MASTER

Proof of concept
Demand driven supply through farming techniques on carcass quality control points

Diepenhorst, Janine G.

Award date:
2023

19 december 2022

Master Thesis

Proof of concept:
Demand driven supply through farming techniques on carcass quality control points

Master Student:	J.G. (Janine) Diepenhorst (1496344)
First supervisor TU/e:	dr. K.H. (Karel) van Donselaar
Second supervisor TU/e:	dr.ir. R.A.C.M. Broekmeulen

Department of Industrial Engineering & Innovation Sciences
Master Operations Management and Logistics
Operations, Planning, Accounting & Control group

Abstract

The conventional pig industry operates supply driven wherein farmers deliver their pigs to farmer's cooperatives who slaughter the pigs and sell the pork as a service for the farmers. However, this system does not result in an optimal profit which can be achieved by tailoring the supply to the needs of customers. Thus far it is not known how the transition to a 'demand driven system' could take place due to complex characteristics like biological products, one-to-many processing, and cooperative agreements. Therefore, a proof of concept was needed to demonstrate if and how pig farming can respond to customer demand.

This thesis found one key metric to facilitate the match of supply and demand, namely a distribution over carcass classes determined by carcass quality. This research was limited to carcass quality (backfat thickness and slaughter weight) and the fattening stage process. Several farming techniques were reviewed through literature research that can serve as quality control points to steer on carcass quality. Thereafter, multiple models were analyzed to link the farming techniques to customer demand. This resulted in a three-stage model. In the first stage it was proven that a farming technique can influence the distribution over the carcass classes. This conclusion was based on the data of an experiment where the feed composition (amino acid) was altered, which was identified as a carcass quality control point. The second stage proved that the supply of all farmers combined can be matched with several demand scenarios in a ratio over farming techniques.

In the third stage it was concluded that an incentive and penalty system can steer farmers towards the ratio of stage 2 such that farmers are incentivized to produce what is desired by the market. This incentive should be interpreted as a monetary addition on top of the weekly meat price to reward demand driven supply. As a desired future outcome, farmers will try to maximize their profit in the system controlled by this proved concept, then the customer demand will be met. This was determined by a utility based multi nominal logit model.

In the future, market research should indicate which distributions over the carcass classes are demanded. This will serve as input for the model which will provide incentives per carcass class that should close the gap between supply and demand optimally. Now that the proof of concept is completed, the industry can reinvent itself to more responsive supply chains.

Keywords: Quality controlled logistics, pig industry, carcass distribution, multi-nominal logit model

Management summary

The main focus of this research was to provide a proof of concept for matching supply and demand from an agricultural cooperative perspective in a segmented market. Two models were developed where the first assesses the ability of the supply to meet the demand and the second indicates how this can be optimally achieved with incentives and penalties on payments for pig farmers. The research limits itself to carcass quality (backfat thickness and slaughter weight) and the fattening stage process.

Problem description

This study was initiated in response to the following trends in the Dutch pork industry: production can no longer compete on price in the international market, demand is high in market segments with distinctive product features (like Vion's Robusto concept), and the pig supply chain gained the ability to evolve due to digitization and increased transparency. Vion responded to these trends by aligning its business towards being demand-driven (Vion Food Group, 2022). There are two types of information flow systems in a supply chain, namely push and pull. A push system is defined as one in which the control information flow is in the same direction as the material flow, a push system is the opposite (Bonney et al., 1999). This flow of information and material in the same direction can be distinguished in the pig chain. To illustrate, Vion Farming (the supply department of Vion) forecasts incoming supply, this forecast is shared with the logistics, production, and sales departments of Vion. All these departments create their plans based on the supply forecasts. While in a pull system, Vion observes the market and sends information upstream through the chain to the farmers. Currently in the push system no actors further on in the pig chain are aware of what the market desires as this is not communicated. The only form of communication to the farmers is a payment table which entails what carcass quality specifications receive a bonus or a penalty. However, this table is criticized within the organization for being too wide and incapable of controlling the supply. With 'too wide' it is meant that the majority of supply is not corrected with a penalty or bonus. Vion Farming was in need of a proof of concept that concerns the question: 'How can Vion Farming respond to the customer demand by controlling its supply chain?'

Pig chain characteristics: The segmented market

Vion wants to serve the national and international market. To meet the needs of these markets, the supply chain was split into concepts. This thesis regards the concept 'Good Farming Balance' with its orientation on the international market. This market has varying demands for products at different times in the year. The pig chain is a 'one-to-many production system' where one carcass can be cut into many different products, while choosing for one product means excluding others. Therefore, Vion decided to split the market into segments and apply different slaughter and cutting patterns to respond to the differentiated demand. After slaughter the carcasses are measured on carcass quality and assigned a class. These classes have a set of cutting patterns which are linked to the specific requirements of each market segment. However, to be demand driven, the demand from market segments has to be converted to quality characteristics and linked to farming techniques within pig production.

Pig chain characteristics: Quality control points

To explore the characteristics of the pig supply chain, a theory driven approach was taken to establish the farming techniques affecting carcass quality. Then a data analysis was executed to set the foundation for modelling. Due to the characteristics of the pig supply chain, steering on the number of pigs is not viable, as farmers cannot scale up and down without existential consequences. However, steering on carcass quality offers a potential solution. Six quality control points were identified regarding carcass quality based on literature research in this thesis. They are as follows: gender, genetics, feed schedule, feed composition (energy), feed composition (amino acid), and delivery strategy.

Pig chain characteristics: Farmer's finances

In the pork supply chain, Vion is the link that connects supply and demand. Vion buys the pigs from farmers according to a weekly meat price and the previously mentioned payment table that incentivizes on carcass quality. However, as stated, this table is criticized because it had no incentives or penalties

for the majority of pigs. The consequences of this wide setup became evident when the effects of piglet prices on slaughter weight were analyzed. The concept was grounded on the notion that when piglet prices rise, farmers will keep their current batch of pigs longer while speculating a piglet price decrease. This relation was found significant when including the omitted variable of the pig price in an OLS analysis. Consequently, the carcass quality of Vion's supply is determined by the market price of piglets rather than the final customer demand. Moreover, it indicates the sensitivity of farmers towards financial incentives as that determines their farming's strategy. This leads to the conclusion that a different setup of the payment table is required and that finances have an effect on the decisions of a farmer.

Pig chain characteristics: Heterogeneity

Before modelling, several forms of heterogeneity have to be considered. First when a farmer delivers its pigs to Vion, the pigs do not have the same quality but rather are subject to a distribution over quality. Secondly, the delivery of one farmer can differ from another farmer. This form of heterogeneity is very important to Vion as all these different farmer's deliveries aggregated enables Vion to serve a wide range of customers. Thirdly, farmers have different behaviors as they have different business circumstances and entrepreneurial mindsets.

As earlier stated, the distribution over carcass classes based on carcass quality can be calculated for incoming supply and these classes are linked to production lines producing certain products. The value and demand for these products can be calculated back to the carcass class. With data analysis it was concluded that the carcass classes were a suitable metric due to the acceptable deviation over the years and a meaningful way to express the heterogeneity among the deliveries from a farmer. The research reoriented itself to find a model that would minimize the difference between the current supply distribution and the demand distribution over the carcass classes.

Modelling

Literature regarding modelling quality-controlled logistics and matching supply and demand was consulted. Since there was no model focusing on heterogeneity, pork quality and the market from a demand-driven perspective in the role of a farmers' cooperation, a gap was found. The literature did include a model steering with a distribution over carcass classes based on carcass quality, it did not include farming techniques (Rijpkema et al, 2010). The model that approaches this study the most is Niemi (2006) who optimized feeding and slaughter decisions with respect to fattening pigs. However, Niemi (2006) only focused on the profit of the fattening farm by proposing to explore the bounds of the payment table rather than focusing on supply chain profit and using these bounds as control mechanisms. Therefore, the major contribution of this thesis is making these decisions from the perspective of the farmers' cooperative with the aim to increase performance throughout the whole supply chain. A model setting incentives and penalties for pig farmers was previously researched however it was focused on controlling Mycobacterium avium infections (van Wagenberg et al. 2013). Thus, this thesis makes a valuable contribution to the Quality Controlled Logistics (QCL) literature and farming models.

The proof of concept was presented in three stages. The first stage will formulate a distribution over the carcass classes as a result of different farming techniques. Data of a feed experiment (n=332) was used including three different finishing feeds varying over levels of lysine, while controlling for gender, genetics, and the other feed phases. The experiment also executed a top-empty delivery strategy, however as delivery strategy is a quality control point on its own, it was decided to isolate the effects of the quality control point lysine. This correction was done by estimating the backfat thickness and slaughter weight of all the pigs for the same fattening period (165 days). The outcome was the isolated effect of these three feed policies on the carcass class distribution. This stage and the experiment proved that farming techniques have an effect on the quality distribution over the carcass classes even in the last 5 weeks before slaughter.

The second stage of modelling assessed the ability to meet demand if Vion would centrally control the farming's decisions. A least square model minimizes the distance between the supply and demand distribution over the carcass classes. This was controlled by assigning a probability per feed policy, hypothesizing that if the feed policies are used in this ratio over all the farmers, then supply and demand will be matched optimally.

The third stage of modelling decentralizes the control from Vion to the farmers by introducing incentives. The model was formulated as a non-linear programming model with utility based multinomial logit component (MNL). The MNL model is also used in assortment planning and can be applied to assign consumer choice probabilities according to utility functions. An objective function was formulated which minimized the total incentive paid per pig by Vion. The farmers are given a utility function consisting of a deterministic and random part. The deterministic part includes the earnings and costs associated with choosing farming policies, which in this proof of concept are the feed policies. Incentives per kg per carcass class are introduced as decision variables in this utility function. These decision variables can control the preferences for a farming policy, as farming policy has an effect on the slaughter weight and the distribution over the carcass classes. The random part of the utility function is unobserved and assumed to be Gumbel distributed. Several assumptions had to be made for the model to run. First, the use of a MNL model requires the independence of irrelevant alternatives assumption. However, the first stage of modelling preserves this already by only including effective farming policies. The other assumptions are: 1. all farmers can only operate the policies from stage 1 and the only outcomes available are linked to the chosen feed policy; 2. all farmers will have the same earnings and costs therefore their deterministic utilities are the same per farmer; and 3. all farmers behave the same by trying to maximize their utilities.

The model was tested with several demand scenarios which resulted in the conclusion that the upper and lower bounds on the incentive decision variables were necessary since they determine the objective value and prevent extreme incentives. Moreover, the number of decision variables can be restricted for more stability, the carcass classes selected for this need to stimulate the farmer to apply the desired farming policy. Before this proof of concept can be implemented, the other quality control points need to be added to capture the set of actions a farmer can take. Results of excluding a farming policy showed that it gives a misperception of reality and misleading outcomes.
Furthermore, this research has to be extended with more information on farmers behaviour and their utilities. So far, earnings and costs were generalized to a deterministic utility while the model captures some random utility for a farmer choosing a policy. Having insight in the farmers utility will create more understanding of the mechanisms steering supply and demand.

Finally, a limitation of this research that should be considered is the further implementation of the incentives and penalties. This thesis showed that theoretically, supply and demand can be matched with incentives on all or some carcass classes. If the policies would be extended, as recommended, and farmers behaviour would be explored, then research should map the expected effects of these new incentives. The model requires accurate data input to have the best performance. Simultaneously, this makes the model an adaptable tool for a robust supply chain as it adjusts itself to new circumstances.
Concluding, this thesis provided a proof of concept of matching supply and demand for Vion Farming. It presented the first tool to produce demand driven within pig production from a farmer’s cooperative perspective.

Preface

This graduation thesis is dedicated to Vion Farming, the supply organization of multiple Dutch slaughter plants, a subsidiary of the Vion Food Group network. The Vion Food Group's core business is to provide safe and high-quality meat products to people around the world in a sustainable manner. This document contains the thesis for the graduation program of the master Operations Management and Logistics for the consumer goods track at Eindhoven University of Technology.
The research is part of the PORQSAT project with Wageningen Lifestock Research, Eindhoven University of Technology and HAS Den Bosch. Further, this research was performed by Janine Diepenhorst, graduation student, and was guided by dr. K.H. (Karel) van Donselaar (TUe), dr. R.A.C.M (Rob) Broekmeulen (TUe), ir. J.B. (Bennie) van der Fels (WUR), and company supervisor, ir. Bart Peijnenburg (Vion).

This document provides the thesis for the graduation assignment at Vion Food Group's Headquarters in Boxtel, the Netherlands.

Terminology

Backfat thickness:	The mm of fat on a pig's carcass which is measured on the back right after slaughter.
Barrow:	A male pig who is castrated
Boars:	A male pig who is not castrated
Customer:	Entity buying
Consumer:	Every end-user in the chain of buying or using services of products
Gilt:	Female pig who has not given birth in her lifetime
GFB:	Good Farming Balance, a concept within Vion focused on the international market
GFS:	Good Farming Star, a concept within Vion focusing on the Dutch national market. Characterized by the 'Beter leven' label.
KPI:	Key Performance Indicator
LP:	Linear Programming model
MILP:	Mixed Integer Linear Programming model
Pigpen:	A pen (Dutch: hok) for pigs on the farm
Pig chains:	Pig supply chains
SIS:	Slaughter Information System, the database containing all measurements from slaughter.
Sow:	A female pig who has given birth
UBN:	Unique Business Number, required by Dutch regulations for all locations keeping animals in order to respond to deceases. This will be used to refer to an unique farmer throughout the report.
VAT:	Value Added Tax (in Dutch: BTW)
Vion:	Vion Food Group Network, the organization as a whole
Vion Farming	The supply department of Vion in the Netherlands

Table of Contents

1. Introduction

1.1. Research orientation

Future of pig production

The global pork industry produces 109,887 million metric tons of pork meat in 2021 (United States Department of Agriculture, 2022). Globally number one in production and fastest growing in volume is China, followed by the EU. Over the last years, worldwide production volumes were quite stable (Shahbandeh, 2021). Despite of western trends exploring meat replacements, other markets were emerging. In addition, as the world population maintains its growth, there is an ever-increasing demand in meat (The world counts, 2022). In the Netherlands, the pig farmers are bound to relatively high safety, quality, and sustainability regulations. Because of these regulations, the production costs are higher which makes competing on price on the international market almost impossible. Nonetheless, 60 percent of Dutch sales is for the international market (Rabobank, 2022). In addition, pork is staged in a price competitive market as it is often seen as a commodity product by consumers. The director of food and agriculture at a Dutch bank, Ruud Huirne, proposed a solution: "This means offering products that are so superior that consumers will come to develop a preference for Dutch pork and are willing to pay a higher price" (Rabobank, 2022). Therefore, these pork chains will have to focus more on the desires of the consumers.

An internal exploratory study at Vion analyzed the possibilities of a demand-driven supply chain design in the pork processing industry, summing up the following market trends:

- Concepts including sustainability, real food, and craftsmanship will become more important in the pork processing industry (ING, 2012);
- Added value thinking will become much more important in the future where the price fighting model that is commonly found in food industries will change towards a cooperation model (BioNext, 2018);
- Demand-driven production is becoming more important due to a high demand in segments with distinctive product features. Moreover, the supply chain is gaining the ability to evolve due to emergence of new collaborations in the chain and the role of digitization and transparency (Berntsen (ABN-AMRO), 2022) (Beuchel & Veldman (Rabobank), 2021).

Due to common successes of Toyota, Dell, and WallMart with demand driven production, an industrial engineering trend was started. However, this strategy cannot be replicated in every industry. For instance, industries like oil, gas, or electricity benefit from a supply driven strategy due to their market characteristics (Melnyk, Davis, Spekman, & Sandor, 2010). Similarly, the pork industry is supply driven because of their supply characteristics. A hybrid solution has to be found concluded the internal exploratory study at Vion. Reaping the benefits from being demand-driven with less waste and more profitability while controlling operations of one-to-many production.

All in all, there can be concluded that exploiting segmented demand can create value (Grunert, Bredahl, & Brunsø, 2004) and a demand driven approach can provide the necessary strategic advantage for the Dutch pork production and its supply chain.

1.2. Company case

Vion the cooperative

The company case will be enrolled for Vion Food Group, from here on referred to as Vion. Vion is an international producer of meat, meat products, and plant-based alternatives with production locations in the Netherlands, Germany and Belgium (Vion Food Group, 2022). Its core business is to provide safe and high-quality meat products to people around the world in a sustainable manner. The strategy of Vion is set on Building Balanced Chains to give farmers a future and customers a difference. Vion is a cooperative with one shareholder, the ZLTO which is an organization for farmers in Zeeland, Noord-Brabant and Zuid-Gelderland who serves the interest of 13,000 affiliated entrepreneurs in the agricultural sector. Such cooperatives occur more often in the agricultural sector where together they own a cooperative factory in order to process their raw materials into end products (Bijman et al., 2012). However, the cooperative Vion does not fit the definition exactly as it is not user owned or user controlled (Bijman et al., 2012). Furthermore, farmers have agreements with the cooperative stating that Vion will buy the animals delivered by the farmers. As long as farmers and Vion have this agreement, farmers cannot offer their animals to the highest bidder but have to deliver them to Vion. The business units of Vion consists of Pork, Beef, Food Service and Retail (Vion Food Group, 2022). The company case will be executed for the Pork business unit responsible for slaughtering and processing roughly 300,000 pigs per week of which 145,000 in the Netherlands.

Vion Farming and concepts

The department facilitating the research is Vion Farming which is responsible for optimally matching the supply of pigs to market demand (Vion Food Group, 2022). As well as controlling and organizing the supply to the production locations of Vion. In close cooperation with the pig farmers, Vion Farming strives to ensure optimal operational management, resulting in safe, and high-quality pork. Vion has developed concepts to allocate different products: organic meat called ‘De Groene Weg’; pork with a higher quality of life for the Dutch retail market called ‘Good Farming Star’ (GFS); and the ’regular’ pork for worldwide sales following international standards called ‘Good Farming Balance’ (GFB). The GFB concept entails pork of high-quality meat tailored to international markets and will be relevant for this research. Together with the pig farmers, Vion aims to produce exactly the products demanded by customers in the desired specifications, requiring targeted co-ordination (Vion Food Group, 2022). However, before this aim can be achieved processes and systems have to be in place to facilitate this. GFB consists out of three supply modules to ensure sufficient diversity of the pigs supplied: Basic, Wide (a wide supply process based on slaughter weight) and Robust (more mature pigs with a higher backfat thickness). All Vion’s concepts and modules have specific payment tables with bonusses and penalties intended to ensure the demand-driven production of pigs. Nonetheless, currently the payment tables are criticized as will be discussed further on.

Vion’s porkchain

The pork chain in a simplified form can be described as follows: breeding farms deliver piglets to farmers, farmers deliver pigs to Vion, who buys the pigs, processes them, and sells them to a wide customer base. Varying farming techniques in production and breeding systems cause variation in quality features such as carcass weight, backfat thickness, and lean meat percentage (Perez, de Castro, & i Furnols, 2009). Simultaneously market segments vary with respect to preferred quality features (Grunert et al., 2004). All supply chain actors have different impacts on the intrinsic meat quality, meanwhile they do not value the same product and production attributes as Trienekens and Wognum (2013) laid out. The farmers are their own entrepreneur, and they make their decisions, but it is the role of Vion to anticipate their choices in order for Vion to reach their goal of matching supply and demand.

1.3. Problem description

Vion's push strategy

Vion has been operating in a complete push strategy. A push system is defined as one in which the control information flow is in the same direction as the material flow (Bonney, Zhang, Head, Tien, & Barson, 1999). This flow of information and material can clearly be seen in the pork chain: no actors upstream are aware of what the market desires as this is not communicated. The only form of communication to the farmers is the payment table. However, the range in this table has been purposefully kept broad such that many different markets could be served. Moreover, within Vion itself the information flow follows the material flow: Production and Sales forecast what the supply will be and create a planning accordingly. There is no sales forecast based on what markets and consumers want. Instead, there is a sales plan trying to sell the predicted supply. Once the pigs arrive at Vion, the system is driven by an automatic classifications system for pork (AutoFOM III) and algorithms determining which product goes to which market based on the supply.

Transitioning to pull

In chapter 1.1 the future of pig production laid out the need for a demand driven strategy. Vion has realized this and adjusted their aim for the organization as a whole and for Vion Farming, as mentioned in chapter 1.2. Being demand driven is best served with a pull strategy (Miclo, Lauras, Fontanili, Lamothe, & Melnyk, 2019). A pull strategy is the opposite of a push strategy and responds to customer requests (Bonney et. al., 1999). The earlier mentioned internal exploratory study at Vion addressed the need for a hybrid solution between 'push' and 'pull' for pork chains. The 'pull' strategy leads to less waste and more profitable supply chains. However, slaughtering one pig leads to over 1200 possible SKU's (Stock Keeping Units) which can be realized for different international markets. In addition, the supply chain complexity of pork is quite high mainly caused by the product (pig) characteristics which are subject to changes through seasons or other natural occurrences (Ivert, Dukovska-Popovska, Fredriksson, Dreyer, & Kaipia, 2015). Thus, it would be an incredibly complex assignment for the Sales and Operations Planning (S&OP) department to deal with a complete pull supply chain. Namely, if one piece of meat, say the ham, is customized towards one market, then the rest of the pig must be pushed towards other markets.
Concluding the current system of operations is push oriented and a change is required. This research explores the possibility of transitioning to a (more) pull strategy by integrating the supply chain partners to align towards a strategy focused on the customer demand in order to add value with the support of modelling.

1.4. Compressed design problem

The problem at hand is a so-called design problem that can be approached with design science (Wieringa, 2014). Within design science there is referred to an artifact, which is an object to be designed like a tool or solution which interacts with the problem context. Design science is the design and investigation of artifacts in context. Accordingly, a design problem improves the problem context by the (re)design of an artifact such that artifact requirements are met in order to meet stakeholder goals.

Problem context:	Transition to a hybrid supply chain (becoming more pull)
Artifact:	by designing a mathematical model
Artifact requirements:	such that supply can be matched with demand
Stakeholder goals:	in order for Vion to increase its profitability and reduce waste in the chain

1.5. Research questions

The design problem will be approached from Vion Farming's context. Therefore, the main research question is formulated as follows: "*How can Vion Farming respond to the customer demand by controlling its supply chain?'* To answer this question a deeper understanding of the underlying processes is required, as well as thorough knowledge on modelling supply and demand. Below sub-questions are defined to achieve this. In appendix A these questions are further divided in another level of sub-questions such that the research methodology can be understood. Answering these questions should fulfill the objective to design a model matching supply and demand and facilitate the transition to a hybrid supply chain.

1) What defines the market for GFB?
2) What has to be influenced in the supply process to control quality?
3) What will be the available input of the model?
4) What model connects the available input and desired output?
5) What is the performance of the model?
6) What extensions are recommended for future research?

1.6. Research scope

A scope was defined to guide the research process. The scope of this research is to control the quality in the supply chain from the supply side, Vion Farming, by the design of a mathematical model, matching supply and demand. Due to the multiple product concepts, varying customer base and large quantity of SKU's, several limitations to the research have to be defined in order to provide an efficient and effective solution.

Carcass quality

First the 'quality' central in this thesis is carcass quality. Within the pork chain there are several quality levels: carcass quality, slaughter quality, and meat quality. Carcass quality entails backfat thickness, muscle thickness, and slaughter weight. The other forms of quality dive much deeper into the chemistry and biology of a pig. Moreover, focusing on carcass quality suits the thesis the most because farmers are paid, and Production assigns carcass classes, accordingly. Essential to establish for the scope is that this research will not take a deep dive in the biological field of quality manipulation within pig farming. Nonetheless literature will be explored to find the right variables and parameters to control carcass quality with the guidance of farming experts.

Literature

Moreover, literature sources were gathered which focus on modelling supply and demand in pork supply chains or comparable supply chains. The focus on the industry and comparable ones should not be neglected as these industries have increased complexity due to quality and safety aspects which should be leading in the design. All in all, several models were reviewed, and relevant aspects were reported.

Time horizon

The scope of this research will be to control the quality for the supply side from the beginning of the pig cycle till two weeks before delivery. This time period is expected to have the most value adding possibilities as the farming choices made at that time will have a high impact on carcass quality. Moreover, two weeks before arrival at the slaughterhouse the planning is made so it would be desirable to not change much after. Further on, this means that the scope is focused on the fattening farm echelon in the supply chain. It can be assumed that farmers will continuously produce pigs even if prices are not desirable because of the high costs and investments of the farmer. Simultaneously, if a farmer decides not to produce and thus not to buy any piglets, it will damage the relationship with the breeding stage prior to the fattening stage since it cannot just pause their processes. As stated, before farmers will deliver only to Vion and will most likely utilize all the pigpens (places for pigs in a fattening farm) they got in order to maximize revenue. Vion will slaughter all the pigs delivered and pays the farmers according to the weekly adjusted pig price and the long-term payment model.

Proof of concept

The proposed change by this research is of high impact for the organization and its supply chain. The mindset of operating push has to be transformed to pull and systems have to be designed to facilitate being demand driven. Therefore, this thesis will provide a 'proof of concept' determining if and how Vion can become demand driven.
Moreover, many things influence carcass quality during farming. Therefore, a selection will be made of influences that can be controlled, referred to as quality control points, from the ones that cannot be controlled. To quantify results of a quality control point, the effect has to be isolated and controlled for in an experiment. One high impact quality control point will be tested in the model, encouraging future extensions. Finally, recommendations will be given to extent the model further such that systems are integrated, and a process of change can be evoked.

