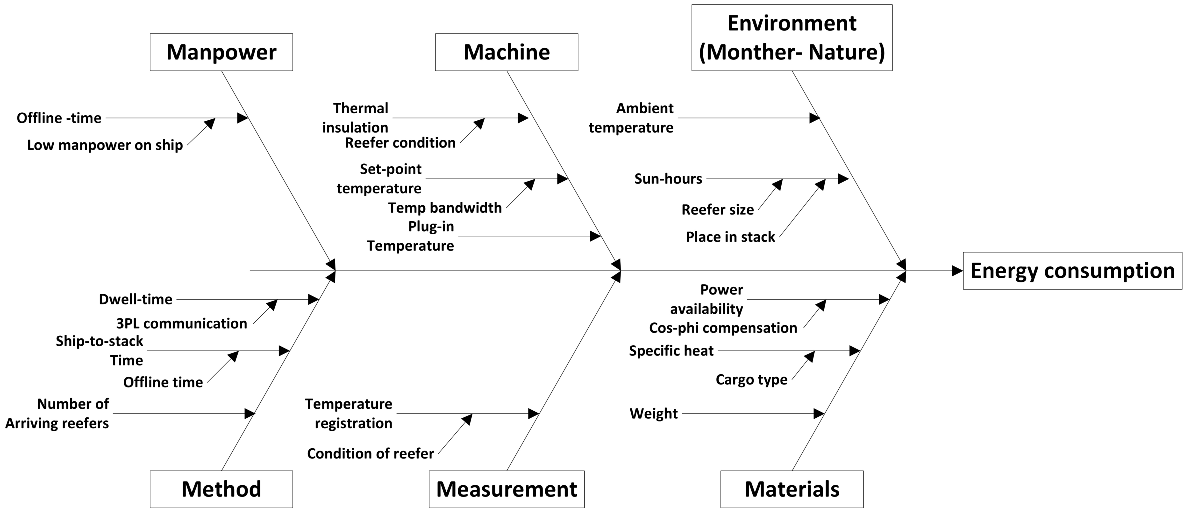
After the initial analysis of the process capability in Chapter 4, the next analysis is performed in this chapter. This chapter gives an in-depth analysis to identify the root cause factors of peak power consumption within the process. First, the possible factors that influence the energy consumption are brainstormed. The factor brainstorm leads to hypotheses which are analysed using a sequential multiple regression analysis applied to the dataset as described in Section 4.2. After the regression analysis, the identified root cause factors are explored further. Finally, the found model is cross-validated, and a conclusion to the analysis is drawn.

5.1. Brainstorm of possible root cause factors

To determine the possible causal factors to the high peak energy, firstly a brainstorm is conducted to gather as much possible causal factors. The factors are later reduced to 11 factors, which are then considered during the multiple regression analysis. The factors are brainstormed with experts from the field from ABB, ECT Delta terminal and theoretics from TU Delft. By selecting experts from ABB, ECT Delta terminal, and the TU Delft people with different views on the process are questioned and different insights are gained. The TU Delft provides factors based on theoretical knowledge, while the experts from the ECT Delta terminal and ABB provide inputs based on close-up experiences with energy consumption of reefers and the systems in place. Via e-mail, the experts are approached and asked if they where willing to contribute to this research. The experts are then asked to set-up a list of a minimum of 5 factors from which they suspect they influence the energy consumption of reefers. All experts returned with a list of minimally 7 factors (ABB 8; ECT Delta terminal 7; TU Delft 9). During this research, it is impossible to hold a physical brainstorm due to time and geographical constraints of the experts. It is acknowledged that performing a brainstorm with all experts in the same room could provide a higher yield as deeper brainstorming is possible.

After all the factors are gathered, the factors are filtered on duplicates. A factor is considered double when it is mentioned twice, or a similar term is used for a factor which is measured using the same metric. When the previously identified factors are filtered for duplicates, they can be organised in a root-cause diagram (Ishikawa diagram). The root cause diagram helps further in brainstorming for root-cause factors as it follows the 6M principle of Six-sigma. The 6M principle divides the root cause diagram is six categories. Manpower, Machine, Mother-nature (environment), Method, Measurement, and Materials. The Ishikawa diagram is shown in Figure 5.1. The principle of an Ishikawa diagram is that for every branch of the fishbone diagram minimally one factor must be identified. This forces the brainstorm session to think about every aspect of a process and nothing is forgotten.

Figure 5.1: Ishikawa diagram



The result of this brainstorm is shown in table 5.1 The complete process is shown in Appendix D. The filtered factors will be considered during the next part of the analysis phase.

Table 5.1: Identified factors for analysis

Factor number	Description	As mentioned by:
1	Number of Arriving reefers	TU Delft
2	Sun-hours	ABB
3	Ambient temperature	ABB, TU Delft, ECT
4	Set-point temperature	ABB, TU Delft, ECT
5	Plug-in temperature	ABB, ECT
6	Dwell time	ABB, TU Delft
7	Offline time	TU Delft, ECT
8	Thermal insulation	ABB, TU Delft, ECT
9	Specific heat/cargo type	ABB, TU Delft
10	Mass of Cargo	ABB, TU Delft
11	Power availability	ECT

5.1.1. Operationalization of brainstormed factors

Not all factors that are described in Table 5.1 can be measured directly. Therefore some of the factors must be operationalised, meaning that they must be measured using another method. The number of arriving reefers, sun-hours, set-point temperature, thermal insulation, and mass of cargo are operationalised by measuring the exact factor. These are referred to as *No_arr_reefers*, *Sun-hours*, *T_set_point*, *Thermal_iso*, and *Weight* respectfully.

The ambient temperature is operationalised by using the ΔT between the set-point temperature and the average ambient temperature. This difference is referred to as the *Delta_T_ambient*. The plug-in temperature is operationalised by using the ΔT between the plug-in temperature and the set-point temperature. This is referred to as the *Delta_T_plugin*. As mentioned before in Section 4.2, the offline time is calculated using the equations developed by Tran (2012). The offline time is referred to as *Offline_time*. Section 4.2 also describes the calculation of the Dwell time as the difference between the plug-in and plug-out time of the reefer. The type of cargo can be operationalised using two methods. It can be either represented by the set-point temperature or the specific heat. In this research, it is chosen to represent the cargo type using the specific heat of the cargo. The specific heat is referred to as *Specific_heat*. The power availability is difficult to operationalise as no data is known regarding this factor. Therefore this factor will not be considered during this research.

5.1.2. Hypothesis development

Following from the previously identified possible factors of influence multiple hypotheses can be developed. During the brainstorm, the experts were asked what factors they considered to have an impact on the energy consumption. Therefore, it is hypothesised that the factors mentioned above, have a direct influence on the total power consumption of the reefers. The conceptual model is shown in Figure 5.2

Hypothesis 1.1

The number of reefers is hypothesised to have a large influence on the total energy consumption. It seems obvious that a larger number of reefers will lead to higher energy consumption. Therefore, it is hypothesised that the number of arriving reefers will have a positive influence on the energy consumption.
H_0 There is no correlation between the energy consumption and the number of arriving reefers.
H_1 There is a positive correlation between the energy consumption and the number of arriving reefers.

Hypothesis 1.2

88% of the time in Rotterdam, the setpoint temperature of reefers is below the ambient temperature. Therefore, with higher ambient temperatures, the reefer will need more active cooling. Hence it is hypothesised that a higher ambient temperature leads to higher energy consumption.
H_0 There is no correlation between the energy consumption and the ambient temperature.
H_1 There is a positive correlation between the energy consumption and ambient temperature.

Hypothesis 1.3

It is likely that reefers warm up as it is exposed to more sunlight. Therefore, it is hypothesised that if there are more sun-hours during a day, the energy consumption is likely to be higher.
H_0 There is no correlation between the energy consumption and the number of sun-hours.
H_1 There is a positive correlation between the energy consumption and the number of sun-hours.

Hypothesis 1.4

It is hypothesised that there is a relation between the temperature set-point of a reefer and its energy consumption. However, the direction of the relation is not known as a reefer with a lower set-point is likely to require intensive cooling and has a broad bandwidth. Reefers with a higher temperature, such as banana reefers, require less intensive cooling but due to the narrow bandwidth requires to be cooled more often.
H_0 There is no correlation between the energy consumption and the set-point temperature.
H_1 There is a correlation between the energy consumption and set-point temperature.

Hypothesis 1.5

If the delta between the plug-in temperature and the set-point temperature is high, the reefer requires immediate cooling once it is connected. Therefore, it is hypothesised that a higher delta plug-in temperature adds to higher energy consumption.

H_0 There is no correlation between the energy consumption and the delta plug-in temperature.

H_1 There is a positive correlation between the energy consumption and the delta plug-in temperature.

Hypothesis 1.6

If reefers are connected for a longer period at the terminal, it is likely that this will lead to higher total energy consumption. Therefore, it is hypothesised that there is a positive correlation between the dwell time and the energy consumption.

H_0 There is no correlation between the energy consumption and the dwell time.

H_1 There is a positive correlation between the energy consumption and the dwell time.

Hypothesis 1.7

Reefers are disconnected during offloading, AGV movement, ASC movement, customs check, and possibly early at sea. If reefers are disconnected for an extended period the temperature of a reefer will drift from its set-point temperature. If the disconnection period is long, this is likely to lead to higher energy consumption. Therefore, it is hypothesised that a longer offline time adds to higher energy consumption.

H_0 There is no correlation between the energy consumption and the offline time.

H_1 There is a positive correlation between the energy consumption and the offline time.

Hypothesis 1.8

The thermal insulation value of a reefer is between 0,4 - 0,9 (W/m^2K), where a value of 0,4 W/m^2K provides better insulation than higher numbers (e.g. 0,9 W/m^2K). The unit of W/m^2K is the amount of energy per second (W = J/s) lost per square meter of insulation (M^2) with a difference of 1°K between inside and outside. Therefore, it is hypothesised that a higher thermal insulation value leads to higher energy consumption.

H_0 There is no correlation between the energy consumption and the thermal insulation.

H_1 There is a positive correlation between the energy consumption and the thermal insulation.

Hypothesis 1.9

The heat properties of a cargo type are defined by the specific heat characteristics of the cargo (J/kgK). The specific heat is defined by the amount of energy (J) required to heat 1 kilogram over 1 °K. Therefore if the cargo is characterised by a lower specific heat the cargo will also lose the invested energy more quickly. Thus, it is hypothesised that cargo with a higher specific heat retains more energy and therefore adds to lower energy consumption at the terminal.

H_0 There is no correlation between the energy consumption and the type of cargo.

H_1 There is a negative correlation between the energy consumption and the type of cargo.

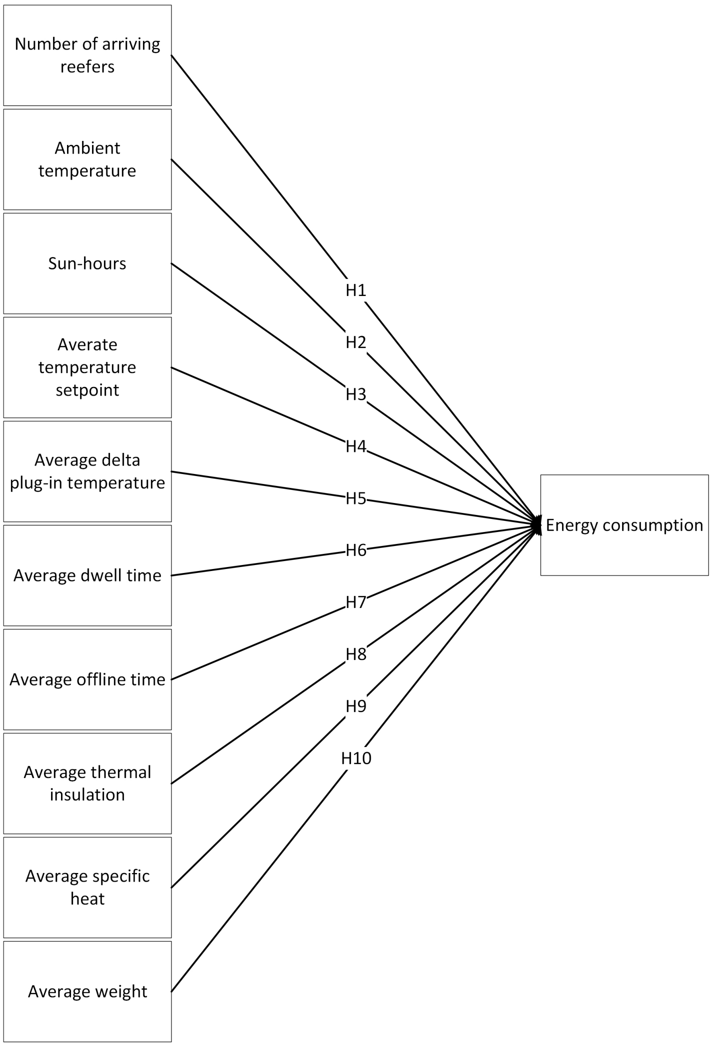
Hypothesis 1.10

Cargo with a larger mass is likely to retain more of its energy compared to lower mass cargo similar as with the specific heat. Therefore, it is hypothesised that a lower cargo mass adds to higher energy consumption.

H_0 There is no correlation between the energy consumption and the cargo mass.

H_1 There is a negative correlation between the energy consumption and the cargo mass.

Figure 5.2: Hypotheses



5.2. Data exploration

Prior to the regression analysis in section 5.3 the brainstormed factors are explored using the IBM SPSS statistical package. The first step in the exploration is to investigate the complete dataset for correlations and trends. For every day of the measurement period (01-01-2014 to 31-01-2015), the average is calculated for each factor. The average of each factor is then analysed to the total energy consumption which is determined by Tushar Nafde. If a factor has an impact on the total energy consumption, it should show that the total energy consumption increases or decreases with a change in the factor. The direction of the relation is hypothesised in the previous section. The Pearson correlation matrix indicates the direction, strength and significance of the bivariate relationships of between all above-brainstormed factors. The complete matrix is shown in Appendix E.1. A summary of the matrix is shown in Table 5.2.

Table 5.2 indicates that seven factors have a statistically significant correlation with energy consumption (flagged with *). The largest correlation is between the total energy consumption and the number of arriving reefers. Furthermore, the Dwell time, Delta plug-in temperature (delta T), Cargo type (specific heat), Thermal insulation, Weight, and Ambient temperatures appear to be correlated with total energy consumption. It is noticeable that the factor "Sun-hours" is not-significant where this was not expected. The offline time is

Table 5.2: Correlation of factors to energy consumption

	Tot_cons_tushar
No_arr_reefers	,886***
avg_dwelltime	,146**
avg_deltaT_plugin	,199***
avg_T_setpoint	-,030
avg_specific_heat	-,225***
avg_thermal_iso	,200***
avg_weight	,388***
avg_DeltaT_ambient	-,163**
Sun-hours	,050
Offline_time	-,011

* p<0,05, ** p<0,01. *** p<0,001

not directly statistically correlated with the total energy consumption, while it often assumed that this has a considerable influence on the energy consumption of reefers.

5.3. Regression analysis to determine influence of factors

After the exploration of the data, a general idea of the influence of certain factors on the total energy consumption is made visible using a correlation matrix. The next step is to perform a multiple regression analysis. Such an analysis enables us to predict the total energy consumption per day. A sequential multiple regression analysis, using the IBM SPSS package, is selected for the analysis. This selection is made based on the decision tree presented by Tabachnick and Fidell (2013, p.29) as there is one continuous dependent variable, multiple continuous independent variables, and there might be covariates. Also, the goal of the analysis is to find the optimal combination of IVs to predict the DV. These characteristics lead to the sequential multiple regression strategy.

To perform a proper regression analysis, the appropriate factors which are included in the analysis must be selected. This is done by using an automatic model for the selecting of factors. An overflow of factors in the regression analysis can lead to an inaccurate analysis. As the famous quote of Albert Einstein says: *"Everything should be made as simple as possible but not simpler"*. Therefore first a model of IV's is selected. The model can be selected using different automated methods. These automated selection methods can be used if there is no large collinearity, no large number of variables compared to the number of observations, which is not more than 1:10, and no ordinal/nominal data is used. The data used in this research complies with these requirements thus the automatic model selection methods can be used. Therefore, a choice must be made regarding which selection method will be used. The difference in selection methods is described next (NCSS, 2017).

Backwards (step down) selection is the most straightforward method of model selection. In backwards selection, all predictors are initially entered in the regression. Next, the predictor with the highest P-value above the threshold of a chosen α is removed, and the model is refitted with the remaining predictors. Again, the predictor with the highest P-value is removed. The procedure is repeated until all predictors have a P-value of less than the chosen α.

Forward (step up) selection is another stepwise selection method. This method adds predictors. The algorithm selects the predictor with the highest R-squared with a P-value under 0,05. Next, the model is refitted with the predictor, and again another predictor is selected, with the highest R-squared and low P-value, of the remaining unused predictors. The adding of predictors is repeated until no remaining unused predictors can be added due to a P-value exceeding 0,05. This method is best used for extensive datasets with many predictors and when collinearity is a problem.

The dataset used for this regression analysis has 393 observations (one year and one month), nine possible independent predictors, and no collinearity problems. Thus, the Backwards selection method is used with an α boundary of 0,05. The outcome of the backward sequential regression analysis is shown in Tables 5.3 and 5.4. What immediately shows is that the backward selection removes four factors from the regression analysis. Three of the removed factors are expected as these were found to be insignificant in the above-shown correlation matrix in Table 5.2 (Set-point temperature, Sun-hours, and Offline time). However, the fourth removed factor is the avg_DeltaT_ambient factor. Which is found to have a $\alpha < 0,05$ after removing the average temperature set-point, sun-hours, and offline time from the regression analysis. Therefore, the model with the highest R^2 contains five root cause factors. As expected the number of arriving reefers explains a significant portion of the variance. The dwell time, plug-in temperature, specific heat, and thermal insulation are the other factors included in the model. Together the model explains 83% of the total variance.

Table 5.3: Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
6	,911	,830	,827	12333

Table 5.4: Regression coefficients

Model		Unstandardized Coefficients		standardized Coefficients	
		B	Std. Error	Beta	t
6	(Constant)	41.088,919	30.417		1,35
	No_arr_reefers	174,390	5,7	,850***	30,43
	avg_dwelltime	6.855,187	959	,198***	7,15
	avg_specific_heat	-22.775,936	8.475	-,081**	-2,69
	avg_thermal_iso	15.218,523	7.423	,062*	2,08
	deltaT_plugin	14.190,340	6.503	,061*	2,18

* p<0,05, ** p<0,01. *** p<0,001

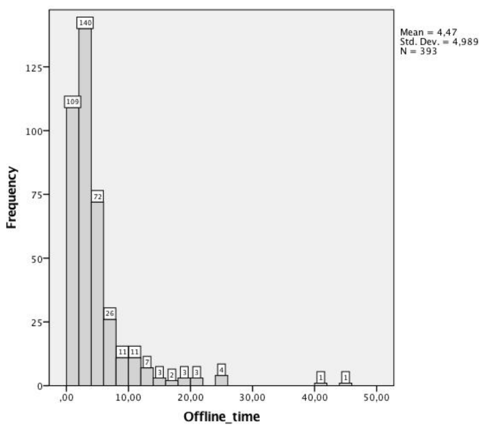
5.3.1. Non-significant factors

The model suggests that the ambient temperature, sun-hours, set-point temperature, and offline time do not influence the total energy consumption significantly. The non-significance of the ambient temperature is counter-intuitive, as it seems logical, that when the ambient temperature is high, and the reefer is in direct sunlight for a longer period, the reefer must work harder to keep the required temperature within the set bandwidth. The statistical insignificance of the ambient temperature compared to the total energy consumption suggests that the ambient temperature does not influence the total energy consumption enough to have a measurable effect. Therefore, it must be concluded that when considering Hypothesis 1.2 from section 5.1.2, H_1 must be rejected and H_0 must be accepted.

