Business Economics Group

MSc Thesis Business Economics

Data Envelopment Analysis in determining factors that influence technical efficiency levels on Dutch dairy farms

Which cow specific expressions can influence farm performances

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Preface

For Dutch dairy farmers, increasing herd size to maximize profits is not a common trend anymore. Dairy farmers are restricted by their outputs and must be creative in their inputs to get the best out of their herds. Besides growing consumer concerns on animal welfare and environmental responsible productivity, efficiency plays a big role in the life of a farmer. Feed costs have grown substantially in the last years, but knowledge on how to use this feed correctly has also made big improvements. I hope that this study can contribute to even more efficient dairy farms. I think many developments have already be made on for example improved cow health, increased productive fitness or feed efficiency, but I think the dairy sector is still in progress to become even more input source efficient.

This thesis is part of the Horizon 2020 GenTORE project. A project that will develop innovative tools to optimize resilience and efficiency. The project consists of multiple European stakeholders and partners that are all active in the dairy and beef cattle industry. I am glad that the results of this thesis not only will be used on national scale but are also included into an international programme.

Regarding the GenTORE project I want to thank Claudia Kamphuis for her critical and pragmatic point of view. It was nice to discuss with someone which is critical with knowledge from another discipline. I want to furthermore thank her for giving me the opportunity and the confidence to present the results of my thesis at the annual project meeting in Basel. For me, it was received as a compliment to present my work in front of researchers from all kinds of disciplines in the dairy and beef cattle industry.

Fortunately, Mariska van der Voort was always willing to help in improving the content of this thesis. I want to thank her for the elaborate brainstorm sessions through the whole research process and for giving me the opportunity to always be critical on my own results and findings. I also want to thank my fellow students and friends for the many discussions we had regarding this research and for showing interest into this study.

Enjoy reading!

Pieter Rooijakkers

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Summary

Milk production per cow has increased substantially in the past decades. Subsequent to the intensification of the dairy sector, consumers have growing concern on aspects like welfare and environmental friendly production. Also due to health and safety demands of food production, a shift in focus on the genetic selection for breeding goals next to milk production has grown.

Focussing on functional traits next to milk production can be both economically beneficial as socially accepted. They contribute to the functionality and the fitness of an individual cow. Furthermore, these so-called hybrid cows have a long-life expectancy which will lead to reduced costs due to savings on health and replacement costs caused by involuntary culling. Functional traits can be divided into several categories which all have specific indicators. For this study, the most important traits were selected from literature concerning *health*, *fertility*, *longevity*, and *feed efficiency*.

It is known that managerial choices are closely related to farm efficiency, however it is not known how this efficiency is related to the expression of functional traits by an individual cow. Therefore, the question arises, in which extent cows can express their functional traits can be influenced by a change in farm management.

In this study, efficiency measures are based on productive efficiency, indicated by a technical efficiency score. Technical efficiency can be interpreted as a relative measure between decision making units (farms) for managerial capacity on a technology level which is in this case milk production. The method that was used in this study to measure technical efficiency is Data Envelopment Analysis, or DEA, which is an econometric, non-parametric linear programming approach capable in measuring whole-farm efficiency. Information of functional traits was used to select a set of variables that does both relate to the production of milk and to functional traits of a dairy herd for the efficiency analysis. In a subsequent comparison between different technical efficient scoring groups, all variables relating to functional traits were included to indicate significant differences between efficient and low(er) efficient farms.

From a dataset of 846 farms it was found that between the years 2013 and 2016 farms were relatively efficient to each other having an average technical efficiency score of around 0.93. Inefficiency means that there is room for input improvement, which are in this case related to functional traits on cow level. Around 23% of all assessed farms remained in the same efficiency range over all years. When one consecutive year is concerned, approximately 50% of the farms seem to remain in the same efficiency range and about an equal amount (approximately 25%) of the farms increase or decrease in technical efficiency groups which were based on the distribution of technical efficiency scores per year.

At last it was found that from the DEA significant differences were found for technical efficiency scores for the variables which are related to the traits of individual cows. Efficient farms include cows that are healthy and fertile, having both low health and breeding and controlling costs. Furthermore, at these efficient farms cows were fed significantly lower concentrates and had significantly higher milk yield per hectare of feeding area. In contrary on having high performance for the functional traits health, fertility and feed efficiency, farms that are efficient had cows present with a significantly lower average age than the cows that were found on farms with low(er) efficiency. Concerning productivity, fully efficient farms produce less milk yield per cow than highly efficient farms but significantly more than on low efficient farms.