Out of scope

The health of a piglet and pig both influence carcass quality if their health is not sufficient. However, every farmer should maintain good health. From a modelling perception it is more an assumption than a variable so it will be kept out of scope.
The full implementation in the organization and further extensions will be out of scope of the thesis. This research places itself on a strategical/tactical level and has to be further enrolled. It defines itself as a proof of concept and it requires future research which will be facilitated within the PORQSAT (Pork Quality and Safety Assessment Tools) project. This thesis is part of the PORQSAT project which is a collaboration between Wageningen University and Research (WUR), the TUE, and Vion. The project is oriented at improving the pork industry in four phases such that it is more resilient for the future.

1.7. Reading guide

This thesis is structured as follows. First the research methodology is presented, defining the research model and justifying methodology choices. In chapter 3, an extensive analysis is shared regarding the demand and supply processes of Vion. In chapter 4, the literature will be discussed regarding the central thesis of this research, namely the matching of the supply and demand in the pork chain with regards to carcass quality. In addition, some modelling techniques will be introduced which will facilitate reaching the research goal. In chapter 5, a data analysis is laid out, focusing on the supply data and its characteristics. The outcome of this analysis supports the modelling decisions when designing the conceptual model in chapter 6. The conceptual model entails the overall structure of the model, the modelling decisions, and the assumptions. Chapter 7 will present the mathematical model which will be a generic solution. In turn, chapter 8 will specify the implementation of the model for Vion Farming. In addition, in chapter 9 the model functionality and performance are tested in the numerical experiments. Both the characteristics and sensitivity are demonstrated in order to understand the mechanisms attributed to the model. Finally, a discussion and conclusion will end this thesis. Then suggestions will be made regarding future research to improve on the shortcomings. Moreover, some managerial insights will be shared to contribute to societal relevance.

2. Research methodology

2.1. Research model & methods

As was briefly introduced in the design problem, chapter 1.4, the methodology of design science was used for this thesis. The design science cycle is a research model focused on a certain artifact (van Aken 2004; Hevner et al. 2004; Wieringa 2014). The artifact is a tool or solution that is required to solve the problem. The design cycle progresses through the following stages: problem understanding, artifact design, artifact validation, and artifact implementation. The advantage of this model is the goal-oriented research towards an artifact. The disadvantage is limiting itself to a certain problem, even more than the DMAIC (Define, Measure, Analyze, Improve, Control) model. The design science cycle is best suited when the most valuable part of the research is the artifact.

Problem understanding

Within this first phase of research, the problem context has to be thoroughly understood. The objective of this phase is to define and analyze the supply and market of GFB. The model is destined to be enrolled for the GFB chain which supplies globally. The market characteristics will be highlighted established by informal company interviews and historical data analysis, answering research question 1. Continuing, the supply will be analyzed via a theory-driven and data-driven approach. Resulting in answering research question 2. The last part of this research phase will explore the current supply and demand performance in order to link the effect of current practices, derived from an analysis of historical data.

Artifact design

In the second phase of this research, the artifact will be designed. Research question 3 regarding the input of the model and research question 2 focusing on the design of the model itself, will be answered. A literature study will support this phase by reviewing similar reported artifacts along with disclosing a research gap. Data analysis will reflect on the properties of supply variables. The literature research and data analysis will specify requirements for the model by evaluating what contributes towards the goal and what is feasible. Moreover, the outcome of this phase will contribute towards filling the research gap.

Artifact validation

The next phase, artifact validation, will validate the model with one quality control point. First experiment data will be used to set up the model. Then several scenarios will be executed to confirm the functionality of the model. Finally, the parameters and variables are tested on sensitivity to create an understanding of the mechanisms.

Artifact implementation

The final phase of the design science cycle is focused on the future of the model. As this thesis is a proof of concept, stating how supply and demand can be matched in terms of carcass quality within the pork chain, there is not much to implement rather to recommend for extension. Finally, the research goal will be reflected upon, to increase profit and reduce waste by demand driven control on quality of pork by steering the supply side of the chain.

2.2. Research sources & reliability

Data provided for this research was through secondary sources. Two main datasets are the core of this research, historical slaughter data and experiment feed policy data. The methods to analyze these data will be descriptive and inferential statistical techniques.

Slaughter data

Every pig is measured a couple of times throughout the slaughter process, all these measurements are collected in one database, SIS (Slaughter Information System). In this database every pig has an ID coupled to an UBN (Unique Business Number, for farmers). This research has access to all slaughter information of every pig slaughtered since the year 2015, thus this dataset contains longitudinal data. This dataset is perfect to understand the supply process. Most of the measurements are done via Autofom III which is praised for its accuracy. However, there are several measurement errors to be taken into account which will be discussed and dealt with in chapter 5 data analysis. Overall, the SIS data is seen as reliable, the whole of Vion's operations run on this so using the data will come close to simulating the operations of Vion. Also, farmers are paid accordingly, and carcasses are sorted to production lines based on these measurements.

Experiment feed policy data

As stated before, one quality control point could be quantified in this research. A research facility executed a controlled experiment with three feed policies and two genders with approximately 55 measurements per gender x feed policy combination. The experiment had the goal to create 'Robusto' worthy pigs, meaning pigs with high quality meat and backfat thickness above 14 mm and an increased feed profit, which is the earnings per pig after deduction of costs for the piglet, feed and other costs. To achieve this a feed company developed two feed strategies. The newly developed strategies were compared to a control feed.
This experiment can be classified as cross-sectional data as it was all gathered in the same trimester. The data needed limited cleaning and can be seen as reliable since it was executed in a controlled environment by an experienced research institute that reported on all the methodology, the implications and findings. All this information is in possession of Vion and is seen as highly confidential.

2.3. Modelling software

The software required to model does not need to exceed the goal of a proof of concept. The results have to be presented in a model that can be widely understood and be extended. Therefore, two tools were used, an excel sheet using excel solver and a python script using the Gekko package (Beal, Hill, Martin, & Hedengren, 2018).
Excel is a tool used by Vion Farming, S&OP of Vion and Vion Sales. The excel solver is a tool which can easily be accessed within excel. The solver will be used with the GRG nonlinear setting with multi start. The tool is sensitive to local optimum and the multi start is a small remedy for this. It achieves the goal of a proof of concept indicating how to match supply and demand. However, when using many variables and complex formulas the results can be far from the optimum and should not be interpreted as reality. Therefore, the excel solver will only be used in stage 2 of modelling which entails a simple formula and a small number of variables.
The python script with the Gekko optimization package (version 1.0.5) does allow complex non-linear problems to be solved optimally. For stage 3 of modelling, this tool was used with the setting of not accepting local optimum in order to find the optimum regardless of the complex formulas and high number of variables.

3. Process analysis

This chapter reports on the demand and supply processes. First the general pork chain is briefly reviewed. Then the characteristics of the demand behind the GFB will be determined such that a suitable model can be chosen. Further on, literature is consulted to find quality control points that govern carcass quality within the scope of this research. The chapter will conclude with an evaluation of the current match of supply and demand.

3.1. General pork chain

The general pork supply chain starts with the breeding of piglets. These piglets are then fattened in the pig fattening process. Once grown to the desired weight and specifications, the pigs are transported to the slaughterhouse where they are processed. The cut pieces of pork are further distributed to other processers or packaging companies. Then these products are transported to retail. Finally, the consumer buys the pork which concludes the farm-to-fork chain, see figure 1. Throughout the supply chain every link makes decisions effecting the quantity and quality (Trienekens and Wognum, 2013). To have a deeper understanding of the pig industry, in appendix B sales data of GFS is used to illustrate what sales figures look like in a one-to-many production setting.

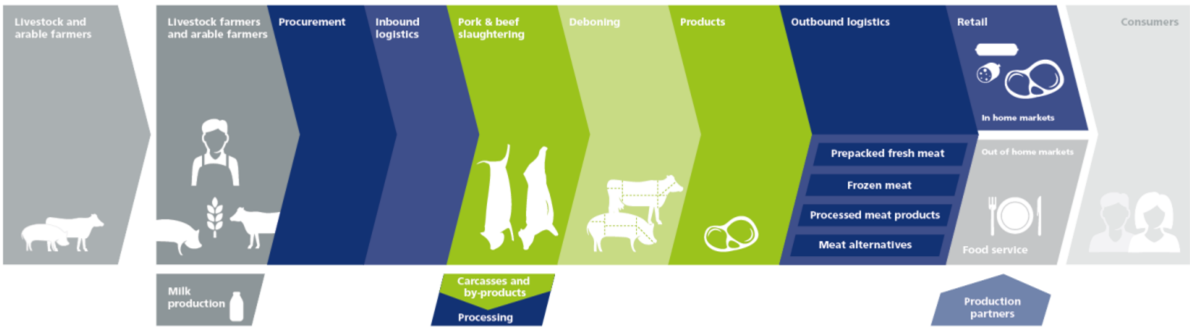


Figure 1. General pork chain (Vion)

3.2. Demand process

Vion produces for the national and international pork market. To meet demand more effectively the concept of GFS was set up, requiring more care for animals and focusing on the Dutch retail market. The pigs for the international market were labelled GFB. The GFS concept is a success considering the following reasons. Farmers are lining up to join the concept due to better payments. The slaughterhouse can operate more effectively by steering on a certain type of pig with a select group of farmers resulting in a uniform supply. The consumer receives transparency since it is known which farmer is part of GFS and which regulations they follow. Hence, the success of focusing on a concept like GFS has made Vion consider setting up more concepts like the Robusto concept designed for Italian and Spanish hams which require pigs with a high backfat thickness (> 14 mm). Within Vion's demand driven strategy, Vion is planning to explore segmented markets and link these with supply concepts like GFS and Robusto. Thus, the model of matching supply and demand should be created for a generic concept such that it can easily be enrolled for all the other concepts.

3.2.1. Good Farming Balance

GFB supplies different markets over the world with significantly different demands, e.g., high demand for fat hams in Italy, in the USA for high quality ribs and in China for pork heads. These different markets create many supply opportunities for Vion. Especially as prices, currencies, and demands fluctuate over the globe. Furthermore, a product-market model that observes the demand trends and calculates which markets are attractive to supply is in development, see next section 3.2.3.

However, the demand is nearly impossible to estimate with the available data. Because historical sales figures from Vion are computed of what was slaughtered subtracting what remained in stock, hence it gives no representation of the demand. The GFB concept has always been supply driven. Sales mostly sells based on contracts with customers for a duration of a half year to a year. In 2020 the contract versus non-contract sales depends on the part of the pig, for the middle of the pig the ratio is 90% contract, the front 50%, and the hams 25%. However, these contracts are created based on which carcasses are expected to be supplied, not what the markets demand. Moreover, there are some promotions, and these are announced a couple of weeks upfront, even then, the size of the promotion is uncertain. As demands and margins of markets change, it can be profitable to control the supply and transition to being demand driven. Therefore, supply has to become flexible. The current supply distribution over carcass quality for GFB is very wide such that it can serve many market segments, see figure 2.

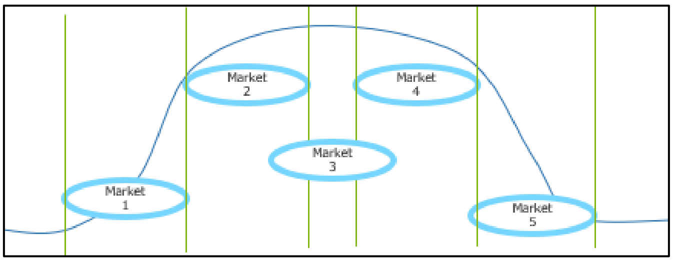
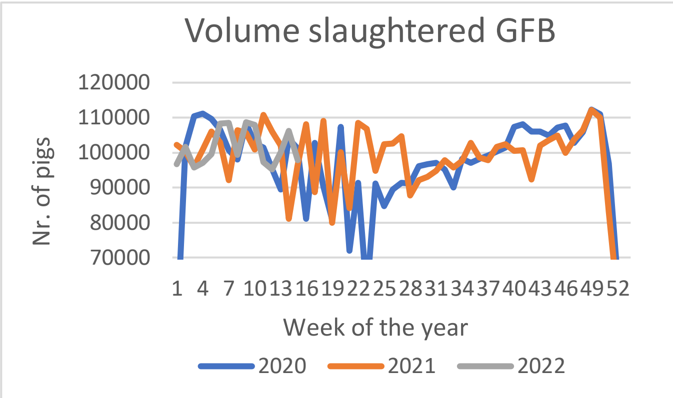


Figure 2. GFB illustrated wide supply (own elaboration)

The slaughter data of GFB show not much seasonality or trend. Moreover, it can be seen that the production facility is running at full capacity in the majority of the time except the summer period. In addition, the data is influenced by COVID-19 when the slaughterhouse was struggling with capacity issues due to high absenteeism, see week 21 and 23 of 2020. The first and last week of the year give a false indication due to the cutoff of the week.



Graph 1. Nr of pig's slaughter GFB 2020-2022 (own elaboration)

3.2.2. Product-market model

The previous section has laid emphasis on the wide supply within the GFB concept to serve many markets. To match markets with the desired product, a product-market model is developed. To understand the power of this model, observe the following figure 3 of the production process.

First the pigs arrive from all farmers indicated by their UBN's, thereafter they are slaughtered. From that point pigs are referred as carcasses. Then the AutoFOM III system sorts all the carcasses based on specifications as backfat thickness, muscle thickness, and slaughter weight. They are assigned a carcass

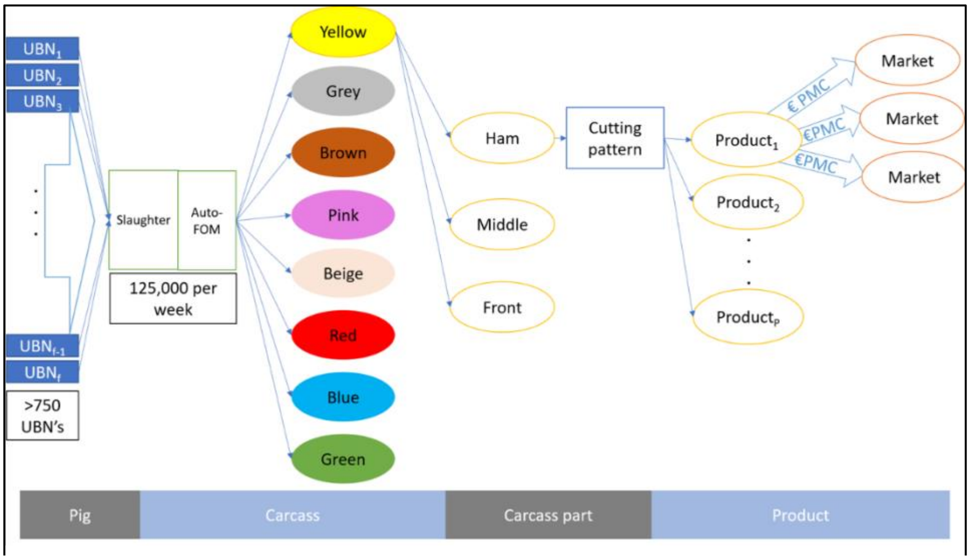


Figure 3. Schematic overview of the supply-demand process within production (own elaboration)

class indicated by a color such that the production department knows what kind of carcass it is. Then the carcasses are cut and sorted by ham, middle or front. Further on, a specific cutting pattern is applied to produce a product. For example, from the same kind of pig e.g., yellow, and the same part, e.g., ham, multiple products can be made based on the cutting pattern. This product is then sold to a customer, all these customers are sorted by country which is called a market.

PMC model

In the product-market combination model (PMC-model) an overview is presented which products earn what in which market. This model is currently only used by the S&OP department and only exists since June 2022. It facilitates S&OP in determining the carcass classes, the flow to the production lines and the sales concepts. More specifically this model can be input for an optimization model for the slaughterhouse determining which cutting pattern is the most profitable. Moreover, an optimization for the farming side could be which pig is the most desired. In the latter, the PMC-model needs to combine the parts of the pig (middle, front, ham, others) and calculate the earnings potential per carcass color. The relevance of this way of operating can best be demonstrated in the following figure 4. This figure shows the earning potential for the same part of the pig for different carcass classes and the fluctuation over time.

Figure 4. Valorisation effect Vion (internal Vion)

In figure 4 the y-axis is not completely specified due to data confidentiality. Nonetheless, it can be stated that selling the desired carcass to a customer can increase the earnings per pig fivefold. Therefore, much potential is seen in a model that communicates the desired pigs to farmers. In order for the results of this research to be of the most use, the demand driven model will be linked with the results of the PMC-model.

In conclusion, for GFB the PMC-model is developed which combines products and markets. This enables optimization models to improve supply chain earnings. In addition, the PMC-model can be the bridge between the market and farming by communicating the earnings potential per carcass class.

3.3. Supply process

Throughout the supply chain every link makes decisions effecting the quantity and quality. According to Trienekens and Wognum (2013) the impact of various chain links on intrinsic meat quality can be listed as follows: breeding determines genotype and carcass composition; feed companies determine diet, vitamins, and minerals; pig farming determines the production-system; and slaughterhouses determine fasting, pre-slaughter handling, stunning and chilling. Besides the effects of these decisions, in every chain link there are external factors influencing the outcome, like: weather, raw material prices (Niemi, 2006; Trienekens & Wognum, 2013; Pourmoayed, Nielsen, & Kristensen, 2016), and health implications (Adzitey, 2011; Ferguson et al., 2006).

In appendix C a small summary is given of qualitative research into farmers strategies and their impact on carcass quality. This research concluded that many strategies of cleaning and medical routines led to good results, there was not one clear way successful, but it was a continuous experiment of farmers exploring what works for their farm.
The literature discussed in this chapter excludes the impact of health of piglets and pigs on carcass quality. Nonetheless if health is not sufficient it will dramatically impact the carcass quality. Albeit regardless of the demand, there should always be strived for good health, so it is not a quality control point rather a condition for farming demand driven. Due to its relevance for carcass quality related literature has been reviewed and presented in appendix D.
Continuing, this section will elaborate on the proven influences on the carcass quality (backfat, muscle, and slaughter weight) in the supply process as well as interference possibilities.

3.3.1. Breeding

Before a piglet is born a whole chain of genetic selection, insemination, and growth of the sow occurs. For the sake of scoping, those stages were excluded. This research focusses on the most effecting factors on carcass quality of these stages, namely, the gender, and the genetics.

Genetics
There are big differences between genotypes in terms of carcass quality such that it is worthwhile to characterize (Gispert et al., 2007; Le Roy, Naveau, Elsen, & Sellier, 1990). When selecting for a certain genotype, carcass quality is the deciding factor. That is either directly (fat, muscle) or indirectly (growth rate, uniformity, robustness) (Preferent KI, 2021; Topigs Norsvin, 2021). This can be explained by the added economic value, since pigs are paid based on carcass quality (Miar et al., 2014). In a study by Khanal, Maltecca, Schwab, Gray, and Tiezzi (2019) genetic correlations were reported of meat quality and carcass composition traits with growth traits ranging from moderate to high in both directions (Khanal et al., 2019). In addition, in the same study high genetic correlations were observed for male and female. All in all, a model in carcass quality cannot exclude genetics.

Gender
Within the pig industry there are gilts (female), barrows(male/castrated), and boars (male/not castrated). In the literature there is no shortage of evidence that there are notable differences between genders in terms of carcass quality (Latorre, Medel, Fuentetaja, Lázaro, & Mateos, 2003; Latorre, Lázaro, Valencia, Medel, & Mateos, 2004; Kim, 2012; Kyriazakis & Whittemore, 2006; Trefan, Doeschl-Wilson, Rooke, Terlouw, & Bünger, 2013). First off, there can be stated that barrows are fatter than gilts (Latorre et al., 2003, 2004; Kyriazakis & Whittemore, 2006; Trefan et al., 2013). Moreover, backfat thickness of boars was lower than found in barrows and gilts (2.27 vs. 2.96 and 2.73 cm, respectively) in the study by Jaturasitha, Kamopas, Suppadit, Khiaosa-Ard, and Kreuzer (2006). Because of the castration performed on male pigs, the hormones flow is affected which results in a lean meat percentage that is lower in barrows, than in boars and gilts (Jaturasitha et al., 2006). Barrows had greater daily food intake and average daily gain which leads to a poorer feed conversion ratio than gilts (Latorre et al., 2003). Resulting in a higher backfat thickness for barrows. The fattening rate for boars is the lowest due to a higher protein growth capacity and a lower feed intake (Kyriazakis & Whittemore, 2006). Moreover, Kyriazakis and Whittemore (2006) state in their book that due to the more efficient growth of protein in boars, if for 1 kg lean meat the cost would be 100 for boars, then equivalently for gilts and barrows, the cost would be 108 and 116 respectively. In appendix E a comparison is presented between barrows, boars and gilts. The data is compiled from Pigmanager and FARM systems and calculations were made according to the industry agreements. The conclusion of appendix E is that boars have a lower feed conversion than barrows, barrows have a lower growth rate than boars, barrows have more backfat thickness and more muscle than gilts and boars, barrows are heavier than boars, and boars have a higher feed price. Thus, barrows are less economical to produce but they give a higher backfat thickness and a greater slaughter weight (Kyriazakis & Whittemore, 2006). Therefore, they are profitable in the end.

3.3.2. Fattening farm

The scope of this research is specified to the time period of the fattening farm: from the moment pigs are placed in the fattening farm till they are transported to the slaughterhouse. During this time, several farming and management decisions impact the pork quality. Below the farmers strategy is laid out according to the guide for carcass quality within the fattening farm (Vermeij, 2015).

Feed schedule

A feed schedule regulates the moment of feed intake and kind of feed. There can be one or multiple phases wherein the pigs can be fed based on the maturation of a pig (Vermeij, 2015). There is restricted feeding or unlimited feeding which have quite some impacts on the carcass quality (Niemi, 2006). For instance, when the feed intake is higher than necessary to reach the maximum protein production, then the rest of the feed will be used for additional fat (Vermeij, 2015). Meal size and feeding rate were identified as two feeding behavior habits related the most to performance (Fornós et al., 2022). Moreover, literature indicates a positive correlation between meal size and feeding rate with the backfat thickness (Fornós et al., 2022). Furthermore, phase feeding can be beneficial due to the following reasoning. At the start of the growth curve, the maximum feed intake in comparison to the maximum pig protein production can be relatively low and hence little fattening occurs. Maintaining good youth growth is crucial for a successful growth curve and the eventual carcass quality. On the end of the growth curve certain types of pigs have a higher feed intake than their energy needs for the protein production. Because of this additional fattening, extra fat is created which results in an increased backfat thickness and lowered meat percentage (Vermeij, 2015). Continuing, another factor of importance is the substance of the feed, either dry or liquid feed. In practice, feeding (liquid) food of waste products is an often-used method to reduce the feeding costs (van Krimpen, Rommers, Binnendijk, & Gerrish, 2006). In a study by van Krimpen et al. (2006), they found that liquid feed had a positive effect on carcass quality, more specifically a higher backfat thickness and less slaughter weight. Another positive finding was the improved effect on meat quality through liquid feeding (van Krimpen et al., 2006). The research of Niemi (2006) reviewed the effects of feeding patterns, concluding that a flexible feeding system responding to the growth of a pig would give the highest performance. Often pigs are fed in phases to serve a growth phase of a pig (Pourmoayed et al., 2016).

Feedcomposition (energy)

The growth and leanness of the pigs will be highly dependent on the feed given (Noblet & Van Milgen, 2004; Pourmoayed et al., 2016). Main part of the feed is the energy value expressed as EW (in Dutch), or net energy. This value is used in important industry wide accepted metrices, like EW-conversion or EW-intake. Expressing feed in EW is necessary because pig feed is not a standardized composition and is created of different food 'wastes'. Feed with a high energy level increases the energy intake and the probability of increasing fat with unlimited feed especially for barrows (Vermeij, 2015). Limiting energy intake is possible by providing feed with a lower energy level. In the finishing phase of a pig, the farmer can intervene with different levels of EW to steer carcass quality.

Feedcomposition (amino acid)

The combination of EW and amino acids is very important for carcass quality (Heo et al., 2008). Levels of amino acids that are too low in feed or a shortage of one or more essential amino acids can limit the protein growth and muscle thickness in pigs (Liao, Wang, & Regmi, 2015; Vermeij, 2015). For instance: a lower meat percentage can be caused by switching early to lower levels of amino acid which results in a higher backfat thickness and a lower muscle thickness. To prevent this the amino acids should be customized towards the weight and genetics. Gilts and boars have a higher amino acid requirement than barrows (Vermeij, 2015). Lysine is the first limiting amino acid (Heo et al., 2008; Hyun et al., 2007; Liao et al., 2015; Whittemore et al., 1993). This amino acid facilitates the growth of protein in a pig. If restricted it stimulates an increase in backfat thickness (Heo et al., 2008; Hyun et al., 2007; Liao et al., 2015; Whittemore et al., 1993). Moreover, it has been found that lysine regulates the metabolites (Yin et al., 2018). Therefore, lysine is used to control the carcass quality. The other amino acids can be expressed as a ratio in relation to lysine, often referred to as the ideal amino acid balance. Because of a higher protein growth, it is advised that boars and fast-growing gilts are fed 5-10% higher amino acids than barrows (Vermeij, 2015). When meat quality is more closely examined, the amino acid balance is criticized in literature (Ferguson et al., 2006; Whittemore et al.,1993). When lysine is restricted far enough, the other amino acids take the overhand in limiting growth. Moreover, if lysine is limited too far, it could lead to mental and physical problems (Liao et al., 2015). Thus, there are bounds to which amino acids should be restricted to maintain quality. Nonetheless, it is a promising measure of dietary effects on carcass quality.