The number of sun-hours and temperature set-point are also not found to have a significant impact directly on the energy consumption. Thus, for hypothesis 1.3 and 1.4, the alternate hypothesis must be rejected, and H_0 must be accepted. The same can be said for the factor of weight, which is also found to be a non-significant predictor of the total energy consumption. Reefers which are lower in mass are more likely to have a higher energy consumption, as mass retains heat more easily. However, it is not found that in times that the energy consumption is high, the average mass of reefers is lower. Thus when answering hypothesis 1.10 of paragraph 5.1.2 H_1 is rejected and H_0 is accepted, thus that the mass of reefers does not have a significant correlation with the total energy consumption.

Also, it was expected that the offline time was a significant influence on the energy consumption. However, as this is found to be non-significant, it shows that the time which the reefer is disconnected is not a significant influence on the total consumption. This could point to the notice of reefers being unplugged early on the ship, and if early unplugging occurs it does not influence the total energy consumption. The regression analysis shows that the offline time is not noticeably longer during high energy consumption periods. To answer hypothesis 1.7, $H_{!}1$ is rejected and H_0 is accepted. To confirm that the reefers are not always unplugged at sea, we can look at the histogram of the offline time. The histogram shows that only occasionally the reefers are plugged out for an extended period, suggesting on-sea plug-out. The mean of the offline time is 4,47 hours, with a standard deviation of 4,9 hours. The regression analysis shows that this occasional early plug-out time does not contribute significantly to the energy consumption. However, it cannot be concluded that early plug-out on the sea does not happen, merely that it does not significantly contribute to the total energy consumption on shore. The instances that it does occur remains an insurance affair if the temperature bandwidth is exceeded.

Figure 5.3: Offline time distribution



5.3.2. Significant factors

To determine the percentage of variance explained by the number of arriving reefers a forward regression analysis is performed using the significant factors. In this regression method (as described in section 5.3) the factors are added one by one. The change in R^2 for each model is assigned to the factor which was added to that model (Tabachnick and Fidell, 2013). As there is no multicollinearity between the factors the, R^2 change can be directly assigned to the added factor.

The regression analysis indicates that the number of arriving reefers explains a large portion of the variance. The forward regression analysis shows that 76,6% of the variance is explained by this key variable. This high value is expected as is it highly logical that when a large number of reefers arrive, the energy consumption increases. The H_0 of Hypothesis 1.1, must be rejected and H_1 accepted. However, the number of arriving reefers is not a variable that can be influenced but is a variable that is a given and will only increase over time due to an increase of reefer usage (World Cargo News, 2017). Therefore it is essential that factors other than the number or arriving reefers are identified next, or the energy consumption will continue to keep growing.

The dwell time accounts for the second largest section of the variance in the energy consumption. In total, the dwell time explains 4,6% of the variance. A significant influence of the dwell time is to be expected as when reefers are plugged in at the terminal for a more extended period; more energy will be consumed. To answer Hypothesis 1.6, H_0 is rejected and H_1 is accepted. Therefore, efforts in reducing the dwell time can contribute to significantly reducing the total energy consumption of reefers at container terminals as there would be fewer containers present simultaneously.

The model developed by the regression analysis also states that at moments when the energy consumption is higher, then there also is a more substantial difference between the set-point and plug-in temperature (a high ΔT). The forward regression analysis shows that the plug-in temperature accounts for 0,4% of the total variance. Thus it can be said that the plug-in temperature has a small but noticeable influence on the total energy consumption, meaning that Hypothesis 1.5 can be answered. From this, hypothesis H_0 can be rejected and H_1 is accepted. After the rejection of Hypothesis 1.5, the question arises: what causes the Δ in temperature between the set-point and plug-in temperature to increase if offline time is not a significant factor in the total energy consumption? An answer to this question can be found in the equations of Tran (2012), which mentions specific heat, thermal insulation, and ambient temperature as other factors that increase the Δ Temperature. The specific heat and thermal insulation are found to have a significant impact on the total energy consumption at the container terminal as is discussed in the following paragraphs.

The regression analysis shows that when a more substantial number of reefers containing cargo with a higher specific heat arrive, the total energy consumption will reduce. In other words, reefers containing (deep)frozen goods (C_P of ±1,7) require more energy to keep the reefer within its bandwidth. Reefers with cargo that has a higher specific heat, such as fruits and fresh fish require less energy to keep the temperature within the bandwidth. Chilled and Banana reefers are often actively cooling due to their more narrow bandwidth. However, temperatures that must be achieved for foods with a higher C_p, require less energy as they retain more energy. With this Hypothesis 1.9 can be concluded. H_0 is rejected and H_1 is accepted. The effect of specific heat accounts for 1,1% of the total variance.

For the thermal insulation of reefers, the analysis shows that an increase of reefers with higher thermal insulation factor leads to a higher energy consumption. (for further explanation see Section 5.4.3. Thus, in moments where there are more older reefers, and reefers in poor condition, the total energy consumption in the container terminal will increase. Therefore, Hypothesis 1.8 can be answered by the following: H_0 is rejected and H_1 is accepted. The effect of thermal insulation is found to have the lowest impact on the total energy consumption. In total, the variance explained by the thermal insulation of reefers is 0,3%.

The above mentioned significant factors will be further investigated in Section 5.4

5.3.3. Sub-conclusion regression analysis

In this section, a sequential multiple regression analysis was performed. Five factors are found to be significant to predict the total energy consumption. Of these five factors, the number of arriving reefers is the variable that explains most of the total variance (76,6%). Apart from the arrival rate, the most obvious factor that is found to be significant is the dwell time. After the number of arriving reefers, this is the factor that is found to have the most impact on the total energy consumption with a total explained variance of 4,6%. It is interesting to see if the dwell time can be reduced, and thus the total energy consumption can be reduced as fewer reefers will be plugged in simultaneously. Furthermore, the analysis shows that older reefers together with frozen cargo significantly contribute to total energy consumption (0,3% and 1,1% respectfully). Also, reefers with a high plug-in temperature difference, compared to their temperature set-point require, provide a significant energy pull. These reefers account for 0,4% of the total energy consumption.

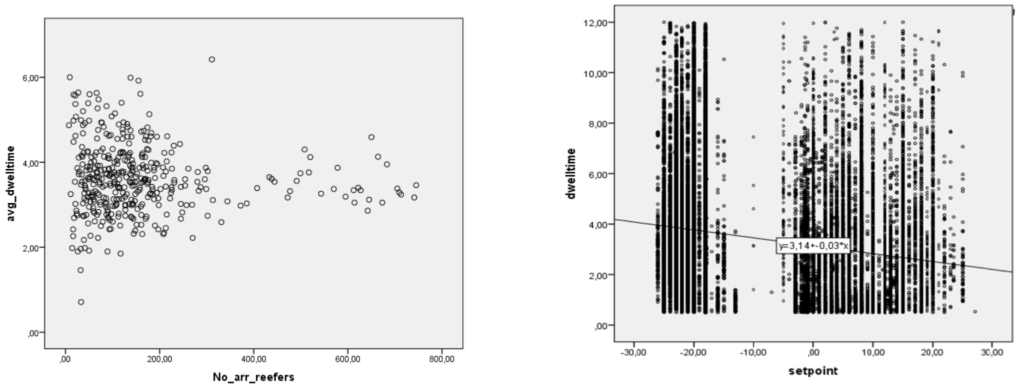
5.4. Deeper analysis of significant factors

The previous multiple regression analysis has shown two factors which add to energy consumption and which are unexplained. These are the influence of dwell time and high ΔT between the set-point temperature and the plug-in temperature. The Six-sigma methodology states that when looking for root causes, one must ask himself "why" for five times (Eckes, 2005). These five times are considered to be a guideline, sometimes fewer iterations (of asking why) are required to find the root cause. Thus, by zooming in on these factors, there is continuously asked why.

5.4.1. Dwell time

Dwell time is found to be an important factor in predicting 4,6% of the total energy consumption of reefers at a container terminal. However, what causes the increase of dwell time? To answer this question factors must be identified which could influence the dwell time. The definition of a high dwell time is that reefers are collected by the customer after a longer period. During this period the containers are plugged in at the terminal. But why are these reefers collected by the customer after a longer time? This could be due to multiple reasons. Firstly, it could be that it is *not possible* for the reefer to be picked up by the customer. If the customer is not able to collect the reefer due to process limitations, it is logical that an increase in the number of arriving reefers leads to a higher dwell time due to capacity restrictions in the process. If this were the case, then there would be a correlation between the number of arriving reefers and the dwell time. However, the dot-plot in figure 5.4a shows that there is no direct observable correlation between the two above mentioned factors. A bivariate correlation test shows that the correlation is a non-significant weak -0.064 relation. The little relation implies that a lack of capacity in the process does not introduce high dwell times as the process is capable of processing the increasing number of arriving reefers. Other issues such as problems with customs clearance and incorrect paperwork could also prevent the customer to collect the reefer.

Secondly, it could be that the customer does not *want* to collect the reefer. In an example, it could be that frozen reefers have a higher dwell time as these products are typically not as time critical as chilled and banana products. Frozen goods typically have a longer shelf life than fresh produce. The extended shelf life could lead to later reefer collection by the customer, as the time pressure is lower. A later pick-up would mean



(a) Dwell time vs number of arriving reefers

(b) Dwell time vs set-point temp

Figure 5.4: Factors on dwell time

there is a negative correlation between the reefer category and the dwell time. When performing a regression analysis, it is shown that there is a significant (P=0,000) correlation ($\beta =,360$) between the type of reefer (set-point temperature) and the dwell time. This relation is shown in Figure 5.4b. As is shown by the graph, the relation does not represent the complete variance as it only explains 13% of the variance ($R^2 = 0,130$). As the dwell time explains 4,6% of the energy consumption, it can be said that the temperature set-point explains 0,6% of the energy consumption ($0,13 * 0,046$). Other factors explaining the rest of the variance in the dwell time remain guessing. However, the apparent relation shows that developing a solution which targets the dwell time of different reefer types is in the line of interests. Such a solution could result in a significant energy consumption reduction.

To statistically test the mediation of dwell time the method developed by Baron and Kenny (1986) is used. The analysis of Baron and Kenny is a four-step analysis. The analysis first shows that the causal variable (set-point temperature) is correlated with the outcome (energy consumption). The second step is to show that the causal variable is correlated with the mediator (dwell time). In the third step, it is shown that the mediator is correlated with the outcome. In the fourth step, both the causal variable and mediator are tested against the outcome. If the causal factor is non-significant, then there is complete mediation. (Hayes, 2012) developed the PROCESS algorithm. The algorithm of Hayes automatically tests for a mediation effect. (Field, 2013) Running the algorithm shows that there is a relation between the set-point temperature and energy consumption with the dwell time as a mediation effect with an effective strength of -,200 (full analysis is shown in appendix E.3.1).

5.4.2. Delta plug-in temperature

Apart from the dwell time, it was found that $\Delta T_{plug\ in}$ between the set-point temperature and the plug-in temperature has a significant (albeit small) impact on the total energy consumption. The $\Delta T_{plug\ in}$ explains 0,4% of the variance in of the total energy consumption. In previous research of van Duin et al. (2016); Nafde (2015) it has been shown that the mass and sun intensity are key variables in the $\Delta T_{plug\ in}$. Therefore, it is interesting to investigate if these conclusions, which are developed by simulation, are consistent. Also, factors which have been found not to have a direct impact on the energy consumption, must have an influence which must be explained. It is known that these factors must have an influence as these are inputs in the equations of Tran and hence must be explained. Therefore, the following hypotheses are developed:

Hypothesis 2.1

When a reefer has a higher mass, the cargo loses energy less quickly. Hence the delta plug-in temperature will be lower. Such a heavier reefer is likely to be able to be unplugged for a few hours.
H_0 There is no correlation between the Delta plug-in temperature and the mass.
H_1 There is a negative correlation between the Delta plug-in temperature and the mass.

Hypothesis 2.2

The research of Nafde (2015) indicates that the sun intensity plays an important role in the delta plug-in temperature. If there are more sun-hours during the day, then the sun-intensity will be higher, and hence the delta plug-in temperature will be higher. Therefore it is hypothesised that there is a positive relationship between the sun-hours and the Delta plug-in temperature.
H_0 There is no correlation between the Delta plug-in temperature and the sun-hours.
H_1 There is a positive correlation between the Delta plug-in temperature and the sun-hours.

Simultaneously the offline time, $\Delta T_{ambient}$ are hypothesised to influence the $\Delta T_{plug\ in}$ and therefore also entered in the regression with the following hypotheses:

Hypothesis 2.3

When a reefer is disconnected, the temperature will drift from the set-point temperature. When the reefer is disconnected longer the delta plug-in temperature is likely to be higher. Therefore a positive correlation is hypothesised.
H_0 There is no correlation between the Delta plug-in temperature and the offline time.
H_1 There is a positive correlation between the Delta plug-in temperature and the offline time.

Hypothesis 2.4

With a higher ambient temperature, the temperature inside the reefers is likely to drift faster and further away from the set-point temperature. Therefore it is hypothesised that higher ambient temperature will lead to a higher delta plug-in temperature.
H_0 There is no correlation between the Delta plug-in temperature and the ambient temperature.
H_1 There is a positive correlation between the Delta plug-in temperature and the ambient temperature.

This model suggests that ΔT_{plugin} acts as a mediator variable in the total model (Figure 5.5). The mediating effect of the $\Delta T_{plug\ in}$ on the energy consumption is tested using the algorithm developed by Hayes (2012). The multiple regression analysis was performed on performed on 60% of the available data with N=236; the residual 40% will be used to cross-validate the found model. The four independent variables are entered directly and result in a R^2 of 0,355. When performing multiple regression analysis, it is found that the reefer weight does not influence the delta plug-in temperature significantly. Therefore, considering hypothesis 2.1 H_1 can be rejected and H_0 accepted. However, the temperature difference between the reefer set-point and the ambient temperature ($\Delta T_{ambient}$) has a strong and significant impact on the delta plug-in temperature (β = -,484; P<0,001). Thus, H_0 of hypothesis 2.4 can be rejected and H_1 accepted. Also the number of sun-hours and the offline-time has a significant impact of β = ,110 (P<0,05) and β = ,198 (P<0,001) respectfully. Therefore H_1 of hypotheses 2.2 and 2.3 can be accepted. The results of the analysis are shown in Table 5.5 and 5.6. The standardised (β) coefficients of Table 5.6 suggest that delta ambient temperature accounts for most of the variance in the plug-in temperature. To determine the variance explained by each factor a forward regression analysis is performed. The forward analysis shows that delta ambient temperature accounts for 30,3% of the delta plug-in temperature. Next, it can be said that the offline time accounts for 3,7% of the variance, sun-hours for 0,7%, and weight for 0,8%. As the Variance Inflation Factor (VIF) of all factors entered are below a score of 4, it can be concluded that there is no multicollinearity present in the model. The maximum VIF score among the entered variables is 1,4 and thus well below the threshold score 5 when there is considered to be a moderate correlation.

Table 5.5: Model summary delta plug-in temperature

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,596	,355	,355	,103

Table 5.6: Coefficients on delta plug-in temperature

Model		Unstandardized Coefficients		Standardized Coefficients	
		B	Std. Error	Beta	t
1	(Constant)	-,284	,107		-2,642
	avg_weight	$6{,}780*10^{-06}$	,000	,103	1,648
	avg_deltaT_ambient	-,010	,001	-,484***	-7,590
	Sunhours	,003	,002	,110*	1,947
	avg_Offline_time	,005	,001	,198***	3,696

* p<0,05, ** p<0,01. *** p<0,001

When comparing the results as mentioned earlier to the findings of (Nafde, 2015), it shows that the mass of a reefer does not have a significant effect on the plug-in temperature. This difference in findings can be explained is when the sensitivity analysis of Nafde is considered. During this sensitivity analysis, on the influence of weight, extreme values of weight were used (5000 kg and 30.000 kg). In practice, the weight of reefers does not vary as much. Considering descriptive statistics of the complete dataset with N=65791, the mean is 30.000 kg with a standard deviation of 5000 kg. Therefore H_1 of hypothesis 2.1 is rejected and H_0 is accepted A different key variable (sun intensity) found by Nafde also shows in the regression analysis as a factor with a significant impact on the plugin temperature. However, the ambient temperature and the offline time of the reefer show to have a more significant impact on the plug-in temperature compared to the sun intensity. Thus it can be concluded that H_0 of hypothesis 2.2, 2.3, and 2.4 are rejected and H_1 is accepted.

The regression analysis in this section shows that factors which initially have been found not to contribute to the total energy consumption do contribute to the difference in plug-in temperature. The mediation of the delta plug-in temperature is tested using the algorithm developed by Hayes (2012). For the offline time, weight, sun-hours, and ambient temperature, the algorithm indicates that the delta plug-in temperature acts as a mediator with effect strength of 268,6; 0,4; 378,3; -350,1 respectfully. The full analysis is shown in Appendix E.5. It can be concluded that the difference in plug-in temperature and its set-point temperature acts as a mediating variable. However, the influence of the delta ambient temperature, sun-hours, and offline time on the total energy consumption can be considered to be very small to negligible.

5.4.3. Thermal insulation

The thermal insulation ability of reefers is found to impact the total energy consumption of reefers. The positive β coefficient of, 062 (P<0,05) indicates that an increase of the thermal insulation value adds to an increase in the total energy consumption of reefers at the container terminal. The forward regression analysis states that the thermal insulation adds 0,3% to the total energy consumption. A higher thermal insulation value indicates an older reefer. In older reefers, the insulation value decreases due to deterioration of the reefer. In an example, the effectivity of the wall insulation decreases over time, also due to wear and tear doors will seal less effective, and the condition of the refrigerant will reduce due to contamination and poor maintenance. These age and maintenance factors lead to an increase in energy consumption per reefer. However, the small β and explained variance of the thermal insulation indicate that the influence of this variable is minimal to negligible.

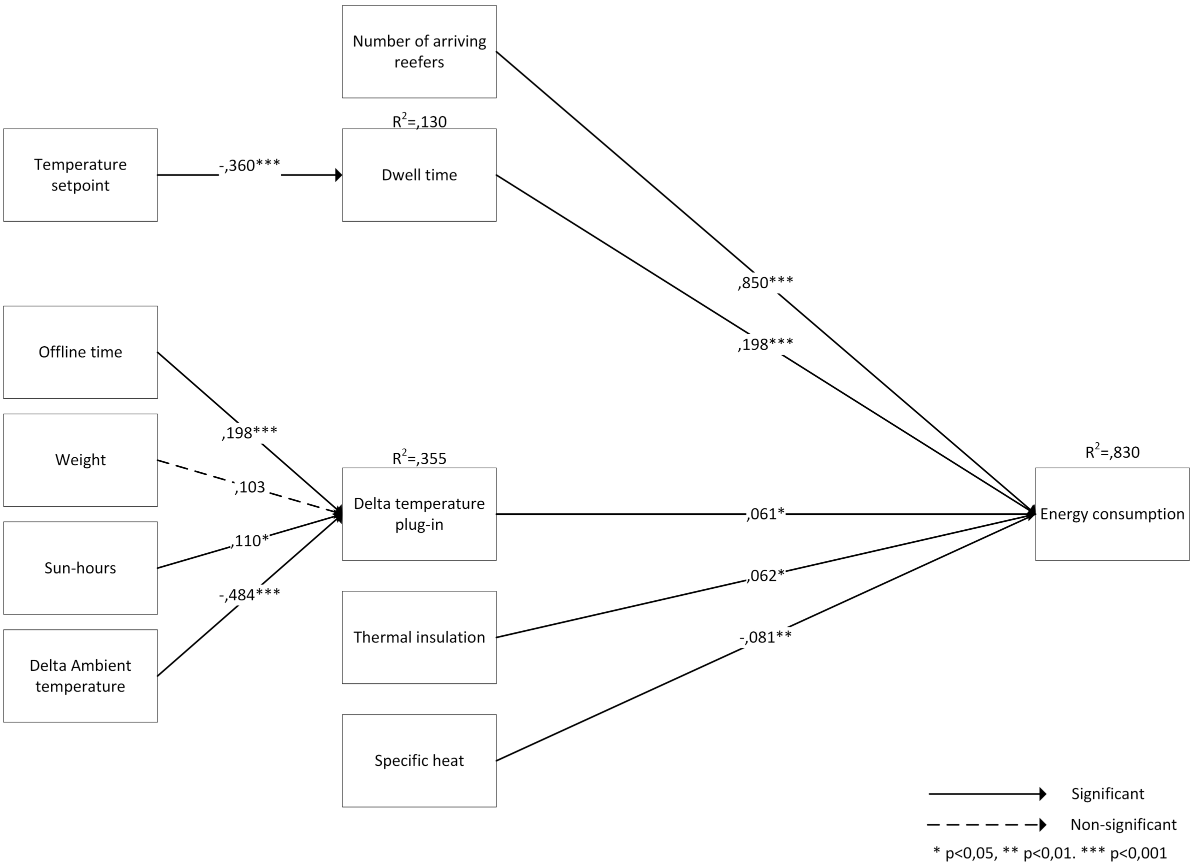
5.4.4. Specific heat

The last factor which is found to have an added value to the total energy consumption is the specific heat of cargo. The specific heat is found to explain 1,1% of the total variance and a β of -0.81 (p<0,01). The specific heat represents the type of cargo which is transported. The specific heat of the cargo is found to have a negative impact on the total energy consumption, indicating that when there are on average more reefers with a higher specific heat, there will be a lower total energy consumption at the terminal. A higher specific heat is typical for fresh produce and frozen (solidified) goods lead to a lower specific heat. The observation that frozen goods consume more energy is supported by the capability analysis in section 4.3. In the analysis, it is found that frozen reefers often consume the most energy. Considering the fact that Chilled and Banana reefers have a more narrow bandwidth and therefore are more often actively cooling, this cooling requires less energy than the cooling of frozen goods as less heat has to be removed.