It could be concluded that DEA is a suitable method in examining the performance of a farm while focussing on cow specific traits. Despite it was not suitable to include every variable, interesting results of efficiency differences relation to functional traits were found. Other efficiency analysis methods were not used but could give interesting insights for the validation of this study. Results are still on farm level; however, they give insights in where the focus should be when analysis on cow level is performed. In a subsequent study, studies on farm and cow level could be combined to correct for high performing cows on low performing farms and vice versa.

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Abbreviations

AMS	Automatic Milking System
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
LP	Linear Programming
PLF	Precision Livestock Farming
SFA	Stochastic Frontier Analysis
TE	Technical Efficiency
TFP	Total Factor Productivity
VRS	Variable Returns to Scale

1. Introduction

Over the years the Dutch dairy cow population has decreased from a total of 2.55 million milking cows in 1984 to 1.6 million milking cows in 2018 (CBS, 2017). Almost 60 years ago, the same amount of milking cows was recorded, however in the meantime milk production has more than doubled from around 4200 kg per cow per year in the 1960's to around 9100 kg per cow per year in 2018 (CRV, 2019; van Dijk, Schukking, & van der Berg, 2015). Besides the intensification of the dairy sector, more and more social pressure also has led to a shift in the genetic selection for other breeding goals instead of milk production increase (Cook & Nordlund, 2009; Pritchard, Coffey, Mrode, & Wall, 2013). Due to healt demands and growing concerns about safe products in combination with high animal welfare, novel functional traits of cow health information receive increasing attention by dairy producers (Egger-Danner, Willam, Fuerst, Schwarzenbacher, & Fuerst-Waltl, 2012). These traits can both be economically beneficial as socially accepted. Furthermore will these breeding goals lead to more sustainable dairy products and increase animal welfare due to its higher robustness (Pritchard et al., 2013). According to Groen (2004) functional traits are characteristics of animals that can increase efficiency by reduced costs of input instead of higher outputs.

Efficiency can have multiple definitions, furthermore focus can be specified on different levels. In this study, efficiency will be approached at farm level. Efficiency can be measured in multiple ways, this study will focus on the technical efficiency of Dutch dairy farms which examines the inefficient use of resources in the production process or the ability of farms to use minimum inputs to produce a given level of output (Allendorf & Wettemann, 2015; Davis, 2018; Korver, 1988). Focussing on the efficiency of an individual cow, a definition by Friggens & Thorup (2015) was found. Individual cow efficiency could be divided into two components, digestive efficiency (for example variations in digestibility or feeding behaviour) and metabolic efficiency (for example quantifying absorbed nutrients in different metabolic functions such as activity, maintenance and production). Farms can have a mix of both inefficient and efficient cows according to the definition of Friggens & Thorup (2015).

1.1. Current situation of efficiency in Dutch dairy farming

Traditional breeding goals in the 20th century was mainly focussed to feed a growing world population. In the dairy sector, milk yield increased by increasing the number of animals per farm. The number of cows was at its highest in the year 1984 with 2.5 million milk and calf cows. This was just before the introduction of the European milk quota to protect the dairy market for overproduction. At that time, there were around 60 000 dairy farms in the Netherlands with a total production of around 13.2 billion kilograms of milk per year. Just before the abolition of the European milk quota, Dutch dairy farms started growing again in milk production with its peak in 2016 where a total of around 14.3 billion kilograms of milk was produced by only around 16 500 dairy farms (CBS, 2017; CRV, 2019). Due to an overproduction of phosphate by the Dutch livestock sector in 2015 in contrast to European regulations, at 1 January 2018 new regulations were introduced to decrease the production of phosphate by limiting the amount of kilograms of phosphate produced per farm (Rijksdienst voor Ondernemend Nederland, 2019). This has a direct effect at the current milk production, but also in the determination of farm specific breeding goals.

Not only farm sizes have increased during the past decades, also the amount of technologies available at the farms have become increasingly popular in dairy farming. Data is being monitored more as ever before and therefore the number of sources of data have increased too. Traditional scoring methods are being replaced by novel sensors, like for example oestrus observing in cows. Tools that record on farm data mostly focus on the identification of events of key features such as for example locomotion in a way of using individual measures for one animal and a single event such as increased activity to detect oestrus (Rutten, Velthuis, Steeneveld, & Hogeveen, 2013). These 'first-generation precision livestock farming' (PLF) tools can be described with a single-event monitoring approach and should be combined into a combined-event monitoring system to perform more precise precision phenotyping by combining several single events (for example increased activity and ruminant activity) together to predict for example oestrus.