Delivery strategy

The final component of the management factors is the placement- and delivery strategy (Leen et al., 2017; Niemi, 2006; Vermeij, 2015), referring to the moment a pig is placed inside the fattening farm and the moment it is transferred out, respectively. Placement strategy is in the majority of cases, bringing the piglets in groups to a pigpen at approximately 25 kg of weight. These groups often stay together till they are in the final phases of growth. Due to hierarchy and heterogeneity in the groups some pigs grow faster than others (Gondret, Lefaucheur, Louveau, & Lebret, 2005). Nonetheless, the farmer often has defined a threshold weight at which he/she wants to market the pigs. Therefore, in most cases a farmer goes into the pigpen and selects a top group, a week later he selects a middle group and finally the rest group to be transported to the slaughterhouse. See figure 7 for an illustration of the process with five delivery stages. The distribution in the figure represents the growth of pigs in a group. Further on, meat quality, backfat thickness, ham, and shoulder weights increased significantly as slaughter weight increases (Latorre et al., 2003, 2004). A higher delivery weight lowers the meat percentage with approximately 0.1% per kilo extra slaughter weight (Vermeij, 2015). This is because for heavier pigs the backfat thickness increases faster than the muscle thickness. Nonetheless, as age increases of a finishing pig, the growth rate decreases (Latorre et al., 2003).

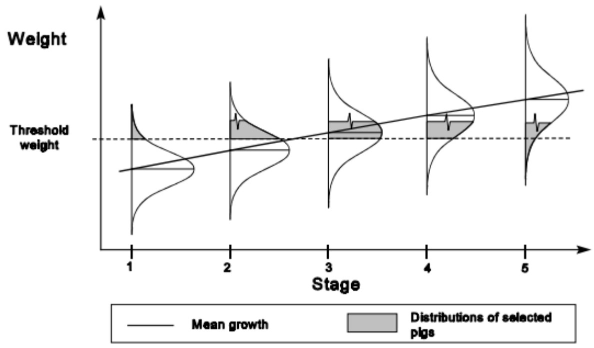


Figure 5. Different delivery stages of a pig, all pigs above the threshold are marketed (Kure,1997)

Finances of a farmer

This section will elaborate on the costs and earnings driving the business. As well as the sensitivity of the industry to price fluctuations. A sector specific journal, the KWIN (quantitative information animal farming) summarizes and elaborates the finances of Dutch farmers every half year (all excluding VAT). These finances are calculated based on standardized uniform agreements which are also published frequently.

The largest direct costs for a fattener farmer are the piglets and the feed. According to the KWIN piglet prices for 2020 were estimated at €46.00 per piglet (Blanken et al., 2021). Moreover, feed was estimated at €26.50 per 100 kg (Blanken et al., 2021). An average pig would eat 252.5 kg thus the expected feed costs are €66.90 per pig (Blanken et al., 2021). If all other finances like housing and health, are included the total costs per average pig in 2020 would be €158 (Blanken et al., 2021). The estimated slaughter earnings were €1.435 per kg slaughter weight (Blanken et al., 2021). Since slaughter weight is averaged on 99 kg, the expected earnings per pig were €142.10 (Blanken et al., 2021). Currently a discrepancy can be seen between the earnings and costs. However, it should be considered that the estimated earnings for 2020 are 2.4 times lower than the average of 2016 till 2019 (Blanken et al., 2021). Another important metric for the finances of a farmer is the turnover rate. A farm has a set number of places. To optimize earnings, farmers strive towards a high-capacity utilization. More pigs in the farm means splitting the fixed costs of housing and electricity over more pigs. Moreover, as payment is done per pig, the more pigs a farmer can deliver in a year, the more income he/she will generate. This is important to keep in mind when altering the delivery strategy because keeping a pig a week longer on the farm will lead to a lower turnover rate. The option should be carefully weighed against the benefits.

Payment system

Farmers are paid according to payment tables. These tables are steering towards a desired pig using carcass quality specifications. Central to the payment system is the pig market price which is announced weekly by Vion. For GFB the payment table is wide in its bounds of specifications. This was purposefully set up by the former management of Vion such that it can support the most markets possible. Consequently, within the widest concept GFB, there are no penalties or bonusses for pigs within the slaughter weight of 78-113 kg with 10-13 mm fat. For 2021 this included 42.3% of all pigs supplied within the concept. It is speculated that this wide setup incentivizes farmers to produce pigs that are not demand driven, but cost driven, see the next section. This would mean that certain markets are served below their potential, for instance for the valuable pork with a high backfat thickness. To elaborate, a higher backfat thickness requires extra feed and a longer stay at the farm, both increasing costs. This is slightly compensated by giving bonusses for above 14 mm of backfat thickness. However, if backfat thickness increases so does slaughter weight and the pigs cannot become too heavy since a slaughter weight above 113 kg is penalized.

Price elasticity supply

Assuming farmers behave economically rational, it can be expected the preference will be for the highest revenue and lowest cost. The lowest cost can be related to fluctuating piglet and feed prices. The highest revenue can be gained by exploiting the bounds of the payment system. If you earn the same price for a wide range of specifications and piglet prices drop, then farmers might decide to market their finishing pigs early and buy the cheaper piglet before prices go up. As a result, pigs delivered to slaughter are of a lighter weight then initially intended. Similarly, if prices rise then heavier pigs are produced.

To prove the existence of these mechanisms and to give an indication of the price sensitivity of farmers, an analysis was performed. It was decided to use an OLS (Ordinary Least Square) regression model with the dependent variable 'slaughter weight', and independent variables, 'feed prices', 'pig prices' and 'piglet prices.' With an OLS model the significance, strength and direction per independent variable can be measured. As well as the R-squared representing the variance explained in the model. The independent variable of 'pig price' was added in the analysis because of an indication of an omitted variable. In the long run, the pig price corrects for the fluctuations in the piglet and feed prices. Thus, to understand the effects, the variable had to be included.

Data preprocessing & cleaning

Available slaughter data from 2017 till 2022 was used to perform the analysis. When results of the model were returned against expectations, company experts explained that the following years had be excluded from the data:

- 2019, due to exploding pig demand in China because of the swine flu breakout;
- 2021 and 2020, due to capacity issues in the slaughterhouse caused by the COVID-19 pandemic. Leading to farmers not being able to deliver their pigs as they desire but whenever there was a spot. As a result, pigs were much heavier than normal;
- 2022, due to extreme price fluctuations because of the war between Ukraine and Russia.

Thus, only the slaughter results of 2017 and 2018 were used. Feed prices were derived from the LEI, a research institute from Wageningen University of Research. Furthermore, for a group of farmers Vion Farming buys and sells the piglets. Therefore, piglet and pig prices of Vion were used. Moreover, some data cleaning has been performed. Slaughtered pigs with a weight under 40kg and above 200 kg are a mistake in the system. All four datasets - slaughter weight, feed price, pig price and piglet price - were all set on a monthly basis. The slaughter weight of t=3 is compared to the average feed price of t=1, 2, 3 and the piglet price of t=3 as well. Piglets need approximately 3 a 4 months to grow before they are marketed, to capture the moment of decision there was chosen for a time horizon of 3 months.

Results

- **For only piglet and pig prices on the slaughter weight**. All independent variables were significant (P<0.000) and the R-squared was quite high (0.685). Piglet prices had a lower effect than pig prices. As expected, piglet prices were positively correlated with slaughter weight. However, there was a high correlation between piglet prices and pig prices (0.8689), the condition number was acceptable though.
- **For average feed and pig prices on slaughter weight.** The results were just significant values (feed p=0.024 & pig p=0.026), R-squared was much less than compared to the piglet prices (0.333). Feed prices were hypothesized to be negatively correlated: high feed prices would lead to earlier selling of finishing pigs, thus less slaughter weight, which turned out to be the case. The correlation between the feed and pig prices were -0.0339, nevertheless the condition number was large, and a warning of multicollinearity was given.
- **For average feed, piglet and pig prices on slaughter weight.** Piglet and pig prices were significant (p<0.000). However, feed prices were not significant (p>0.1). The r-squared was the highest overall with '0.698'. Piglet prices were directed positive as expected. The condition number was high with a warning of multicollinearity.

From this analysis there can be concluded that slaughter weight is strongly affected by prices of piglets, and less but still effected by prices of feed. Literature confirms the findings (Niemi, 2006; Pourmoayed, Nielsen, & Kristensen, 2016; Trienekens & Wognum, 2013). These findings indicate that farmers are sensitive to prices. This can be explained by the farmers finance section showing that not every year a pig will be profitable, thus farmers have to be creative and entrepreneurial in order to be competitive. Relevance for this research can be found in that farmers produce pigs according to payment, meaning that matching supply and demand can be achieved by creating mutual benefit for Vion and its farmers. Moreover, the current mismatch between demand and supply can be further corrected now a source of variability has been found.

3.3.3. Slaughterhouse

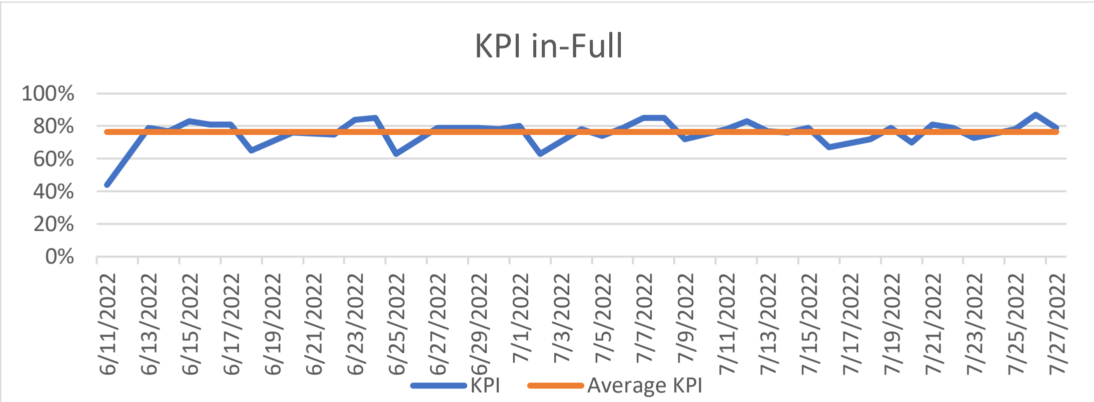
From the farmer the pigs are transported to the slaughterhouse. Transport can be stressful and negatively impact the meat quality and therefore measures are taken to minimize this. Once in the slaughterhouse, the supply is matched with the demand. However, first a pig enters and is slaughtered, the carcass is cleaned, inspected, and graded. Then intensive measurements are done, and the system takes over with AutoFOM III, an automatic classification system for pork determining which product goes to which market. Then carcasses are cut in half and cooled. After a cooling process of 24 hours or more, the cutting process starts. Every carcass is divided into a carcass class depending on its backfat thickness, leanmeat percentage, slaughter weight, and animal code (boar, gilt or barrow). From there on out it is delivered to the customer of Vion.

3.4. Supply & the market mismatch

So far, the demand and supply process have been extensively discussed. As the thesis research strives towards a better matching of supply and demand, this section will elaborate on the current performance of meeting demand.

Within GFB there are countless customers and many variations of contracts. Some for half a year, others for a month and some sales are spotsales. When too much supply is offered, Sales will focus on selling it and this can occur with a discount. On the other hand, if not sold, it will remain in inventory until it perishes. It was hard to quantify how much meat got spoiled. For the cold warehouses a KPI is tracked measuring the amount of kg still in inventory that passed its last sales date. However, two things have to be noted regarding this KPI. First, it accounts for the volume in the warehouse currently spoiled, if the spoiled products are cleaned out then the KPI is set to 0 again. No known historical data is tracked for this. Secondly, some products are for one specific country which is really strict regarding its best before date. That means if their last sales date is passed then there are still two months to sell in other markets. Nonetheless to give a perception a snapshot was taken on 11th august 2022, where 87,787 kg of meat was over date, of which 26,677 kg was older than two months.

A reason for a mismatch of supply and demand is because customer orders are created with quite some variability. A customer order is made based on what the expected supply will be. The supply is forecasted by models which are based on historical data. These models forecast the expected quantity and the distribution over the quality classes. There are two types of supply forecasts in use: long and short term. The long term is a regression model used for a period of 16 weeks upfront where quantities of the corresponding week in the previous year are used as well as current piglet prices. Then the short-term forecast is created where a list of UBN's is generated who are planning to deliver in the next eight days. For every UBN the average slaughter weight of deliveries in the same week over the last 3 years is computed. This weight is averaged again over all the UBN's, and some bounds are added (+0.2 kg and -0.2kg). Then there will be searched for corresponding weeks with similar deliveries of which the carcass color distribution was taken. Furthermore, it has become evident so far that there is quite some variability in the supply process, see chapter 3.3. These uncertainties effect the mismatch between supply and demand. As a result, a customer order is made for a product with certain specifications like backfat thickness or slaughter weight. When this pig is not supplied to Vion, then sales offer the same product from a pig with a different backfat thickness or slaughter weight which is available. In graph 2 below, the performance of the KPI in-full is shown. In-full means that the actual customer order is delivered on time and no alternative needed to be offered.



Graph 2. In-full, the ratio of orders delivered complete without any intervention for 11-6-2022 till 27-7-2022 (own elaboration)

Thus the 'in full' KPI has shown that on average 24% of the orders did not get fulfilled in full in the period of 11-6-2022 till 27-7-2022. Some customers have been willing to accept a product with different specifications when their product was not available. A week of order data was analyzed (20-6-2022 till 27-06-2022). From the 131 incomplete orders, 14 were found to have been offered a product with a different slaughter weight or backfat thickness. This was concluded when an order missed a specified amount for a certain product while in the same customer order the missing amount was ordered for a similar product, see example from the dataset below in figure 6. There should be noted that 12 of the 14 orders this concerned were rest orders. For rest orders the customers agreed upfront to a deviation of their amount ordered.

Cust. nr.	Order nr.	Description	Rest Order	In-Full orderlines	Ordered	Units	Delivered	Perfor-mance
A	1	Ham Speck 9,4-10,3kg	No	FALSE	3700	KG	3011	81.38%
A	1	Ham Speck 8.1-9.3kg	No	TRUE	450	kG	384	85.33%

Figure 6. Two orderliness of the same order and customer illustrating shortage handling of ham 9.4-10.3 kg (own elaboration)

Concluding, for GFB there is quite some waste due to inventory exceeding their last sales date. Moreover, on average 24% of orders are not delivered on time in full. Both of these cases indicate a mismatch between supply and demand. Future implementatoin can use these KPI's to quantify improvement.

4. Literature study

4.1. Literature overview

4.1.1. Introduction

Within food supply chain networks, the product quality has been identified as an essential attribute (Akkerman, Farahani, & Grunow, 2010; Yu & Nagurney, 2013). Food supply chains differ in control from regular supply chains. Therefore, deteriorating products have been extensively studied over the decades (Goyal & Giri, 2001; Nahmias, 1982; Raafat, 1991). Besides the inclusion of product quality itself, the variability over the quality may cause supply chain disruptions and as a result poor customer satisfaction (Rijpkema, 2014). Variability may have a significant impact on performance which creates a need for logistics strategies that reduce the negative impact of variability in product quality (Rijpkema, 2014). For instance, to ensure satisfying levels of revenue, the need for a quality system to predict the valued products of pigs more precise than the weight was proposed by Albornoz, González-Araya, Gripe, and Rodríguez (2015). Moreover, a controlled level of variability can be exploited to increase profit as meat quality attributes, like fat and muscle mass, are desired in different proportions by different customer segments (Grunert et al., 2004). In a study by Kempster (1989) the necessity for improved matching of carcass/meat quality and industry requirements was already established.
This is a supply chain challenge, especially considering that the internal quality of meat resulting from the primary production can only deteriorate. Therefore Den Ouden, Dijkhuizen, Huirne, and Zuurbier (1996) argued that the consumer demand should be directly converted to primary producers. Nonetheless, the meat supply chain has always operated the other way around: the supply pushed their products to the market. For instance, pork farmers control their litter size and daily growth rate efficiency-driven, and not demand-driven (Den Ouden, 1996). This strategy is a consequence of different actors in the chain that need to address different challenges (Trienekens & Wognum, 2013). Supply chain integration can align the interests (Den Ouden et al., 1996) and the modelling of supply and demand can improve overall supply chain performance (Rijpkema, Hendrix, Rossi, & van der Vorst, 2016; Rong, Akkerman, & Grunow, 2011). To address this challenge the definition of "Quality Controlled Logistics" was first introduced by van der Vorst, Tromp, and Van der Zee (2005).

4.1.2. Quality controlled logistics

Quality controlled logistics (QCL) is defined as follows: Directing goods flows with different quality attributes to different logistical distribution channels (with different environmental conditions) and/or different customers (with different quality demands) (van der Vorst et al., 2005). QCL is a means of combining predictive modelling and logistic critical points to find the moments of intervention in the chain where this can still uphold optimal quality at the final point of sale (Schouten, Van Kooten, van der Vorst, Marcelis, & Luning, 2010). In a paper by van der Vorst, van Kooten, Marcelis, Luning, and Beulens (2007) the full concept of QCL was elaborated upon, presenting an overview of logistics decisions translated to QCL decisions where two of them touch the essence of this research namely:

- "Determine customer requirements for specific market segments. Use product quality information to cluster harvested products into homogeneous batches and choose the best distribution channels." (van der Vorst et al., 2007)
- "Use product quality information to determine position CODP and specific environmental conditions in the complete supply chain needed to meet specific market segment requirements." (van der Vorst et al., 2007)

The QCL concept inspired Rijpkema (2010) to extend it towards the pork supply chain by trying to match production systems, processing systems and market segments. Furthermore, Macheka, Spelt, van der Vorst, and Luning (2017) developed a diagnostic tool combining logistics and quality control through defining maturity levels in both dimensions. For the dimension of logistics, the advanced level was characterized by utilizing reliable real-time information on product availability, actual demand, and product quality requirements based on van der Vorst, van Kooten, and Luning (2011). Regarding the quality dimension, the advanced level was typified by the use of procedural methods based on scientific knowledge, the use of advanced equipment, e.g., a computerized grading system (standardized and internationally acknowledged) and quality control activities that are product specific and statistical underpinned (Luning, Bango, Kussaga, Rovira, and Marcelis, 2008). Finally, essential for modelling QCL are the actors in fresh produce chains that need to implement logistics and quality control activities that are aligned with the context characteristics in which they operate (Macheka, 2018).

4.1.3. Modelling Quality Controlled Logistics

The increased supply chain performance with the support of QCL on process design became evident with the simulation tool named ALADIN (Agro-Logistic Analysis and Design INstrument) (van der Vorst et al., 2005). ALADIN was designed to enable QCL and support the decision maker to trade off logistics costs and service (product quality and availability) when assessing specific (re)designs of the food supply chain network. Another example of a network design problem focusing on quality is a green meat supply chain where a fuzzy multi-objective programming model was developed to balance the logistics and quality objectives (Mohammed & Wang, 2017). This research recommended to formulate the maximization of meat quality as an objective for future research. Moreover, Rijpkema, Rossi, and van der Vorst (2010) developed an allocation model of supply from pork farmers to different production locations under the assumption that different production locations result into different product yields. They compared a transportation costs minimization with a net value maximization strategy by taken into consideration quality distributions per farmer and different product yields per production location. The distributions were derived from a variety of carcass quality features (e.g., weight, lean meat ratio) in order to divide the carcasses into different quality classes and compute its probability distribution. Similarly, a stochastic programming scenario-based model was applied in a case study on the uncertainty in supply of quality from the farmers to slaughterhouses (Rijpkema et al., 2016). The model generates plans that fulfil slaughterhouse quality demands at a predefined service-level while minimizing transportation costs. Because no accurate information on livestock quality delivered by individual farmers was used while making allocation decisions, product quality was uncertain on arrival at the slaughterhouse. Reducing this uncertainty allowed decision makers to improve the match between supplied products and end markets (Rijpkema et al., 2016). Instead of using predetermined service levels in the allocation problem, Rijpkema, Hendrix, and Rossi (2015) modelled expected shortfall from the demanded quality with a bi-criterion algorithm. Moreover, sharing the viewpoint on QCL of van der Vorst et al. (2007), Rong et al. (2011) advocated for differentiation of product flows based on the absolute batch quality by tracing quality changes through the entire supply chain network in the temperature-controlled logistics environment. Many decisions on farmers level will determine the meat quality as was discussed in chapter 3. As the growth of pigs is heterogeneous, models for pork planning have taken different growth stages into account (Plà-Aragonés, Rodríguez-Sánchez, & Rebillas-Loredo, 2013). Moreover, in chapter 3 it was also stated that the variable cost of a farmer largely consists of feed. Therefore, changes in allocation of feeds, the length of a fattening period and factors determining the optimality of these decisions impact the profitability of the pig fattening stage significantly. For this reason, Den Ouden, Huirne, Dijkhuizen, & Van Beek (1997) developed a dynamic linear programming model to weigh additional pig quality with its associated costs. Another solution was to combine market conditions (price volatility) and pig production to secure the profitability of farmers (Niemi, Liu, & Pietola, 2011). This was analyzed with a stochastic dynamic programming algorithm and a scenario analysis, evaluating different price and/or quantity fixing contracts. Concluding, meat quality is hard to predict and assess due to variations and inconsistencies.

4.1.4. Modelling Supply & Demand

Besides the quality being a crucial attribute in modelling supply and demand for the pork industry, so is the unique characteristic of one-to-many processing in meat cutting. With attention towards the pork and meat industry, optimization models for cutting were computed. The first paper presenting this formulated a LP (linear programming) model with the objective to maximize the return from selling products yielded from cutting patterns applied to animal carcasses (Whitaker & Cammell, 1990). This model was extended further in a deterministic formulation which considered multi-products yielded from different cutting patterns applied to the carcasses over multi-periods with a batch quality distribution on carcasses and perishability (Albornoz et al., 2015). They proposed that future research should develop a stochastic model that considers probabilities for different types of arriving batches, to make the production planning more robust. Moreover, regarding the decision making, a LP- model was introduced to find the optimal production plan of a pork processing plant by optimizing the product value (Reynisdóttir, 2012). The model includes production levels, inventory levels, and additional supply from a vendor. Changes in quality were taken into account by assuming a fixed percentage of product deterioration at the end of the planning horizon in order to balance inventory. A simplification of this research was the assumption of homogeneous carcasses and thus similar output per carcass.

Furthermore, a dynamic programming model was introduced which supports farmers to decide to market cattle or to keep it for further fattening (Clark & Kumar, 1978). This model takes into consideration sale yard prices depending on the time of year, breed, and weight. In addition, the model decides on whether or not to replace sold cattle for the period in question. Nonetheless, the model of Clark and Kumar (1978) only focusses on the optimality from the farmers perspective. Continuing, for pig production a dynamic programming model was developed to determine optimal feeding policy to produce pigs of specified weight and carcass composition with support of a published pig growth model (Glen, 1983). Another form of modelling aimed at the control of pork was done via system dynamics modelling reported by Piewthongngam, Vijitnopparat, Pathumnakul, Chumpatong, and Duangjinda (2014). The model published enables the integration of important factors at each breeding level (great grandparents, grandparents, and parental stocks) that will affect the number of fattening pigs. Nonetheless, Niemi (2006) stated, no matter how the model of optimal timing on marketing an animal is solved the principle is as follows: "It is optimal to market a pig when the marginal net revenue from fattening an additional day is equal to the opportunity cost of replacement." Furthermore, the same study stated that the growth of a pig and related constraints can be characterized as a set of equations. More specifically, a pig's live weight is split into energy, protein water and ash. Growth can be modelled for all components separately. In addition, to include the genotype as well, it was modelled as a maximum at which the amount of lean and fatty tissue in pigs can increase. Finally, Niemi (2006) published a dynamic programming model including the growth model and genotype constraint for optimizing feeding and slaughter decisions regarding fattening pigs. This model was further extended for precision feeding in a simulation model where the optimal feeding and slaughter policy was determined.

Worth mentioning is the production planning's model presented by Benseman (1986) for the dairy industry. Taking into account the seasonal patterns, different product yields and quality resulting into significant increase in profitability. The product quality was controlled with quotas and penalties, very similar to the pork industry nowadays. These quotas and penalties are set by the cooperation.

4.2. Research gap

From the previous section can be concluded that although many uncertainties were included in different supply chain echelons, a combination of heterogeneity, pork quality, and the market were not found. Moreover, as outlined in the introduction, the company wants to be demand driven, therefore a model facilitating this is desired. Since the supply chain stages of breeding and feeding lead to the eventual product quality, these need to be included.

The uncertainty in the supply of quality of pork was included in the models by Rijpkema et al. (2015) and Rijpkema et al. (2016). These aimed at reducing this uncertainty and the transportation costs in slaughterhouse allocation. However, these models are designed from a supply driven perspective. Neither do the models specify the underlying characteristics of the product quality. A demand driven model that was discussed, was the model with the objective to maximize the return from selling products yielded from cutting patterns applied to animal carcasses (Whitaker & Cammell, 1990). The modelling approach fits the current research problem. The reason these models can be seen as demand driven is because the different patterns are applied to match the customer demand. Nonetheless, it does not include quality- or demand uncertainties. A later model did extent with a batch quality distribution of the carcasses (Albornoz et al., 2015). However, the effect of those patterns or solutions on quality itself was not included in the literature.