5.5. Developed model

Considering the aforementioned independent, mediating and dependent variables the model can be drawn. Figure 5.5 shows the developed model. Figure 5.5 shows the found relationships and their strengths between the factors and the total energy consumption. The overview indicates the convincing strength of the number of arriving reefers and dwell time. Other factors such as delta plug-in temperature, thermal insulation, and specific heat add very little to the total energy consumption.

Figure 5.5: Developed model



5.6. Cross validation

According to Tabachnick and Fidell (2013) cross-validation with a second sample is highly recommended for stepwise regression methods. The method of cross-validation is based on the principle that *"If a model can be generalised, then it must be capable of accurately predicting the same outcome variable from the same set of predictors in a different group of people."* (Field, 2013).

Cross-validation of the developed model is done through some steps. Initially, the data is split up into two sections to create *"the different group of people"* to which Field refers. The larger section is used for the development of the model (model training), and the smaller section is used for cross-validating the model (model testing). Tabachnick and Fidell (2013) suggest that using an 80% and 20% division of the data is appropriate for cross-validation. However, in this research, a division of 60% and 40% is used. Meaning that a random 60% is used for the development of the model as mentioned above and the remaining 40% is used for the cross-validation model testing. The ratio between the training and test section of 60% and 40%, respectively, is selected as this ratio puts an higher emphasis on the testing of the strength of the prediction. During this research, the cross-validation of the identified factors is more important than the accuracy of the prediction. Thus, a ratio of 60% and 40% is chosen. Secondly, the developed regression equation is used to predict the value of the energy consumption of the smaller cross-validation sample. After this, the predicted energy consumption and actual energy consumption are correlated to find the correlation coefficient (R). The correlation coefficient is squared to obtain the R^2 for the smaller sample (R^2_{40}). In this correlation analysis, a significant discrepancy between the R^2 between the 60% sample (R^2_{60}) and 40% sample indicates a lack of generalizability of the found model. (Tabachnick and Fidell, 2013; Field, 2013) Besides comparing the R^2 the Mean Squared Error (MSE) for both samples are also compared.

A quick validation check of the random generated sections of SPSS shows that the sum of energy consumption, of the random selected 60% in the training section, is equal to 61%. Thus it can be said that the random generated groups are properly spread over the training and test sections.

5.6.1. Dwell time validation

As found in section 5.4.1 the temperature set-point of the reefer explains 13% of the variance of the dwell time. For verification purposes, it is attempted to predict the dwell time using the temperature set-point of the reefer. Equation 5.1 is used to predict the dwell time. Equation 5.1 is developed using the coefficients found during the regression analysis in section 5.4.1.

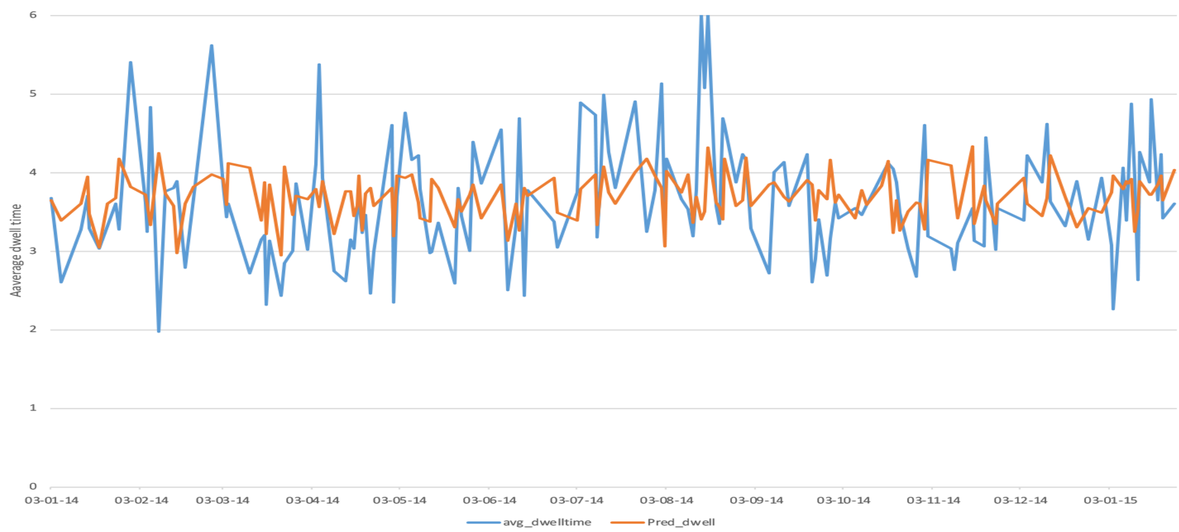
$$Y'_{dwell} = 2,598 + -0,76 * X_1 \tag{5.1}$$

$$\begin{aligned} &Where: \\ &Y'_{dwell} : Predicted\ dwell\ time\ (days) \\ &X_1 : Average\ temperature\ set-point\ (°C) \end{aligned}$$

The actual and predicted dwell times are compared and are shown in Figure 5.6. Considering this figure, it becomes clear that (as expected) the complete dwell time cannot be explained using the temperature set-point alone, which was already suggested by the low R^2. To empirically verify that the set-point temperature does predict some of the dwell time the predicted and actual values are correlated. The correlation coefficient (R=0,186; P<0,05) is then squared to obtain the R^2. The calculated R^2 can be considered to be the R^2 of the remaining 40% of the dataset, which is R^2_{40} = 0,035. The calculated R^2_{40} is less but not far from the R^2_{60} presented by the regression model according to Tabachnick and Fidell (2013).

The MSE for the training sample shows to be $MSE_{60} = 0,64$. For the test sample the MSE is $MSE_{40} = 0,56$. The difference between these MSE's is 13%, indicating that the test section has a lower mean squared error. The difference between both the R^2 and MSE's is not large, indicating that the model predicts equally well for the training sample and the test sample and can be considered to be consistent.

Figure 5.6: Predicted value vs actual value of dwell time



5.6.2. Delta plug-in temperature validation

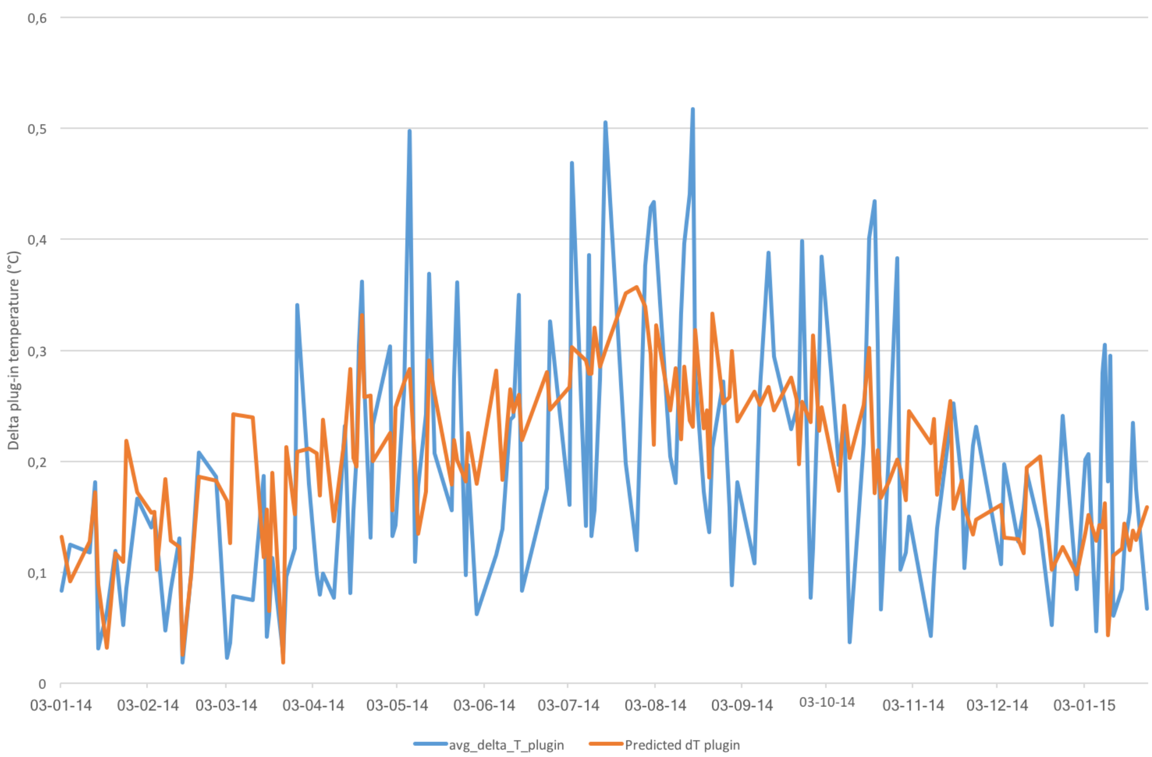
For the prediction of the delta plug-in temperature first the prediction equation must be generated. This is done using the coefficients found in the multiple regression model as found in Table 5.6. Using these coefficients the regression equation is the following:

$$Y'_{plug-in} = -0,284 + -0,01 * X_1 + 0,003 * X_2 + 0,005 * X_3 + (6,78 * 10^{-6}) * X_4 \tag{5.2}$$

$$\begin{aligned} &Where: \\ Y'_{plug-in} &: Predicted\ delta\ plug-in\ temperature\ (°C) \\ X_1 &: Average\ delta\ ambient\ temperature\ (°C) \\ X_2 &: Number\ of\ sun\ hours\ (hours) \\ X_3 &: Average\ offline\ time\ (hours) \\ X_4 &: Average\ weight\ (kg) \end{aligned}$$

Using Equation 5.2 the plug-in temperatures for the remaining 40% of the dataset is predicted. The results will then be compared with the actual delta plug-in temperatures. Both the actual values and the predicted delta plug-in values are shown in Figure 5.7. Reviewing this figure indicates that the found regression equation follows the same trend as the actual delta plug-in temperature. However, it also shows that the model does not explain all the variation and is not accurate in predicting the dwell time.

Figure 5.7: Predicted value vs actual value of delta plug-in temperature



The prediction is validated by calculating the R^2 and MSE of both the training and testing datasets. As mentioned before, the R^2 of the smaller 40% dataset (R^2_{40}) can be calculated by correlating the predicted values and the actual values and squaring the correlation coefficient (R). The correlation coefficient between the predicted and actual values is 0,466 (P<0,001), resulting in an $R^2_{40} = 0,217$. This value is less but not far from the R^2_{60} of the rest of the model, indicating that there is no large discrepancy between the predicted values and the actual values.

Apart from comparing the R^2 of the training sample with the test sample, the mean squared error of both samples is also compared. The mean squared error for the training sample used for the delta plug-in regression analysis is $MSE_{60} = 0,01057$. For the test sample the mean squared error is $MSE_{40} = 0,01061$. The difference between these MSE is minimal at 0.43%. Thus it can be concluded that the found model predicts the delta plug-in temperature evenly well for the training sample as for the test sample. Both the small discrepancy between the R^2 and MSE between the training and test section leads to the conclusion that the model for the delta plug-in temperature can be considered consistent.

5.6.3. Total energy consumption model validation

To be able to compare the predicted energy consumption values with the actual values, first, the energy consumption has to be predicted. The prediction is made using Equation 5.3. This equation is developed with the unstandardized coefficients as developed by the multiple regression analysis of section 5.3. These coefficients can be found in Table 5.4. 5.3 is applied to the test data sample (with N= 157).

$$Y'_{cons} = 41088,919 + 174,39 * X_1 + 6855,187 * X_2 + -22775,936 * X_3 + 15218,523 * X_4 + 14190,34 * X_5 \tag{5.3}$$

$$\begin{aligned} &Where: \\ &Y'_{cons}: Predicted\ total\ consumption\ (kWh) \\ &X_1: Number\ of\ arriving\ reefers \\ &X_2: Average\ dwell\ time\ of\ arriving\ reefers\ (hours) \\ &X_3: Average\ specific\ heat\ of\ arriving\ reefers\ (J/kg * K) \\ &X_4: Average\ thermal\ insulation\ of\ arriving\ reefers\ (W/m^2 * K) \\ &X_5: Average\ delta\ temperature\ between\ plug-in\ and\ set-point\ (°C) \end{aligned}$$

First, let us visually investigate the predicted total energy consumption versus the total energy consumption as determined by Nafde (2015). Both these values are found in Figure 5.8. The Figure shows that both the predicted value and the actual value follow the same trend and seem to be correlated. In two instances the regression equation produces a false and impossible negative consumption value. In these two instances, there are few arriving reefers, and the dwell-time is low, leading to an over-representation of the specific heat which results in a negative power consumption. These outliers are not representative and have a large influence on the analysis. As it is only two instances in which this occurs, it is decided that these cases are removed from the cross-validation set to get a more accurate view of the models' accuracy.

Figure 5.8: Predicted value vs actual value of total energy consumption

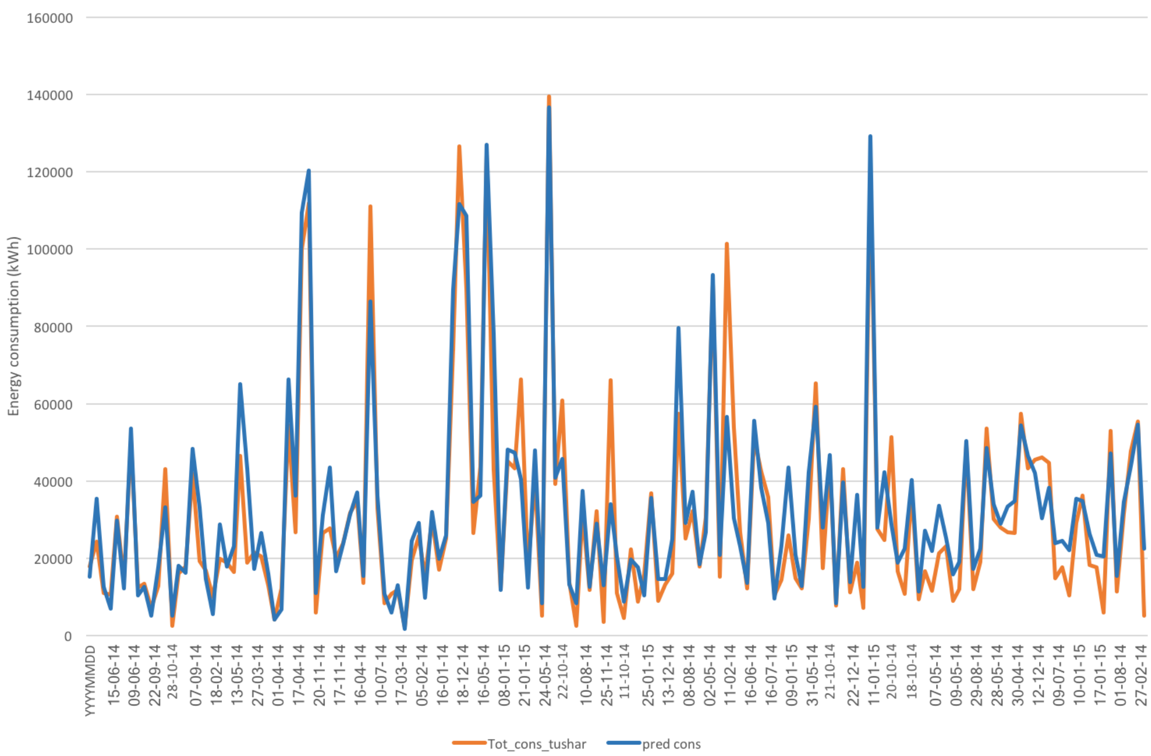


Table 5.7 shows the descriptive statistics for both the total consumption that was developed by Nafde (2015) and the predicted total consumption using Equation 5.3. Considering the values in Table 5.7 it can also be concluded that the differences between the minimum, maximum, mean, and standard deviation are small. Further strengthening the possibility that the model accurately predicts the energy consumption based on the five factors found.

Table 5.7: Descriptives between actual and predicted consumption (kWh)

	Minimum	Maximum	Mean	Std. Deviation
Actual consumption	2.169	139.457	30.533	27.155
Predicted consumption	1.619	136.641	33.092	25.746

When correlating the consumption predicted using Equation 5.3 with the actual consumption it shows that the predicted and actual values have a high and significant correlation with an R-value of 0,877 (P<0,001). The correlation between the actual and predicted values is squared so that it can be compared to the R^2 of the training sample (R^2_{60}). The R^2_{40} of the test sample is $R^2 = 0,769$. It is to be expected that R^2_{40} is lower than R^2_{60} (0,830), in this case the difference is 0,061. As the model is developed to fit 60% of the total available data, it is logical that the remaining 40% of the data fit the same data, albeit less. Comparing the R^2_{40} to R^2_{60} shows that there is no large discrepancy between the R^2 of the larger R^2_{60} and smaller R^2_{40} section of the data. Indicating that the model correctly and consistently predicts the total energy consumption.

The mean squared errors for both the training sample and the test sample are large. High MSE are logical as the values of total energy consumption are large; thus it is likely that errors are large as well. The MSE for the training sample is $MSE_{60} = 152.099.083$ and for the test sample $MSE_{40} = 98.521.931$. When considering these

MSE, it shows that MSE_{40} is lower than the MSE for the training sample by -35%. A lower MSE indicates that the model would predict the energy consumption for the test sample more accurately than for the training sample which is remarkable. The difference between both MSE's is significantly large, however as there is no large discrepancy among R^2 and the MSE changed positively, it is concluded that the model predicts correctly and consistently predicts the total energy consumption.