With the help of these first-generation PLF's it is possible to record on farm data in datasets that can be used to measure the efficiency of a sector, in this case the Dutch dairy sector. Nowadays efficiency is mostly measured from a productive (technical), allocative or environmental aspect. In this study, the focus will be on the efficient levels of the input to output ratio relative to a set of farms, which can be seen as measuring the technical efficiency. Technical efficiency (TE) measures in the Netherlands were already performed by Reinhard, Lovell, & Thijssen (1999), Brümmer, Glauben, & Thijssen (2002), Kovacs & Emvalomatis (2011) and Dandi (2017). These studies found high mean TE scores between 80 and 91% for the Dutch dairy sector concerning inputs like fixed and variable costs, labour, land and number of cows.

1.2. Desired situation of efficiency in Dutch dairy farming

With the help of variables that are recorded with precision livestock farming tools and existing datasets, it is possible to measure relative efficiencies of a selected group of farms. However, the results of a TE score are not related to individual cows. Today, more and more cow specific data will be recorded and the first generation PLF tools can be replaced by second generation PLF tools for a more precise measurement of farm and cow performances. These tools combine single-event monitoring to predictions on cow states in for example fertility or lameness detection in an early stage (Friggens, Kaya, & Roozen, 2017). With the help of these early warnings, a farmer can have a better success rate of for example inseminations and can prevent diseases more easily which will eventually lead to reduced costs. These enhanced data recordings could furthermore be used to measure a farms' efficiency not only on its financial position, but also on the health status, viability and performance of the dairy herd. In a desired situation, a farmer knows the status of every individual cow and the relation to his whole farm performance. Every farmer should keep track of the advantages and shortcomings of his dairy herd so that deliberate farm management adjustments can be made.

1.3. Problem definition

In which extent cows can express their functional traits can be influenced by farm management (Egger-Danner et al., 2014). Because farm management is closely related to farm efficiency, improving farm efficiency can help farmers to optimize their dairy herds. However, it is not known how farm efficiency (and therefore farm management change) is related to this expression of functional traits by individual cows and in what extent the variables that influence farm efficiency are related to functional traits. Both in international and in Dutch literature on dairy farming, many studies estimate or measure farm efficiency, but do not make the translation from farm efficiency to individual cow expression.

1.4. Research questions

How can on farm level efficiency indicate differences related to cow specific traits?

1. Which indicators of farm level efficiency can influence the performance of individual cows and therefore change the expression of traits related to farm performance?
2. What are the technical efficiency differences between Dutch dairy farms?
3. How are influencing variables on farm efficiency related to traits of individual cows?

1.5. Demarcation

In this report, data between 2013 and 2016 from Flynth Advisors & Accountants will be used. With the help of information from literature, preliminary knowledge and statistical selection methods, variables will be chosen for further research. Only the variables that are chosen will be used for making up the results.

1.6. Outline

This thesis consists of a literature study and a data analyses part. Chapter 1 gives a brief introduction of the current and desired situation. Also, the problem is stated, and the research questions are given that should be answered in this thesis. Chapter 2 is a literature review of efficiency analyses in Dutch and international dairy farming, functional cow traits and the relation of these traits with economics values. Chapter 3 consists of the Material and Methods and gives an explanation about the practices that were used to construct this report. In Chapter 4, variable selection takes place, a stepwise explanation is given in towards the final set of variables that are used for DEA. Furthermore, this chapter gives a visual overview and explanation of the results from the performed DEA. Chapter 5 discusses the results and in Chapter 6 a conclusion is given. In Chapter 7 recommendations are given that are useful for further research. Furthermore, references and appendices are reported.

2. Literature

2.1. Introduction to data envelopment analysis

Several studies have shown that dairy farmers are able to improve their farm efficiency. Productive efficiency can be indicated by Technical Efficiency (TE). In this thesis, Decision Making Units (DMU's) will be represented by farms. Furthermore TE can be interpreted as a relative measure for managerial capacity on a technology level, such as milk production (Mareth, Thomé, Cyrino Oliveira, & Scavarda, 2016).

Statistically, methodologies which can measure or predict relative TE, can be divided in a parametric and a non-parametric approach. The two approaches differ in pre-defined assumptions and model structures. Non-parametric models can be subdivided in deterministic and probabilistic methods. Parametric methods need functional forms (such as Cobb-Douglas or translog models) and error distributions or can be estimated statistically. When a farm is assumed as efficient, it has efficient input use or output production and is operating on a best practice frontier. Because efficiency is measured relatively, between all selected farms, farms that are operating under efficient conditions and use their inputs in the best way possible relatively to the other farms (or produce relatively the most output possible from a given set of inputs). Farms operating on an efficient level, are located on a so-called best practice production frontier. Deterministic models assume that inefficiency is caused by an deviation from a best practice frontier, probabilistic models encounter inefficiency with the use of an error term and random noise (Mareth et al., 2016)**.** Many studies have estimated TE using multiple methods with different results based on different types of data, however there is no clear advantage of using one method over the other (Resti, 1999). Frontier estimation methods can be visualised as in Figure 1.