Further, a model approaching this gap can be found in the pig production dynamic programming model determining optimal feeding policies to produce pigs of a certain weight and carcass composition (Glen, 1983). However, it is missing product quality uncertainty and it excludes important factors determining quality besides feeding. The study by Niemi (2006) approached the current research requirements as the pig production was controlled by models. In addition, the same study focused on another research problem, namely how the optimal feeding and slaughter policies change when prices of pig meat, feeds, piglets, carcass quality premiums or slaughter premiums change. By isolating the effects of all different price changes and considering its price elasticity's, the effect of market conditions on the optimal decisions for pig production was laid out. Nonetheless, the perspective of the research was from the farmers and how they can optimize their profit. This is how farmers currently operate and their outcome is pushed to the market regardless of demand. As the industry is innovating to become more demand driven, the consumer demand should be directly converted to primary producers as advocated by Den Ouden et al. (1996). Therefore, the current thesis will explore demand driven production meanwhile increasing the overall profitability of the supply chain.

In addition, the study by Niemi (2006) estimated optimal feeding and slaughter patterns of an individual pig recommending future research to extent the analysis to large heterogeneous groups of pigs.

Important to highlight before modelling techniques are evaluated is the nature of Vion, namely a cooperation. As Benseman (1986) indicated, a cooperation can interact with bonusses and penalties. To match supply and demand from the role of the cooperation gives another dimension to the research gap. Thus, to fulfill the research gap and to facilitate the research of the thesis, a model is required focusing on heterogeneity, pork quality and the market, from a demand-driven perspective in the role of a farmer's cooperation. This model needs to take the demand from customer segments as input and processes it to quality characteristics. Matching this information to the attributes steering the pork quality while including its uncertainties from the pig production for groups of pigs. As a result, the supply side of the pork chain can customize itself to the customer demand. This all should result into maximization of profit and reduction of waste.

Finally, this thesis research will contribute to the QCL literature. As outlined in the previous chapter, much potential is seen in this concept (Heising et al., 2017; Macheka, 2018; Rijpkema, 2010; Schouten et al., 2010; van der Vorst et al., 2007, 2011). A model converting the consumer demand to quality control points which can be manipulated, is missing within this line of research based on the results of this literature study.

4.3. Modelling techniques

This part of the chapter will elaborate on the modelling techniques appropriate to this thesis. Within operations research a wide array of models have been developed. This can mostly be categorized as stochastic or deterministic. Deterministic models assume that everything is known and the same input in the model will always produce the same output. However, reality is quite different from those models due to uncertain environments and variable processes. Therefore, stochastic models were developed, introducing randomness and increasing modelling complexity. In contrast to deterministic models the output can vary per run. The trade-off between model complexity and model relevance was carefully weighed in this section.

4.3.1. Linear and non-linear programming

As laid out in the literature study, many supply and demand models resort to a linear programming model (LP) for optimization. This model has been extended to handle both deterministic and stochastic problems. It requires an objective function that will either minimize or maximize the objective. In addition, it requires constraints that limit the objective function. When running, the model searches for an optimum that does not violate any constraints. The constraints and objective function are represented by linear relationships. In order to solve these models several assumptions have to be checked, namely: proportionality, additivity, divisibility, and certainty. An extension of the LP model is the non-linear programming model that is a process of solving an optimization problem however the constraints and objective function can take non-linear forms. Enabling a modelling technique that is less restrictive.

In addition, the LP has been extended to include integers, like in a mixed integer linear programming (MILP). An application for instance by Ohlmann and Jones (2011) formulated an integer linear programming to determine the optimal marketing decisions for pig farming. They used vectors to represent the transition probabilities between carcass classes. Nonetheless, the LP is not the most suited model when dealing from a perspective of imperfect information. This thesis orients itself on another echelon in the supply chain which is independent and owns more information regarding operations. The modelling technique might require a different dimension.

4.3.2. Agency based modelling

The thesis at hand requires a model that matches supply and demand while the supply is controlled by an agent who makes independent economical decisions. Moreover, the agent has to make decisions in an uncertain environment and their actions have variable outcomes. Such models have been researched in the agent-based modelling field (Bonabeau, 2002). A Markov Decision Process (MDP) is a form of agency-based modelling which operates with markovian behavior meaning only the information of the current state is relevant, history is not. Appendix F will elaborate on the application of MDP and its advantages regarding this research. The shortcoming of MDP with the available data is that the model would assume farmers behavior in the system would be homogeneous, as they would choose the policy with the highest reward minus costs. While farmers are much more complex in reality. So far there has been stated that heterogeneity is required for the model. Nonetheless, this thesis encounters three forms of heterogeneity: among pigs delivered by the same farmer, among pigs of different farmers, and for different farmers behaviors. The heterogeneity among farmers and their behaviors cannot be neglected when building a model for independent agents. To illustrate the importance of farmers behavior, the study of Alho (2015) analyzed questionnaires completed by 682 Finnish milk and meat producers revealing heterogeneity in the perceived valuation of benefits that farmers receive as members of agricultural producer cooperatives (Alho, 2015). Another study in the dairy industry addressed the heterogeneity of farmers' preferences for improvements in dairy cow traits using farmer typologies (Martin-Collado et al., 2015). Surprisingly this study found that preferences for cow trait improvements are intrinsic to farmers and not to production systems or breeds. The heterogeneity of farmers was argued for by Ollila (1994) who researched farmers cooperatives as market coordinating institutions. Stating that in low uncertainty, low complexity environments it can be assumed that agents seek rationality and utility. While in complex and uncertain environments actors will work with bounded rationality and opportunistic behavior (Ollila,1994).

Multinomial choice model

Besides MDP, another model that can operate as an agency-based model is the multinomial logit (MNL) random utility model. This model is part of discrete choice models, which have been developed to describe the behavior of consumers when they are faced with a variety of mutual exclusive choices (Anderson, De Palma, & Thisse, 1988). Thus, it reflects the consumer choice between variants of a differentiated product, which is a good with a common consumption objective but with different characteristics. Discrete choice models can either be binomial, two alternatives, or multinomial, three or more alternatives. The main difference between the MNL model and a classical utility maximization model, like the MDP, would be that the utility U_j is assumed to be partly unobserved, so that an individual's choice is uncertain (Hess, 2014). Then the utility values can vary among individuals due to heterogeneity in preferences (Anderson et al., 1988; Hess, 2014). The probability of choosing the good/product/policy is determined based on the utility function of that policy relative to the summed utilities over all alternatives. As a result, every policy will receive a probability to be picked, this is an advantage of MNL. Moreover, the heterogeneity is included much better than for the MDP. The model can aggregate over all the heterogeneous consumer choices and try to steer them together to an overall desired supply.

Finally, in literature a combination can be found of an MNL and MDP model. In Bizzotto et al. (2011) there is the multinomial markov chain model applied to simulate sleep stages. Moreover, in forest evolution it was applied by Boltz and Carter (2006) stating that MNL estimation is advantageous in that it generates a smoother distribution of transition probabilities across size classes, correcting for variance in the data and model estimation errors imposed by limited samples. Furthermore, another advantage named was the preserving of the simple linear form of matrix models that facilitates the integration into economic optimization studies (Boltz & Carter, 2006). Moreover, another forest research, regarding sorting growth of trees in classes and creating a transition matrix with the logit regression, argues that a benefit of the MNL methodology is that it allows a multi-response analysis.

4.4. Other literature findings for modelling

The literature has provided insights that will support the modelling. This final section will list the most relevant findings and potential application within this research. First, within the literature of modelling quality several sources made use of quality distribution models to estimate supply flows (Albornoz et al., 2015; Plà-Aragonés, 2013; Rijpkema et al., 2015, 2016; Rong, 2011). Supply from the farmers to the slaughterhouses is variable but not completely random, it can be estimated with distributions. Further on, two papers made use of quality behavior models by computing a complex pig growth model (Niemi, 2006; Niemi et al., 2011). The model measured the amounts of protein and energy deposited into the body each day (growth of lean and fatty tissue). Such a model has too much depth for this research. Nonetheless, such mechanism will be taken into account in a more practical form. Instead of focusing on protein or energies, the future model will steer with certain feed, genetics, and pig farming methods to influence growth of lean and fatty tissue. Continuing, several papers have considered prices of raw materials for pig farming and the market prices (Den Ouden et al., 1997; Niemi, 2006; Niemi et al., 2011). Such variables have to be included due to the cost sensitive nature of the commodity product of pork. By balancing the costs and revenues central in the model, the supply chain actors can be sustained, and the supply chain becomes resilient.

5. Data analysis

This chapter will present a data analysis to create a deeper understanding of the variables. The ultimate objective of the model is to match supply and demand through farming techniques. To achieve this, there has to be understood which variables would be appropriate to use. This chapter will contribute to the research question of what the input of the model will be.

5.1. Data selection

The data to be analyzed in this chapter is the initial farmers distribution and the policy distribution of one quality control point, namely lysine. With distribution there is referred to the probability of a pig being assigned a certain carcass class based on quality characteristics. The initial farmers distribution is then the probability before any changes are suggested and just depending on which farmer delivers the pig. The policy distribution refers to the new probability if a certain farming policy is employed. First the initial farmers distribution will be analyzed to assess the stability over the years. Second, data will be analyzed from a controlled experiment in which the effects of three feed policies (varying levels of lysine) were isolated and measured. The data will be elaborated upon below.

Initial farmers distribution
To forecast the initial farmers distribution the data has to be observed per UBN for GFB. SIS data will be used for this. The years of data to be used is from 2018, 2019, 2020, 2021. The GFB concept exists since 2017, while in this year it had only less than half of the UBN's of the proceeding years. Therefore, to reduce the risk of error the years of 2017 and earlier were excluded. As earlier stated, the years, 2019, 2020, and 2022 had quite some effects of external influences (swine- flu and COVID-19 capacity issues) this will be taken into account when analyzing the data.

Policy distribution lysine
As stated, a controlled experiment provided data on the effect of several feed policies through external research by a feed research company. The test farm had 3 experiments groups with different feed policies and controlled for genetics (Topigs Norsvin TN 70 (Maternal) x TN Tempo Sire line). The genetics that were used are the most common amongst farmers. Moreover, the experiment included barrows and gilts. The piglets were placed in the fattening department at 25 kg in groups per gender in three rounds. In total there were 8 departments, every department had 6 pigpens and per pigpen there were 8 pigs of one gender.
The feeding occurred over three phases (start, growth, and finishing) where the first two phases were the same for all the test groups. Only the finishing feed was adjusted meaning that until day 133 all the pigs were fed the same and changes only occurred in the last 5 weeks.

	Lysine	**EW**
Feed policy 1	High	Low
Feed policy 2	Average	Average
Feed policy 3	Low	Average

Table 1. Feed policy description (own elaboration)

As can be seen in table 1, lysine was continuously decreased relative to policy 1, and the EW was increased. The experiment hypothesized that a decrease of lysine and an increase in EW would increase the backfat thickness. This is in-line with the literature findings of chapter 3.3.2. Further on, two datasets were provided, one containing all data regarding the experiment setup and one regarding all the slaughter data. The experiment data set contains 333 rows while the slaughter dataset has 1611 rows.

5.2. Data preprocessing

5.2.1. Initial farmers distribution

This section will elaborate on the pre-processing steps such that the characteristics of the data can be understood. The slaughter data contains all the available information of every pig slaughtered. Thus, which farmer delivered the pig, all its measurements, its gender, and its concept.
The data has columns with years and weeks, however not with months which were inserted manually. Further, all pigs that do not have a UBN number were deleted from the dataset. Approximately 6% of all slaughtered pigs lose their tag before measurements, resulting in the system not linking the pig to a farmer (UBN). Further on, all other Nan (Error: Not A Number) values were deleted. In the production facility the line speed can be quite quick, leading to errors in measurements. When measurements go wrong a Nan value appears. To give a perception in 2019 this occurred for 0.12% of the measurements. Continuing, farming experts advised the following bounds for slaughter weight, <40 or >200 is not realistic for a fattening pig. Measurements of the slaughter weight are performed while the carcass is hanging on its hook. If someone pools the hook at the wrong moment or there is just a part of the carcass on the hook, then wrong measurements are registered. Continuing, an average farmer delivers 6000 pigs per year because he/she has 2000 places and makes 3 rounds of 4 months. However, there are some very small non-commercial companies bringing their pigs to slaughter. For instance, the breeding farm brings their sows once they do not give piglets anymore. These farmers are not the ones being targeted for intervention, either because it is not their business model, or they do not have the scale. It was decided to cut off UBN's delivering below 1500 pigs per year. Meaning that farmers with 500 places or less will not be in the dataset. Finally, as much of the data analysis focusses itself on the distribution over the carcasses, it was decided to only analyze the GFB slaughter data. The inclusion of other concepts will give a misconception of the distribution. In table 2 below the size of the data sets per pre-processing step were reported.

Year	Original size	Size with UBN's	Size without Nan and impossible values	Size without UBN<1500	Final size only GFB
2018	7,577,745	7,122,219	7,043,394	6,388,533	3,745,081
2019	7,427,755	6,88,0197	6,797,536	6,294,087	4,146,849
2020	7,368,443	6,754,385	6,667,533	6,297,258	4,099,324
2021	7,450,710	6,790,879	6,714,535	6,411,634	4,304,938

Table 2. Data cleaning steps of SIS data 2018, 2019, 2020, and 2021 (own elaboration)

5.2.2. Policy distribution lysine

Missing values
The initial 384 pigs planned for the experiment finally resulted in a dataset of 333 pigs. The mortality of the experiment was a total of 26 pigs. Average over the whole industry is 2.5% according to the KWIN (Blanken et al., 2021). So, the mortality is quite high but due to the small sample size farming experts labelled it as acceptable. The other 25 pigs were not sent to slaughter for unknown reasons but not related to mortality. Below in the table the numbers can be seen per policy.

	Mortality	Not send to slaughter
Feed policy 1	7	4
Feed policy 2	7	5
Feed policy 3	12	16

Table 3. Feed policies missing values

The experiment dataset provides insight regarding gender, birthdate, slaughter date, housing, and feed policy per pig. All pigs were given an ear tag, which allowed the experiment to link the slaughter data. Ear tag numbers ranged from 1-999, once 999 was reached they started at 1 again, thus double numbering could occur. To correct for this a DATA_ID was created that combined the ear tag and gender. Continuing, the slaughter dataset and the experiment data set were matched based on the

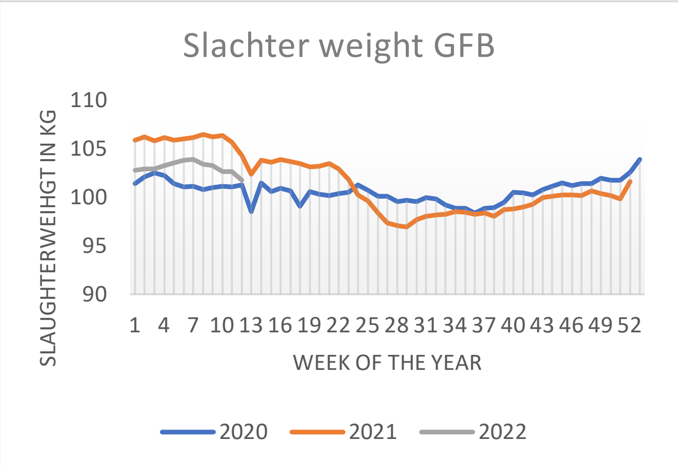
DATA_ID. As a result, 20 row values were missing. By manually searching for the missing values, 19 instances where the gender in the datasets did not match were found. After consulting the farming experts, they reasoned that a distinction between gilts and barrows is often subject to classifications errors in the slaughterhouse. The remaining missing ID did not exist in the slaughter dataset and was thus deleted.
For another 36 values the slaughter date of the experiment dataset was many days off from the slaughter date of the slaughter dataset. Here the Data_ID existed double, so it had to be corrected manually.

5.3. Data analysis & visualization

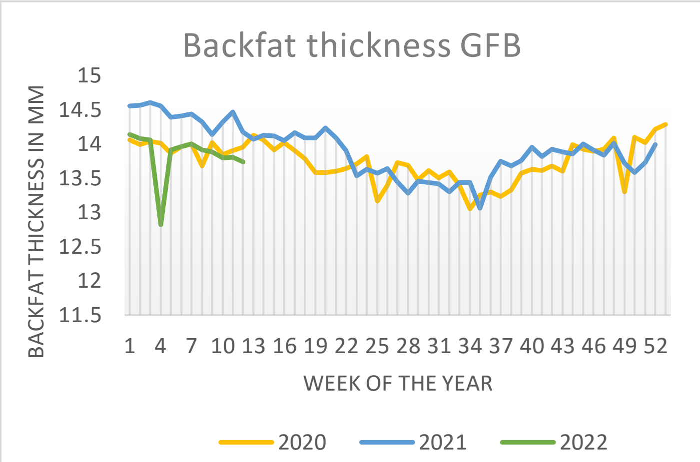
5.3.1. Initial farmers distribution

Seasonality and carcass classes

There is seasonality present as during the summer pigs eat less and as a result, they will create less fat and have a lower weight, see graph 3 and 4. The slaughter weight clearly changes through the year as well as backfat thickness.



Graph 3. Average slaughter weight of GFB in 2020, 2021, and 2022 (own elaboration)



Graph 4. Average backfat thickness of GFB in 2020, 2021, and 2022 (own elaboration)

To analyze the data, a time horizon has to be determined to calculate the carcass distribution. If set to a year, then the whole seasonality would be ignored. Meaning that if extremely fat pigs are desired, then no farmer would seem to be able to deliver them since the summer would compromise this. Furthermore, set on a weekly basis will not give an accurate view since farmers often deliver their best pigs first, a week later the second-best pigs, and finally the rest group. Meaning that big deviations will occur if the distribution is set weekly. Similar problems but of lesser scale will occur with months. Nonetheless, a pig cycle is approximately 3 till 4 months therefore using trimester would be the most appropriate as it will certainly capture a farming cycle and still incorporates seasonality. Thus, once the dataset is sorted on trimester, a carcass color can be assigned according to the specifications. The distribution over the carcass colors quantifies the heterogeneity of pigs and makes it more tangible. Once assigned a color, the sum is taken over all the deliveries and the ratio per color is determined per trimester. To have a deeper understanding of the distribution observe the following figure 7. Note this figure is an illustration of the colors and classes that does not reflect reality due to data confidentiality. The actual distribution is only presented in confidential appendix G. In this figure the ratio between the different carcass classes for the whole of supply of GFB is presented. The x-axis represents the increasing slaughter weight in kg and the y-axis the backfat thickness in mm.

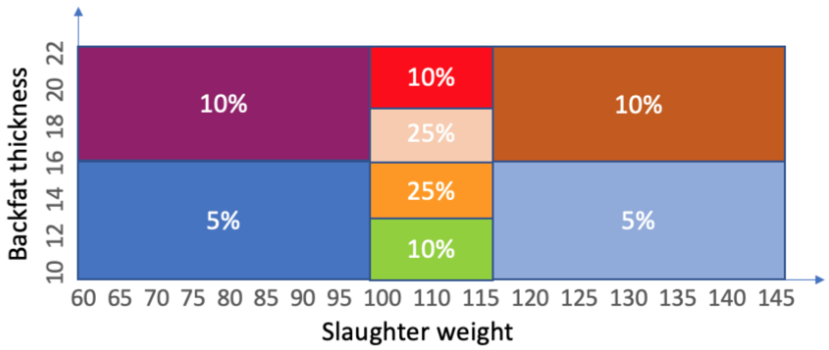
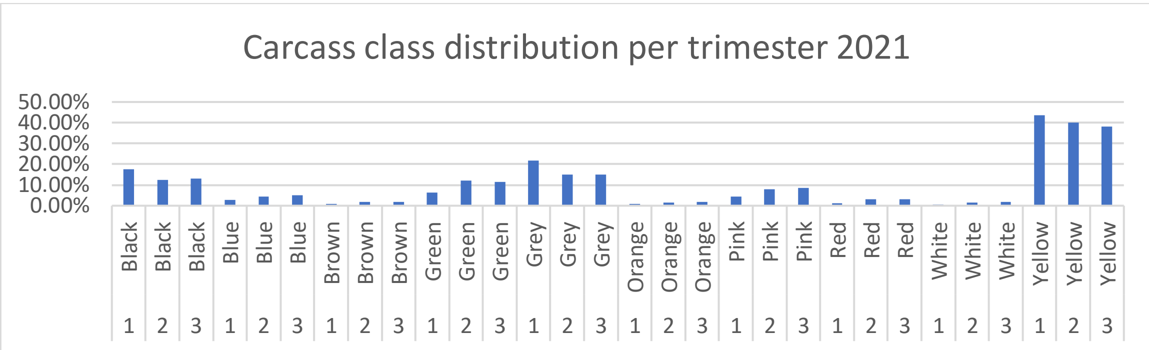
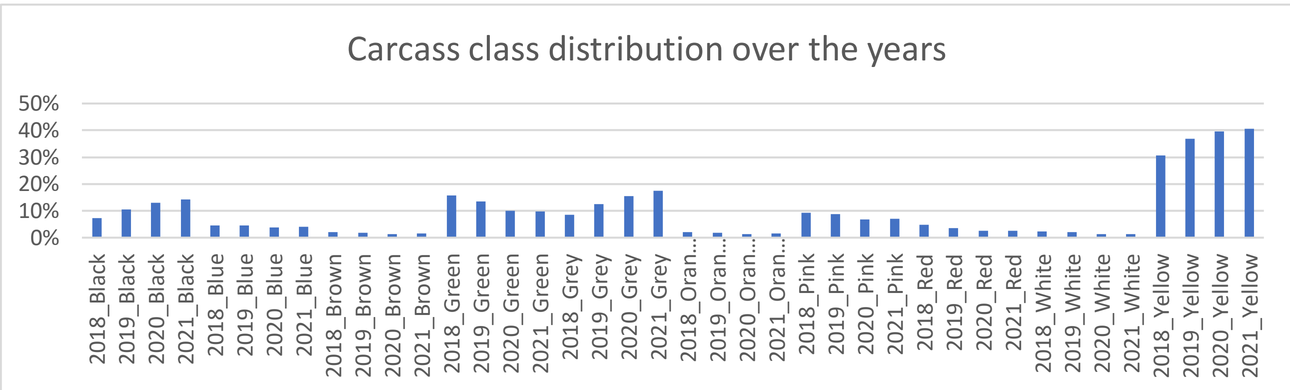


Figure 7. Illustration of aggregated farmers distribution over the carcass classes (own elaboration)

Thus, in the illustration the supply consisted of 10% purple pigs and 25% orange pigs. The distribution over the carcass classes is very important for steering on quality in the pig production. A change in a farming technique can lead to a shift from one carcass color to another. For instance, if a farming technique increases backfat then applying it would lead to more brown, purple, and red pigs.
When observing the carcass class distribution over the year 2021, the seasonal trend becomes evident see graph 5 below as the carcass classes are sorted per trimester. As was shown in the confidential appendix G, the heavier carcass classes are grey, black, and yellow, you can see a clear drop in the second trimester of these colors.



Graph 5. Distribution over the carcass classes per trimester (own elaboration)



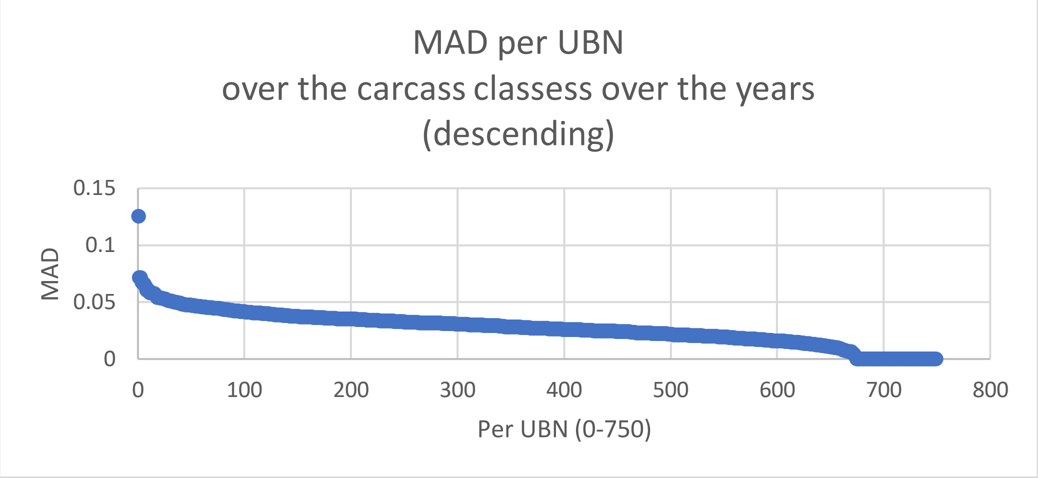
Graph 6. Distribution over the carcass classes over the years (own elaboration)

When analyzing the carcass class distribution over the years, 2018, 2019, 2020, 2021, graph 6 can be made. It can be concluded that not much changes for the colors in the middle of the matrix, blue, and orange, through the years. However, when listing which colors increase over the years - namely grey, black, and yellow - the trend of pigs getting heavier can be detected. Because graph 6 uses ratios, it is logical that the colors brown, green, and pink decrease as they border the heavier colors. This trend of increased weight is seen throughout the whole industry. Reasons for this are capacity issues due to

COVID-19 forcing pigs to stay on the farm longer, as well as an increased growth rate overall. This increase in growth rate is also not incidental but the result of decades investing in genetics and feed to maximize a farmer's income.
In confidential appendix G the distribution over the carcass classes of two random farmers was compared to show that the deliveries per farmer can differ significantly.

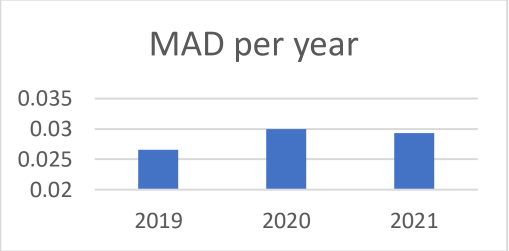
Deviation of carcass classes

The distribution over the carcass classes is an important variable for matching supply and demand. Due to this, the mean absolute deviation (MAD) over the years was quantified to conclude if it is a stable metric. For the data analysis the year 2018 is used as a base. The MAD is calculated for every UBN for the same trimester over the years. In graph 7 this is plotted for the 750 UBN's with decreasing deviation.