5.7. Chapter-conclusion

A sequential multiple regression analysis with backward feature selection was used to determine what factors contribute to the total energy consumption of reefers at the container terminal. The analysis was performed using IBM SPSS. Table 5.4 shows the regression coefficients and the standardised regression coefficients. When reviewing these coefficients, it becomes clear that, after training on 60% of the data, the number of arriving reefers explains most of the total energy consumption (76,6%), followed by the dwell time of the reefers (4,6%). Other significant factors have less (to none) impact on the total energy consumption, the type of cargo (specific heat) accounts for 1,1%, thermal insulation of the reefer for 0,3%, and the delta plug-in temperature for 0,4%. The negative influence of the specific heat indicates that an increase of frozen cargo increases the energy consumption. The positive influence of the thermal insulation indicates that older reefers (with a higher insulation value) add to the total energy consumption at the terminal. The R^2 of the found model is 0,83. Using this model, the total energy consumption was predicted for the remaining 40% of the dataset. This shows that the developed model can predict the total energy consumption accurately. Correlating the predicted scores with the actual scores shows that there is no substantial discrepancy between the R^2 of 60% of the model and the R^2 of the remaining 40% of the dataset. The Mean Squared Error of the training samples are also compared to the MSE of the test samples and indicates that the MSE of the test sample is lower than the training sample. Considering the R^2 and MSE it is concluded that the developed model accurately predicts the total energy consumption.

A more in-depth analysis of contributing factors to the total energy consumption indicated that the dwell time and delta plug-in temperature are acting as mediators. A bivariate regression analysis indicated a significant correlation between the set-point temperature and the dwell time (R^2=0,13). The relation implies that reefers with a lower temperature are more likely to have a longer dwell time. It is shown that the dwell time, acts as a mediator between the temperature set-point ant energy consumption. However, the temperature set-point only represents 13% of the variance in dwell time thus cannot be considered to be a root cause. When performing a multiple regression analysis, it is shown that the delta plug-in temperature has three significant correlated factors (R^2 = 0,355). The regression coefficient and standardised regression coefficient can be found in Table 5.6. The offline time, sun-hours, and delta ambient temperature have an impact on the delta plug-in temperature which is confirmed by predicting 40% of the data.

Thus, the first three sub-question of this research can be answered. These sub-questions are:

1. *What factors can be considered to be the root-cause of energy consumption?*
   As mentioned above the factors found that can be considered root cause factors are the number of arriving reefers and the dwell time. The plug-in temperature, thermal insulation, and specific heat of the cargo are small variables that have little influence on the total energy consumption.

2. *How does the root-cause effect the energy consumption?*
   The regression analysis clearly showed that the number of arriving reefers effects the total energy consumption the most as 76,6% can be explained by this factor. The influence of the other factors are as

follows: Dwell time accounts for 4,6%, Specific heat for 1,1%, plug-in temperature 0,4%, and thermal insulation 0,3%. In total this explains 83%, the remaining 17% is explained by other factors that are currently unknown.

3. *Can the found root cause factors be used to predict the energy consumption*
   For validation purposes the model found, with 60% of the data, was used to predict the total energy consumption of the remaining 40% of the data. The regression coefficients as shown in Table 5.4 where used to predict. Comparing the prediction to the actual energy consumption showed that the identified root cause factors can be used to predict the energy consumption.

After the identification of the root cause factors in this chapter, suggestions for improvement are made in the next chapter.

6 Improve

After identification of root cause factors in the previous chapter, the next step in this research is the search for improvements in the identified factors. As mentioned in Section 5.7, the total number of reefers and the time the reefers spent at the terminal impact the total energy consumption the most. Other variables such as the thermal insulation, plug-in temperature, specific heat of the cargo, offline time, sun-hours, weight, and ambient temperature do not have a large influence on the total energy consumption. Improving on these factors would, therefore, provide a low yield. Attempting to reduce arrival rate of reefers, with the goal of reducing peak energy consumption, is impossible as no influence can and should be issued on the variable. For the coming years, it is even expected that the number of reefers, which are put through the container terminal, will increase (Dekker, 2014). Hence, this chapter will attempt in reducing the dwell time of the reefers.

6.1. Prerequisites for low energy consumption

Before diving into a the development to attempt to reduce dwell time,0 basic requirements for low energy consumption, encountered during this research, are discussed. When these are complied with, the total energy consumption will be reduced before additional improvements designed to reduce the dwell time. These are the following:

- As discussed at the beginning of this thesis in Section 2.1.2 the correct use of capacitor banks will reduce the reactive power and thus increase the available active power. Correct $cos(\phi)$ compensation installations result in a lower total power demand. This is a highly technical solution which is a prerequisite for efficient energy use. Therefore, regardless of solutions that are found to reduce the dwell time, it is wise to install appropriate capacitor banks at the container terminal. It is likely that large consumers such as a container terminal already features such an installation. However, it is advised to recalibrate the system periodically.

- Apart from the technical requirements it is essential that existing regulations regarding the thermal insulation are enforced. Even though the thermal insulation is not shown to have a large effect on the total energy consumption, it is a prerequisite that the reefers are well insulated. For cargo owners, it is advisory to check the insulation capabilities of a reefer to reduce the chance of loss of cargo.

- The use of smart energy distribution systems, such as developed by van Duin et al. (2016); Nafde (2015) also have shown the ability to reduce the total energy consumption significantly. Therefore it is wise to adopt such a smart energy distribution system. Such a system can both be applied onboard the ship and on the shore.

6.2. Reducing dwell time

Besides the efforts mentioned in section 6.1 above, efforts must be made to reduce the dwell time. To reduce the dwell time, a method must be developed to force the hinterland transporter to pick up reefers as soon as possible. Currently, customers have some days of "demurrage-free time", the free time is a predetermined time the reefer is allowed to be stored at the terminal without additional costs. After the demurrage-free time, the customer is required to pay additional demurrage costs for the temporary storage of the reefer. The duration of the free time is different per customer. Generally, the free time is two days (APM terminals, 2016; LLC Maher Terminals, 2016). Larger shipping companies often negotiate longer free times (ECT Delta terminal, 2017). For the shipping company, offering a longer free time is beneficial for customers of the terminal, as this offers the 3PL more flexibility. Meanwhile, for the terminal, a longer free time equals to less revenue. The terminal has included the exceeding of the free time as a part of their business model. Hence, when the free time is exceeded the terminal starts to make money on reefer storage. Therefore the process owner has no incentive to attempt to reduce the dwell time, as the terminal makes a profit if the dwell time is high. The added energy consumption is not a problem for the terminal due to the added profits. However, many companies these days do care about the sustainability of their operation; hence the process owners are likely to be open to reducing the dwell time when no costs associated with the necessary measures. To reduce the dwell time, it is not as simple as reducing the free time or increasing the costs for exceeding of the free time. As the critical to quality tree shows in Section 3.2, customers of the process ask a long free-time and a low dwell time as this increases the flexibility of transport and the shelf life of the cargo respectfully. The terminal wishes for a short free time with a competitive price when exceeded; the terminal has no incentive to reduce the dwell time if the revenue is decreased.

6.2.1. Targeting short stay reefers

Good communication between the terminal and the 3PL is essential. Owners of perishable cargo prefer to receive the cargo quickly as this increases the shelf life and thus the value of the goods. Groente en Fruithuis (2017) mentioned that the arrival of the ship, the container terminal develops an offloading scheme and hence know the approximate time a reefer will be offloaded. For cargo owners it would be interesting to know when their cargo is offloaded, this enables the hinterland transporter to be ready for the pick up directly when it is offloaded. Such communication can even eliminate the need for connecting the reefer as it will be transported directly. The cargo owner is the last stop in the cold chain of the reefer. Thus, when the reefer arrives at the cargo owner it is unpacked and the cargo is processed. Meaning that an entire step of energy usage in the cold chain is skipped hence reducing the energy consumption. To eliminate connecting of the reefer a form communication, between the terminal and hinterland transporter, is a requirement. If the terminal decides not to connect a reefer, they are prone to insurance claims. When the choice is let to the owner of the cargo, it becomes their responsibility. The owner of the cargo has knowledge about the content of the reefer and its thermodynamic properties. Thus, the cargo owner knows if the cargo is capable of being unplugged for a few hours extra. It is likely that the owner decides to plug in the most critical reefers with a short shelf-life and narrow temperature bandwidth. Reefers with a short shelf life are less likely to exceed the free time, but the large quantity contributes significantly to the number of plugged-in reefers.

6.2.2. Targeting long stay reefers

As explained in the introduction of this section (6.2) reducing high dwell times uncovers a conflict of interest with the container terminal and their revenue. High dwell times lead to increased revenue for the container terminal, meaning that the terminal has no necessity for attempting to reduce high dwell times, with the consequences for the environment. The increase in revenue is enough to compensate for the increase in energy consumption that is associated with long dwell time. Therefore, for the terminal to implement improvements, it is a requirement that there is no loss of revenue. Otherwise, the container terminal will simply not implement changes and keep the revenue high at the expense of the environment.

A method to reduce the long stay of reefers is to apply the concept of revenue management on pricing. Revenue management is a methodology that moves from the traditional *static* pricing method to a *dynamic* pricing. The dynamic pricing principle originates from airlines and hotels. Airlines first used the concept of dynamic pricing to avoid flying aircraft with empty seats onboard. Since introduction, the method increased in popularity as is shown by the recent article of Prick (2017) in the Dutch news. By reducing the price at the right time, seats that otherwise would go empty, are filled. The framework assumes that the supply capacity is fixed and aims to find the right price to encourage and discourage the selling of products at the right time, this ensures that the overall collected revenue is maximised. In other industries, the use of dynamic pricing has become key drivers in the performance of the companies. (Bitran and Caldentey, 2003) Dynamic pricing models are base on the assumptions that (i) there initially is a fixed capacity and (ii) the seller has perfect information about the demand distribution in the upcoming future. In section 3.4 the Groente en Fruithuis stated that importers do not view price as a critical factor in the transportation selection process. Thus proposing a pricing based strategy has risks. However, it is also found in section 3.4 that customers identify fast transhipment as a critical factor, and dynamic pricing strategy is a method of achieving faster transhipment.

Revenue management would enable container terminals to determine the price reefer storage per day, making it dependent on the expected total energy consumption. It must be noted that it is essential that the dynamic pricing is implemented post free-time. If free times where to be abandoned, large shipping companies would always pay a higher price, for large ships cause high arrival peaks and thus high predicted energy consumption. This effect would work against current deals in which a larger customer receives a better price. However, by continuing to use free time, the revenue management strategy starts when the reefer exceeds its free time. When the free-time is exceeded, the price is dependent on the expected energy consumption at the terminal. In an example, considering a typical period of 3 weeks (Figure 6.1) in September, it shows that after a big arrival peak of a large deep sea ship, the number of plugged-in reefers decreases together with the energy consumption. Meaning that the post-free time reefer storage price also decreases. However, Table 4.4 shows that there is a 43% chance for a reefer to exceed a free-time of three days. Reefers exceeding the free-time will pay a competitive price for the temporary reefer storage. The terminal anticipates the arrival of a large ship (in this example) a week later. Therefore, the energy consumption is expected to rise. Together with the rise in energy consumption the price of reefer storage will climb. The sudden increase in storage price motivates hinterland transporters to pick up the reefer, while simultaneously generates a higher revenue for the terminal. When hinterland transporters do not pick up the reefer before the new peak, the price will increase significantly.

A less sophisticated method of dynamic pricing is the application of peak pricing. Peak pricing is the principle much used by energy utility companies. During moments when a peak is expected a fee is added to the price. The added fee is a less "fine-tuned" and less complex method of revenue management. Energy utility companies use this principle to motivate consumers to use off-peak moments; this gives a more evenly distributed demand over time. In the case of reefers at the terminal, it can be considered to be impossible to move reefers from the peak to off-peak moments. However, it does motivate customers to remove the container prior to a peak pricing moment without the added complexity. Peak load pricing provides a higher transparency than dynamic pricing strategies.

The impact of such a measure is estimated to reduce the total energy consumption by approximately 2,1% to 23%. The effect size depends on how well the customers respond to peak pricing and therefore, the quantity of dwell time reduction. What is considered to be a peak, also impacts the reduction quantity. It is assumed that peak pricing is implemented when the energy consumption is predicted to exceed an amount of, e.g. >80.000 kWh and that customers respond by retrieving the reefer quick and hence reducing the dwell time. However, the reduction of dwell time to an average of 1 cannot be considered to be realistic but indicates the direction of the result. A more realistic result is the reduction of the dwell time to 3 days with a peak pricing when the energy consumption is predicted to exceed 40.000 kWh. This results in an estimated energy reduction of 5,5% or 674.533 kWh. The details of this analysis are explained in Section 6.4.

A requirement for both revenue management tactics (dynamic- and peak pricing) is that the energy consumption can be predicted accurately and reliably with the data available to the container terminal. Equation 5.3 in Section 5.6.3 enables us to do exactly that. However, this equation contains variables that are not known by the terminal before the arrival of the reefer. Such as the dwell time, thermal insulation, plug-in temperature, and specific heat. The thermal insulation, plug-in temperature, and specific heat account for a low explained variance and are impossible to know prior ship arrival. Therefore, these cannot be used to predict the energy consumption. It is important that the prediction can be made with the data available to the container terminal. If this cannot be achieved it would render the found model obsolete. Hence as many factors as possible are sought to predict the energy consumption. As mentioned before the thermal insulation, plug-in temperature, and specific heat are impossible to know before the arrival of the ship. However, it may be possible to predict the dwell time of the arriving reefers using data known to the terminal. As mentioned in Section 5.4.1 the temperature set-point explains a small portion of the variance, it is interesting to see if the dwell time can be predicted based on other known variables. If this is achieved, then the energy consumption can still be accurately predicted. Performing a regression only including the number of arriving reefers and dwell time shows that it still explains 82,6% of the variance.

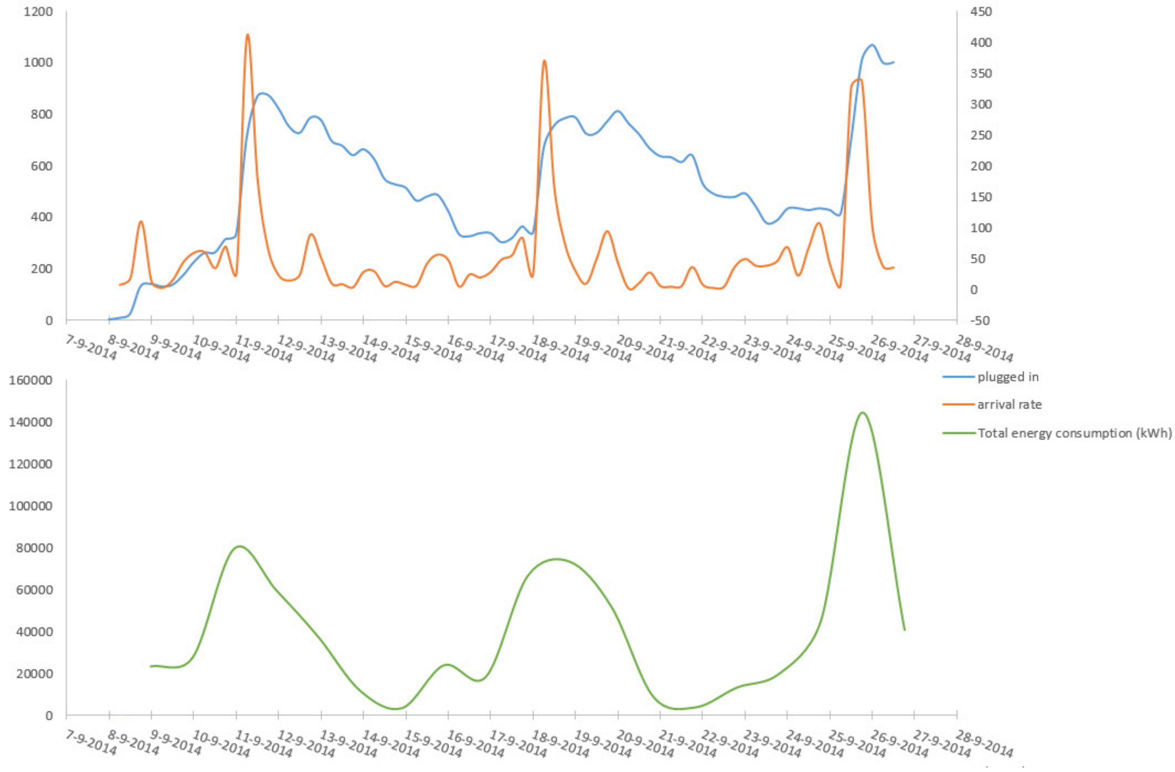
6.3. Dwell time prediction model

In this section the it is attempted to develop a model to predict the dwell time. Firstly the used method is described, after which the analysis and the model is described and cross-validated.

6.3.1. Methodology to develop dwell time prediction model

The prediction model for the dwell time is developed by designing a neural network in the IBM SPSS software package. An artificial neural network is an analysis method where an algorithm fits weighted connections between multiple independent variables to attempt to predict the dependent variable. The methodology is

Figure 6.1: Number of plugged in reefers, arrival rate, and energy consumption



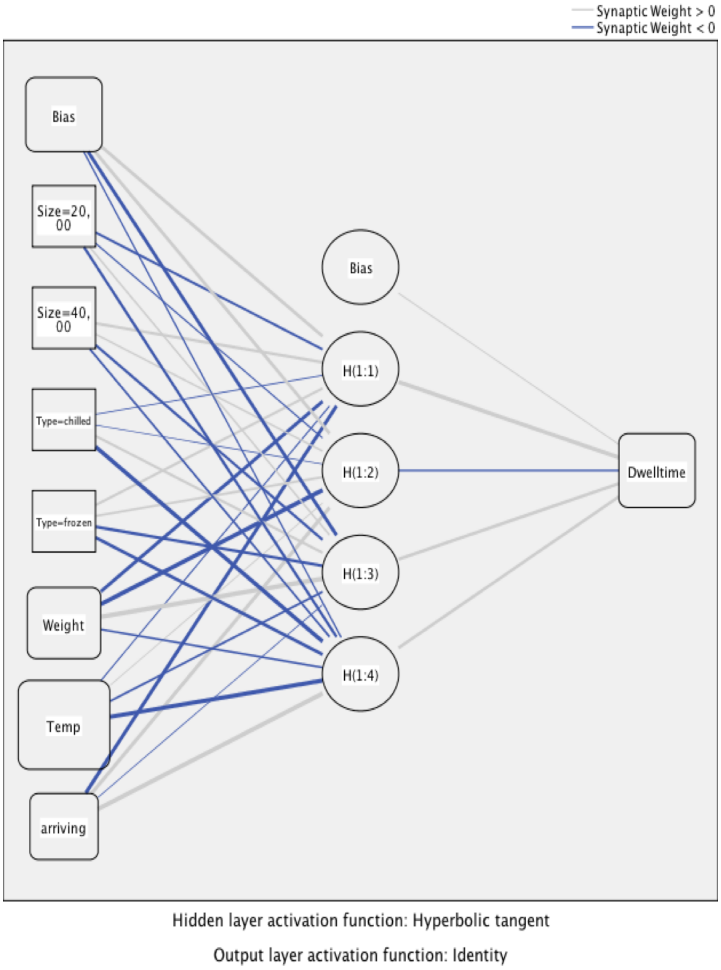
often applied to large datasets. As done before in section 5.3, the dataset of a neural network split up into two sections of 60% and 40%. The section of 60% is used to train the network and is referred to as the "training section", the remaining 40% is the "test section". Using the training section, the algorithm develops a network that consists of 3 layers (input-, hidden-, and output-layer). The input layer consists of all the independent variables, in the output layer the dependent variable is represented. The hidden layer contains unobservable nodes, using the hidden nodes the algorithm attempts to link the IV to the DV as accurately as possible. This layer is where the developed model remains, this layer is difficult to interpret due to the complex nature of neural networks. However, the output can offer valuable insights into the prediction power of a network that uses the variables that are known before reefer arrival.

In neural networks, two algorithms are the most commonly used for creating the neural network. These are the Multilayer Perceptron (MLP) and the Radial Basis Function (RBF). The MLP algorithm is widely used and performs well for prediction purposes. MLP uses the Back Propagation technique to assign the weights on each connection. The RBF is primarily used for categorised data and can be used less accurate for prediction purposes. (University of British Columbia, 2009) As our goal is to predict the dwell time, during this analysis the Multilayer Perceptron algorithm is used.