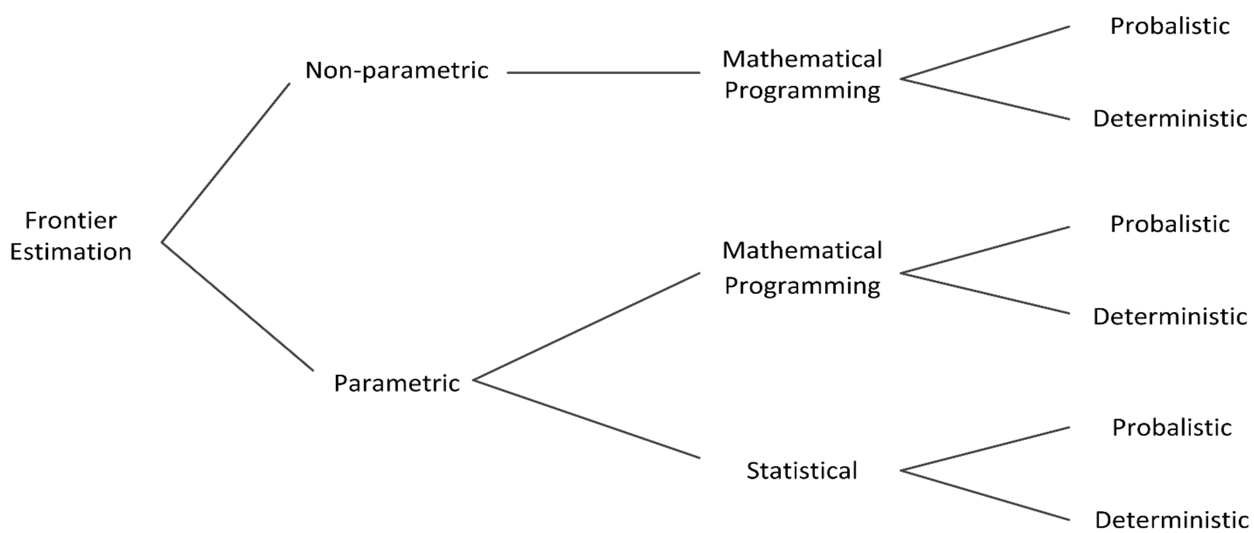

Figure 1: Frontier estimation methods as in Mareth et al. (2016)

Data Envelopment Analysis (DEA), which is the method that will be used in this study, is a non-parametric approach that measures productive efficiency of an industry. DEA is an econometric linear programming (LP) approach which is capable of measuring whole-farm efficiency by measuring relative efficiencies between DMU's which are specialised dairy farms in this study. Because the DEA approach is non-parametric, it requires very few assumptions and makes it useful to examine multiple inputs and multiple outputs that are considered by the DMU's without being restricted by complex and unknown pre-established model structures. Other than performance measurement that only measures performances of farms based on partial productivity indicators like for example feed efficiency, DEA is able to consider all inputs and outputs that are related to a farms' efficiency (Avkiran, 2011).

2.1.1. Efficiency analyses in literature

Mareth et al. (2016) performed a systematic review of 85 papers to indicate the differences between frontier estimation methods and their results in dairy farming. Mareth et al. (2016) concluded that the mean TE varied between the method of estimation and also according to the functional form but did not find that the mean TE varied between cross-sectional or panel data that was used. This finding is, however, contradicting with other reviews on this topic which also looked into frontier estimation methods in dairy farming (Bravo-Ureta et al., 2007; Rivas, 2003). In all review studies, mean TE varied according to the geographical location of the countries that were assessed and mean TE also varied according to the herd size on the farm. In the review studies that were found, it was not confirmed that mean TE varied according to the income level of the country or on the land size which is used by a farm.

Of all papers that were assessed, studies that used a non-parametric method yielded an average mean TE of 79.9%. For parametric studies this was somewhat lower, namely 78.8%. This indicates that it does matter which method is chosen for measuring technical efficiency. Furthermore Bravo-Ureta et al. (2007), Mareth et al. (2016) and Rivas (2003) found that the dimensionality of a model showed significant variations between the assessed papers. It does therefore matter which amount of in- and output variables is chosen, because this can influence efficiency scores substantially. Including too many variables in the selection will lead to an overestimation of TE scores. This finding was also indicated by Wagner & Shimshak (2007).