Graph 7. Mean absolute deviation per UBN over the years 2018-2021, sorted descending (own elaboration)

Only one UBN is above the 8% MAD, this UBN delivered 1599 pigs in 2019. Moreover, when analyzing the 34 UBN's with an MAD above 5%, then 25 of the 34 UBN's deliver below the average of 6000 pigs per year. For 750 UBN's the MAD was calculated. Some UBN's only delivered in one year resulting in an MAD of 0, this was the case for 77 UBN's.

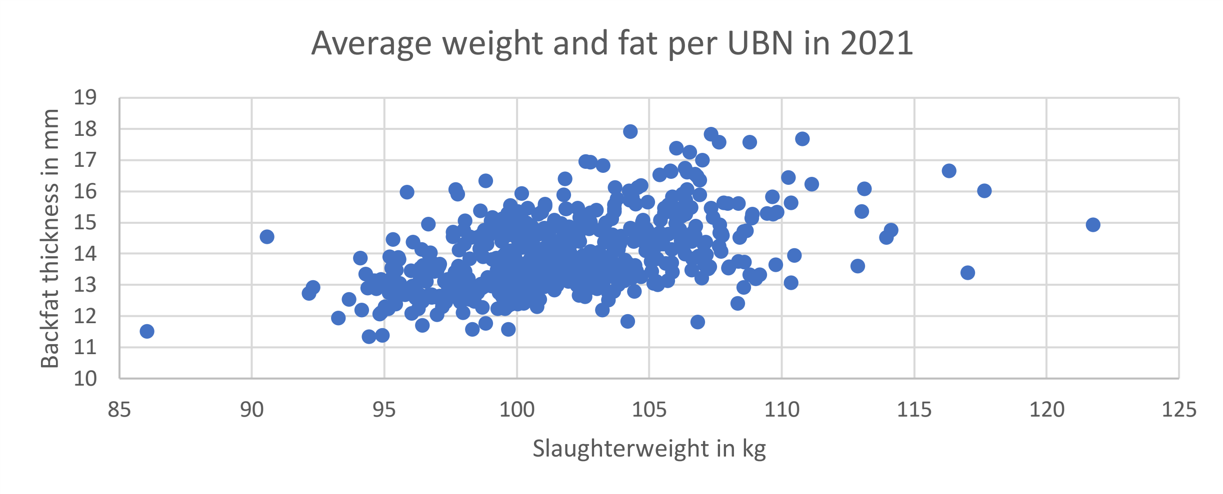


Graph 8. Mean Absolute Deviation per year 2019, 2020 and 2021 (own elaboration)

Furthermore, the average MAD over all the UBN's per year was reviewed, see graph 8. As expected, it increased for 2020 and 2021 due to COVID-19. Furthermore, the deviation was observed per carcass class. The four highest deviations were in the carcass classes yellow, grey, green, and black which are the heaviest classes except for green. In addition, green borders yellow and is affected by the shift to heavier pigs.

Heterogeneity farmers

So far, the heterogeneity among pigs from the same farmer has been extensively discussed in the form of carcass classes. Confidential appendix G already indicated some heterogeneity among farmers. However, it should be clearly understood that farmers differentiate and should not be treated the same. In graph 9 below, the average slaughter weight and average backfat thickness per UBN is shown in 2021.



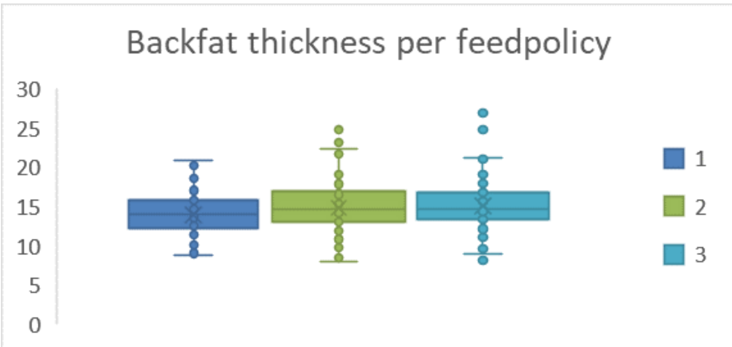
Graph 9. Average slaughter weight and backfat thickness per UBN in 2021 (own elaboration)

Graph 9 shows the averages per farmer are widely different. To illustrate, different carcass classes indicate different products, the levels of backfat thickness in the carcass matrix range from, <12, 12-14, 14-16, 16>. Now observe graph 9, the averages of the farmers fall in different classes. Note that his concerns averages meaning that the distributions of farmers over their slaughter weight and backfat thickness are surrounding the average. It can be concluded that farmers distributions are heterogenous.

5.3.2. Policy distribution lysine

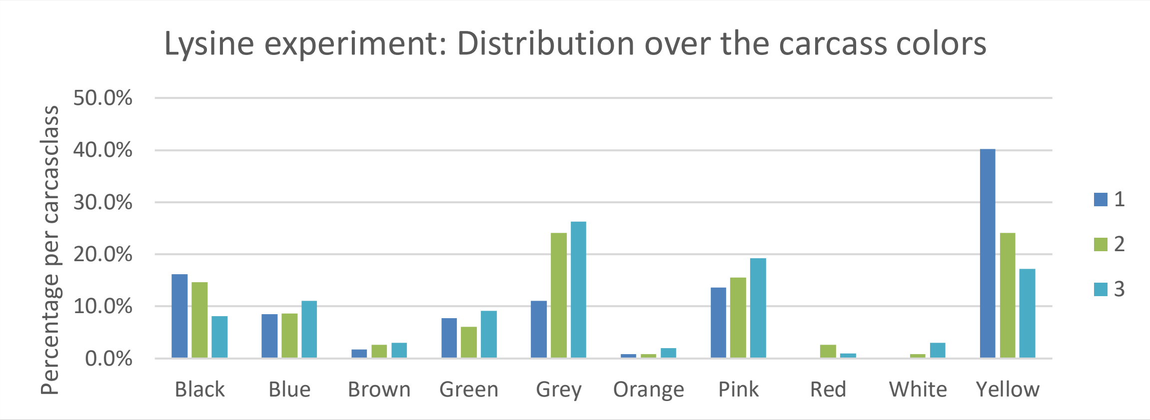
In this section, the data of the feed experiment will be discussed. The three feed policies were sorted by gender-experiment groups and the results are presented in confidential appendix H due to data confidentiality. The sample size per gender-experiment group is as follows: barrows feed policy 1 = 57, barrows feed policy 2 = 58, barrows feed policy 3 = 55, gilts feed policy 1 = 60, gilts feed policy 2 = 58, and gilts feed policy 3 = 44.
The results of the experiment are as follows. The average age increased per feed policy, this is because pigs were selected based on weight and it seems like pigs with feed policy 3 have lower growth. This can especially be seen for gilts with feed policy 3 as these have a higher age and a much lower slaughter weight. Secondly, the average backfat thickness increases over the feed policies. Hence a relation can be observed between reducing lysine and increasing backfat thickness. However, it seems for barrows that feed policy 3 in comparison to feed policy 2 is the most effective for backfat thickness. According to the one-way ANOVA test there was found a statistically significant difference between the groups and their effects backfat thickness, F= 4.6873, p-value= 0.0098. In confidential appendix I the assumptions of the ANOVA are checked and some post-hoc testing analysis are done. The post-hoc testing indicated that the only differences found significant was between feed policy 1 and 3.

Moreover, this thesis orients itself on the distribution over slaughter weight and backfat thickness. This experiment was focused on lysine which is an amino acid used to manipulate muscle growth and backfat thickness. Due to this reason boxplots were computed per feed policy over the backfat thickness, see graph 10.



Graph 10. Boxplots per feed policy on backfat thickness according to lysine experiment in mm (own elaboration)

It can be observed that per policy the outliers become more extreme. Moreover, the whiskers of the boxplots are different as well, indicating difference in variability. To create a deeper understanding of this variability the results of the experiment are expressed in the distribution over the carcass classes in graph 11, similar as done for graph 5 and 6.



Graph 11. Lysine experiment distribution over the carcass colors (own elaboration)

The distribution is quite different per policy as can be seen in the graph. Within policy 1 there were no carcasses assigned to red or white. Black and yellow decrease over the policies while blue, brown, grey, orange, and pink increase. All in all, there can be concluded that the choice of farming policy influences the distribution over the carcass classes.

5.3.3. Conclusion

Carcass classes are assigned to a pig based on backfat thickness and slaughter weight. These classes can be used as a metric to deal with heterogeneity among pigs of different carcass qualities. Over the years the distribution over the carcass classes per farmer do not deviate much. If the deviation was really high over the years, then it would be hard to quantify and rely on the effects of farming policies.
Moreover, it has been found that farmers are different from each other in terms of the carcass quality of their supply. Steering every farmer to one distribution could result in losses of small carcass classes that are only supplied by a few farmers. Therefore, there should be steered over the whole supply to one desired demand distribution.
Finally, the lysine experiment data was analyzed indicating a significant effect of the feed policy and showing that the feed policies lead to change in the carcass class distribution.

6. Conceptual model

This chapter will outline the model in conceptual terms. The conclusions of the process analysis, the literature study, and the data analysis will function as context for the model. First the purpose and requirements will be listed for the design of the artifact. Then the ideal model will be illustrated based on all identified quality control points. Followed by an outlining of the modelling stages in conceptual terms.

6.1. Setup

This section will elaborate on the purpose, requirements, and characteristics of the model. This research attempts to fulfill a rigorous aim, contributing scientific knowledge, as well as a relevant aim, providing a practical solution. This section will elaborate on the balance of a rigorous and relevant contribution of the model. Moreover, it will report on what will be in the model and what the setup will be.

6.1.1. Purpose & requirements

According to the research goal, the artifact (a mathematical model) should meet its stated requirements (matching supply and demand) to reach the stakeholders goal (for Vion to increase its profitability and reduce waste in the chain). In addition, the artifact should contribute to answer the main research question:

How can Vion Farming respond to the customer demand by controlling its supply chain?

It has been reasoned that the distribution over the carcass classes is the key metric to match supply and demand. Previous analysis of literature and data found that this key metric can be influenced with farming techniques. So, for the model to meet its requirements, it should have the purpose of matching the supply distribution over the carcass classes with the demand distribution via farming techniques, hence the following question:

How can the supply distribution over the carcass classes be shifted such that supply is better matched with demand and more profit is generated by Vion?

There are more requirements for the model namely, closing the research gap with a model matching supply and demand by including heterogeneity of farmers and pigs, focus on pork quality, and steering towards the market. In addition, this thesis strives to contribute towards the QCL literature by converting demand to quality control points on which can be steered.
Besides the rigorous requirements for literature, there is a relevant side specifying towards Vion. The requirement of a proof of concept, whether and how supply and demand can be matched in the context of Vion Farming. With the underlying objective to evoke further change such that Vion can meet its aim to be demand-driven.
The relevance of the model for Vion Farming is as follows:

- Insight in understanding the effect of farming policies on the supply distribution over the carcass classes;
- Improves information flow between Vion Farming and the Sales department through a model connecting them;
- Proof that, given the assumptions, supply and demand can be matched through price incentives and penalties.

Throughout this report it has become evident that a high complexity is involved in modelling pig production. Therefore, the model characteristics have to be defined in order for the model to be applicable and fulfilling its purpose and requirements:

- Demand and supply are both modelled as distributions over carcass classes rather than expressed in quantities. It is not the desire of a farming cooperative and its suppliers to influence the supplied quantity. This is because of the farmer's economic necessity to have a high utilization rate on the farm and its supply chain partners are dependent on the continuous cycle of supply. Moreover, everything supplied by the farmers has to be slaughtered and sold by Vion according to the agreements of this cooperation;

- Demand driven supply cannot be achieved with one farmer producing demand driven. To effectively supply the market according to their demands, it requires Vion's central control. This has to be managed centrally for several reasons.
    - First, Vion can serve many market segments due to the scale of their supply and the wide range of carcass quality offered. This thesis expects that supply chain profitability is currently not maximized due to the push strategy. To maximize supply chain profitability the whole supply of Vion should be matched with the market segments.
    - Second the farmer will not be financially incentivized for this. The most profitable strategy for a farmer would be to minimize costs and maximize earnings with the current payment table. He/she would not deviate from this to produce demand driven unless Vion offers a different payment strategy.
- Farmers are heterogeneous and should be treated as such. However, steering individual farmers requires among others, a lot of farm specific data and a deeper understanding of farmers' individual behavior. Before such research can take place, it has to be proven that there can be operated demand driven in this particular industry. The model will have to operate on an aggregated level of supply (e.g., concept level like GFB) while preserving the heterogeneity of a farmer by accounting for uncertainty.

6.1.2. Ideal model with all identified quality control points

A theory driven approach was taken to identify the quality control points for carcass quality within the fattening farm process, chapter 3. The following quality control points were found: genetics, gender, feed schedule, feed composition (energy), feed composition (amino acid), and delivery timing. This paragraph elaborates on the ideal model.

Dimensions

The variables gender and genetics add dimension in which the other quality control points operate. Because not every gender nor genetic will respond the same towards a farming policy. Therefore, the model should take this into account. Moreover, it is not a purpose of the model to recommend another genetic or gender to a farmer because this can have major implications for its business. For instance, changing genetics might require new business partners, changing to new feed, or adjusting to a new type of pig behavior.

Furthermore, the feed schedule should also be modelled as a dimension, but then through time as a feed policy has different effect in different stages of life. There are several methods to set up the feed schedule. The most common method applied by farmers is to synchronize the feed phases with growth phases: start, growth, and finish. Adding the feed schedule as a dimension, enables the model to include sequential decision making over time. Then the model can steer with different feed policies at different points in time

Quality control points

The rest of the quality control points are the feed composition (energy), feed composition (amino acid), and delivery timing. The feed composition (energy) or EW should function as a farming policy in the model. Similar as the feed composition (amino acid) which will be expressed in terms of lysine, as it is done in the industry. The assumption remains that lysine will be used in a ratio for the other amino acids which is referred to as the ideal amino acid balance. The final quality control point is the delivery timing. Here the growth of a pig is cut short or extended based on what is expected to be gained and what is expected to be the cost.

Ideal model

The quality control points are combined in an overview of interaction in figure 8. It can be seen that for a given demand distribution over the carcass classes the model will consider the different policies, their costs, and earnings. The outcome will be an optimal demand-driven incentive.

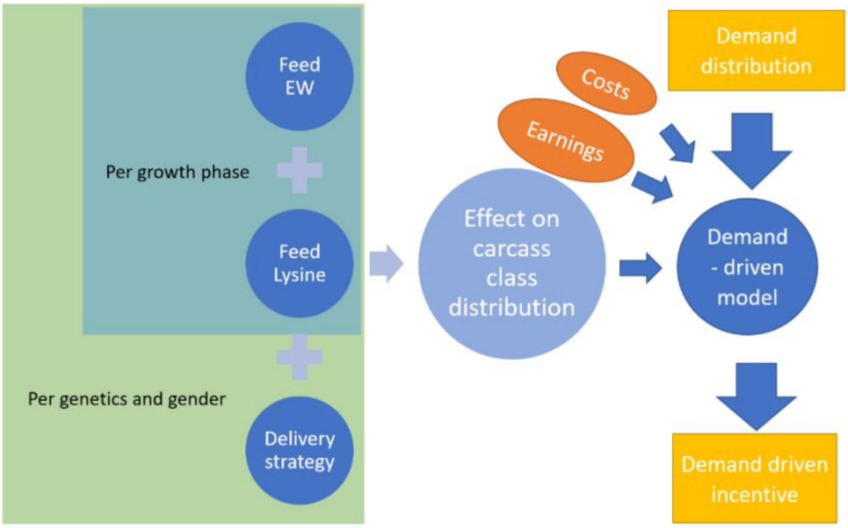


Figure 8. Schematic indication of data relations (own elaboration)

6.1.3. Stages of modelling

The model will be the proof of the concept to match supply and demand by an economical incentive such that the interests are aligned of the farmer with the farmer's cooperative. However, there are several stages involved in proving this concept. For every stage a question was defined.
First it has to be established whether the supply distribution over the carcass classes can be influenced by a farming policy. Thereafter the effects have to be quantified. If this stage is not successful, then the basis of the model will be insufficient to match supply and demand. This first stage will answer the question:

'Which farming policy has what effect on the supply distribution over the carcass classes?'

Secondly, there has to be confirmed that a given demand distribution can be matched with supply. The second stage will weigh the ability to meet the demand given the policies of stage 1 and a desired demand distribution over the carcass classes. In this stage there will be assumed Vion has central control over the farmers decisions. Reasoning that if supply and demand cannot be matched with complete control, then it cannot be matched with the given farming's policy from stage 1. This stage answers the following question:

'Can supply be matched with a given desired demand distribution over the carcass classes if policies are centrally controlled?'

If the previous stage has indicated that it is possible to meet demand, then the next stage will determine how it is met. Decisions made by farmers have been proven to be sensitive to price fluctuations so there will be searched for an optimum monetary incentive such that the desired demand distribution is met. Additionally, the research goal was set on increasing Vion's profitability which should be incorporated as well. The following question will be answered:

'What incentive has to be offered such that a farmer's management is steered to match supply and demand while maximizing Vion's profit?'

If all three stages can be answered successfully then the proof of concept is established, and it can be stated that supply and demand can be matched with farming policies stimulated by economic incentives.

6.2. Stage 1: Effect of policies

The effect of the farming policies has to be established and quantified. If there is controlled for the dimensions of genetics, gender, and growth phase, then the effects of a policy can be isolated. Required for this stage is to express every policy in a probability distribution over the carcass classes. The figure below shows how the policies are all influencing the carcass classes.

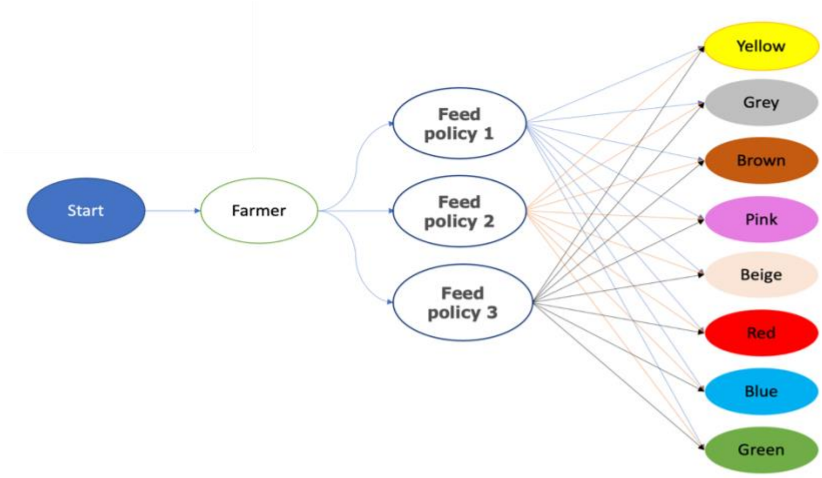


Figure 9. The effect of three feed policies on the carcass classes (own elaboration)

For this stage it is crucial to only consider relevant policies meaning that the policy should have an effect and a different effect then already existing policies have. If this is not preserved from stage 1, then the results from stage 2 and 3 will be biased.

6.3. Stage 2: Ability to meet demand

In order for the model to be truly demand driven, a future scenario will be assumed wherein the Sales department provides the demand distribution over the carcass classes. The demand distribution can be formulated in many different ways, for instance, the objective to serve as many customers as possible or to serve only the highest paying segments. Moreover, the demand will vary over time as was seen in chapter 3. The formulation of the demand distribution is out of scope of this thesis as a separate study should be dedicated towards it. Nonetheless, this stage of the model should be capable to function for every demand distribution offered as long as it can be expressed as a distribution over the carcass classes.

Given this demand distribution and the farming policy distributions of stage 1, the question arises: is Vion able to meet the demand if Vion Farming centrally controlled the farmers decisions? This stage is crucial because it enables communication between supply and demand. The outcome of this phase will be whether supply can match the demand. This is where the information flow changes from push to pull: from Vion Farming sharing upfront their expected supply and then sending it down the pipeline, to the Sales department sharing their demand distribution and Vion Farming steering its supply. If the outcome of this stage is that it is not possible to match supply and demand, then either there has to be expanded with more farming policies or Sales compromises needs to compromise their desires.

To not overcomplicate the model, it was decided to create a small optimization model, nonlinear programming, which minimalizes the least square difference between the desired demand and supplied distributions given the farming policies. This method is effective for matching and has its minimum at zero. The decision variables will be formulated as a ratio over the farming policies, indicating the fraction of farmers that should use a certain farmers policy in order for supply and demand to be optimally matched. The benefit for expressing it in ratio is because it will serve as input of the third stage. Finally, as some carcass classes are bigger than others there was decided to include a weight factor in this stage. This weight factor is a parameter per carcass class because the incentive in the next stage will be determined per carcass class as well. The function of this factor is to balance out the incentives if the size of a certain class gives undesired results. For instance, a really small carcass class could receive a really high incentive to balance out its size. However, a farmer will observe this very high incentive and decide to steer with its farming's techniques towards this class while it might not be desired to steer in that direction.

6.4. Stage 3: Appropriate incentive

Conceding that the previous stage concluded that demand and supply can be matched then this stage will proceed. The objective function of this stage is to minimize the costs of Vion such that the goal of increasing Vion's profitability can be achieved.

There was decided that the MNL technique would be most fitting for this proof of concept. This technique allows the distribution over the aggregated supply to be steered instead of per individual farmer while preserving the heterogeneity of the farmers.
As earlier stated only Vion in the supply chain can take the central coordinating role and has the ability to steer the aggregated supply, only Vion can coordinate the maximization of the supply chains profitability. However, the importance of farmers heterogeneity has been emphasized throughout this thesis report as well. The MNL model is often used in consumer choice modelling where it is relevant what the aggregated level of consumers wants even though every consumer is heterogenous (Hess, 2014).
The MNL method is a utility-based model. Every policy will have a utility function, this includes a deterministic part of cost and earnings per policy and a random utility part. The earnings are constructed from a perspective of a farmer choosing for a policy that maximizes its profitability. Resulting in the payment according to the weekly meat price per kg and the incentive per kg slaughter weight. The incentive can also be a cost when it is negative, resulting in a penalty. The incentive will be determined per carcass class. The random utility part is what preserves the farmers' heterogeneity and expresses the currently unknown factors that determine for a farmer which farming policy he/she chooses. This random part is assumed to Gumbel distributed.

A nice property of MNL is the formulation of probabilities over the alternatives in a closed form solution. These probabilities are determined by the utility function of the policies and thus by the incentives per carcass class. Stage 3 is an extension of stage 2 with the characteristic of the supply chain not being centrally organized. The probability over the policies based on the utility of the MNL model will be set equal to the optimal ratio over the policies according to stage 2. In this way, supply will be matched with demand to its supply chain optimum.

A farmer can only choose from the set of policies in the model and cannot decide not to choose. Due to this property the independence of irrelevant alternatives assumption has to be defended. Ensuring no irrelevant alternatives are included since every policy will be attributed some probability. This is secured by proving the relevance of a policy in stage 1.

Finally, the incentive has to be constrained with an upper and lower bound. Especially the lower bound is required as the minimization objective will push the decision variables to extreme penalties otherwise. If these bounds are not present, a 'fair' incentive will depend on chance rather than careful consideration.