6.3.2. Dwell time prediction model development

For the developed model to be usable to predict the dwell time, it is required that only variables are used that are known prior to the arrival of the ship. Therefore the original dataset, supplied by ABB, is used. The dataset (N = 23968) describes the size of the container, the reefer weight, type of reefer (frozen or chilled), temperature set-point, and the dwell time. The dwell time is calculated from the plug-in and the plug-out time as is the number of arriving reefers. Apart from the dwell time, it is assumed that this is the data which

Figure 6.2: Neural Network



is available for the container terminal prior to arrival. ABB (2017a) has indicated that the terminal also has access to the origin and destination data. However, this data is not included in the available dataset hence cannot be used in the neural network.

The neural network is performed with the MLP algorithm, standardised rescaling of covariates, and with training and testing sections of 60% ($N = 23968$) and 40% ($N = 15827$) respectfully. The dataset is a subsection of the original dataset with N=39795. The used data is from 07-2014 to 01-2015. This subset is selected to eliminate seasonality in the training section. The 60% training section are reefers from 07-2014 until 10-2014. The test section is the remaining data. Performing the neural network results in the following network: The network has a sum of squared errors of 11249; thus the mean squared error is 0,469 and a relative error of 0,939. This high relative error indicates that the neural network as shown in Figure 6.2 is not accurate, as 93,9% of the predicted values are not accurate (University of British Columbia, 2009). The factors that predict a small percentage of the dwell time are shown in Table 6.1. The inability of the factors to predict the dwell time means that, with the data known before the arrival of the ship, it is impossible to predict when the container will be picked up accurately. The dwell time does not depend sufficiently on the known data for an accurate prediction. It could be that the dwell time depends more on factors outside the reefer characteristics, e.g. the availability of hinterland transport, the type of next modality. The investigation hereof is impossible to test during this research as such data is not available.

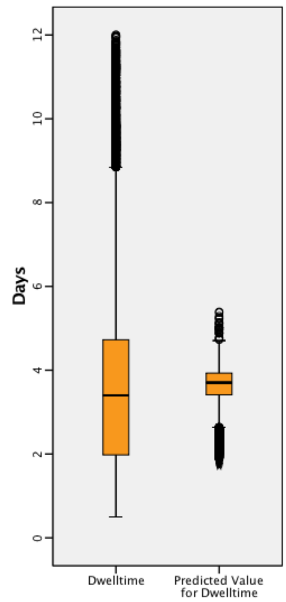
Table 6.1: Importance of factors in neural network

	Importance	Normalized Importance
Temperature setpoint	,566	100,0%
Reefer weight	,227	40,2%
number of arriving reefers	,131	23,2%
Reefer type	,038	6,8%
Reefer size	,038	6,6%

6.3.3. Cross-validation

The developed model of Figure 6.2 is cross-validated using the remaining 40% of the dataset. Cross-validation is performed to confirm that the results and the accuracy of the training section also hold for the test section. The measured dwell time and the predicted dwell time are visualised the box-plot of Figure 6.3. The figure shows the actual dwell time together with the dwell time predicted using the neural network model. When reviewing the model, the inaccuracy of the model becomes clear. The first and third quartile lines of the predicted dwell time fall completely within the third quartile of the actual dwell time, indicating that it does not completely cover the range of the actual dwell time.

Figure 6.3: actual dwell time and predicted dwell time box-plots



The mean squared error of the test sample is 0,457 ($MSE = \frac{SSE}{N_{test}} = \frac{7237}{15827}$). The relative error of the test sample is 0,968 (96,8%). Between the training sample and the test sample no large discrepancy in mean squared errors (2,57% change) and relative errors (3,14% difference) is shown. This means that the model found in section 6.3.2 is consistent in incorrectly predicting the dwell time.

The neural network analysis shows that it is impossible for the terminal to predict the dwell time with the available data before arrival. The consequence of this is that the accuracy of the total energy consumption prediction is reduced. The only factor that can be used to predict the total energy consumption is the number of arriving reefers. This factor can explain 76,6% of the variance within the total energy consumption. Thus the question arises if the total energy consumption prediction model, using only the arrival rate, is accurate enough to be used for dynamic pricing purposes?

6.4. Market possibilities for dynamic pricing

As mentioned above the dwell time cannot be predicted using the available data. This causes the accuracy of the energy consumption prediction model to be reduced. A reduced accuracy in demand prediction means that it is inadvisable to use a dynamic pricing model as, for such a complex model, perfect knowledge of demand is required. For the less complex method of peak pricing perfect knowledge of the demand is less essential. For peak pricing, it is merely required to know when the energy consumption crosses a set limit. Above this limit, the peak pricing will be introduced.

6.4.1. Price sensitivity

The main concern for an effective peak pricing implementation is the price-sensitivity of the demand. A price sensitive demand means that customers are sensitive to changes in demurrage price and are willing to pick the reefer up quicker. (Elmaghraby and Keskinocak, 2003) Currently exceeding free-time will cost on average €120,- for the first three days after the free time. after the initial three days exceeding the free time, the costs will climb further. (CMA CGM, 2017; OOCL, 2016; MOL, 2017; APL, 2016; ZIM, 2017) Fact is that temporary reefer storage is a part of the total supply chain which makes it likely to be *less* price sensitive. The price sensitivity is discussed with 5 Dutch meat, fruit, vegetable, and fish importers to get a feel for the price sensitivity. During the discussion with the Dutch importers, it became clear that it is always attempted to avoid demurrage costs due to the added costs and the value of the products. Thus the importers pick-up the container, or outsource the collection of the container, as soon as possible. Thus, importers will not (temporarily) store the container at the terminal, even if the demurrage costs are lower. Importers prefer to have the goods as quick as possible for better control over the product. Importers agree that does happen that a reefer cannot be collected within the allowed demurrage free-time. Often such a problem occurs due to incorrect customs papers, or other issues. However, it is always attempted to avoid these issues. Therefore it can be concluded that there is a low price elasticity on the dwell time for reefers. If the price decreases, there will be no increase in reefer storage. (Verdi import, 2017; BUD Holland, 2017; Schoonderwoerd Vlees, 2017; Jan Zandbergen, 2017)

Although there is a low price elasticity and thus a dynamic pricing system would not work, a peak pricing mechanism would enforce a stronger incentive for the early collection of the reefer.

6.4.2. Effect of peak pricing

A successful implementation of a peak pricing policy could lead to a reduction of the dwell time. An important question is: what is the effect size of a change in the dwell time that can be expected on the total energy consumption. The effect size is calculated by experimenting with different values using the model found in Chapter 5. Using this model, the effect size on the total energy consumption is calculated when the dwell time is reduced during peak moment. This method stimulates a positive effect of peak pricing on the peaks and hence reducing the peak energy consumption.

First, using the data available for the terminal, it is predicted when an energy peak will occur. The only variable that can be used to predict ànd is known by the terminal is the number of arriving reefers. Therefore, this variable is used to predict the occurrence of peaks. The regression analysis was refitted using only the number of arriving reefers as the independent variable to obtain the prediction formula. The equation that is a result of the refitted model is shown below in Equation 6.1. The model is refitted using the complete dataset (N=393) and has an R^2 of 0,785. The dataset is not split for cross-validation purposes as the initial model was already cross-validated. Therefore, it is assumed that this model, which uses only one variable of the model found in section 5.3, also can be considered consistent.

$$Y'_{cons\_simple} = 3539 + X_1 * 175,6 \tag{6.1}$$

$$Where:$$
$$Y'_{cons\_simple} : Simplified\ predicted\ consumption$$
$$X_1 : number\ of\ arriving\ reefers$$

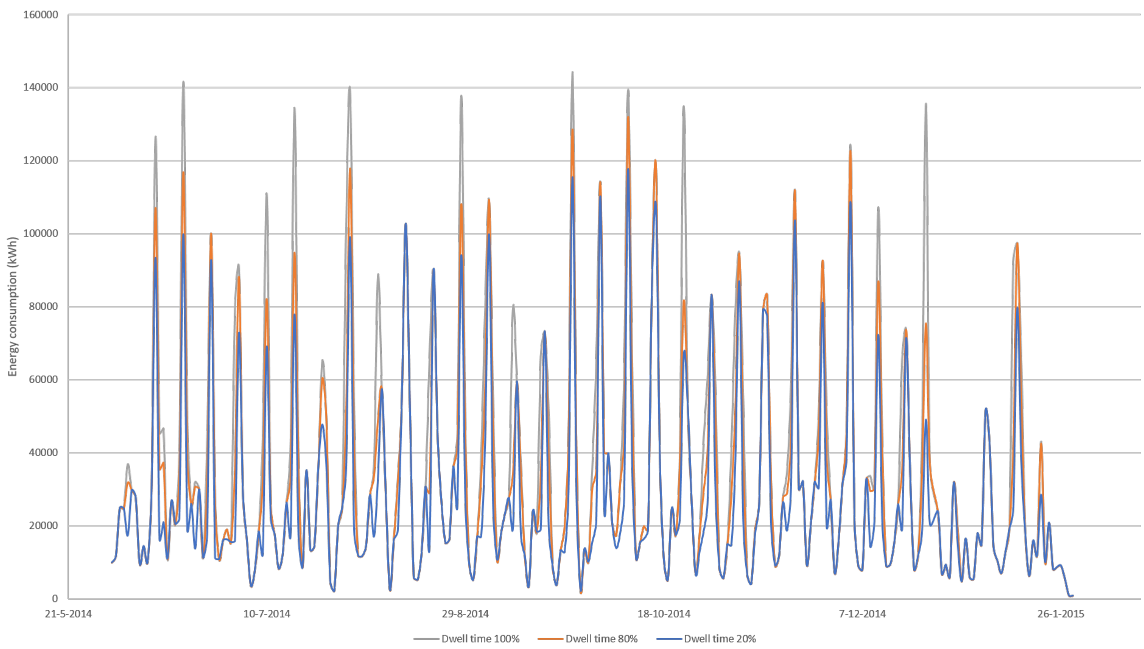
When the energy consumption was predicted to exceed a set peak (80.000 kWh, 60.000 kWh, 40.000 kWh, or 30.000 kWh), the dwell time was lowered (to 1, 2, or 3 days) assuming that customers respond positively to peak pricing. With the new dwell time, the energy consumption was recalculated for the peaks using the complete regression formula found in Chapter 5 (equation 5.3). The resulting differences are shown Table 6.2. As can be seen in Table 6.2 the peak pricing introduction value is essential, a lower introduction value will result in more peaks to which peak pricing will be applied, thus higher energy savings. However, if the peak introduction value is set too low (e.g. 20.000 kWh) regular variances in energy consumption will be considered as peaks, and peak pricing will be applied to false peaks. Also, a reduction of dwell time to 1 day on average cannot be considered to be realistic. Most shipping companies have negotiated a demurrage free time of 3 days hence customers are more likely to use the demurrage free-time entirely. Table 6.2 shows that if the dwell time decreases, together with a decrease in peak limit, the energy consumption also reduces significantly. Depending on what the terminal considers to be a peak energy consumption moment, the total yearly energy consumption can reduce approximately 5,5 % to 11,6%. This reduction is the same as a reduction equal to the consumption 230 to 480 households over the course of a year or €54.000 to €113.000.

Table 6.2: Estimated energy reduction due to dwell time reduction

		Peak pricing introduction value (kWh)							
		80.000		60.000		40.000		30.000	
		kWh		kWh		kWh		kWh	
	1	-487.284	-4,0%	-511.914	-4,2%	-1.347.706	-11,1%	-2.803.095	-23,0%
Dwell time (days)	2	-355.470	-2,9%	-364.303	-3,0%	-964.481	-7,9%	-2.036.800	-16,7%
	3	-261.342	-2,1%	-262.517	-2,2%	-674.533	-5,5%	-1.408.178	-11,6%

The impact of reducing the dwell time on the peaks is shown in Figure 6.4. In this figure, it is shown what will happen to the amplitudes of the peaks when the dwell time is reduced. When reviewing this figure, it becomes clear that merely reducing the dwell time is not powerful enough to completely remove peaks in energy consumption. However, it indicates the direction of improvement. Figure 6.4 shows that the amplitude of the peaks has been reduced significantly with a decrease in dwell time. This figure is generated with a peak pricing introduction value set at 30.000 kWh over the second half of the year 2014 and thus eliminating seasonality. A lower introduction value means that the model results in multiple negative values as the dwell time then is applied to days where there is a low number of reefer arrivals, this leads to an over-representation of

Figure 6.4: Influence of dwell time on energy consumption



the specific heat in the regression equation. However, the figure shows even that if the dwell time will reduce to a single day, peaks will still occur due to the high number of reefer arrivals.

6.4.3. Advantages and disadvantages of peak pricing

Implementing a measure such as peak pricing has advantages and disadvantages for the terminal. This section discusses the possible advantages. The first advantage of peak pricing is the following, due to the increasing trend in reefer usage the reefer stacks become increasingly filled over the upcoming years. Applying peak pricing stimulates customers for an earlier reefer collection; hence there is more overall capacity. However, the added incentive is likely to decrease the dwell time which leads to a concentration of on-site traffic movements. This concentration is due to an increased number of reefers which will be collected in a close time frame. Hence, traffic movements at the terminal will become more intense with the risk of traffic jams. However, container terminals are often set up broad from design and have a high road capacity which is developed for peak moments

The requirement to predict the demand for the next period leads to additional work and therefore higher administrative costs. This increases billing complexity as free times are different per reefer and exceeded free-times must be calculated with pre-determined (peak)prices. However, the increase in demurrage prices during peaks could lead to an increase in revenue for the terminal. During this research, it is impossible to accurately predict the increase in revenue for the terminal. A rough estimation is an increase of the revenue by 2% - 4%. This estimation is based on the assumption that the dwell time does not decrease as the exact decrease in dwell time is impossible to predict. In the calculation of this estimation the current revenue was based on the known dwell time per reefer, the demurrage costs of MOL (2017), and a peak pricing fee of €50,-. In the calculations the additional fee is charged once per reefer if the demurrage-free time was exceeded and if the reefer was present during a peak moment. In the calculations the added fee is not charged per day, applying such a method would significantly increase the revenue. However, such prices could be relative too high. If a peak pricing fee is added per day of "violation" it is recommended to reduce the peak pricing fee. A higher peak pricing fee will lead to an increase in revenue. If the customers respond positively to the peak price incentive the added revenue will decrease as the dwell time decreases. It is likely that the revenue decrease overall will be 0%, the energy saving would still be 5,5% to 11%.

Due to peak pricing, the prices for customers have a chance to increase if the reefer is not collected timely. This price increase will put the relationship with the terminals' customer under pressure as the shipping company will have to calculate a higher price to the cargo owner. Therefore, it is essential for a terminal to frame the peak pricing policy as a green and sustainable measure and not as a "cash-cow". In the current society sustainability is an increasingly important topic which companies want to make visible. This green image must explain the possible higher price compared with competitors and must compensate for the possible reduction in the attractiveness of the terminal. It must also be stretched that a peak pricing measure is not an increase in price as they remain the same if customers collect the reefers within the demurrage free-time.

For customers, a measure such as peak pricing could lead to a perceived less transparent pricing mechanism. Therefore, it is essential that the terminal communicates any peak price fees timely and clear to enable the customer to collect the reefer before the introduction of the peak prices.

Table 6.3: Advantages and disadvantages of peak pricing

Advantages	Disadvantages
Current stack capacities become future proof	Increased administrative costs
Shorter dwell times	Increase traffic concentration
5,5% to 11,6% lower total energy consumption.	Timely and clear communication required
No added costs for container terminal	
Green image	

6.5. Six-sigma out of business context

In the first Chapter of this thesis, a sub-question regarding the usage of Six-sigma in a broader perspective is asked. In this section, the application of the Six-sigma methodology in this research is discussed and reviewed. The Six-sigma methodology is developed by companies looking to improve their production processes. Therefore, the methodology is highly suitable for the application to all sorts of processes in which the root cause to an unwanted pattern must be improved upon. As the method was corporately developed, it is focused on corporations and how they operate. The in-house development imposes a few issues when applying the Six-sigma methodology on a broader perspective outside a single business.

Firstly, during the measurement phase, it is essential that the needs and requirements of customers are determined. Usually, the requirements are determined from a company perspective. When this is performed from the perspective of a company the requirements can be determined by communicating with the customer and discussing their requirements. Outside of the business context, customers are identified as a group of actors and not as specific companies. Therefore making it difficult to get needs and requirements specified for the capability analysis as each customer has different specific requirements. Hence, customer CTQ requirements must be assumed based on research and are applied to a group of actors rather than a single customer. This method may not provide the same strong base as that a traditional Six-sigma project would have when performed within a company.

Secondly, after the requirement boundaries are determined, the Six-sigma methodology analyses the current process capability. Process capabilities provide essential insights into the process and act as the first contact with the available data. This step is critical for the researcher to get a feel for the capabilities of a process, its limitations, and its weak points. However, at this point a significant limitation of the Six-sigma methodology outside the business environment becomes apparent. The company focused basis of Six-sigma means that the capability analysis is performed on the data of one single company; making it difficult to generalise the findings regarding the capabilities of such a process. For a regular Six-sigma project this would not be a problem as it only needs to be applied to the company in which the research is performed. For scientific research it is always attempted to generalise the findings of a study.

Thirdly, the primary added value of the measurement phase is providing a reference benchmark for the next improvement and implementation iteration. When the Six-sigma methodology is applied outside a business context, implementation of a suggested improvement is often not possible as implementation is the responsibility different actors within the system, each with their own agenda. Hence the added value for the process capability benchmark, as calculated in the measurement phase, is reduced. The execution of the measurement phase could therefore be seen as an obligation when using Six-sigma when the added value to the research is lower. However, if the in this research proposed measure is implemented, the performed calculations provide a reference frame for future research. This reference frame enables the researcher to calculate the effect of the implementation with new data after implementation.

Apart from the previously mentioned limitations during the measurement phase, there are positive notes that must be made when discussing Six-sigma. Firstly, the method provides a helpful backbone throughout the research. The clear DMAIC buildup of the research stimulates the researcher to ask the right questions at the right moment during the research and to gain a complete picture of the problem. This argument is also mentioned by Yang et al. as a key strength of the Six-sigma methodology. However, for complete utilization of the six-sigma methodology the traditional Six-sigma methodology must be altered slightly so it is applicable within a broader context. Yang et al. (2007) discuss the attempt of Samsung to change the DMAIC cycle and replace this with a DMAEV cycle (Define, Measure, Analyze, Enable, and Verify), showcasing the potential of modifications to DMAIC. In the DMAEV cycle the first three phases of Define, Measure, and Analyze are identical with the traditional DMAIC cycle. Hereafter, the Enable phase essentially is the same as the Improve phase. However, in the Enable phase the improvement to the root cause is not implemented but an improvement plan is developed. In the Verify phase of Yang et al. a test-plan is developed, executed and the results are discussed. This method already provides a broader application framework of the six-sigma methodology as the implementation and control parts of DMAIC are replaced. However, the DMAEV methodology also is developed in-house of a company (Samsung) to improve it's supply chain. Therefore, the DMAEV methodology lacks in the consideration of market possibilities. Extending the Six-sigma methodology with a market analysis would include considerations of all actors and hence providing a feedback loop by verifying the improvement with the involved actors. The development of Samsungs' DMAEV method shows that Six sigma truly is meta-level tool which provides a backbone throughout research.

Secondly, the Six-sigma methodology provides correct tools and descriptions for the specific phase which can be used. In the example of a scientific study such as this, the Define phase is an extension of the research proposal, Introduction, and literature research. Many issues that should traditionally be discussed in the define phase (according to six-sigma) are already discussed prior to the define phase. However, the six-sigma methodology then provides additional tools to discuss and verify needs and requirements and the voice of customer (VOC), which would otherwise not be discussed. For this, the Six-sigma method provides the Critical-To-Quality tree as a tool to determine the needs and requirements of the customers. During the Define phase, the Six-sigma methodology enables the researcher to get a complete overview of the problem quickly. Additionally, during the Analysis phase, conventional scientific statistic analyses methods, such as multiple regression and design of experiments, are suggested. The application of these proven scientific analysis methods adds to the rigour of the research (Yang et al., 2007).