Within the studies of Bravo-Ureta et al. (2007) and Mareth et al. (2016) differences were made for six global regions within these regions, also a difference was made between Western and Eastern Europe. Results on papers on Oceanian data were merged with papers on Western European dairy farming. The region where the Netherlands is located (Western Europe and Oceania) showed statistically higher results than other geographical regions such as Asia, Latin America or Africa. Significant differences between different global and European regions were found, based on various types of data, methods and variables which were used but also between the amounts of cases that were assessed. Most cases were found for studies on Asian, North American and European and Oceanian dairy farms. Because there were significant differences found between multiple geographical regions, it does not make sense to compare the results of this study with results from studies of other regions. In the Netherlands, multiple studies measuring TE scores were found, these studies will be consulted in chapter 2.1.2.

2.1.2. Efficiency analyses in Dutch dairy farming

In Dutch dairy farming several efficiency analyses have been performed to indicate the technical efficiency score of the sector. Various methods have been used and will be summarized below. Results of studies on Dutch dairy farming are represented in Table 1.

In 1999, Reinhard et al. (1999) estimated environmental efficiency by performing a parametric stochastic translog production frontier. Both with an input and an output orientation. In their model, nitrogen surplus was treated as a detrimental input. The authors mentioned that farms can only be competitive in the agricultural sector when outputs are produced with marketable inputs efficiently as possible. By knowing the technical efficiency level of Dutch dairy farming, it is possible to indicate how competitive this sector is. Furthermore, by including multiple years technical (or environmental) improvement or deterioration can be measured.

In 2000, Reinhard, Knox Lovell, & Thijssen extended the approach of measuring TE and added another detrimental input, namely phosphorus surplus. The model was formed in a way that the environmental effects (phosphorus and nitrogen surplus and energy use) were used as conventional inputs rather than undesirable outputs. Also, energy use was considered. In this subsequent study, Reinhard et al. (2000) extended the research with technical and environmental efficiency scores using data envelopment analysis (DEA) in addition to the already performed stochastic frontier analysis (SFA), both input and output oriented. For the DEA, a variable returns to scale approach is used. This means that technical levels of farms with equal size are compared relatively to each other, an approach that will also be used in this study. The conventional inputs in this case consisted of three categories, labour, capital and variable inputs. Output was defined in a single index of dairy farm output containing milk, livestock and roughage sold. Waste emissions were treated as another factor of production besides conventional production outputs. Reductions in these emissions resulted in a reduced output and therefore it was able to measure the environmentally detrimental input usage. Technical and environmental efficiency with SFA and DEA for the years 1991 until 1994.

Brümmer et al. (2002) also used this timeframe, however he estimated the total factor productivity (TFP) growth which was decomposed in technical change, technical efficiency, allocative efficiency regarding inputs and outputs and scale efficiency. In this study, farms from Germany, Poland and the Netherlands were analysed. The part of TFP change is represented by allocative effects caused by market or behavioural conditions. For this research, four categories of inputs were used namely, capital, labour, land and intermediate inputs (such as concentrates, roughage, fertilizer and other purchases). Outputs were divided into milk production and other outputs. Dutch dairy farms were found with very high technological levels, which were only subject to modest rates of change. Growth should depend on allocative components more than increasing the level of technology, more than was the case for farms located in Germany or Poland. Because in this study also multiple years are assessed, technical change through the years will be examined by comparing mean TE scores, like in the study of Reinhard et al. (2000).

Kovács & Emvalomatis (2011) measured technical efficiency of Dutch dairy farms with the help of DEA and compared this score with Hungarian and German dairy farms. The authors indicated that farms that are inefficient are wasting inputs because they do not produce the maximum attainable output with the quantity of inputs used and the possibility of reducing costs concerning a timeframe of 2001 until 2005. Inputs were divided into six categories namely, capital, labour, material inputs (deflated farm specific costs), livestock and purchased feed (as deflated monetary value). Outputs were divided into milk production and other outputs (such as beef and veal and other outputs). Scale efficiencies were calculated by indicating the difference between constant returns to scale (CRS) and variable returns to scale (VRS), further explained in chapter 3.2. Focussing on Dutch dairy farms, this scale efficiency was found high, on average 0.96. This means that adjusting scale can only improve efficiency with 4% on average while maintaining the best practices that are already performed by an efficient farm.

Dandi (2017) did his thesis on the effects of scale on productivity and technical efficiency. Technical efficiency was estimated using SFA. Farms were studied concerning the same data set that is used in this thesis for the years 2011 to 2014. In this study it was concluded that intensification had a negative correlation with technical efficiency, and that the use of an automatic milking robot showed a positive correlation with technical efficiency. Furthermore, there were no much differences found in terms of technical efficiency between different size classes of farms. In his model Dandi (2017) use one output (milk income) and three inputs (labour costs, capital and other costs). To analyse the effects of scale production on efficiency, several explanatory variables were included namely, intensification, pasture size, automatic milking robot availability, concentrate costs, age of first calving, and age of farm manager.