There are some assumptions necessary for this stage to run the model. These assumptions simplify reality and future research should seek to relax these. They are listed as follows:

- Assumption 1. Policy world: all farmers can only operate the policies in set S and the only outcomes of distributions that are available are linked to the chosen farmings policy.
- Assumption 2. Same deterministic utilities: all farmers will have the same earnings and costs therefore their deterministic utilities are the same per farmer.
- Assumption 3. Farmers behavior: all farmers will maximize their utilities

7. Mathematical model

Sets
Set S with all the farming policies - $i\epsilon S$ *(i=1, 2, 3)*
Set CC with all the carcass classes - $j\epsilon CC$ *(j=1, ..., 10)*

Decision variables
x_i :Decision variable ratio of farming policy $i\epsilon S$
b_j :Decision variable incentive per kg slaughter weight for carcass class $j\epsilon CC$

Variables
u_i :Utility function for policy $i\epsilon S$
P_i :Probability of choosing policy $i\epsilon S$
ε_i :Random utility for policy $i\epsilon S$, Gumbel distributed

Parameters
c_i :Cost of policy $i\epsilon S$
DD_j :Fraction of demand distribution for carcass class $j\epsilon CC$
D_{ij} :Fraction of supply distribution for carcass class $j\epsilon CC$ when policy $i\epsilon S$ is applied
$E[w_{ij}]$:Expected slaughter weight for carcass class $j\epsilon CC$ as a result of policy $i\epsilon S$
r :Price per kg of slaughtered meat
w_j :Weight factor for carcass class $j\epsilon CC$
$lb,\ ub$:Lower-bound and upper-bound of incentive per kg

7.1. Model 1. Ability to match demand with centrally controlled supply

For a given desired demand distribution this model will calculate if supply can match the distribution. This will be determined based on the farming policy distributions. The objective of this model is to minimize the least squares between the demand and supply distribution summed over the number of carcass classes. Moreover, a weight factor is introduced which will serve as a parameter that can be set to correct for unequal sized classes.

$$Min \left\{ \sum_{j=1}^{|CC|} (DD_j - \sum_{i=1}^{|S|} w_j x_i D_{ij})^2 \right\} \qquad (1.1)$$

The demand distribution is input for the model, hence a demand-driven model, represented by the parameter DD_j. In addition, D_{ij} is derived from the supply distribution per i^{th} policy. Therefore, only decision variable x_i has to be constrained. The variable x_i is a ratio per i^{th} policy $i\epsilon S$ thus the sum over all x_i has to be constrained to 1, constraint 1.2. Moreover, x_i is given a nonnegativity constraint, constraint 1.3.

$$s.t. \qquad \sum_{i=1}^{|S|} x_i = 1 \qquad (1.2)$$

$$x_i \geq 0 \qquad (1.3)$$

7.2. Model 2. Incentive to match demand and decentral controlled supply

The objective function of the model of stage 3 is to minimize the total incentive paid per pig by Vion. The expenditure depends on the incentive per kg per carcass class and the slaughter weight. The slaughter weight is depended on the farming policy and the carcass class. In formula 2.1 is the objective function presented.

$$Min. \sum_{i=1}^{|S|} \sum_{j=1}^{|CC|} E[sw_{ij}]\, b_j D_{ij}\, x_i \qquad (2.1)$$

The first constraint 2.2 is the composition of the utility function which is subject to the decision variable, b_j the incentive per kg per j^{th} carcass class $j \epsilon CC$. This utility function represents the earnings, costs, and the unobserved utility for a farmer choosing the i^{th} policy. The earnings consist of a weekly meat price per kg and the incentive per kg per carcass class. As the incentive is paid per carcass class, the fraction of the distribution per class j is multiplied and there is summed over all the classes. The costs of the choosing farming policy will be included per kg as well. Finally, for heterogeneity the uncertainty variable, ε_i is introduced, representing the unobserved utility assumed to be Gumbel distributed.

$$u_i = \sum_{j=1}^{|CC|} E\left[sw_{ij}\right]\left[r + b_j - c_i\right] D_{ij} + \varepsilon_i \quad \forall\, i \epsilon S \quad (2.2)$$

Continuing, the second constraint is determining the variable P_i which is calculated based on Multinomial Logit model. It represents the probability of i^{th} policy chosen based on the utility function of 2.2. Constraint 2.3 assures that for every farming policy the probability is calculated. Every alternative is assigned a probability even though therefore it is important that the assumption of independence of irrelevant alternatives holds.

$$P_i = \frac{e^{u_i}}{\sum_{k \epsilon S} e^{u_k}} \qquad \forall\, i \epsilon S \quad (2.3)$$

In stage 2 the optimum ratio per farming policy x_i was found that minimized the difference between the supply and demand distributions. Setting this outcome as a constant for this stage links the decision variable of the incentive b_j to match supply and demand, see constraint 2.4.

$$P_i = x_i \qquad \forall\, i \epsilon S \quad (2.4)$$

Finally, the decision variable has to be constrained in order to conclude a fair incentive.

$$lb \leq b_j \leq ub \qquad \forall\, j \epsilon CC \quad (2.5)$$

8. Numerical experiments

This chapter will explore the model functionality by testing different scenarios while modifying the model.

Stage 1: Supply distribution based on farming policies

Isolating effect of feed policy

This proof of concept contains one quality control point namely feed composition (amino acid) quantified by the lysine experiment. Including multiple policies would surpass the requirement of the proof of concept which can be established with one quality control point. In addition, the feed composition (amino acid) was the most desired to test as in the practical field, among farmers, it is still debated whether changing lysine levels would have significant effects on carcass quality.

Within the lysine experiment a delivery strategy was used of two moments, a top-empty strategy. The delivery strategy is a separate quality control point therefore the effects of these control points should be isolated. This was performed by estimating the slaughter weight and backfat thickness for all pigs at the same age. There should be noted that this will be an estimation, especially considering that a growth rate has to be fitted. In addition, the piglets do not have the same age to start with because they are bought based on a start weight (25 kg). The experiment only provided measurement data of one point in time, the slaughter date, thus to determine a growth rate external data was required. In the paper of Schinkel et. al. (2002), data was presented of growth of pigs on two farms with two different collection methods. Per farm 240 barrows and 240 gilts were measured on carcass quality, these results were published in table 1 of their paper. Within the lysine experiment dataset, the median age was 164 days, the average was 165.5, the minimum 146 and the maximum 186 days. The paper of Schinkel et. al. (2002) was used to calculate 4 growth rates, from 146 to 165 days, from 167 to 190 days, for both barrows and gilts separately. These ages were selected because measurements were taken at intervals in the research by Schinkel et. al. (2002). In appendix J the growth rates are presented per available age for backfat thickness and slaughter weight. These growth rates were used to estimate the backfat thickness and slaughter weight of all the pigs of the experiment at age of 165 days. Then the carcass distribution could be recalculated as presented in table 4, for more detailed data see appendix J.

Feed policy	Black	Blue	Brown	Green	Grey	Orange	Pink	Red	White	Yellow
1	12.8%	9.4%	2.6%	9.4%	12.0%	3.4%	8.5%	0.9%	0.9%	40.2%
2	19.0%	2.6%	5.2%	7.8%	22.4%	3.4%	8.6%	3.4%	5.2%	22.4%
3	5.1%	12.1%	5.1%	10.1%	23.2%	6.1%	16.2%	3.0%	11.1%	8.1%

Table 4. Supply distribution of lysine experiment corrected to age=165 days (own elaboration)

Checking independence of irrelevant alternatives assumption

The MNL model as presented in this thesis has a given set of policies of which a farmer has to choose. There is no zero-option where a farmer chooses no farming policy. Thus, it is important that the alternatives included are relevant. The relevance of the chosen policies is partly defended in the literature of chapter 3 and the data analysis of chapter 5. However, table 4 can be used to show that the distribution over the carcass classes is different for every farming policy. In table 5 below, all policies are compared to each other, the absolute deviation is calculated and summed up.

Comparing policies	Black	Blue	Brown	Green	Grey	Orange	Pink	Red	White	Yellow	Sum of all
1 & 2	6.2%	6.8%	2.6%	1.6%	10.4%	0.0%	0.1%	2.5%	4.3%	17.8%	52.3%
1 & 3	7.7%	2.7%	2.5%	0.7%	11.2%	2.7%	7.7%	2.1%	10.2%	32.1%	79.6%
2 & 3	13.9%	9.5%	0.1%	2.3%	0.8%	2.7%	7.6%	0.4%	5.9%	14.3%	57.5%

Table 5. Absolute deviation between the policies from the outcomes of table 4 (own elaboration)

Demand scenarios

The current situation within Vion is working with a push strategy. As a result, there is not a determined demand distribution. To test the model several demand scenarios were developed. The scenarios were formed out of the earnings per kg per carcass class, which was an outcome of the PMC model. In table 6 the sequence of the carcass classes sorted on value per kg is shown. Brown being the lowest in value and red the highest in value per kg. Besides the earnings, the current supply distribution over the carcass classes of Vion was used as well to keep serving the current market segments. Below the explanation behind the calculation of the scenarios is presented as well as table 7 showing the probabilities per carcass class per scenario.

Brown<	White<	Green<	Yellow<	Pink<	Orange<	Blue<	Black<	Grey<	Red<

Table 6. Order of least to most earning carcass colors per kg from the PMC model (own elaboration)

Scenario 1 *"Gradual change 25%"*
For scenario 1, the two highest earning classes are increased with 25% of their original fraction of the distribution (GFB in 2021) and the two highest after that with 10%. Similar but opposite was done for the 4 lower classes. The result was almost but not exactly 100% thus the small rest was compensated with the biggest carcass class yellow.
Scenario 2 *"Gradual change 50%"*
Same method as 1 but then with 50% and 25%
Scenario 3 *"Gradual change 75%"*
Same as method 1 but then with 75% and 50%
Scenario 4 *"Extreme"*
The previous scenarios were all derived from the original supply distribution. Scenario 4 is designed completely based on the earnings per classes. The low earning classes 'white' and 'brown' were given a 0.5% share, which is not 0 because Vion does want to keep serving its markets.

	Red	Grey	Black	Blue	Orange	Pink	Yellow	Green	White	Brown
Scenario 1	3.3%	21.7%	15.7%	4.4%	1.4%	7.0%	35.4%	8.9%	1.1%	1.1%
Scenario 2	3.9%	26.1%	17.8%	5.0%	1.4%	7.0%	29.9%	7.4%	0.7%	0.7%
Scenario 3	4.6%	30.4%	21.4%	6.0%	1.4%	7.0%	23.5%	4.9%	0.4%	0.4%
Scenario 4	10.0%	25.0%	19.0%	13.0%	10.0%	10.0%	8.0%	5.0%	0.0%	0.0%

Table 7. Demand scenarios based on earnings per kg per carcass class (own elaboration)

Stage 2: Ability to meet demand

The outcome of the least square model of stage 2 will not be manipulated throughout the experiments. The model's simplicity will stay intact. The output of this stage, the ratio over the policies, will serve as input for stage 3. All scenarios lead to different ratios over the feed policies. In table 8 the results are shown, the least square column in the table refers to the outcome of the objective function, see formula 1.1. The output should be interpreted as follows, if the demand is equal to scenario 1, then the optimal match of supply and demand will be met if 55% of the farmers follow feed policy 1, 45% feed policy 2, and 0% feed policy 3.

	Feedpolicy 1	Feedpolicy 2	Feedpolicy 3	OFV Least squares
Scenario 1	55%	45%	0%	0.0058
Scenario 2	27%	73%	0%	0.0083
Scenario 3	0%	100%	0%	0.0145
Scenario 4	0%	50%	50%	0.0325

Table 8. Stage 2 ratio of policies per demand scenario (own elaboration) (OFV=objective function value)

There can be seen that the scenarios shift from a preference of policy 1 to policy 3. Moreover, the value of the objective function in the first scenarios are closer to 0 then in the last scenarios. Meaning the first demand scenarios can be matched better with the available farming policies. This is interesting to observe considering there are only three farming policies in which are almost able to meet the demand scenarios already. The independence of irrelevant alternatives assumption was strengthened with the outcome of table 4, showing different farmers' distributions per policy. Moreover, table 8 shows that these policy distributions are differentiating and relevant enough to match supply and demand for these scenarios.

Stage 3: Proof of concept, Incentive to match supply & demand

To understand the sensitivity and the limitations of the proof of concept model, this section will experiment with several conditions on modelling. First the model was run for all the carcass classes (|CC|=10) and all the feed policies (|S|=3). A lower and upper bound for the incentives was used of -0.5 and 0.5 respectively, the bounds are necessary to prevent extreme outcomes and the value of 0.5 is the maximum of the current payment table.

Scenario	OFV € paid per pig	Black	Blue	Brown	Green	Grey	Orange	Pink	Red	White	Yellow
1	- € 23.80	0.5	-0.5	-0.5	-0.5	-0.486	-0.5	-0.5	0.5	-0.5	-0.231
2	- € 25.84	0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	0.198	-0.5	-0.283
3	- € 26.48	0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	0.119	-0.5	-0.294
4	€ 5.46	0.5	-0.5	-0.5	-0.5	0.194	-0.5	-0.5	0.5	-0.5	0.289

Table 9. Results of the stage 3 model with its objective value and the incentives per kg per carcass class in euros, |CC|=10, |S|=3, lb=0.5, and ub=0.5 (own elaboration) (OFV= objective function value)

In table 9 the result of the run is presented per scenario. The value of the objective function minimizing the total incentive paid per pig is in the second column (OFV) followed by the incentive per kg per carcass class in euros. From the first scenario, two conclusions can be drawn. First, the objective function representing the payment per pig from Vion is negative, - € 23.80 on average paid per pig. Thus, the penalties exceed the incentives. The current bounds of the decision variables are not sufficient to come to a 'fair' incentive. Secondly there can be concluded that many of the variables barely change over the demand scenarios, e.g., blue, green, orange and pink remain the same. This can be the result of too many decision variables.
To come to a more acceptable balance between incentives and penalties, the bounds have to be adjusted. As most of the OFV's in table 9 are negative, the lower bound will be adjusted to determine per scenario an outcome where the payment per pig (OFV) would be considered a 'fair' incentive. Defining which incentive is 'fair' exceeds the goal of this research and should be accessed in future research. However, two requirements can be set to approach a fair incentive. Namely, incentives have to exceed the penalties to ensure farmers continuity, thus OFV has to be above 0. Moreover, the sum of incentives and penalties should be below of what can be earned with matching supply and demand for the continuity of Vion. This is currently hard to estimate as the demand is not known yet. However, other price models can be used as verification of the value per carcass class. Comparing the lowest to highest earning carcass class was at a certain point in time an estimated difference of 0.15 euro per kg, with an average over all the classes of 0.09 euro per kg. An average pig weighs approximately 100 kg thus the incentive paid by Vion should be below 9 euros. Through trial and error, the bounds were further adjusted where some runs did not provide solutions. In table 10 below the results of some runs are shown. See appendix K for the more detailed outcome of this analysis.

Scenario	OFV € paid per pig	LB	UB
1	€ 0.41	-0.200	0.500
2	€ 3.80	-0.175	0.500
3	€ 1.45	-0.420	0.500
4	€ 2.40	-0.200	0.500

Table 10. Results of adjusting the upper and lower bound to an objective value approximating zero, |CC|=10, |S|=3, and ub=0.5 (own elaboration) (OFV= objective function value)

It can be concluded that the model is capable of calculating a reasonable outcome per scenario. If Vion Sales would provide a probability per demand scenario, then the most suited bounds can be calculated. Observing the incentives per carcass class still shows that the majority of the variables are equal to the lower bound. So not every incentive on a carcass class contributes to steering supply. To control for this, three different combinations of carcass classes were tested, based on: MAD, the position in the carcass matrix, and the grouping of effects of policies. First the MAD per carcass class over the policies was calculated. Reasoning the following, if only a limited number of policies are available then the carcass classes with the highest deviation determine the outcome. The classes with the highest MAD are also the biggest classes meaning their impact is higher. The results are shown in table 11 below.

Scenario	OFV € paid per pig	LB	UB	Black	Grey	Yellow
1	€ 2.50	-0.60	1.05	0.875	-0.600	-0.047
2	€ 0.34	-0.69	1.20	0.988	-0.690	-0.129
3	€ 1.33	-0.65	2.00	1.588	-0.650	-0.650
4	€ 0.22	-0.50	0.50	0.476	0.089	-0.500

Table 11. Results of restricting the decision variables, CC= {black, grey, yellow}; |S|=3; ub and lb are adjusted to objective around 0 (own elaboration)

The upper and lower bound were both adjusted in this analysis because if the variables do not have enough freedom, then supply and demand cannot be matched. Still the variables gave acceptable solutions with these three classes. Other combinations of classes were experimented as well, like the four corners of the carcass class matrix. However, these only functioned with a (very) high upper bound providing undesired incentives. In addition, another combination was evaluated which was based on the effect of the policies on the carcass class, for instance yellow would increase per policy, black similarly, while grey and pink decrease per policy. These classes were grouped depending on the direction of the effect of a policy on the carcass class. The classes with the biggest size in their group were selected resulting in the following three classes, black, green, and yellow. The result of running the model is presented in table 12 below for an upper and lower bound of 0.5 and -0.5 eurocents per kg per carcass class.

	OFV € paid per pig	Black	Green	Yellow
Scenario 1	€ 2.10	-0.5	-0.171	0.310
Scenario 2	€ 4.23	-0.5	-0.209	0.428
Scenario 3	€ 2.60	-0.5	-0.192	0.375
Scenario 4	€ 0.81	-0.5	-0.172	0.315

Table 12. Results of restricting the decision variables to black, green and yellow, objective value and the incentives per kg per carcass class in euros, |CC|=3, |S|=3, ub=1, lb=-1 (own elaboration)

Carcass classes have different sizes which effects the size of the incentive given. To correct for this size difference, the weight factor was included in stage 2 which has to be set manually. As an experiment the weight factor for carcass class 'black' was set on 1.5 to have approximately equally sized classes and the same run was repeated as table 11, using the same bounds as well. Outcomes of stage 3 can be seen in table 13, the outcome of stage 2 is shown in appendix K.

Scenario	OFV € paid per pig	Black (w=1.5)	Grey	Yellow
1	- € 13.75	0.217	-0.600	-0.217
2	- € 16.60	0.321	-0.690	-0.301
3	- € 15.47	0.412	-0.650	-0.358
4	- € 0.13	0.450	0.084	-0.500

Table 13. Results of using weight factor same parameters as table 11, CC={black, grey, yellow}; |S|=3; lb and ub see table 11 (own elaboration)

Comparing the incentives of table 12 to table 13 shows that the class grey has approximately the same incentives. However, for yellow and black the incentives changed, for black they all decreased which is logical considering the effect of the weight factor on the model. The overall solution decreased quite a bit. So, the weight factor is a suited tool to correct for size, results should be carefully considered though.
So far, the model bounds were manipulated, the decision variables restricted, and a weight factor was used. Now the input will be changed to indicate its relevance.
First off, the policy world assumption results in a simplified view of reality. To show the consequences, one policy, policy 3, was taken out of the equation. See table 14 for the results with |CC|=10 and S= {1,2} only for scenario 1, 2 and 3.

Scenario	OFV € paid per pig (|S|=3)	Min. paid per pig (|S|=2)
1	- € 27.26	- € 47.24
2	- € 27.20	- € 49.01
3	- € 10.66	- € 29.46
4	- € 30.07	

Table 14. Results of restricting the policies with all the decision variables, |CC|=10; S= {1,2}; ub=0.5, and lb=0.5 (own elaboration)

The outcomes completely differ and give the wrong interpretation of reality. This shows that to have accurate and thus effective incentives, sufficient policies have to be included.
Finally, sensitivity towards the parameters was tested, the overall pig price was increased and decreased having quite an effect on the incentives and the objective value, see appendix K. First it can be concluded for future results the pig price per kg should be accurate to come to the right incentives. Secondly, if the pig price increases due to competition or increased costs, then the incentives can be recalculated to maintain the match between supply and demand. As a result, the pork chain will be more robust to market influences.

Conclusion

The upper and lower bounds are necessary, they determine the objective value and prevent extreme incentives. Moreover, the number of decision variables can be restricted for more stability. The carcass classes chosen for this need to motivate the desired management from the farmer. Before this can be implemented, more policies need to be added to capture the set of actions a farmer can take. Weight factors can be used to compensate for the size differences of some classes. Finally, the change in market prices does influence the utility per farmer and thus the calculated incentives. The model requires accurate data input to have the best performance. However, this makes the model an adaptable tool suitable for a robust supply chain.

9. Discussion & conclusion

The research goal was stated as: transitioning to a hybrid supply chain (becoming more pull) by designing a mathematical model such that supply is matched with demand in order for Vion to increase its profitability and reduce waste in the chain. The result of this study was a proof of concept for demand driven supply through farming techniques on carcass quality control points. This chapter will start by briefly reviewing the research questions. Afterwards the link with academic literature will be discussed. Finally, this chapter will end with listing the shortcomings from this research and recommending future research.

9.1. Answering research questions

1) What defines the market for GFB?

The market of the international concept GFB is supplied with a 'push' or supply driven mindset. The Sales department forecasts their sales for the coming period based on expected supply, then contracts are made with customers. Therefore, not much is known regarding the market demand. The forecasted supply compared to the actual is always subject to variability and uncertainty effecting the mismatch between supply and demand. Besides the supply driven mindset, the characteristic of one-to-many production complicates matters more. Namely, from one pig 1200 SKU's can be made varying over the international market. Newly developed models within Vion calculate the highest value over all the articles, based on this it can recommend slaughter patterns and produce higher earning articles. These models can also be used as a tool to translate the market demand to a value per carcass class.

2) What has to be influenced in the supply process to control quality?

A theory-driven approach was taken to identify quality control points. The following six quality control point were found in the literature that control carcass quality: genetics, gender, feedschedule, feedcomposition (energy), feedcomposition (amino acid), and delivery strategy. Genetics, gender, and feedschedule are rather dimensions and moments in time then actual control variables. Nonetheless the dimensions are affecting the carcass quality. Other influences like pig and piglet health were excluded since they are conditions rather than steering techniques. If the demand changes it will still not require anything other than good overall health. Further on, an outline was given of the finances of a farmer showing that managing costs and earnings is crucial. The current payment table seems to be hindering the match between supply and demand as it is too wide. Farmers let cost prices determine their production output because their revenues are not affected by that. Therefore, the payment table should steer to a desired outcome rather than to be too broad.

3) What will be the input of the model?

Process and data analysis indicated that a good metric to match supply and demand is the distribution over the carcass classes. Carcass classes are assigned to a carcass based on carcass quality measurements (slaughter weight and backfat thickness). These classes were created by Production to organize the flow of product through the facility to the most efficient articles and markets. A farmer delivers multiple pigs, per farmer the probability of a certain carcass class can be calculated and a distribution over the carcass classes derived. When the distribution per farmer was analyzed per year, it was found that the deviation for the majority of farmers was below 5% on average over the years 2018, 2019, 2020, and 2021, indicating a suitable metric. Aggregating over all these farmers will result in a distribution over the carcass classes for the whole supply of Vion. This supply distribution has to be matched with a demand distribution.
Moreover, the data analysis showed when comparing farmer's supply distributions that farmers are heterogeneous. This had to be carefully considered when designing the model since preserving the differences within the supply flow is important to keep serving all market segments.
Further regarding the input of the model, this proof of concept only required one quality control point. Namely a feed experiment where the first restricting amino acid, lysine, was lowered over three feeds. The three different feeds were given to groups of pigs in the last growth phase, approximately 5 weeks

before slaughter. The slaughter results were compared, and a one-way ANOVA analysis was run (n=332, F= 4.6873, p-value= 0.0098).
Finally, the model should consider that Vion is a cooperative and farmers make their own management decisions. If Vion wants farmers to change their way of operating, Vion should incentivize the farmers to do that.

4) *What model connects the available input and desired output?*

Modelling occurred in three stages, first establishing if a supply distribution over the carcass classes can be influenced with farming techniques referred to as policies. Then assessing the ability to match the supply distribution with the demand distribution given these policy distributions. Finally, a model was required that takes the financial aspects of a farmer and Vion in consideration. A literature study supported the modelling decision for the last stage which was a utility based multinomial logit model in a LP with the objective to minimize the total incentive paid by Vion while the utility was formulated based on the profit of a farmer. The MNL model preserves the heterogeneity among farmers and their behaviors (Hess, 2014). In addition, the model provides a nice solution to express the probability of choosing a policy based on a farmer's utility. There were some assumptions necessary for the model. Assumption 1, policy world: all farmers can only operate the policies in set S and the only outcomes of distributions that are available are linked to the chosen feed policy. Assumption 2, same deterministic utilities: all farmers will have the same earnings and costs therefore their deterministic utilities are the same. Assumption 3, farmers behavior: all farmers will maximize their utilities. Moreover, because of the use of the multi nominal logit model another assumption has to be made, the independence of irrelevant alternatives, stating that any policy added to the set of farming policies (S) will decrease all other policies likelihood by an equal fraction.
The desired output is to prove that demand can be matched with supply and a tool of how this can be accomplished.

5) *What is the performance of the model?*

The model in stage 1, shifting the distribution over the quality distributions exceeded expectations and showed that through farming techniques the quality can be influenced significantly even in the last 5 weeks before slaughter. The model in stage 2 showed that demand and supply can be matched with the difference between them approaching 0 even when only three farming policies are considered. The last model indicated that fair incentives can be formulated that match supply and demand. The optimal incentives changed over the demand scenarios and are sensitive to an upper and lower bound posed on the incentive. The method of establishing the upper and lower bound was done by first setting the bounds to the extremes of the current payment table, so taking the highest incentive and penalty currently used. Then with trial and error the bounds were adjusted to resulted into acceptable bounds rather than optimal. Nonetheless, the method was sufficient to meet the objective of establishing a 'fair' incentive. A fair incentive should meet the following requirements: the incentives should exceed the penalties per farming policy thus the objective value of the model has to be above 0, and the incentives should not exceed the probable earnings for Vion in order for the supply chain to profit which is estimated to be on 9 euros for this research.
The model of stage 3 was initially set on 10 decision variables but could be reduced to less. However, the choice of these variables has to be carefully considered. In the future when more policies are added then the carcass classes have to be selected that steer to the desired farmer's behavior. Currently this decision is influenced by the effect of the limited available policies. Moreover, a sensitivity analysis of the parameters found that if pig prices increase or decrease it has an effect on the incentives thus incentives should be determined regularly to be responsive to market changes. Finally, the model is sensitive to the size of carcass classes; if a lot of pigs supplied are in one class, then putting incentives or penalties on this class will have a greater effect then the smaller classes. There can be corrected for this manually with a weight factor, nonetheless, if the weight factor is used then results should be interpreted carefully.

6) *What extensions are recommended for future research?*

As this is a proof of concept, future research is required for continuity. Based on the promising results of the model the policies should be extended over all the quality control points, namely delivery strategy and feed composition. This would lead to assumption 1, policy world being less restricting since set S is reflecting reality more. Similarly, more data has to be gathered on the effect on different genetics and genders. This can either be accomplished with blockchain technology gathering big data or more controlled experiments like executed within this research. Continuing, the farmers situation and behavior has to be researched such that utility functions can be formulated accordingly, relaxing assumption 2 and 3. Finally, Vion Sales has to develop their desired demand distribution, they could calculate demand scenarios and give these a certain probability of occurring. If then the ideal incentives and variable bounds are calculated per scenario and multiplied by the probability of occurring, the matching of demand and supply can be organized on an aggregated level. After this, future research should explore on a farmer's individual level, which policy should he/she use considering the new incentives.