Thirdly, the Six-sigma method stimulates the researcher to continuously ask "why" in order to get a complete picture of the model and to find the root cause of the problem.

In the end, the Six-sigma methodology can be considered to be a tool at meta-level. The Six-sigma methodology is different for every company and project. It provides a framework in which multiple techniques and tools can be integrated. Few projects follow the exact framework of six-sigma using every suggested tool. However, the meta-tool Six-sigma provides a base from which can be deviated when applied in a different context, making it a highly valuable tool for a vast range of studies.

6.6. Chapter-conclusion

In this chapter, it is attempted to find an improvement to achieve a reduction in dwell times. It is argued that attempting to reduce the dwell time would provide the most yield. The proposed solution was a complex dynamic pricing model to better align the demand and supply of temporary reefer storage, or a peak pricing scheme. A requirement for dynamic pricing is the perfect knowledge and prediction capabilities of the demand. Therefore, it is attempted to predict the demand (expected energy consumption) using only the variables known to the terminal before the arrival of the ship. After the creation of a Neural Network, it is shown to be impossible to predict the dwell time, which is an important factor in the energy consumption prediction model of Chapter 5. With the available data for this research, it is shown not to be possible to predict the dwell time, reducing the accuracy of the energy consumption prediction. A requirement for dynamic pricing is that the demand is price sensitive. After discussions with Dutch meat, vegetables, fruit and fish importers is became apparent that the demand is not price-sensitive as importers prefer the cargo as quickly as possible. Hence, it is inadvisable to introduce a complex dynamic pricing system where demand prediction and price elasticity are essential. Thus, a simpler system, known as "Peak pricing", can be considered to be a more suitable solution. Peak pricing introduces an additional fee when a peak in energy consumption is expected and does not require a price-sensitive demand or a highly accurate demand forecast. When Peak pricing is introduced, and the customers respond positively to peak pricing, the total energy consumption has the potential to reduce consumption by approximately 5,5% - 11,6% (removed from the peaks). This calculation is based on the assumption that customers respond positively to the peak pricing mechanism and will do their best to pick up the reefer as quick as possible. Leading to a reduction of the dwell time to 3 days on average. Discussions with the Dutch importers indicated that the main concern for importers is quick access to the cargo, even if demurrage prices are low. Therefore, to stimulate early pickup of reefers a peak pricing scheme is preferred over a dynamic pricing scheme.

Thus, the fourth and fifth sub-question of this research can be answered. These sub-questions are:

4. *What are possible improvements on the root cause that will improve peak energy consumption?*
   The cause for which an improvement is developed is for the dwell time. The two proposed methods are the implementation of a dynamic pricing scheme or a peak pricing method. After attempts to predict the dwell time to enable accurate prediction of the energy consumption, the suggested method of reducing the dwell time is the implementation of peak pricing. Peak pricing introduces an additional fee

when the energy consumption is expected to be high. Hence, introducing an added incentive to collect the reefer before expected peaks.

5. *What is the market potential of the possible improvements?*
   After discussions with Dutch perishable food importers, it became clear that the market for temporary reefer storage is not price-dependent. Hence a dynamic pricing scheme is not recommended. However, a correct implementation of peak pricing could lead to a total energy reduction of 5,5 % to 11,6% of the total yearly energy consumption. The total energy savings are equal to the yearly energy consumptions of 230 to 480 two-person households or €54.000 to €113.000.

After the development of an improvement the, in this research applied, Six-sigma methodology is discussed in Section 6.5. This leads to the answering of the final sub-question of this research:

6. *Is Six-sigma suitable to be applied in a broader context?*
   The Six-sigma methodology provides a clear backbone throughout the research. The framework extends traditional scientific research and gives hand-holds to ask the right questions at the right time. The analysis methods are the same as when performing traditional scientific research. However, during the measurement phase is where the methodology finds the most resistance to being applied outside the business context. Process capabilities are different for each company and cannot be generalised outside a business context. However, the goal of the measurement phase is to gain insight into the process. Therefore, even as the customer needs and requirements and the respective process capabilities will change it provides an insight into the process for the researcher. The added value of a benchmark provided by the measurement phase is not the case outside the business context as suggested improvements often cannot be implemented.

7

Conclusions to this research

In this chapter, the research is concluded and discussed. First conclusions are drawn and secondly the (sub)research questions are answered. In the conclusion section, also the theoretical and practical contributions of this research are discussed.

7.1. Conclusions

In the global race against energy consumption, the consumption of reefers is a much-investigated topic. Previous research is found to focuses on technical improvements of reefers and its control systems. In this thesis, a more process-based view is taken by investigating the root cause factors of high peak consumption. By applying a Six-sigma methodology, a solution for peak behaviour of energy consumption is suggested.

In the analyse phase a sequential multiple regression analysis led to a model explaining the energy consumption (R^2=0,83 p<0,001). In the model it is found that the number of arriving reefers (R^2=0,766; β=0,85; p<0,001) and plugged-in time of reefers (R^2=0,046; β=0,198; p<0,001) can be considered to be the root causes of high energy consumption. The plug-in temperature, thermal insulation of the reefers, and the cargo type are factors that are found to have a negligible impact on the energy consumption. The temperature set-point, offline time, weight, ambient temperature, and sun-hours are found to be non-significant.

Following the identification of the root cause factors, improvements are suggested to reduce the peak consumption behaviour. It is argued that it is impossible to reduce highest contributing factor to energy consumption: the number of arriving reefers. The number of arriving reefers is the core business of a terminal and is likely to increase over the coming years (Dekker, 2014; World Cargo News, 2017). The difference in plug-in temperature compared to the set-point temperature, thermal insulation, and type of cargo are also not considered in the improvement phase as these contribute minimally, and any improvements would provide minimal yield. Additionally, current international legislation regarding the insulation factor of reefers is sufficient to keep the core temperature of reefers within the set bandwidth during the offline time, without adding significantly to the energy consumption. Therefore, an improvement to reduce the dwell time is suggested. However, reducing the dwell time is likely to result in lower revenue for the container terminal. The revenue depends on the dwell time as demurrage costs are a part of a terminals revenue model. Demurrage costs are fees charged when a reefer exceeds the demurrage-free time, which is a predetermined time that the reefer is allowed to be plugged in at the terminal without additional costs. Hence, the terminal has no incentive to implement measures to reduce the dwell time of reefers. Therefore, to reduce the energy consumption, an improvement must be cost-free for the terminal or add revenue. Hence the improvement is sought in revenue management methods. Two revenue management methods are considered, these are a dynamic pricing scheme and a peak pricing fee. Dynamic pricing is a complex method which is increasingly applied in a range of industries. Dynamic pricing continuously redetermines the price of a product or service based on the current demand. For dynamic pricing, it is imperative that the demand is accurately predicted. With the model found in the regression analysis, an accurate prediction is possible. However, the terminal has no knowledge regarding the plug-in temperature, thermal insulation, and type of cargo. These variables are impossible to predict prior to the arrival of a reefer. Thus, it is attempted to predict the energy consumption using the data available for the terminal which is included in the prediction model and which might be possible to predict. To increase the consumption prediction accuracy, an attempt is made to predict the dwell time using a neural network (N=65791). The network proved it to be impossible to predict the dwell time with the data known prior to the arrival of the ship with a relative error of 93,9%. As the dwell time cannot be predicted, a dynamic pricing model depends only on using the number of arriving reefers to predict the energy consumption. Therefore, there are two significant downsides regarding a dynamic pricing scheme: (1) A dynamic pricing model assumes perfect knowledge about the demand, which is shown not to be the case before the arrival of the ship. (2) A dynamic pricing model assumes the demand of goods and service to have a high price elasticity. However, five Dutch importers of meat, fish, vegetables, and fruit have indicated that this is not the case. Considering these two downsides a peak pricing scheme promises a better yield, thus can be considered to be a more suitable solution. Peak pricing introduces an additional fee when a peak in energy consumption is expected and does not require a price-sensitive demand or a highly accurate demand forecast

Efforts to reduce the dwell time of the reefer using the introduction of a peak pricing scheme will lead to a significant energy reduction. If the dwell time reduces to an average of 3 days, the total energy consumption will reduce by 5,5% - 11%. However, it is difficult to interpret the effectiveness of peak pricing measures prior to implementation. The exact effect of peak pricing on the total revenue of the terminal is unknown at this point, as it is unknown to what extent customers respond to a such an incentive. It is estimated that, due to a single peak pricing fees of €50, revenues will increase by 2% to 4%. However, if customers respond positively to the incentive the dwell time will decrease together with the revenue. It is likely that in total the revenue will not decrease.

This master thesis adds towards current research in reefer consumption as it shows the direction for future research. In this thesis, it is shown that the influence of offline time, reefer condition, ambient temperature, and sun exposure on the total energy consumption has been over-estimated in previous research. The small influence of these variables has shown that research towards such technical issues will not provide a high yield in regions with a similar climate compared with Rotterdam. The variables with the highest influence are the number of reefers and the connection duration. Thus research towards impact reduction of these variables is likely to provide a higher yield. As previous research has shown reducing the impact of plugged in period proves to have a high yield.

The practical influence of this research is that it has shown that the case of reefer energy consumption is not a very elegant problem. The research has shown that factors that were assumed to be sensitive, such as insulation properties and sun-exposure, do not influence the total energy consumption significantly. Therefore, measures such as high stacking of reefers, with the purpose to reduce sun exposure and increase insulation value, is not likely to influence the energy consumption in similar climates. As mentioned before research into similar solutions will provide a low yield. Practically, such measures will only add to the movements with reefers if bottom reefers are collected and disrupt the process. This research gives direction to container terminals on possibilities to stimulate customers to quickly collect the reefers with the purpose of reducing the energy consumption. This research also shows that reefers can be disconnected for several hours while staying within the bandwidth. The data has indicated that offline time will not add significantly to the total energy consumption as the mass of the cargo is likely to keep the temperature within the bandwidth. Additionally, it is not shown that reefers are plugged out at sea on a regular basis. In the instances in which reefers might be unplugged, it is not shown to have a high influence on the energy consumption as since reefers can be disconnected for several hours. Also, the predictive capability of this research supplies the container terminal with information of what can be expected. This enables the terminal to plan capacity accordingly and reduces the variation in the process. Finally, this research shows that 5,5% to 11% of the peak energy consumption can be reduced if customers respond positively to implementation of a peak pricing scheme.

7.1.1. Answer to research questions

1. *What factors can be considered to be the root-cause of energy consumption?*
   As mentioned above the factors found that can be considered root cause factors are the number of arriving reefers and the dwell time. The plug-in temperature, thermal insulation, and specific heat of the cargo are small variables that have little influence on the total energy consumption.

2. *How does the root cause effect the energy consumption?*
   The regression analysis shows that the number of arriving reefers effects the total energy consumption the most, as this factor can explain 76,6%. The influence of the other factors are as follows: Dwell time accounts for 4,6%, Specific heat for 1,1%, plug-in temperature 0,4%, and thermal insulation 0,3%. In total this explains 83%, the remaining 17% is explained by other factors that are currently unknown.

3. *Can the found root cause factors be used to predict the energy consumption*
   For validation purposes the model found, with 60% of the data, was used to predict the total energy consumption of the remaining 40% of the data. The regression coefficients as shown in Table 5.4 where used to predict. Comparing the prediction to the actual energy consumption showed that the identified root cause factors can be used to predict the energy consumption.

4. *What are possible improvements on the root cause that will improve peak energy consumption?*
   The root cause for which an improvement is developed is for the dwell time. The two proposed methods are the implementation of a dynamic pricing scheme or a peak pricing method. After attempts to predict the dwell time to enable accurate prediction of the energy consumption the suggested method of reducing the dwell time is the implementation of peak pricing. Peak pricing introduces an additional fee when the energy consumption is expected to be high. Hence, introducing an added incentive to collect the reefer prior to expected peaks.

5. *What is the market potential of the possible improvements?*
   After discussions with Dutch perishable food importers, it became clear that the market for temporary reefer storage is not dependent on the price. Hence a dynamic pricing scheme is not recommended. However, a correct implementation of peak pricing could lead to a total energy reduction of 5,5 % to 11,6% of the total yearly energy consumption. The total energy savings are equal to the yearly energy

consumptions of 230 to 480 two-person household or €54.000 to €113.000.

6. *Is Six-sigma suitable to be applied in a broader context?*
   The Six-sigma methodology provides a clear backbone throughout the research. The framework extends traditional scientific research and gives handholds to ask the right questions at the right time. The analysis methods are the same as when performing traditional scientific research. However, during the measurement phase is where the methodology finds the most resistance to being applied outside the business context. Process capabilities are different for each company and cannot be generalised outside a business context. However, the goal of the measurement phase is to gain insight in the process. Therefore, even as the customer needs and requirements and the respective process capabilities will change it provides an insight into the process for the researcher. The added value of a benchmark provided by the measurement phase is not the case outside the business context as suggested improvements often cannot be implemented.

The above-mentioned sub-questions lead to the answer to the main research question.

> *How can the peak energy consumption of reefers at container terminals be reduced after identification and improvement of the root cause factors?*

The root cause analysis performed in this research indicates that the number of arriving reefers and the dwell time of reefers can be considered to be the root cause of peak energy consumption at terminals. By applying a peak pricing scheme, the peak energy consumption of reefers at container terminals will decrease with approximately 5,5% to 11,6%. In such a peak pricing scheme the customer is required to pay an additional fee if the reefer is not collected when the demurrage free-time is exceeded and when a new peak consumption moment is expected. Measures aiming to improve the insulation values, offline time, and sun-exposure will not provide enough yield in the western European climate as these factors are found to have a negligible impact on the total energy consumption.

8

Reflections and recommendations

In this final chapter, the limitations of this master thesis are reflected upon and discussed. Next, suggestions for future research are given to direct further research. Lastly, a short list of management recommendations is given. This reflects upon findings encountered in this research during interviews.

8.1. Reflection

Like any other research, this research as some limitations. For readers to properly estimate the value of this research, it is essential that these limitations are discussed. The limitations, as are discussed here, can provide starting points for future research.

1. This research is performed in the year 2017 while the used dataset is dated from 01-01-2014 to 31-01-2015. In the three years between the period of the data collection and the analysis, aspects can be subject to change. Therefore, it is possible that research with more recent data would provide a different outcome. Although, when considering the convincing high explained variance of the number of arriving reefers and dwell time, it is not likely that the outcome of such research would yield different answers.

2. This research is a follow-up study on the work of Nafde (2015). The energy consumption output simulated by Nafde is used as an input for this study. To be able to use the work of Nafde as a comparison, assumptions made previously must also be made in this research. During this research, it is found that some assumptions such as ambient temperature, insulation values, and specific heat could have been made more accurate. More accurate assumptions will lead to a more accurate energy consumption simulation and therefore a prediction model with an increased accuracy. However, this requires re-running the simulations performed by Nafde. Rerunning the simulation was impossible during this research due to time and experience limitations.

3. The data used in this research originates from a Dutch container terminal, it is likely that ambient temperature has a higher influence in other locations with a warmer average temperature and more sun-hours. With a higher ambient temperature, the sun-exposure and insulation values become increasingly important. When this research is performed using data from a different (tropical)climate,

sun-exposure and insulation values could show to have a higher impact and thus could result in a different outcome.

4. In this research, it is assumed that the customer is always able to collect the reefer when preferred. In practice, it occurs that a customer is not allowed to collect the reefer due to issues with paperwork and customs. In example, the paperwork of a container might not be correct. Another reason that would make it impossible for a customer to collect is that it occurred that a terminals' computer system can be infected with a virus, making it impossible for the terminal to process reefers. Cyber criminality becomes an increasing risk in the next years and already has occurred.

5. Only the import of reefers is considered in this research. During this research, the available data only comprised of imported reefers. When reefers for export are also considered in a research a more complete picture of the energy consumption will be found. Currently, the precise energy consumption of the export reefers is unclear. However, similar factors as identified in this study can be expected for export reefers.

6. Only large container terminals are considered in this research. The largest container terminals are capable of welcoming the worlds' largest container ships and are designed to have an efficient operation. Smaller terminals are not considered in this research. The operation methods at smaller terminals can be different from larger terminals, and this can lead to a higher (or lower) influence of factors such as the plug-in temperature, offline time, sun-hours, and thermal insulation. In example, if a smaller terminal operates by stacking the reefer lower and further apart the insulation value of each reefer could have an increased influence on the energy consumption.

7. As it is unknown from what terminal the data originates, the exact internal process cannot be considered in this research. Therefore different internal variables that may impact the dwell time cannot be compensated for during this research which reduces the generalizability of this research.

8.2. Suggestions for further research

During this research, some topics were identified which were impossible to cover during this study but are highly interesting for further research. These suggestions are shown below in no particular order.

1. During this research there are different factors which are related to the ambient temperature. In example, the offline time could have a higher impact when the ambient temperature is significantly higher from the set-point temperature. Therefore, it can provide different insights when this research is repeated for terminals which are characterised by a different weather climate.

2. It is known that cargo owners attempt to collect the reefer as quick as possible (or outsource the collection). However, it would provide many insights to investigate the exact reasons for reefers to be collected late and to seek improvements in this process. A question that can be asked is what causes the late collection of reefers?

3. Develop the prediction model more accurately and using more data available to the terminal such as destination. This involves rerunning the simulations of Nafde and refit the model with recent data. When new data of new factors are included in the research, this increases the accuracy. Perhaps other variables that were not known during this research can predict the dwell time. This will increase the accuracy of the model and thus the efficiency and perhaps clears the way for a dynamic pricing scheme.

4. During this research it is suggested that a peak pricing scheme is implemented. However, it is unclear to how customers would react to the implementation of such a measure. Therefore it is recommended to perform research towards the effects of the peak pricing scheme after implementation. It is interesting to see what the effects are on the dwell time, customer satisfaction, revenue, and overall energy consumption. Outcomes of such research can be compared to the calculations performed in the measurement phase of this research.

5. Furthermore research towards different solutions for energy reduction must continue. Efforts to reduce the energy consumption while the reefer is plugged in show promising results in reducing the total energy consumption. Research, as performed by van Duin et al. (2016), shows promising results and can be considered to be in the right direction.

6. Another suggestion for further research is the development of a smart planning tool for connecting reefers. By spreading the connection of reefers it is avoided that many reefers turn on simultaneously draw a peak of electricity. The plug in temperature is known thus it can be calculated when the reefer will start cooling. Therefore, it can be calculated when reefers must be plugged in such that minimal reefers are cooling simultaneously.

8.3. management recommendations

During this research multiple things were encountered which require mentioning and discussion.

1. When discussing the topic of this research an often heard solution is that stacking the reefers high and close together could reduce the energy consumption. The theory behind such a solution is that the reefers are less exposed to the sun and will be better insulated in the centre of such a high and compact stack. This research has shown that the sun-hours have minimal impact on the energy consumption. Also, the insulation value has minimal impact on the energy consumption, thus improving the isolation properties with such a measure would have a negligible impact on the total energy consumption. On the contrary, such an impact would have a significant impact on the operation. Higher stacking of reefers would lead to an increase of crane movements as more reefers must be moved to retrieve the container when the customer comes to collect. It is possible that these additional crane movements use more energy than the savings. Additionally, the added movements would be counterproductive.

2. As it is found that the sun-hours do not influence the energy consumption directly it can be said that the installation of sun-shading would not reduce the energy consumption. It must be noted that the influence of the sun is low in our climate. Shinoda and Budiyanto (2014) have shown that in the warmer tropical climate of Indonesia the application of sun-shading has a potential to reduce the energy consumption by 12%. The saving potential indicated by Shinoda and Budiyanto from a tropical climate is likely to be significantly smaller in a moderate maritime climate as in the Netherlands. Therefore, it is likely that a roof does not provide enough yield to compensate for the added costs of installation and operation with a roof. The operation is mentioned here as the roof must be able to open for the ASC to be able to reach the container. Hence the roof must consume energy, which reduces the energy savings.