From the studies that measured or predicted efficiency levels of Dutch dairy farming it becomes clear that dairy farms in the Netherlands reached high scores on efficiency in the past. In comparison with the findings in Mareth et al. (2016), who found a mean TE level for western European countries of 0.80, dairy farms in the Netherlands are performing on a high technical level relatively of which an overview is summarized in Table 1.

Table 1: Overview efficiency studies in Dutch dairy farming

Authors	***Year***	***Panel***	***Method(s)***	***Orientation***	***MTE***	***Sample size***
Reinhard et al.	1999	1991 - 1994	Stochastic translog production frontier	Input Output	0.903 0.894	613
Reinhard et al.	2000	1991 - 1994	SFA SFA DEA (VRS) DEA (VRS)	Input Output Input Output	0.889 0.899 0.811 0.784	613
Brümmer et al.	2002	1991 - 1994	TFP	Output	0.896	141
Kovács & Emvalomatis	2011	2001 - 2005	DEA (CRS) DEA (VRS)	Output Output	0.89 0.92	178
Dandi	2017	2011 - 2014	SFA	Output	0.91	2046

MTE = Mean Technical Efficiency, SFA = Stochastic Frontier Analysis, DEA = Data Envelopment Analysis, VRS = Variable Returns to Scale, CRS = Constant Returns to Scale, TFP = Total Factor Productivity

From Table 1 it becomes clear studies on the technical efficiency levels in Dutch dairy farming used various inputs. In Appendix I, a more elaborated table is shown including in- and output variables. The variables capital, labour, land and variable inputs are returning variables and are used in the studies performed on Dutch dairy farming. Variable inputs is an input which is composed by various costs or quantities that occur on variable basis, varying between the studies. Some studies included extra variables to measure for example environmental effects (Reinhard et al., 2000, 1999), or to measure the effect from a given technology like implementing an automatic milking system (AMS) (Dandi, 2017). With exception of the findings in Reinhard et al. (2000), TE scores of around 0.90 were found. Multiple methods of efficiency analyses were used, and differences in TE score were found which was already indicated by Mareth et al. (2016), written in chapter 2.1.1. These differences could not only occur by the method or in- and outputs that are used but can also occur due to technology improvement throughout the years. This can however not be confirmed because no similar methods, sample sizes or in- and outputs were found between the found studies in Table 1.

2.2. Functional traits

Functional traits, traits that contribute to the functionality and fitness of an individual cow, rather than production characteristics, began to raise attention when negative genetic correlations were observed in the 90's between milk yield and fitness traits. Increasing milk yield led to involuntary losses and an increase in veterinary visits. Due to the findings of the loss in milk yield and increase in veterinary visits, together with an increased importance of growing concerns about animal welfare and consumer demands for healthy and natural products, breeding goals started to include functional traits (Egger-Danner et al., 2014). Nowadays, milk yield is no longer ranked as the most important trait to select for in a breeding programme. From a survey of (Egger-Danner et al., 2014), respondents indicated that so-called hybrid cows that are healthy, have a long life expectancy but are also highly productive are desired. According to Bo (2009), breeding goals should include aspects that lead to an increased income, reduced costs, easier management and advantages the sales of products. This is possible when besides traits for a higher production of milk or beef, traits for a better fertility, fewer diseases and a higher live expectancy lead to reduced costs are considered due to savings on health and replacement costs. Cow temperament and milking speed lead to an improvement of management.

Pritchard et al. (2013) mentions that a farm income only can be sustained when an optimal balance between maximum production and minimal costs is realized. Reduced profitability is associated with costs related to health problems that eventually lead to involuntary culling. However, they also mentioned that health traits tend to have low heritability, which means that slow genetic gain implies and breeding effects will most likely be visible in the long term. Therefore yearly attention on breeding results for health traits should lead to moderate positive improvements in a cumulative way. Brickell & Wathes (2011) suggest that the increase of economic feasible life of cows also improves the efficiency of dairy production by lowering replacement costs. Fuerst-Waltl & Baumung (2010) divided the selection for traits into two categories; production and functional traits. Production traits are related to the production of output products such as milk or beef and functional traits to include both economic and socio-economic impact by improving animal welfare but also production sustainability. Within functional traits, several categories can be composed (Groen et al., 1997): health, fertility, calving ease, feed efficiency and milkability. Within Groen et al. (1997) longevity is not included as functional trait. Pritchard et al.(2013), indicated a somewhat similar set of functional traits, health (feet and legs or udder), longevity and fertility (calving interval, days to first service) as most common. Also in the earlier mentioned review about novel traits and phenotyping strategies in dairy cattle by Egger-Danner et al. (2014) similar categories on functional traits were found, however they also included metabolism. General characteristics of functional traits are that they are negatively correlated to milk production. Selecting for production levels solely will therefore lead to a deterioration of functional traits. However, improving functional traits can contribute to higher farm income by for example a prolonged economic cow life, or a reduction on veterinary costs.