9.2. Discussion & recommendations

Literature

A literature gap was identified within the analysed literature on modelling QCL and matching of supply and demand. To fulfill the research gap and to facilitate the research of the thesis, a model was required focusing on heterogeneity, pork quality and the market, from a demand-driven perspective in the role of a farmer's cooperation. The model should convert the demand from customer segments to quality characteristics. Matching these characteristics to the attributes steering the pork quality while including its uncertainties from the pig production for groups of pigs (Den Ouden et al. 1997; Macheka, 2018; Plà-Aragonés et al., 2013; Rijpkema et al., 2010, 2016). As a result, the supply side of the pork chain can align itself to the customer demand (Den Ouden et al., 1996). This all should result into maximization of profit and reduction of waste (Grunert et al., 2004; Rijpkema, 2014, 2016; Rong et al. 2011). Literature did include a model steering with a distribution over the carcass classes based on carcass quality (Rijpkema et al, 2010). Only this model was focused on allocation of farmers to production locations. Moreover, the model closest to this study was Niemi (2006) who published a dynamic programming model including the growth model of pigs and genotype as constraint for optimizing feeding and slaughter decisions regarding fattening pigs. The major contribution this thesis provided was making these decisions from the perspective of the farmers' cooperative increasing performance through the whole supply chain. While Niemi (2006) focused on the profit of the fattening farm, proposing the mechanisms of exploring the payment bounds rather than steering with it. A model setting incentives and penalties for pig farmers was researched however it was focused on controlling Mycobacterium avium infections (van Wagenberg et al. 2013). Thus, this thesis makes a valuable contribution to the QCL literature and farming models.

Limitations

The proof of concept only had one quantified quality control point, feed composition (amino acid) through the lysine experiment. Quantifying lysine in the final growth phase was the most desired quality control point to research. Because the delivery strategy is more know, similarly for EW since farmers already use these techniques. The reduction in lysine for more backfat is known with feed companies but informal interviews showed it was not known by every farmer. In addition, changing the feed in only the last growth phase shows that supply and demand can still be matched in the last 5 weeks, something that was heavily debated in the past at Vion. Nonetheless, the other genders, genetics and feed phases still have to be measured for the delivery and feed strategy in order to have a complete model that reflects reality. In the sensitivity analysis excluding one policy indicated that not having all the policies gives an inaccurate result. Moreover, the lysine experiment was conducted in one trimester of the year, meaning that it is affected by seasonality and future research should explore other seasons as well. Continuing, this research has to be extended with more information on farmers behaviour and their utilities. For this thesis the earnings and costs were generalized to a deterministic utility while the model captures some random utility for a farmer choosing a policy. Having insight in the farmers utility will create more understanding of the mechanisms steering supply and demand.

Finally, the last limitation that should be considered is the further implementation of the incentives and penalties. This thesis showed that theoretically, supply and demand will be matched with incentives on all or some carcass classes. If the policies would be extended as recommended and farmers behaviour would be explored, then research should map the expected effects of the new incentives. The following questions should be reviewed, will the incentives be per carcass class or remain on slaughter weight and backfat thickness? Which time horizon fits the incentive system best? Incentives on which classes will affect other classes or farmer's behaviour?

Recommendations

Future research has been explored in the research question but to summarize there has to be extended on the policies in terms of genetics, genders, feed phases, seasonality, and more quality control points. More research has to be collected on farmers behaviour and utility. All this supply-based research has been planned to either be continued by the PORQSAT project or by Vion Farming. The development of the demand distribution has been planned as well by the S&OP and Sales department of Vion. Parallel to these researches, it is recommended to research the matching of supply and demand on a farmer's individual level. This would require data on the initial conditions at the farm in terms of genetics, feed, etc. Fortunately, a blockchain is in development that will collect the farming data for GFB. In 2020 this was enrolled for GFS, Vion is still exploring which data is valuable to collect. This thesis contributed to that process, enabling quality control points to be collected on a broader scale. Finally, a 'fair' incentive has to be determined where all parties agree upon and that is expected to increase supply chain profit in the most likely scenarios.

All in all, this thesis provided a proof of concept of matching supply and demand from Vion Farming. The first tool to produce demand driven in pig production from a farmer's cooperative perspective.

Bibliography

Adzitey, F. (2011). Effect of pre-slaughter animal handling on carcass and meat quality. International Food Research Journal, 18 (2).

Akkerman, R., Farahani, P., & Grunow, M. (2010). Quality, safety and sustainability in food distribution: a review of quantitative operations management approaches and challenges. OR spectrum, 32 (4), 863–904.

Alagoz, O., Hsu, H., Schaefer, A. J., & Roberts, M. S. (2010). Markov decision processes: a tool for sequential decision making under uncertainty. Medical Decision Making, 30 (4), 474-483.

Albornoz, V. M., González-Araya, M. C., Gripe, M. C., & Rodríguez, S. V. (2015). A mixed integer linear program for operational planning in a meat packing plant. In Icores (pp. 254–261).

Alho, E. (2015). Farmers' self-reported value of cooperative membership: evidence from heterogeneous business and organization structures. Agricultural and Food Economics, 3 (1), 1–22.

Anderson, S. P., De Palma, A., & Thisse, J.-F. (1988). A representative consumer theory of the logit model. International Economic Review, 461–466.

Beal, L., Hill, D., Martin, R., & Hedengren, J. (2018). Gekko optimization suite. Processes, 6 (8),106. doi:10.3390/pr6080106

Beaulieu, A., Aalhus, J., Williams, N., & Patience, J. (2010). Impact of piglet birth weight, birth order, and litter size on subsequent growth performance, carcass quality, muscle composition, and eating quality of pork. Journal of animal science, 88 (8), 2767–2778.

Bellman, R. (1957). A markovian decision process. Journal of mathematics and mechanics, 679–684.

Benseman, B. (1986). Production planning in the new zealand dairy industry. Journal of the Operational Research Society, 37 (8), 747–754.

Berntsen (ABN-AMRO), P. (2022). Het varken als het ultieme kringloopdier. Retrieved from https://www.abnamro.nl/nl/media/het-varken-als-het-ultieme-kringloopdier_tcm16-141286.pdf

Beuchel, M., & Veldman (Rabobank), R. (2021). Varkenshouderij: keuzes maken wordt belangrijker dan ooit. Retrieved from https://www.rabobank.nl/kennis/d011126020-varkenshouderij-keuzes-maken-wordt-belangrijker-dan-ooit

Bijman, J., Iliopoulos, C., Poppe, K. J., Gijselinckx, C., Hagedorn, K., Hanisch, M., . . . others (2012). Support for farmers' cooperatives (Tech. Rep.). Wageningen UR.

BioNext. (2018). Bionext trendrapport 2017: Ontwikkeling biologische landbouw en voeding nederland. Retrieved from https://bionext.nl/application/files/4115/6579/2244/ Bionext_trendrapport_2017.pdf

Bizzotto, R., Zamuner, S., Mezzalana, E., De Nicolao, G., Gomeni, R., Hooker, A. C., & Karlsson, M. O. (2011). Multinomial logistic functions in markov chain models of sleep architecture: internal and external validation and covariate analysis. The AAPS journal, 13 (3), 445–463.

Blavi, L., Solà-Oriol, D., Llonch, P., López-Vergé, S., Martín-Orúe, S. M., & Pérez, J. F. (2021). Management and feeding strategies in early life to increase piglet performance and welfare around weaning: A review. Animals, 11 (2), 302.

Boltz, F., & Carter, D. R. (2006). Multinomial logit estimation of a matrix growth model for tropical dry forests of eastern bolivia. Canadian Journal of Forest Research, 36 (10), 2623–2632.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the national academy of sciences, 99 (suppl_3), 7280–7287.

Bonney, M., Zhang, Z., Head, M., Tien, C., & Barson, R. (1999). Are push and pull systems really so different? International journal of production economics, 59 (1-3), 53–64.

Clark, J., & Kumar, S. (1978). Planning beef production: An application of dynamic programming. Review of Marketing and agricultural Economics, 46 (430-2016-31700), 315–326.

Den Ouden, M. (1996). Economic modelling of pork production-marketing chains. Wageningen University and Research

Den Ouden, M., Dijkhuizen, A. A., Huirne, R. B., & Zuurbier, P. J. (1996). Vertical cooperation in agricultural production-marketing chains, with special reference to product differentiation in pork. Agribusiness: An international journal, 12 (3), 277–290.

Den Ouden, M., Huirne, R., Dijkhuizen, A., & Van Beek, P. (1997). Economic optimization of pork production-marketing chains. ii. modelling outcome. Livestock Production Science, 48 (1), 39–50.

Feng, L., Li, B., Podobnik, B., Preis, T., & Stanley, H. E. (2012). Linking agent-based models and stochastic models of financial markets. Proceedings of the National Academy of Sciences, 109 (22), 8388–8393.

Ferguson, N., et al. (2006). Basic concepts describing animal growth and feed intake. Mechanistic modelling in pig and poultry production, 22–53.

Fix, J., Cassady, J., Holl, J., Herring, W., Culbertson, M., & See, M. (2010). Effect of piglet birth weight on survival and quality of commercial market swine. Livestock Science, 132 (1-3), 98–106.

Fornós, M., Sanz-Fernández, S., Jiménez-Moreno, E., Carrión, D., Gasa, J., & Rodríguez-Estévez, V. (2022). The feeding behaviour habits of growing-finishing pigs and its effects on growth performance and carcass quality: A review. Animals, 12 (9), 1128.

Georgeff, M., Pell, B., Pollack, M., Tambe, M., & Wooldridge, M. (1998). The belief-desire-intention model of agency. In International workshop on agent theories, architectures, and languages (pp. 1–10).

Gispert, M., i Furnols, M. F., Gil, M., Velarde, A., Diestre, A., Carrión, D., . . . Plastow, G. (2007). Relationships between carcass quality parameters and genetic types. Meat science, 77 (3), 397–404.

Glen, J. (1983). A dynamic programming model for pig production. Journal of the Operational Research Society, 34 (6), 511–519.

Gondret, F., Lefaucheur, L., Louveau, I., & Lebret, B. (2005). The long-term influences of birth weight on muscle characteristics and eating meat quality in pigs individually reared and fed during fattening. Arch Tierz Dummerstorf , 48 , 68–73.

Goyal, S. K., & Giri, B. C. (2001). Recent trends in modeling of deteriorating inventory. European Journal of operational research, 134 (1), 1–16.

Grunert, K. G., Bredahl, L., & Brunsø, K. (2004). Consumer perception of meat quality and implications for product development in the meat sector—a review. Meat science, 66 (2), 259–272.

Guevarra, R. B., Lee, J. H., Lee, S. H., Seok, M.-J., Kim, D. W., Kang, B. N., . . . Kim, H. B. (2019). Piglet gut microbial shifts early in life: causes and effects. Journal of animal science and biotechnology, 10 (1), 1–10.

Heising, J. K., Claassen, G., & Dekker, M. (2017). Options for reducing food waste by quality-controlled logistics using intelligent packaging along the supply chain. Food Additives & Contaminants: Part A, 34 (10), 1672–1680.

Heo, S., Yang, Y., Jin, Z., Park, M., Yang, B., & Chae, B. (2008). Effects of dietary energy and lysine intake during late gestation and lactation on blood metabolites, hormones, milk compositions and reproductive performance in primiparous sows. Canadian Journal of Animal Science, 88 (2), 247–255.

Hess, S. (2014). Latent class structures: taste heterogeneity and beyond. In Handbook of choice modelling. Edward Elgar Publishing.

Heyer, A., Andersson, H., Lindberg, J., & Lundström, K. (2004). Effect of extra maternal feed supply in early gestation on sow and piglet performance and production and meat quality of growing/finishing pigs. Acta Agriculturae Scandinavica, A, 54 (1), 44–55.

Hyun, Y., Kim, J., Ellis, M., Peterson, B., Baker, D., & McKeith, F. (2007). Effect of dietary leucine and lysine levels on intramuscular fat content in finishing pigs. Canadian journal of animal science, 87 (3), 303–306

ING. (2012). Food 2030: Samenwerking vanuit een nieuwe mindset. Retrieved From https://www.ing.nl/media/ING_EBZ_Food_2030_Samenwerking_vanuit_een_nieuwe_mindset_tcm162-52911.pdf

Ivert, L. K., Dukovska-Popovska, I., Fredriksson, A., Dreyer, H. C., & Kaipia, R. (2015). Contingency between s & op design and planning environment. International Journal of Physical Distribution & Logistics Management.

Jaturasitha, S., Kamopas, S., Suppadit, T., Khiaosa-Ard, R., & Kreuzer, M. (2006). The effect of gender of finishing pigs slaughtered at 110 kilograms on performance, and carcass and meat quality. Science Asia, 32 (3), 297–305.

Kempster, A. (1989). Carcass and meat quality research to meet market needs. Animal Science, 48 (3), 483–496.
Khanal, P., Maltecca, C., Schwab, C., Gray, K., & Tiezzi, F. (2019). Genetic parameters of meat quality, carcass composition, and growth traits in commercial swine. Journal of animal science, 97 (9), 3669–3683.
Kim, G.-W. (2012). Analysis of carcass quality grades according to gender, backfat thickness and carcass weight in pigs. Journal of Animal Science and Technology, 54 (1), 29–33.
Kure, H. (1997). Optimal slaughter pig marketing. In Dutch/danish symposium on animal health and management economics (pp. 39–47).
Kutner, M. H., Nachtsheim, C. J., Neter, J., and Li, W. (2004). Applied linear statistical models (5th). New York, NY: McGraw-Hill Irwin.
Kyriazakis, I., & Whittemore, C. T. (2006). Whittemore's science and practice of pig production. John Wiley & Sons.
Lanferdini, E., Andretta, I., Fonseca, L., Moreira, R., Cantarelli, V., Ferreira, R., . . . Abreu, M. (2018). Piglet birth weight, subsequent performance, carcass traits and pork quality: A meta-analytical study. Livestock Science, 214 , 175–179.
Latorre, M., Lázaro, R., Valencia, D., Medel, P., & Mateos, G. (2004). The effects of gender and slaughter weight on the growth performance, carcass traits, and meat quality characteristics of heavy pigs. Journal of animal science, 82 (2), 526–533.
Latorre, M., Medel, P., Fuentetaja, A., Lázaro, R., & Mateos, G. (2003). Effect of gender, terminal sire line and age at slaughter on performance, carcass characteristics and meat quality of heavy pigs. Animal Science, 77 (1), 33–45.
Leen, F., Van den Broeke, A., Aluwé, M., Lauwers, L., Millet, S., & Van Meensel, J. (2017). Optimising finishing pig delivery weight: participatory decision problem analysis. Animal Production Science, 58 (6), 1141–1152.
Le Roy, P., Naveau, J., Elsen, J. M., & Sellier, P. (1990). Evidence for a new major gene influencing meat quality in pigs. Genetics Research, 55 (1), 33–40.
Liao, S. F., Wang, T., & Regmi, N. (2015). Lysine nutrition in swine and the related monogastric animals: muscle protein biosynthesis and beyond. SpringerPlus, 4 (1), 1–12.
Luning, P., Bango, L., Kussaga, J., Rovira, J., & Marcelis, W. (2008). Comprehensive analysis and differentiated assessment of food safety control systems: a diagnostic instrument. Trends in Food Science & Technology, 19 (10), 522–534.
Macheka, L. (2018). Understanding the influence of context characteristics, logistics control and quality control on postharvest losses: a case of zimbabwean tomato supply chains (Unpublished doctoral dissertation). Wageningen University and Research.
Macheka, L., Spelt, E., van der Vorst, J. G., & Luning, P. A. (2017). Exploration of logistics and quality control activities in view of context characteristics and postharvest losses in fresh produce chains: A case study for tomatoes. Food Control, 77 , 221–234.
Martin-Collado, D., Byrne, T., Amer, P., Santos, B., Axford, M., & Pryce, J. (2015). Analyzing the heterogeneity of farmers' preferences for improvements in dairy cow traits using farmer typologies. Journal of dairy science, 98 (6), 4148–4161.
Melese, Z. T. (2022). Enhancing pig health and welfare using data-driven approach.
Melnyk, S. A., Davis, E. W., Spekman, R. E., & Sandor, J. (2010). Outcome-driven supply chains. MIT Sloan Management Review, 51 (2), 33.
Miar, Y., Plastow, G., Moore, S., Manafiazar, G., Charagu, P., Kemp, R., . . . others (2014). Genetic and phenotypic parameters for carcass and meat quality traits in commercial crossbred pigs. Journal of Animal Science, 92 (7), 2869–2884.
Miclo, R., Lauras, M., Fontanili, F., Lamothe, J., & Melnyk, S. A. (2019). Demand driven mrp: assessment of a new approach to materials management. International Journal of Production Research, 57 (1), 166–181.
Mohammed, A., & Wang, Q. (2017). The fuzzy multi-objective distribution planner for a green meat supply chain. International Journal of Production Economics, 184 , 47–58.
Nahmias, S. (1982). Perishable inventory theory: A review. Operations research, 30 (4), 680–708.
Niemi, J. K. (2006). A dynamic programming model for optimising feeding and slaughter decisions regarding fattening pigs. MTT Agrifood Research Finland.

Niemi, J. K., Liu, X., & Pietola, K. (2011). Price volatility and return on pig fattening under different price-quantity contract regimes (Tech. Rep.).
Noblet, J., & Van Milgen, J. (2004). Energy value of pig feeds: Effect of pig body weight and energy evaluation system. Journal of Animal Science, 82 (suppl_13), E229–E238.
Nowak, P., Zaworska-Zakrzewska, A., Frankiewicz, A., & Kasprowicz-Potocka, M. (2021). The effects and mechanisms of acids on the health of piglets and weaners–a review. Annals of Animal Science, 21 (2), 433–455.
Ohlmann, J. W., & Jones, P. C. (2011). An integer programming model for optimal pork marketing. Annals of Operations Research, 190 (1), 271–287.
Ollila, P. (1994). Farmers'cooperatives as market coordinating institutions. Annals of Public and Cooperative Economics, 65 (1), 81–102.
Ott, R. L., and Longnecker, M. (2010). An introduction to statistical methods and data analysis. Belmon, CA: Brooks/Cole.
Perez, C., de Castro, R., & i Furnols, M. F. (2009). The pork industry: a supply chain perspective. British Food Journal.
Piewthongngam, K., Vijitnopparat, P., Pathumnakul, S., Chumpatong, S., & Duangjinda, M. (2014). System dynamics modelling of an integrated pig production supply chain. Biosystems Engineering, 127 , 24–40.
Plà-Aragonés, L. M., Rodríguez-Sánchez, S. V., & Rebillas-Loredo, V. (2013). A mixed integer linear programming model for optimal delivery of fattened pigs to the abattoir. J. Appl. Oper. Res, 5 , 164–175.
Pourmoayed, R., Nielsen, L. R., & Kristensen, A. R. (2016). A hierarchical markov decision process modeling feeding and marketing decisions of growing pigs. European Journal of Operational Research, 250 (3), 925–938.
Preferent KI. (2021). Onze beren preferentki. Retrieved from https://preferentki.com/onze-beren/
Raafat, F. (1991). Survey of literature on continuously deteriorating inventory models. Journal of the Operational Research society, 42 (1), 27–37.
Rabobank. (2022). Pig farming in the netherlands: from added costs to added value. Retrieved from https://www.rabobank.com/en/about-rabobank/background-stories/food-agribusiness/nederlandse-varkenshouderij-van-meer-kosten-naar-meerwaarde.html
Rekiel, A., Więcek, J., Batorska, M., & Kulisiewicz, J. (2015). Effect of piglet birth weight on carcass muscle and fat content and pork quality–a review. Annals of Animal Science, 15 (2), 271–287.
Reynisdóttir, K. (2012). Linear optimization model that maximizes the value of pork products (Unpublished doctoral dissertation).
Richetin, J., Sengupta, A., Perugini, M., Adjali, I., Hurling, R., Greetham, D., & Spence, M. (2010). A micro-level simulation for the prediction of intention and behavior. Cognitive Systems Research, 11 (2), 181–193.
Rijpkema, W. (2010). Logistics modelling of pork supply chains; application of quality-controlled logistics for sustainable development.
Rijpkema, W. A. (2014). Effective use of product quality information in food supply chain logistics. Wageningen University and Research.
Rijpkema, W. A., Hendrix, E. M., & Rossi, R. (2015). Bi-criterion procedures to support logistics decision making: cost and uncertainty. Journal of the Operational Research Society, 66 (12), 2086–2091
Rijpkema, W. A., Hendrix, E. M., Rossi, R., & van der Vorst, J. G. (2016). Application of stochastic programming to reduce uncertainty in quality-based supply planning of slaughterhouses. Annals of Operations Research, 239 (2), 613–624.
Rijpkema, W. A., Rossi, R., & van der Vorst, J. G. (2010). Use of livestock quality estimates for improved allocation planning of meat processors.
Rosner, B. (2015). Fundamentals of Biostatistics (8th). Boston, MA: Cengage Learning.
Rong, A., Akkerman, R., & Grunow, M. (2011). An optimization approach for managing fresh food quality throughout the supply chain. International Journal of Production Economics, 131 (1), 421–429.
Schouten, R., Van Kooten, O., van der Vorst, J., Marcelis, W., & Luning, P. (2010). Quality controlled logistics in vegetable supply chain networks: how can an individual batch reach an individual

consumer in the optimal state? In Xxviii international horticultural congress on science and horticulture for people (ihc2010): International symposium on 936 (pp. 45–52).
Shahbandeh, M. (2021, Apr). Production of pork worldwide, 2021. Retrieved from https://www.statista.com/statistics/237570/pork-production-worldwide/
The world counts. (2022). Globally, we consume around 350 million tons of meat a year. Retrieved from https://www.theworldcounts.com/challenges/consumption/foods-and-beverages/world-consumption-of-meat/story
Topigs Norsvin. (2021). Eindberen topigs norsvin. Retrieved from https://topigsnorsvin.nl/producten/eindberen/
Trefan, L., Doeschl-Wilson, A., Rooke, J., Terlouw, C., & Bünger, L. (2013). Meta-analysis of effects of gender in combination with carcass weight and breed on pork quality. Journal of Animal Science, 91 (3), 1480–1492.
Trienekens, J., & Wognum, N. (2013). Requirements of supply chain management in differentiating european pork chains. Meat science, 95 (3), 719–726.
United States Department of Agriculture. (2022). (January 2022 ed.).
van der Vorst, J. G., Tromp, S., & Van der Zee, D.-J. (2005). A simulation environment for the redesign of food supply chain networks: modeling quality controlled logistics. In Proceedings of the winter simulation conference, 2005. (pp. 10–pp).
van der Vorst, J. G., van Kooten, O., & Luning, P. A. (2011). Towards a diagnostic instrument to identify improvement opportunities for quality controlled logistics in agrifood supply chain networks. International journal on food system dynamics, 2 (1), 94–105.
van der Vorst, J. G., van Kooten, O., Marcelis, W., Luning, P., & Beulens, A. J. (2007). Quality controlled logistics in food supply chain networks: integrated decision-making on quality and logistics to meet advanced customer demands.
van Krimpen, M., Rommers, J., Binnendijk, G., & Gerrish, P. (2006). Effect van bijproducten op de slacht-en vleeskwaliteit van vleesvarkens effect of food waste products on slaughter and meat quality of growing finishing pigs (Tech. Rep.). Animal Sciences Group.
van Wagenberg, C. P., Backus, G. B., Wisselink, H. J., van der Vorst, J. G., & Urlings, B. A. (2013). Impact of test sensitivity and specificity on pig producer incentives to control mycobacterium avium infections in finishing pigs. Preventive veterinary medicine, 111 (3-4), 286–296.
Vermeij, I. (2015). Handboek varkenshouderij 2015.
VionFoodGroup. (2022). Vionfoodgroup about us. Retrieved from https://www.vionfoodgroup.com/about-vion
Whitaker, D., & Cammell, S. (1990). A partitioned cutting-stock problem applied in the meat industry. Journal of the Operational Research Society, 41 (9), 801–807.
White, D. J. (1993). A survey of applications of markov decision processes. Journal of the operational research society, 44 (11), 1073–1096.
Whittemore, C., et al. (1993). The science and practice of pig production. Longman Scientific and Technical.
Wolter, B., & Ellis, M. (2001). The effects of weaning weight and rate of growth immediately after weaning on subsequent pig growth performance and carcass characteristics. Canadian Journal of Animal Science, 81 (3), 363–369.
Yin, J., Li, Y., Han, H., Liu, Z., Zeng, X., Li, T., & Yin, Y. (2018). Long-term effects of lysine concentration on growth performance, intestinal microbiome, and metabolic profiles in a pig model. Food & function, 9 (8), 4153–4163.
Yu, M., & Nagurney, A. (2013). Competitive food supply chain networks with application to fresh produce. European Journal of Operational Research, 224 (2), 273–282.

Appendix

Appendix A. Research questions & sub-questions

1. What defines the market for GFB?
1.1. What characterizes the GFB market?
1.2. What has been the demand for the GFB chain based on historical sales data?
1.3. What has been the performance of Vion with regards to meeting the demand?

2. What has to be influenced in the supply process to control quality?
2.1. Which factors are important for a higher carcass quality within farming?
2.2. Which quality control points can be derived from literature, in order to respond to changes in demand?
2.3. What governs the behavior of farmers?
2.4. What has been the effect of the current payment table?

3. What will be the input of the model?
3.1. What are the variables which control the match of supply and demand?
3.2. What are the parameters that define the match of supply and demand?
3.3. Which assumptions have to be made for the model?