3. During this research it was mentioned that reefers are often unplugged at see by the shipping company for two possible reasons. Firstly, reefers must be unplugged when the shipped is moored for the quay cranes to be able to start offloading immediately. Secondly, shipping companies would purposely

disconnect reefers at sea to save on more expensive fuels. During this research it became clear that often a few reefers (±15) are disconnected before mooring of the ship, enabling the quay cranes to start offloading. Then, when the ship is adequately docked, the personnel of the ship can disconnect the remaining reefers while the quay cranes started. Considering the second reason, the dataset reviewed in this research has not shown that early disconnecting is standard procedure. In occasions where it might have happened, it has not been a significant impact on the energy consumption.

4. Selectively offloading a ship based on the difference between the current temperature and the set-point temperature could have some influence on the total energy consumption. However, operationally this is very difficult for the container terminal. The goal of a terminal is to achieve a short turn around time (TAT), hence the ship is offloaded as quickly as possible. When the quay crane operator must select the correct container to offload, possibly this requires the temporary movement of different reefers which must be offloaded later. As mentioned before in section 8.2 an option could be to offload the reefers as quickly as possible, connect the plug of a reefer but not the electricity, and let the computer generate a cooling plan for reefers based on their delta plug-in temperature and other characteristics. The computer system is then able to allocate energy subsequently to the developed cooling plan.

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A CTQ-tree research

To establish critical to quality factors, the websites of container terminals were researched. It is assumed that the terminals know what customers need and require and thus advertise with these services on their websites. The results can be found in Table A.1. When looking at the keywords that are found on their websites it can be seen that a few terms are repeatedly mentioned, these are: Fast (5/7), Reliability (4/7), and Safety (4/7).

Table A.1: Keywords from terminal websites

Port	Terminal company	Keywords
Rotterdam	APM Terminals	Safety, Innovation
	Rotterdam world gateway	Reliable, Sustainable, Safety, Competitive
	ECT rotterdam	Reliable, Innovation, Safety, Fast
	Uniport multipurpose Terminals	Flexible, Fast, Clear pricing
Hamburg	HLLA terminals	Fast, Efficient
	Eurogate	Reliable, Safety, Fast
Antwerp	PSA terminals	Reliable, Fast, Efficient,

*All information has been found on the website of the terminal companies.

B High Level process map

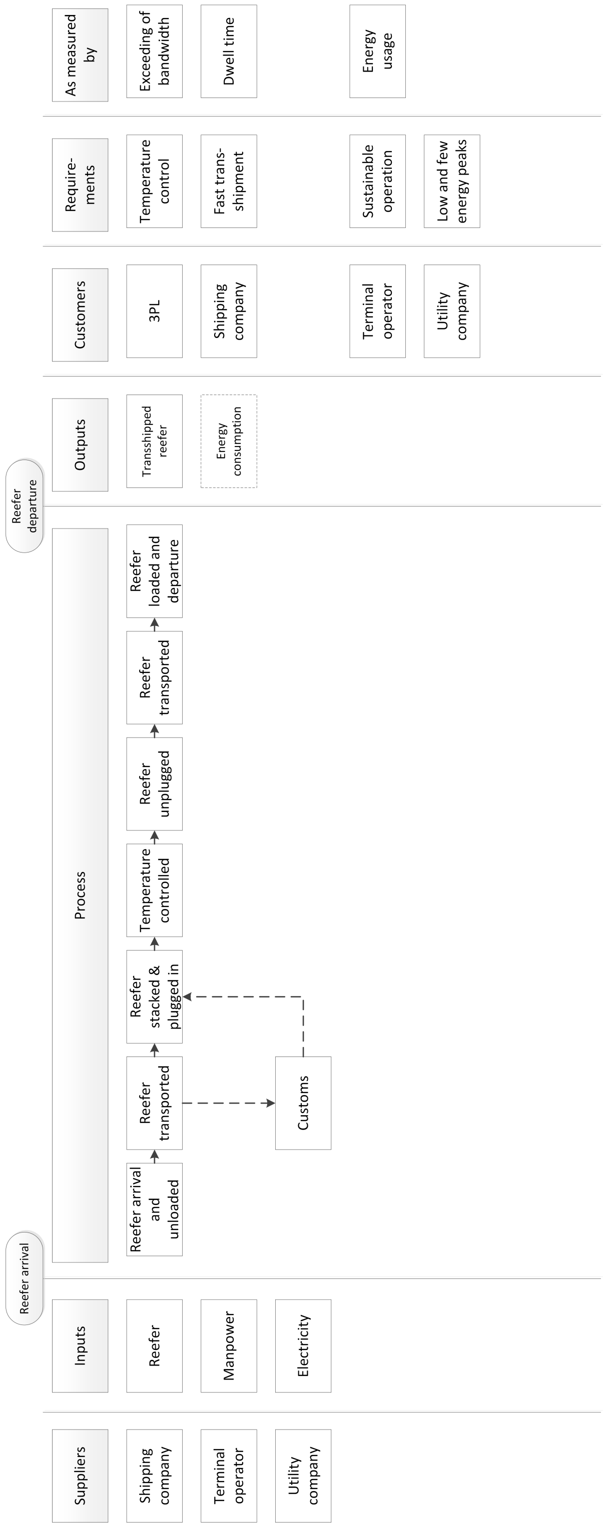

Figure B.1: High-level process map

C Analyses towards influences of assumptions

C.1. Analysis for assumption regarding average ambient temperature

Two-Sample T-Test and CI: KNMI temperature; Assumed temperature

Method

μ_1: mean of KNMI temperature

μ_2: mean of Asumed temperature

Difference: μ_1 - μ_2

Equal variances are not assumed for this analysis.

Descriptive Statistics:

Table C.1: Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
KNMI temperature	395	19172	20686	1041
Asumed temperature	397	19227	20568	1032

Estimation or difference:

Table C.2: Estimation of Difference

Difference	95% CI for
Difference	
-55	(-2933; 2822)

Test:

Null hypothesis H_0: μ_1 - μ_2 = 0

Alternative hypothesis H_1: μ_1 - $\mu_2 \neq 0$

Table C.3: T-test

T-Value	DF	P-Value
-0,04	789	0,970

C.2. Analysis for assumption regarding insulation values

Two-Sample T-Test and CI: insulation value of 0,4; insulation value 0,4-0,9

Method

μ_1: mean of insulation value of 0,4

μ_2: mean of insulation value 0,4-0,9

Difference: μ_1 - μ_2

Equal variances are not assumed for this analysis.

Descriptive Statistics

Table C.4: Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
insulation value of 0,4	397	12941	13152	660
insulation value 0,4-0,9	397	19227	20568	1032

Estimation or difference

Table C.5: Estimation of Difference

Difference	95% CI for
Difference	
-6286	(-8692; -3880)

Test

Null hypothesis H_0: μ_1 - μ_2 = 0

Alternative hypothesis H_1: μ_1 - $\mu_2 \neq 0$

Table C.6: T-test

T-Value	DF	P-Value
-5,13	673	0,000

D Factor Brainstorm

Table D.1: Factors for analysis brainstorm

Initial brainstorm factors			Filtered for duplicates		
Factor	Description	As mentioned by	Factor	Description	As mentioned by
1.1	Sun-hours	Daan	1	Sun-hours	Daan, ABB
1.2	Ambient temperature	Daan	2	Ambient temperature	Daan, ABB, TU Delft, ECT
1.3	Set-point temperature	Daan	3	Set-point temperature	Daan, ABB, TU Delft, ECT
1.4	Plug-in temperature	Daan	4	Plug-in temperature	Daan, ABB, ECT
1.5	Dwell time	Daan	5	Dwell time	Daan, ABB, TU Delft
1.6	Offline time	Daan	6	Offline time	Daan, TU Delft, ECT
1.7	Thermal insulation	Daan	7	Thermal insulation	Daan, ABB, TU Delft, ECT
1.8	Cargo type	Daan	8	Specific heat/cargo type	Daan, ABB, TU Delft
1.9	Transshipment time	Daan	9	Transshipment time	Daan
2.1	Set-point temperature	ABB	10	Mass of Cargo	ABB, TU Delft
2.2	Mass of cargo	ABB	11	Number of Arriving reefers	TU Delft
2.3	Specific heat of cargo	ABB	12	Surface are of reefer	TU Delft
2.4	Thermal insulation	ABB	13	Reefer condition refrigerant	ECT
2.5	Plug-in temperature	ABB	14	Power availability	ECT
2.6	Sun-light	ABB			
2.7	Ambient temperature	ABB			
2.8	Dwell time	ABB			
3.1	Dwell time	TU Delft			
3.2	Number of arriving reefers	TU Delft			
3.3	Ambient temperature	TU Delft			
3.4	Thermal insulation	TU Delft			
3.5	Mass of cargo	TU Delft			
3.6	Specific heat of cargo	TU Delft			
3.7	Surface area of reefer	TU Delft			
3.8	Offline time	TU Delft			
3.9	Set-point temperature	TU Delft			
4.1	Set-point temperature	ECT			
4.2	Plug-in temperature	ECT			
4.3	Ambient temperature	ECT			
4.4	Reefer condition/age/insulation	ECT			
4.5	Reefer condition refrigerant	ECT			

Table D.1: Factors for analysis brainstorm

Initial brainstorm factors			Filtered for duplicates		
Factor	Description	As mentioned by	Factor	Description	As mentioned by
4.6	Offline time	ECT			
4.7	Power availability	ECT			

E Full description of statistical tests

E.1. Correlation matrix section 5.4

Table E.1: Correlation matrix all variables

Correlations		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Tot_cons_tushar (1)	Pearson corr	1	,886**	,146**	,199**	-,030	-,225**	,200**	,388**	-,163**	,050	-,011
	Sig. (2-tailed)		,000	,004	,000	,558	,000	,000	,000	,001	,322	,832
	N	393	393	393	393	393	393	393	393	393	393	393
No_arr_reefers (2)	Pearson corr	,886**	1	-,064	,115*	,016	-,145**	,136**	,357**	-,106*	,040	-,011
	Sig. (2-tailed)	,000		,209	,022	,759	,004	,007	,000	,036	,425	,824
	N	393	393	393	393	393	393	393	393	393	393	393
avg_dwelltime (3)	Pearson corr	,146**	-,064	1	,163**	-,294**	-,071	-,007	,267**	-,210**	-,034	-,087
	Sig. (2-tailed)	,004	,209		,001	,000	,160	,895	,000	,000	,507	,083
	N	393	393	393	393	393	393	393	393	393	393	393
avg_deltaT _plugin (4)	Pearson corr	,199**	,115*	,163**	1	-,172**	-,020	,089	,215**	-,479**	,264**	,222**
	Sig. (2-tailed)	,000	,022	,001		,001	,686	,077	,000	,000	,000	,000
	N	393	393	393	393	393	393	393	393	393	393	393
avg_T_setpoint (5)	Pearson corr	-,030	,016	-,294**	-,172**	1	-,152**	,018	-,618**	,657**	,062	,174**
	Sig. (2-tailed)	,558	,759	,000	,001		,002	,721	,000	,000	,220	,001
	N	393	393	393	393	393	393	393	393	393	393	393
avg_specific _heat (6)	Pearson corr	-,225**	-,145**	-,071	-,020	-,152**	1	-,392**	-,160**	-,104*	,125*	-,010
	Sig. (2-tailed)	,000	,004	,160	,686	,002		,000	,001	,040	,013	,843
	N	393	393	393	393	393	393	393	393	393	393	393
avg_thermal_iso (7)	Pearson corr	,200**	,136**	-,007	,089	,018	-,392**	1	,211**	,132**	-,247**	-,019
	Sig. (2-tailed)	,000	,007	,895	,077	,721	,000		,000	,009	,000	,710
	N	393	393	393	393	393	393	393	393	393	393	393
avg_weight (8)	Pearson corr	,388**	,357**	,267**	,215**	-,618**	-,160**	,211**	1	-,493**	-,014	-,201**
	Sig. (2-tailed)	,000	,000	,000	,000	,000	,001	,000		,000	,776	,000

Table E.1: Correlation matrix all variables

Correlations		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	N	393	393	393	393	393	393	393	393	393	393	393
avg_deltaT _ambient (9)	Pearson corr	-,163**	-,106*	-,210**	-,479**	,657**	-,104*	,132**	-,493**	1	-,285**	,099
	Sig. (2-tailed)	,001	,036	,000	,000	,000	,040	,009	,000		,000	,051
	N	393	393	393	393	393	393	393	393	393	393	393
Sunhours (10)	Pearson corr	,050	,040	-,034	,264**	,062	,125*	-,247**	-,014	-,285**	1	,064
	Sig. (2-tailed)	,322	,425	,507	,000	,220	,013	,000	,776	,000		,204
	N	393	393	393	393	393	393	393	393	393	393	393
Offline_time (11)	Pearson corr	-,011	-,011	-,087	,222**	,174**	-,010	-,019	-,201**	,099	,064	1
	Sig. (2-tailed)	,832	,824	,083	,000	,001	,843	,710	,000	,051	,204	
	N	393	393	393	393	393	393	393	393	393	393	393

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

E.2. Sequential Multiple Regression Analysis Energy Consumption

Table E.2: Entered and removed variables to the model of energy consumption

Variables Entered/Removed[a]			
Model	Variables Entered	Variables Removed	Method
1	Offline_time, avg_specific_heat, avg_dwelltime, Sunhours, No_arr_reefers, avg_T_setpoint, avg_deltaT_plugin, avg_thermal_iso, avg_weight, avg_deltaT_ambient		E nter
2		Sunhours	Backward[b]
3		avg_weight	Backward[b]
4		Offline_time	Backward[b]
5		avg_deltaT_ambient	Backward[b]
6		avg_T_setpoint	Backward[b]

a: dependent variable is Tot_cons_tushar
b: criterion: Probability of F-to-remove >= ,100

Table E.3: Model Summary of Sequential Multiple Regression Energy Consumption

Model Summary [g]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,912[a]	,832	,824	12420,990	832	111,053	10	225	000
2	,912[b]	,832	,825	12393,802	000	,011	1	225	915
3	,912[c]	,831	,825	12372,487	000	,220	1	226	640
4	,912[d]	,831	,826	12362,405	000	,629	1	227	429
5	,911[e]	,830	,826	12353,532	000	,671	1	228	413
6	,911[f]	,830	,827	12332,846	000	,230	1	229	632

a. Predictors: (Constant), Offline_time, avg_specific_heat, avg_dwelltime, Sunhours, No_arr_reefers, avg_T_setpoint, avg_deltaT_plugin, avg_thermal_iso, avg_weight, avg_deltaT_ambient

b. Predictors: (Constant), avg_specific_heat, avg_dwelltime, Sunhours, No_arr_reefers, avg_T_setpoint, avg_deltaT_plugin, avg_thermal_iso, avg_weight, avg_deltaT_ambient

c. Predictors: (Constant), avg_specific_heat, avg_dwelltime, Sunhours, No_arr_reefers, avg_T_setpoint, avg_deltaT_plugin, avg_thermal_iso, avg_deltaT_ambient

d. Predictors: (Constant), avg_specific_heat, avg_dwelltime, No_arr_reefers, avg_T_setpoint, avg_deltaT_plugin, avg_thermal_iso, avg_deltaT_ambient

e. Predictors: (Constant), avg_specific_heat, avg_dwelltime, No_arr_reefers, avg_deltaT_plugin, avg_thermal_iso, avg_deltaT_ambient

f. Predictors: (Constant), avg_specific_heat, avg_dwelltime, No_arr_reefers, avg_deltaT_plugin, avg_thermal_iso

g. Dependent Variable: Tot_cons_tushar

Table E.4: ANOVA Sequential Multiple Regression Energy Consumption

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	171334604745,498	10	17133460474,550	111,053	,000
	Residual	34713279014,921	225	154281240,066		
	Total	206047883760,419	235			
2	Regression	171332852426,045	9	19036983602,894	123,934	,000
	Residual	34715031334,374	226	153606333,338		
	Total	206047883760,419	235			
3	Regression	171299078682,430	8	21412384835,304	139,879	,000
	Residual	34748805077,989	227	153078436,467		
	Total	206047883760,419	235			
4	Regression	171202859693,202	7	24457551384,743	160,032	,000
	Residual	34845024067,218	228	152829052,926		
	Total	206047883760,419	235			
5	Regression	171100250620,840	6	28516708436,807	186,860	,000
	Residual	34947633139,580	229	152609751,701		
	Total	206047883760,419	235			
6	Regression	171065094637,487	5	34213018927,497	224,939	,000
	Residual	34982789122,932	230	152099083,143		
	Total	206047883760,419	235			

Table E.5: Coefficients of Sequential Multiple Regression Energy Consumption

Coefficients								
Model		Unstd. Coeff.		Stand. Coeff.	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tole	VIF
1	(Constant)	25837,845	36257,167		,713	,477		
	Offline_time	139,022	166,403	,024	,835	,404	,915	1,093
	avg_specific_heat	-21297,423	8800,910	-,076	-2,420	,016	,755	1,325
	avg_dwelltime	7161,459	1054,038	,207	6,794	,000	,805	1,242
	Sunhours	24,411	229,052	,003	,107	,915	,782	1,280
	No_arr_reefers	172,807	6,500	,843	26,584	,000	,745	1,342
	avg_T_setpoint	330,467	352,560	,045	,937	,350	,322	3,106
	deltaT_plugin	9193,171	8349,649	,039	1,101	,272	,585	1,710
	avg_thermal_iso	16573,387	7937,209	,068	2,088	,038	,711	1,407
	avg_weight	,307	,654	,020	,470	,639	,416	2,404
	avg_deltaT_ambient	-187,488	225,806	-,039	-,830	,407	,332	3,011
2	(Constant)	25789,037	36174,890		,713	,477		
	Offline_time	139,142	166,035	,024	,838	,403	,915	1,093

Table E.5: Coefficients of Sequential Multiple Regression Energy Consumption

Coefficients								
Model		Unstd. Coeff.		Stand. Coeff.	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tole	VIF
	avg_specific_heat	-21225,119	8755,507	-,076	-2,424	,016	,760	1,317
	avg_dwelltime	7160,665	1051,704	,207	6,809	,000	,805	1,242
	No_arr_reefers	172,786	6,483	,842	26,650	,000	,746	1,341
	avg_T_setpoint	339,519	341,428	,046	,994	,321	,342	2,926
	deltaT_plugin	9289,626	8282,277	,040	1,122	,263	,592	1,690
	avg_thermal_iso	16432,387	7809,030	,067	2,104	,036	,731	1,368
	avg_weight	,306	,652	,020	,469	,640	,416	2,403
	avg_deltaT_ambient	-194,086	216,677	-,041	-,896	,371	,359	2,785
3	(Constant)	34433,026	31071,946		1,108	,269		
	Offline_time	130,619	164,753	,022	,793	,429	,926	1,079
	avg_specific_heat	-21797,792	8654,999	-,078	-2,519	,012	,775	1,291
	avg_dwelltime	7209,849	1044,660	,209	6,902	,000	,813	1,229
	No_arr_reefers	174,091	5,846	,849	29,780	,000	,914	1,094
	avg_T_setpoint	257,899	293,221	,035	,880	,380	,462	2,166
	deltaT_plugin	9717,547	8217,688	,042	1,183	,238	,599	1,669
	avg_thermal_iso	17055,768	7681,800	,070	2,220	,027	,753	1,328
	avg_deltaT_ambient	-194,783	216,299	-,041	-,901	,369	,359	2,785
4	(Constant)	36083,720	30976,847		1,165	,245		
	avg_specific_heat	-21881,377	8647,305	-,078	-2,530	,012	,775	1,291
	avg_dwelltime	7128,487	1038,760	,206	6,862	,000	,821	1,218
	No_arr_reefers	173,861	5,834	,848	29,801	,000	,917	1,091
	avg_T_setpoint	262,333	292,929	,036	,896	,371	,462	2,165
	deltaT_plugin	11248,192	7981,171	,048	1,409	,160	,634	1,577
	avg_thermal_iso	16719,620	7663,840	,068	2,182	,030	,755	1,324
	avg_deltaT_ambient	-176,026	214,826	-,037	-,819	,413	,363	2,751
5	(Constant)	39205,140	30719,653		1,276	,203		
	avg_specific_heat	-22004,637	8639,791	-,079	-2,547	,012	,775	1,290
	avg_dwelltime	7036,058	1031,876	,204	6,819	,000	,831	1,203
	No_arr_reefers	174,605	5,759	,851	30,320	,000	,939	1,064
	avg_T_setpoint	107,212	223,374	,015	,480	,632	,793	1,261
	deltaT_plugin	14849,201	6657,444	,064	2,230	,027	,910	1,099
	avg_thermal_iso	15216,311	7435,655	,062	2,046	,042	,801	1,248
6	(Constant)	41088,919	30416,878		1,351	,178		
	avg_specific_heat	-22775,936	8474,810	-,081	-2,687	,008	,803	1,246
	avg_dwelltime	6855,187	958,993	,198	7,148	,000	,959	1,043
	No_arr_reefers	174,390	5,732	,850	30,426	,000	,945	1,058