2.2.1. Functional traits in data recording systems

Traits (both functional and production) are nowadays widely recorded by sophisticated data collection systems. Recently more and more collection systems arise that collect phenotypic data, which are closely related to functional traits (Cole, 2014). Information on these traits can be automatic or manually recorded on farm or in laboratories. Results of the information are often stored in databases that can be made available for research. In the next paragraphs, economic indicators and currently available sensor data on functional traits together with an explanation on the feed efficiency functional trait will be described which contribute to the selection of variables in chapter 3.3.

Economic indicators of functional traits

Economic values of *health* can be found in losses of future income when replacing animals before reaching the optimal economic age before culling. Unhealthy cows are often not productive and are therefore temporarily not providing income (Groen et al., 1997). Besides losses on future income, reduced slaughter values occur with unhealthy cows. Also, veterinary costs are higher, together with costs before disposal in unhealthy dairy herds. For *fertility* economic values can be find in insemination costs (including additional inseminations) and in the replacement policy of the farmer. Also (just like health) veterinary costs are higher at unfertile farms and increased culling rates can be observed. Lactation cycles will be increased which will reduce the optimal utility of a cow's milk production. *Calving ease* can be economically defined in calf losses and also in veterinary fees (Korver, 1988). For *feed efficiency* body weight measures and composition is an important indicator dependent on assumed feed prices and the intake of roughage and concentrates. Also the dynamics of residual feed intake have been indicated as an important economic value by several studies (Lu et al., 2018). *Milking speed* can be economically defined in labour and electricity costs. Furthermore, the presence of automatic milking systems (AMS) is an economic indicator for this functional trait. *Longevity* increases the average herd yield because there is a higher proportion of cows in the higher producing age-groups available. Also, replacement costs will be reduced which allows an increase in milking herd size, if no further restrictions are present. However, this depends on the costs of growing new animals versus the salvage value of a cow. Furthermore an increase in herd size can also lead to an increase in culling rates (Groen et al., 1997; Lu et al., 2018)

Functional traits and data collection systems

Besides economic indicators of functional traits, functional traits can also be related to other information available from on farm data collection systems such as for example AMS. For example, mastitis is the most common trait related to *udder health.* Mastitis can be indirectly measured by an prolonged elevated Somatic Cell Count (SCC) but also Electrical Conductivity (EC) which can be integrated in an AMS can be used as an indicator for mastitis (Pritchard et al., 2013). Feet and leg health is often recorded by linear type classification systems manually. Locomotion measures, either manually by farmers, breeding associations or veterinaries or by activity sensors are indicators for feet and leg conditions. Behaviour sensors track the position of cows which gives information on feeding and lying time but also on visit frequencies of AMS systems. Also information from hoof trimming could be an information source on feet and leg conformation traits (Egger-Danner et al., 2014). Calving dates, insemination dates and natural mating dates, pregnancy test results and hormone assays are information for *fertility disorders*. When a cow shows oestrus behaviour, a change in physical activity can be observed such as standing heat and mounting behaviour. Fertility indicators can be find in techniques that use for example pedometers to monitor physical activity or measuring body condition score which has a favourable relationship with fertility (Pryce et al., 2015). Furthermore, the type of farm bedding, flooring type and herd density in the housing system add information on factors that influence animal health (Egger-Danner et al., 2014).

Feed efficiency

Functional traits can be found in health, fertility and longevity characteristics and influence the efficiency of an individual cow. However reflecting to the definition of Friggens & Thorup (2015), efficiency of an individual cow can be divided into a digestive efficiency component including feeding behaviour and digestibility, and a metabolic efficiency component where the different metabolic functions (maintenance, production and activity) are included. Therefore, feeding efficiency is an important factor to include searching for useful variables for further analyses. Good fitness in functional traits like health, fertility and longevity relate to an improved feeding efficiency. For example, a negative energy balance is generally related to poorer health and fertility (Veerkamp, 2010). Because feed costs cover a large amount of a farms' variable costs, selecting for feed efficient dairy cattle is an important topic (Pryce, Wales, De Haas, Veerkamp, & Hayes, 2014). Feed efficient cows not only contribute to cost savings, also environmental impact of a dairy farm will decrease due to a more efficient use of raw materials and a lower greenhouse gas production. Most important factors for feed intake are energy needs for milk production and maintenance of the body (de Haas & Veerkamp, 2001). Feed rations for Dutch dairy mostly consist of hay, grass and corn silage and added concentrates