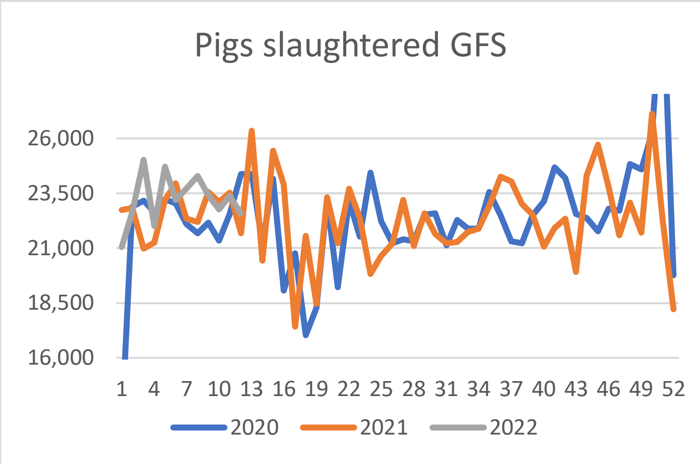
4. What model connects the available input and desired output?
4.1. Which model fits the allocation of supply to the demand?
4.2. What is the desired output of the model?
4.3. How does the allocation model contribute towards already existing literature?

5. What is the performance of the model?
5.1. How does the model perform on several demand scenarios?
5.2. How robust is the model under sensitivity analysis?
5.3. Which limitations have to be considered within the model?

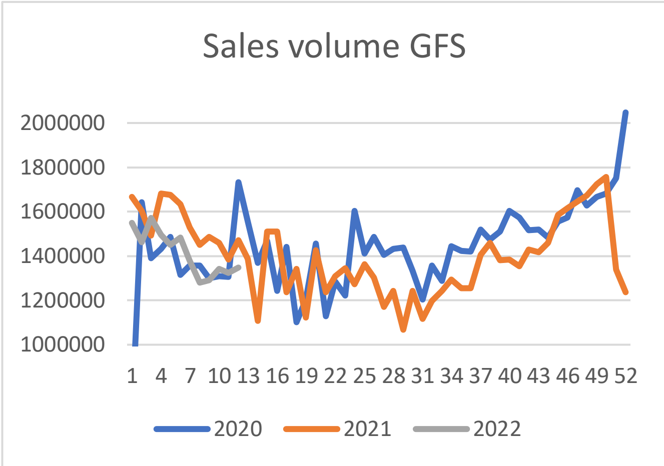
6. What extensions are recommended for future research?
6.1. What are the shortcomings of this research?
6.2. What should future research focus on?
6.3. Which implementations ensures future usage of the model?

Appendix B. Understanding industry through GFS

The GFS concept has much more detailed sales data available than GFB due to its more compact market. Therefore this appendix will use the GFS concept to explain the mechanisms of producing one-to-many. First, seasonality can be seen in the demand trend for pork in the Netherlands. Peak moments are Christmas and Easter when families come together and dine extensively. Moreover, there is more seasonality when zooming into specific products for instance, there is a higher demand for lean meat and barbecue meat in the summer. Graph 12 shows the sales data in kilos throughout the year and graph 13 presents the number of pigs slaughtered, all for the GFS concept.



Graph 12 Pigs slaughered GFS 2020-2022

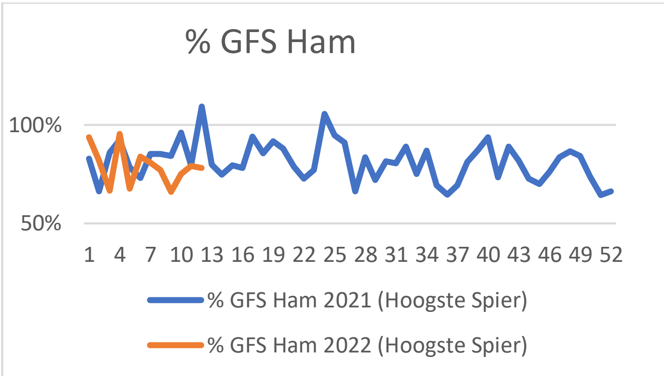


Graph 13. Sales volume GFS 2020-2022

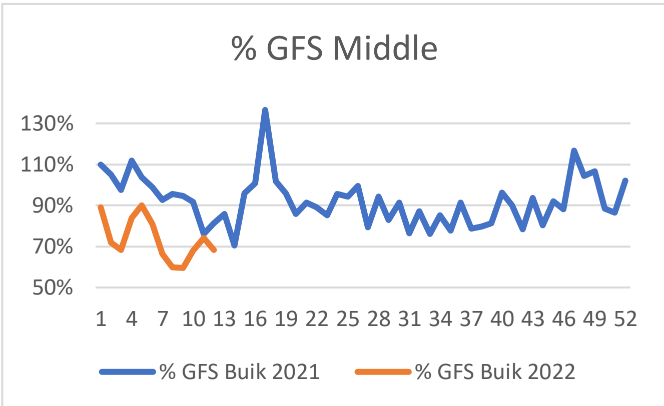
Pork is not sold per carcass but rather per article which is cut out of a body part. The carcass is split in ham, middle and front. A slaughtered pig will always give one carcass, while demand often asks for one part at a certain period in the year. The demand of different articles and parts have to be matched through complex valorization at Vion. The figure 14 and 15 indicate this.

As the graph indicates the Christmas peak is extremely high as no other event throughout the year influences sales to this extend. This is best seen in the number of pigs slaughtered. It is important to note that Christmas 2021 got restricted last minute due to COVID-19 therefore the sales stayed behind. Furthermore, the low point in the beginning of 2020 is due to the cut-off of the week and thus does not represent an event. All in all, it can be stated that sales are highest for easter, and Christmas and the summer has a lower sales trend than the winter as was expected.

For the GFS Ham in 2021 two peaks are seen, one in week 13 which was easter and one in week 25, which was the hottest week of the whole year resulting into a BBQ demand. For the middle in 2021 for GFS, in week 17 a tremendous peak is seen. This week included the holiday of Kingsday during which most people remained at home due to COVID-19.



Graph 14. Percentage of Ham GFS sold 2021 and 2022



Graph 15. Percentage of Middles sold GFS 2021 and 2022

Appendix C. Outcome PORQSAT HAS students

In the PORQSAT project students interviewed GFS farmers who delivered either continuously high (>75% of pigs within concept in the years 2015-2021) or showed significant growth (>4% in the years 2018-2020). The 25 interviewed farmers were subject to 31 notable changes in their slaughter results (carcass quality) in the period 2015-2022. Of these changes 11 were due to changes in genetics. More often than not, farmers were forced to change genetics due to external circumstances. Some farmers changed genetics to experiment with results and increase performance. Moreover, nine of the notable changes were related to health. Health issues can be crippling for a farmer's revenue and tracing the cause can be really hard. Furthermore, another six causes were related to changing to another breeding farm. Yet again quite often not a voluntarily choice but due to external circumstances. These changes highly impacted the pork quality. Thus, the qualitative research of the interviewed 25 GFS farmers resulted in the conclusion that many (contradicting) strategies can lead to good results. Nevertheless, success in the qualitative study meant delivering within the GFS bounds as good as possible. While in the GFB these concept bounds are much wider, leading to a higher deviation in supply.

Appendix D. Effect of health of pigs and piglets on carcass quality

Piglets health

Farmers can operate in a so called 'closed farms' meaning they operate their own breeding stage and use their own piglets for the fattening stage. Moreover, farmers can sell piglets and keep some for fattening, these are referred to as 'half-open farms.' 'Open farms' only operate the fattening stage and buy piglets from a breeding farm. If piglets stay on the same farm, a closed farm, they are less confronted with outside bacteria. Some genetics of piglets match well with one farm but not with another (qualitative research PORQSAT, 2022).

A literature review by Rekiel, Więcek, Batorska, and Kulisiewicz (2015) found a consensus on studies performed by different research centers showing conclusive evidence that the quantity and quality of slaughter products obtained from pigs depends on genetic and environmental factors (Blavi et al., 2021). Once a piglet is born it feeds from their mother till, they have to transition to solid feed. This transition to feed is a very important and vulnerable moment, it can define the pig's development (Nowak, Zaworska-Zakrzewska, Frankiewicz, & Kasprowicz-Potocka, 2021; Guevarra et al., 2019). If this transition fails and no other actions are successful, the pig will be unable to achieve compensatory growth rates during the growth-finish periods and take longer to reach market weight (Wolter & Ellis, 2001). This will have an economic impact because the market weight can be reduced (resulting in less payment) or increased barn occupancy (Blavi et al., 2021). Furthermore, the effect of birth weight on the carcass quality is highly debated in literature (Rekiel et al., 2015). High birth weight increases the likelihood of a pig being full value at the end of its finishing phase (Fix et al., 2010). The same study observed a lower survival rate for a lower piglet birth weight. Moreover, the effect of birth weight on slaughter quality was found insignificant (Beaulieu, Aalhus, Williams, and Patience, 2010), while the birth weight was found positively effecting carcass quality in the (Heyer, Andersson, Lindberg, and Lundström, 2004). In a meta-analysis by Lanferdini et al. (2018) it was concluded that the carcass and meat quality are not influenced by the weight of the piglets at birth.

Pig's Health

Another finding from the qualitative research of the GFS farmers, appendix C, was that the health on the farm was crucial for the success. However, there is a spectrum of health, a serious decease spreading through a farm could be detrimental, in comparison to an individual pig coughing. Research by Melese (2022) explored the relation between the slaughter weight of various body parts and suboptimal conditions. These conditions were defined as limping, coughing, diarrhea, limp wound, and cough limp. With an ANOVA test (n=93) it was concluded there were no significant difference between the group of pigs with suboptimal conditions and without. It is advised that farmers have to be alert on any signs of sickness and determine a moment of euthanizing on time since the economical investment in a pig increase with time (Vermeij, 2015).

Appendix E. Differences genders

In figure 10 a comparison is presented between barrows, boars, and gilts. The data is compiled from Pigmanager and FARM systems, calculations were made according to the industry agreements (uniformerings afspraken). Finally, the results and benchmarks are published every half year and are industry wide accepted. Similar as in the literature figure 6 shows the following:

- Boars have a lower feed conversion than barrows
- Barrows have a lower growth rate than boars
- Barrows have more backfat thickness and more muscle
- Barrows are heavier than boars
- Boars have a higher feed price per 100 EW

Barrows are less economical to produce but they give a higher fat and a greater slaughter weight (thus increasing muscle size) (Kyriazakis & Whittemore, 2006). Therefore, they are profitable in the end.

	Average	Boars +Gilts	Boars +Gilts +Barrows	Barrows +Gilts
Nr of results	458	210	15	79
Nr of pigs	2527,1	2422,4	2557,8	2649,8
Growth/pig/day	879	898	864	854
KG feedintake/pig/day	2,23	2,22	2,24	2,27
EW feedintake/pig/day	2,45	2,45	2,49	2,5
Feedconversion	2,54	2,47	2,6	2,67
EWconversion	2,8	2,74	2,88	2,93
Corrected growth/pig/day	881	899	866	855
Corrected EW conversion	2,73	2,68	2,81	2,86
KG slaughter weight	99,2	98,6	100,2	100,3
Starting weight	26,3	26,2	26,1	26,8
Meat %	59,5	59,7	59,5	59,2
Backfatthickness	13,53	13,22	13,82	14,01
Musclethickness	69,17	68,37	69,64	70,02
Loss %	2,4	2,2	2,5	2,7
Price startfeed/100kg	33,73	22,54	34,32	33,37
Price transitionfeed/100kg	29,79	29,56	31,24	29,39
Price pigfeed/100kg	27,36	27,43	27,68	27,1
Price powerfeed/100kg	29,97	29,95	29,34	29,44
Price additivefeed/100EW	19,5	19,24	19,05	19,33
Price total feed/100EW	25,87	25,91	25,07	25,55
Netto voerkosten kg/groei	0,722	0,709	0,722	0,749

Figure 10. Agrovision Kengetallenspiegel January-December 2021 (version March 2022)

Appendix F. Modelling choice: MDP

This appendix will briefly argue what an MDP is and why it would be a suited choice for modelling this research problem. In chapter 4 the disadvantages of an MDP were listed which led to the final choice of a MNL model.

A Markov Decision Process (MD) is derived from dynamic programming and seems to be introduced by Bellman (1957). Since then, many applications have been formed over many industries, like population harvesting, agriculture, inventory, scheduling, investments etc. (White, 1993). A MDP is a mathematical approach for modeling decision making when outcomes are partly random and partly under the control of a decision maker or agent. There is a set of states and actions. Furthermore, probabilities are defined linking the current state to the next state based on a choice of action. After the action is taking a reward is given to the agent. The set of action chosen is called a policy. All in all, the model searches for the best policy per agent.

The study that was closest related with the current research problem, as was concluded in the literature study, was by Niemi (2006). They used a MDP in order to calculate the economical beneficial feeding method and slaughter timing. More specifically, how the optimal feeding and slaughter policies change when prices of pig meat, feeds, piglets, carcass quality premiums or slaughter premiums vary. As an extension on Niemi (2006), another Markov hierarchical decision model was developed by Pourmoayed et al. (2016) which takes into account the in-homogeneity of animals with respect to growth and feed conversion rate. Moreover, research by van Wagenberg, Backus, Wisselink, van der Vorst, and Urlings (2013) implemented a MDP in order to calculate penalty costs. This could be used by slaughterhouses to issue and create incentives for farmers to control Mycobacterium avium infections.

MDP also have some limitations especially when regarding the thesis at hand. First, they have extensive data requirements, because data is needed to estimate the transition probability function and the reward function for each possible action (Alagoz, Hsu, Schaefer, & Roberts, 2010). The other disadvantage was listed in chapter 4.3.

All in all, MDP could be suited for future modelling when the initial conditions and behavior of every individual farmer is modelled based on an abundance of data. This could be realistic for Vion when a research project is done into farmer behavior (PORQSAT) and when blockchain technology is implemented for GFB.

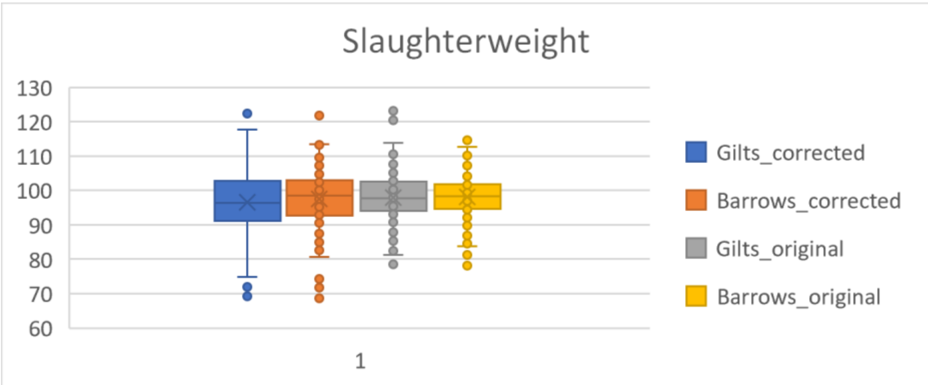
Appendix J. Growth rates deducted from Schinkel et. al. (2002)

Below is a table derived from Schinkel et al. (2002) where the growth rate was computed per age in days. The average growth rate was calculated for two different ranges, 146 till 165 and 167 till 190. These were chosen to match the ages of the pigs in the experiment dataset.

	Slaughter weight		Backfat thickness	
Age (days)	Barrows	Gilts	Barrows	Gilts
146	0.6670	0.7149	0.0208	0.0109
153	0.4733	0.8733	0.0093	0.0173
155	0.0357	0.5643	0.0143	0.0200
162	0.8238	0.7481	0.0199	0.0117
163	1.0778	1.3250	0.0222	0.0147
165	0.8750	1.6583	0.0400	0.0467
146-165	**0.6588**	**0.9807**	**0.0211**	**0.0202**
167	0.7619	0.7619	0.0190	0.0071
169	0.8904	1.0062	0.0138	0.0104
182	1.3873	1.3120	0.0062	0.0087
190	0.7500	0.6357	0.0207	0.0154
167-190	**0.9474**	**0.9290**	**0.0150**	**0.0104**
192	0.7600	0.7080	0.0244	0.0244
195	0.8231	0.6769	0.0469	0.0277
203	0.5885	0.7239	0.0303	0.0247

Table 18. Growth rates derived from paper of Schinkel et al. (2002)

The growth rates of table 18 were used to correct the dataset. In graph 18 the boxplots are shown for the corrected data versus the original data.



Graph 18. Boxplots of gilts and barrows, original and corrected (own elaboration)

As expected, the distribution becomes wider in the corrected version. The delivery strategy is often used to create a homogenous supply. Figure 16 below shows the new distribution over the carcass classes with the number of pigs per class.

Feedpolicy 1	Black	Blue	Brown	Green	Grey	Orange	Pink	Red	White	Yellow	Total
Nr. of carcasses	15	11	3	11	14	4	10	1	1	47	117
D_{ij}	12,8%	9,4%	2,6%	9,4%	12,0%	3,4%	8,5%	0,9%	0,9%	40,2%	100,0%

Feedpolicy 2	Black	Blue	Brown	Green	Grey	Orange	Pink	Red	White	Yellow	Total
Nr. of carcasses	22	3	6	9	26	4	10	4	6	26	116
D_{ij}	19,0%	2,6%	5,2%	7,8%	22,4%	3,4%	8,6%	3,4%	5,2%	22,4%	100,0%

Feedpolicy 3	Black	Blue	Brown	Green	Grey	Orange	Pink	Red	White	Yellow	Total
Nr. of carcasses	5	12	5	10	23	6	16	3	11	8	99
D_{ij}	5,1%	12,1%	5,1%	10,1%	23,2%	6,1%	16,2%	3,0%	11,1%	8,1%	100,0%

Figure 16. Corrected distribution over the carcass classes (own elaboration)

Appendix K. Numerical Experiments

This appendix includes the results of the numerical experiments.

Lower bound adjustments |CC|=10 and |S|=3
Through trial and error, the bounds were adjusted where some runs did not provide solutions. In table 19 below the results of some runs are shown.

Scenario 1		Scenario 2		Scenario 3		Scenario 4	
lb	OFV	lb	OFV	lb	OFV	lb	OFV
-0.5	- € 23.80	-0.5	- € 25.84	-0.5	- € 26.48	-0.51	- € 26.33
-0.4	- € 3.30	-0.41	- € 18.11	-0.41	- € 9.17	-0.5	€ 5.46
-0.3	€ 21.34	-0.4	No solution	-0.405	- € 17.61	-0.49	- € 25.47
-0.2	€ 30.72	-0.39	- € 15.83	-0.4	€ 11.26	-0.4	- € 18.85
-0.1	€ 31.78	-0.3	€ 0.28	-0.39	€ 1.49	-0.3	- € 0.63
		-0.2	€ 16.36	-0.3	€ 7.38	-0.2	€ 9.86
		-0.1	€ 28.51	-0.2	€ 27.26	-0.1	€ 26.84
				-0.1	€ 31.68		

Table 19. Results of adjusting the lower bound and keeping the upper bound of 0.5 objective value and the incentives per kg per carcass class in euros, |CC|=10, |S|=3 (own elaboration)

The results of table 19 shows that the solution near an objective function of 0 will be with a lower bound between -0.3 and -0.4. For scenario 2 a lower bound of -0.4 did not give a solution. The values surrounding -0.4 did. In scenario 3 something interesting occurs as the objective function does not increase constantly over the lower bounds like the other scenarios. In scenario 4 this was detected again. The reason for this instability of the incentives can be the number of decision variables far exceeding the number of policies. Therefore, other runs were continued with less decision variables.

Decision variables restricted CC= {black, grey, and yellow} and |S|=3
In table 20 the outcome of running the model with all policies but with only the decision variables set for black, grey, and yellow.

	OFV € paid per pig	Black	Grey	Yellow
Scenario 1	€ 20.68	€ 1.00	€ 0.01	€ 0.11
Scenario 2	€ 22.79	€ 1.00	€ 0.04	€ 0.14
Scenario 3	€ 20.22	€ 1.00	- € 0.01	€ 0.10
Scenario 4	€ 23.73	€ 1.00	€ 0.10	€ 0.18

Table 20. Results of restricting the decision variables to black, grey and yellow, objective value and the incentives per kg per carcass class in euros, |CC|=3, |S|=3, ub=1, lb=-1 (own elaboration)

Similar as before the lower bound was adjusted again while the upper bound was set on 0.5 euro cents per kg per carcass class, results in table 21 below.

Scenario 1		Scenario 2		Scenario 3		Scenario 4	
lb	OFV	lb	OFV	lb	OFV	lb	OFV
- € 1.00	€ 20.68	- € 1.00	€ 22.79	- € 1.00	€ 20.22	- € 1.00	€ 23.73
- € 0.80	€ 33.39	- € 0.80	€ 24.25	- € 0.80	€ 43.64	- € 0.80	€ 30.07
- € 0.60	€ 19.82	- € 0.60	No solution	- € 0.60	€ 22.16	- € 0.60	€ 18.66
- € 0.40	€ 24.53	- € 0.40	No solution	- € 0.40	€ 20.70	- € 0.40	€ 24.98
- € 0.30	No solution	- € 0.30	No solution	- € 0.30	€ 26.98	- € 0.30	No solution
- € 0.20	No solution	- € 0.20	No solution	- € 0.20	No solution	- € 0.20	No solution

- € 0.10	No solution	- € 0.10	€ 26.13	- € 0.10	No solution	- € 0.10	No solution
€ 0.00	€ 20.27	€ 0.00	€ 20.92	€ 0.00	€ 24.95	€ 0.00	€ 19.04

Table 21. Results of adjusting the lower bound and keeping the upper bound of 0.5 objective value and the incentives per kg per carcass class in euros, CC= {Black, Grey, Yellow}, S=|3| (own elaboration)

More results with no solution then previous runs. Reason for this can be that the upper bound should be adjusted too to allow more freedom for the model to calculate. Moreover, restricting the decision variables does not give a continuous increasing objective value when increasing the lower bound, as was seen in the results of all the decision variables included.

Model input sensitivity: setting the weight factor

The weight factor can only be adjusted in stage 2 resulting in different ratios. In chapter 8 the weight factor for only the carcass class 'black' was increased to 1.5. In table 22 below the ratios and OFV are shown corresponding this experiment.

	Feedpolicy 1	Feedpolicy 2	Feedpolicy 3	OFV Least squares
Scenario 1	68%	23%	9%	0.0101
Scenario 2	41%	46%	13%	0.0125
Scenario 3	9%	77%	14%	0.0167
Scenario 4	0%	41%	59%	0.0270

Table 22. Stage 2 ratio of policies per demand scenario, w_{black}=1.5 (own elaboration)(OFV=objective function value)

Comparing table 22 to table 8 in chapter 8, it can be concluded that all the ratios changed at least 9% and all the OFV took different values. Adjusting the weight factor has quite some consequences and the outcomes have to be interpreted carefully. The weight factor can be adjusted such that it represents a future scenario, for instance growth of the carcass class black with 150% and to estimate the effect on the carcass classes.

Model input sensitivity: increasing and decreasing pig prices

The pig price continuous fluctuates over the weeks and years based on the market. The pig price effects the utility function of a farmer as well, so it was decided to test the model for different prices. First in table 23 is shown the results of the pig price of 1.80 per kg as was used in all the previous runs.

Scenario	OFV € paid per pig	Black	Blue	Brown	Green	Grey	Orange	Pink	Red	White	Yellow
1	- € 23.80	0.5	-0.5	-0.5	-0.5	-0.486	-0.5	-0.5	0.5	-0.5	-0.231
2	- € 25.84	0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	0.198	-0.5	-0.283
3	- € 26.48	0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	0.119	-0.5	-0.294
4	€ 5.46	0.5	-0.5	-0.5	-0.5	0.194	-0.5	-0.5	0.5	-0.5	0.289

Table 23. Results of the stage 3 model with its objective value and the incentives per kg per carcass class in euros, pig price = 1.80, |CC|=10, |S|=3, lb=0.5, and ub=0.5 (own elaboration)

In table 24, the pig price was doubled to 3.60 per kg, this is extremely high. There can be seen that the incentives change a lot. Thus, this increases in pig price matters for the match between supply and demand.

Scenario	OFV € paid per pig	Black	Blue	Brown	Green	Grey	Orange	Pink	Red	White	Yellow
1	- € 38.62	0.014	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.432
2	- € 37.69	0.088	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.474
3	- € 16.00	0.5	-0.5	0.5	-0.5	-0.244	-0.5	-0.5	0.5	0.5	-0.5
4	- € 23.15	-0.491	-0.5	-0.5	-0.5	0.447	-0.5	-0.5	0.5	0.5	-0.5

Table 24. Results of the stage 3 model with its objective value and the incentives per kg per carcass class in euros, pig price = 3.60, |CC|=10, |S|=3, lb=0.5, and ub=0.5 (own elaboration)

Finally, another extreme was taken where the pig price was halved to 0.90 per kg, see table 25. Similarly, the incentives are completely different. Meaning that accurate data is crucial, and the incentive should be adjusted frequently.

Scenario	OFV € paid per pig	Black	Blue	Brown	Green	Grey	Orange	Pink	Red	White	Yellow
1	- € 21.58	0.332	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.074
2	- € 21.98	0.406	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.116
3	€ 0.62	0.5	-0.5	0.5	-0.5	0.187	-0.5	-0.5	0.5	-0.5	-0.205
4	- € 33.53	0.153	-0.5	-0.5	-0.5	-0.338	-0.5	-0.5	0.5	0.5	-0.5

Table 25. Results of the stage 3 model with its objective value and the incentives per kg per carcass class in euros, pig price = 0.90, |CC|=10, |S|=3, lb=0.5, and ub=0.5 (own elaboration)