Table E.5: Coefficients of Sequential Multiple Regression Energy Consumption

Coefficients							
Model	Unstd. Coeff.		Stand. Coeff.	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tole	VIF
deltaT_plugin	14190,340	6503,474	,061	2,182	,030	,950	1,052
avg_thermal_iso	15218,523	7423,202	,062	2,050	,041	,801	1,248

Table E.6: Excluded variables of Sequential Multiple Regression Energy Consumption

Excluded Variables[a]						
Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
2	Sunhours	0,003b	,107	,915	,007	,782
3	Sunhours	0,003c	,099	,921	,007	,782
	avg_weight	,020c	,469	,640	,031	,416
4	Sunhours	,003d	,106	,916	,007	,782
	avg_weight	,016d	,380	,705	,025	,421
	Offline_time	,022d	,793	,429	,053	,926
5	Sunhours	,010e	,327	,744	,022	,846
	avg_weight	,017e	,395	,693	,026	,421
	Offline_time	,020e	,699	,485	,046	,938
	avg_deltaT_ambient	-,037e	-,819	,413	-,054	,363
6	Sunhours	,011f	,392	,695	,026	,863
	avg_weight	,000f	,013	,990	,001	,685
	Offline_time	,021f	,751	,453	,050	,951
	avg_deltaT_ambient	-,011f	-,315	,753	-,021	,624
	avg_T_setpoint	,015f	,480	,632	,032	,793

a. Dependent Variable: Tot_cons_tushar

b. Predictors in the Model: (Constant), avg_specific_heat, avg_dwelltime, Sunhours, No_arr_reefers, avg_T_setpoint, avg_deltaT_plugin, avg_thermal_iso, avg_weight, avg_deltaT_ambient

c. Predictors in the Model: (Constant), avg_specific_heat, avg_dwelltime, Sunhours, No_arr_reefers, avg_T_setpoint, avg_deltaT_plugin, avg_thermal_iso, avg_deltaT_ambient

d. Predictors in the Model: (Constant), avg_specific_heat, avg_dwelltime, No_arr_reefers, avg_T_setpoint, avg_deltaT_plugin, avg_thermal_iso, avg_deltaT_ambient

e. Predictors in the Model: (Constant), avg_specific_heat, avg_dwelltime, No_arr_reefers, avg_deltaT_plugin, avg_thermal_iso, avg_deltaT_ambient

f. Predictors in the Model: (Constant), avg_specific_heat, avg_dwelltime, No_arr_reefers, avg_deltaT_plugin, avg_thermal_iso

Table E.7: Residuals of Sequential Multiple Regression Energy Consumption

Residuals Statistics[a]					
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-11390,468	132904,797	31410,691	26980,290	236
Residual	-53423,285	51392,672	,00000	12200,930	236
Std. Predicted Value	-1,586	3,762	,000	1,000	236
Std. Residual	-4,332	4,167	,000	989	236

a. Dependent Variable: Tot_cons_tushar

E.3. Regression analysis dwell time

Table E.8: Descriptive statistics dwell time regression analysis

	Mean	Std. Deviation	N
avg_dwelltime	3,6083	,85665	236
avg_T_setpoint	-13,2652	4,05051	236

Table E.9: Model summary dwell time regression analysis

Model	R	R Square	Adj. R^2	Std. Err. of Est.	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,360	,130	,126	,80085	,130	34,890	1	234	,000

Table E.10: ANOVA of dwell time regression analysis

Model		Sum of Squares	df	Mean Square	F	Sig.
	Regression	22,377	1	22,377	34,890	,000c
1	Residual	150,077	234	,641		
	Total	172,454	235			

Table E.11: Coefficients of dwell time regression analysis

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2,598	,179		14,524	,000
	avg_T_setpoint	-,076	,013	-,360	-5,907	,000

E.3.1. Mediation effect of Dwell time Section 5.5

Table E.12: Mediation model of dwell time

Model	4
Y: (DV)	energy consumption
X:(IV)	set-point temperature
M:(mediator)	dwell time
sample size	61253

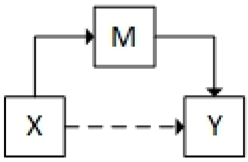

Table E.13: Model summary regression of set-point on dwell time

R	R-sq	MSE	F	df1	df2	p
,182	,033	4,397	2093,619	1,000	61251,000	,000

Table E.14: Coefficients regression of set-point on dwell time

	coeff	se	t	p	LLCI	ULCI
constant	3,142	,013	249,967	,000	3,118	3,167
set	-,031	,001	-45,756	,000	-,033	-,030

Table E.15: Model Summary regression of set-point and dwell time on energy consumption

R	R-sq	MSE	F	df1	df2	p
,149	,022	9837,763	698,701	2,000	61250,000	,000

Table E.16: Coefficients regression of set-point and dwell time on energy consumption

	coeff	se	t	p	LLCI	ULCI
constant	97,169	,845	114,975	,000	95,513	98,826
dwell	6,374	,191	33,352	,000	6,000	6,749
set	-,347	,033	-10,539	,000	-,411	-,282

Table E.17: Covariance matrix of regression parameter estimates

	constant	dwell	set
constant	,714	-,115	,011
dwell	-,115	,037	,001
set	,011	,001	,001

******************* DIRECT AND INDIRECT EFFECTS ************************

Table E.18: Direct effect of set-point on energy consumption

Effect	SE	t	p	LLCI	ULCI
-,347	,033	-10,539	,000	-,411	-,282

Table E.19: Indirect effect of set-point on energy consumption

	Effect	Boot	SE	BootLLCI	BootULCI
dwell	-,200	,009	-,216	-,184	

Number of bootstrap samples for bias corrected bootstrap confidence intervals: 1000

Level of confidence for all confidence intervals in output: 95,00

NOTE: Some cases were deleted due to missing data. The number of such cases was: 30

E.4. Multiple Regression Analysis Plug-in temperature

Table E.20: Descriptives Multiple Regression Analysis Plug-in temperature

	Mean	Std. Deviation	N
deltaT_plugin	,1888	,12689	236
avg_weight	28475,2739	1921,85657	236
avg_deltaT_ambient	-24,3203	6,22669	236
Sunhours	4,7496	4,00147	236
Offline_time	4,6722	5,08979	236

Table E.21: Model Summary Multiple Regression Analysis Plug-in temperature

Model	R	R^2	Adj. R^2	Std. Error of Est.	Change Statistics				
	60%				R Square Change	F Change	df1	df2	Sig. F Change
1	,596a	,355	,344	,10280	,355	31,769	4	231	,000

Table E.22: ANOVA Multiple Regression Analysis Plug-in temperature

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,343	4	,336	31,769	,000c
	Residual	2,441	231	,011		
	Total	3,784	235			

Table E.23: Coefficients ANOVA Multiple Regression Analysis Plug-in temperature

Model		Unstand. Coefficients		Stand. Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
	(Constant)	-,284	,107		-2,642	,009		
	avg_weight	6,780E-06	,000	,103	1,648	,101	,719	1,391
1	avg_deltaT_ambient	-,010	,001	-,484	-7,590	,000	,686	1,458
	Sunhours	,003	,002	,110	1,947	,053	,881	1,136
	Offline_time	,005	,001	,198	3,696	,000	,978	1,023

E.5. mediation of Delta plug-in temperature

Table E.24: Mediation model Delta plug-in temperature

Model	4
Y: (DV)	Energy consumption
X:(IV)	Offline time, Weight, Sun-hours, and Delta ambient temperature
M:(mediator)	Delta plug-in temperature
sample size	391

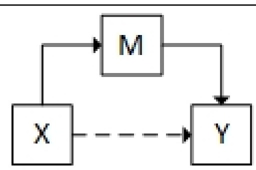

Table E.25: Model summary regression of offline time, weight, sun-hours, and ambient temperature on Delta plug-in temperature

X	R	R-sq	MSE	F	df1	df2	p
Offline	,2215	,0491	,0142	20, 1823	1	391	,0000
Weight	,2154	,0464	,0143	19,0167	1	391	,0000
Sun-hours	,2637	,0695	,0139	29,2170	1	391	,0000
Delta ambient temp	,4791	,2295	,0115	116,4883	1	391	,0000

Table E.26: Coefficients regression of offline time, weight, sun-hours, and ambient temperature on Delta plug-in temperature

	coeff	se	t	p	LLCI	ULCI
constant	,1661	,0081	20,5279	,0000	,1502	,1820
Offline	,0054	,0012	4,4925	,0000	,0031	,0078
constant	-,2084	,0916	-2,2742	,0235	-,3886	-,0282
weight	,0000	,0000	4,3608	,0000	,0000	,0000
constant	,1520	,0093	16,4096	,0000	,1338	,1702
sunhr	,0081	,0015	5,4053	,0000	,0052	,0111
constant	-,0460	,0226	-2,0395	,0421	-,0904	-,0017
dTamb	-,0095	,0009	-10,7930	,0000	-,0113	-,0078

Table E.27: Model Summary regression of offline time, weight, sun-hours, ambient temperature, and Delta plug-in temperature on energy consumption

X	R	R-sq	MSE	F	df1	df2	p
offline time	,2066	,0427	786222586	8,6974	2,0000	390,0000	,0002
Weight	,4055	,1645	686212626	38,3846	2,0000	390,0000	,0000
Sun-hours	,1989	,0395	788810502	8,0291	2,0000	390,0000	,0004
Delta ambient temp	,2131	,0454	783988622	9,2778	2,0000	390,0000	,0001

Table E.28: Coefficients regression of offline time, weight, sun-hours, ambient temperature, and Delta plug-in temperature on energy consumption

	coeff	se	t	p	LLCI	ULCI
constant	23030,7863	2740,2124	8,4047	,0000	17643,3490	28418,2237
dTin	49495,9246	11883,5830	4,1651	,0000	26132,0209	72859,8283
Offline	-330,1308	291,0938	-1,1341	,2574	-902,4403	242,1788
constant	-131164,63	20222,1505	-6,4862	,0000	-170922,70	-91406,556
dTin	28277,9326	11086,3246	2,5507	,0111	6481,4913	50074,3738
weight	5,4676	,7160	7,6363	,0000	4,0599	6,8754
constant	22178,8824	2864,1293	7,7437	,0000	16547,8164	27809,9485
dTin	46667,6801	12033,1842	3,8782	,0001	23009,6508	70325,7095
sunhr	-18,3753	369,9251	-,0497	,9604	-745,6723	708,9216
constant	13906,4439	5912,3734	2,3521	,0192	2282,3299	25530,5579
dTin	36722,7501	13183,3370	2,7855	,0056	10803,4450	62642,0553
dTamb	-406,4809	262,3191	-1,5496	,1221	-922,2173	109,2556

******************* DIRECT AND INDIRECT EFFECTS ************************

Table E.29: Direct effect of offline time, weight, sun-hours, and ambient temperature on energy consumption

	Effect	SE	t	p	LLCI	ULCI
Offline time	-330,1308	291,0938	-1,1341	,2574	-902,4403	242,1788
Weight	5,4676	,7160	7,6363	,0000	4,0599	6,8754
Sun-hours	-18,3753	369,9251	-,0497	,9604	-745,6723	708,9216
Delta ambient temp	-406,4809	262,3191	-1,5496	,1221	-922,2173	109,2556

Table E.30: Indirect effect of offline time, weight, sun-hours, and ambient temperature on energy consumption

X		Effect	Boot SE	BootLLCI	BootULCI
Offline time	dTin	268,6106	99,0108	131,0888	525,7229
Weight	dTin	,3933	,1406	,1580	,7224
Sun-hours	dTin	378,2946	107,9053	207,1913	638,7488
Delta ambient temp	dTin	-350,0805	91,3823	-531,9361	-174,9186

F Neural Network analysis

Table F.1: Case processing summary

		N	Percent
Sample	Training	23968	60,2%
	Testing	15827	39,8%
Valid		39795	100,0%
Excluded		0	
Total		39795	

Table F.2: Network Information

Input Layer	Factors	1	Reefer size
		2	Reefer type
	Covariates	1	Reefer weight
		2	Temperature setpoint
		3	number of arriving reefers
	Number of Units		7
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1a		4
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Dwell time
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

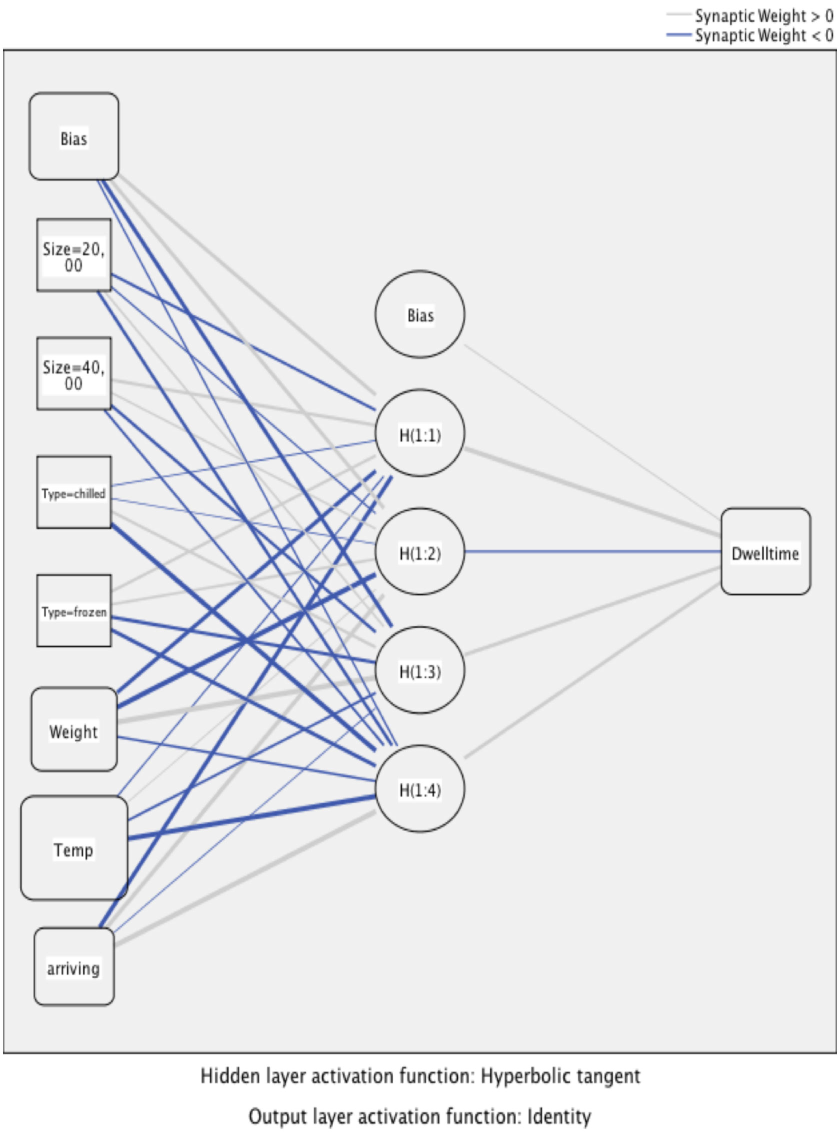

Figure F.1: Neural Network summary

Table F.3: Summary Neural Network Model

Training	Sum of Squares Error	11249,420
	Relative Error	,939
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	0:00:00,16
Testing	Sum of Squares Error	7237,312
	Relative Error	,968

Table F.4: Neural Network Parameter Estimates

Predictor		Predicted				
		Hidden Layer 1				Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	Dwell_time
Input Layer	(Bias)	0,449	0,456	-0,479	-0,157	
	[Size=20,00]	-0,278	-0,148	-0,226	-0,329	
	[Size=40,00]	0,310	0,172	-0,303	-0,256	
	[Type=chilled]	-0,093	-0,011	0,289	-0,638	
	[Type=frozen]	0,287	0,272	-0,323	-0,416	
	Weight	-0,468	-0,776	1,146	-0,230	
	T_setpoint	-0,123	0,112	-0,242	-0,619	
	arriving	-0,529	0,509	-0,090	0,816	
Hidden Layer 1	(Bias)					0,117
	H(1:1)					0,564
	H(1:2)					-0,151
	H(1:3)					0,408
	H(1:4)					0,338

Table F.5: Neural Network Independent Variable Importance

	Importance	Normalized Importance
Temperature setpoint	,566	100,0%
Reefer weight	,227	40,2%
number of arriving reefers	,131	23,2%
Reefer type	,038	6,8%
Reefer size	,038	6,6%

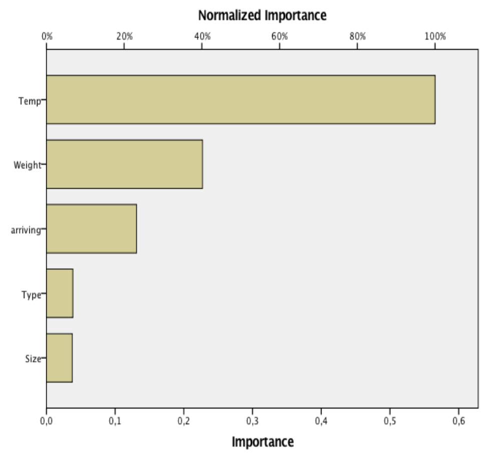

Figure F.2: Neural Network normalized variable importance

Glossary

Terms

Terms	Definition
Dwell time	Difference between plug-in and plug-out time ($t_{plugin} - t_{plugout}$)
Energy consumption	Sum of energy usage (kW/h)
Reefers	Temperature controlled containers
Root-cause	Deeper underlying cause that can be considered to be at the origin of the problem.

Acronyms

Acronyms	Definition
3PL	Third party logistics
40' and 20'	Forty foot and twenty foot
6M	Manpower, machine, mother-nature, method, measurement, materials
AC	Alternating Current
AGV	Automated Guided Vehicles
ASC	Automated Stacking Cranes
CTQ	Critical to Quality
DMAIC	Define, Measure, Analyze, Improve, and Control
DMAEV	Define, Measure, Analyze, Enable, and Verify
DOE	Design of Experiments
Dpu	Defects per unit
FTY	First Time Yield
Genset	Add-on generator set
P(d)	Probability of a defect
PoR	Port of Rotterdam
SMA	Shape Memory Alloys
TAT	Turn Around Time
TEU	Twenty foot Equivalent Unit
VOC	Voice Of Customers
Z	number of std. dev. from the mean

Symbols

Symbol	Definition
A	Surface area (M^2)
C_p	Specific heat (J/kGK)
I	Amperage (A)
K	Termal insulation (W/M^2K)
M	Mass of cargo (kG)
P	Active power (kW)
Q	Reactive power (kW)
Q	Cooling/heating power (kW)
S	Apparent power (kW)
t	Time (s)
U	Voltage (V)
δT	Temperature difference (°C)
ϕ	Phase change
$cos\phi$	Power factor