In the Netherlands, grasslands contribute to about 50% of all agricultural soils. The remainder soils contain mostly potatoes, fruits or other vegetables, but feeding crops such as corn and grain are also widely grown. Dairy farmers are often self-sufficient in feed, however there exist regional differences. For example, at peat soils, less arable crops such as corn or grains are cultivated due to bad cultivation circumstances for these crops. At sand, and clay most arable crops are cultivated (Plomp, Prins, van Schooten, & Pinxterhuisse, 2010). Farmers that are not able to cultivate or are low on their own feeding crops, but still want to provide their cows with mixed rations of grass, roughage and concentrates are able to purchase roughage. The purchasing behaviour of farmers of roughage can therefore be different according to different regions in the Netherlands depending mostly on soil type (Kool, 2017).

2.2.2. Overview functional traits

In Table 2, an overview is given for indicators that can be found from current data recording systems. Indicators for functional traits are based on the results from the performed literature study. Furthermore, availability in the dataset that is used in this study is given. With the help of this information, variable selection can take place.

Table 2: Overview of functional traits and their indicator together with their availability in the used dataset

Trait	***Indicator***	***Explanation***	***Available***
Health	Replacement rates	Indicator of frequent disposal	Yes
	Slaughter revenues	Indicator of reduced quality and weight	No
	Veterinary costs	Indicator of frequent veterinary visits	Yes
	Disposal costs	Indicator of frequent disposal	No
	(Increased) SCC	Indicator for udder health	Yes
	EC	Indicator for udder health	No
	Locomotion measures	Indicator for lameness	No
	AMS visits	Indicator for lameness	No
	Hoof trimming information	Indicator for lameness	No
	Floor type, farm bedding	Indicator for cow welfare	No
	Herd density	Indicator for cow welfare	No
Fertility	Insemination costs	Indicator of succeeded inseminations	Yes
	Calving interval	Indicator for fertility	Yes
	Culling rates	Indicator of disposal of unfertile cows	Yes
	Calf losses	Indicator of unsuccessful births	No
	Veterinary costs	Indicator of frequent veterinary visits	Yes
	Insemination and calving dates	Indicator of succeeded inseminations	No
	Pregnancy tests	Indicator of succeeded inseminations	No
	Pedometer results	Indicator of oestrus	No
Longevity	Replacement rates	Indicator of herd age management	Yes
	Culling rates	Indicator of herd age management	Yes
	Age	Indicator of herd age management	Yes
	Disposal costs	Indicator of herd age management	No
	Herd size	Indicator of herd age management	Yes
Feed efficiency	Land area	Indicator of extensiveness of farming	Yes
	Purchased feed	Indicator of extensiveness of farming	Yes
	Concentrate application	Indicator of feed additives	Yes
	Body condition score	Indicator for cow fitness	No
	Milk production	Indicator of returns from feed application	Yes

SCC = Somatic Cell Count, EC – Electrical Conductivity

2.3. Literature summary

In literature, already multiple efficiency analyses (including DEA) were performed in dairy farming globally. Average TE scores were found in Western European countries at around 0.80. Studies that were performed in the Netherlands showed higher average TE scores, around 0.90. These scores give a relative indication of all farms in a dataset, high average TE scores represent an efficient sample of farms relatively to each other. This means that the farms that were included in the Dutch were relatively highly efficient. The studies used multiple analysis methods and both input and output orientated approaches. Differences were found in the method of analysis that will be used in reviews on efficiency analysis in dairy farming from Bravo-Ureta et al. (2007), Mareth et al. (2016) and Rivas (2003), but also in which geographical location is used for analysis. Furthermore, differences between papers having various dimensions were found in the assessed reviews. It is therefore important that not only the right variables are included in the model, but also the number of variables must be considered to prevent overestimation or loss of information. In literature, it was not suggested concretely how many variables should be selected, however stepwise variable selection will give information on how adding or removing input or output influence the model (Wagner & Shimshak, 2007).

Variables that are selected in this study must have a link with the performance of individual cows. In Dutch dairy farming, former studies found that Dutch dairy farmers are at a highly technical efficient level relatively to each other. From the literature study on functional traits these variables have been found and multiple indicators for functional traits appear on the dataset that can be used for this study. Next to production traits like milk yield, functional traits arise awareness from breeders and dairy farmers. The functional traits can be subdivided into four categories: *health*, *fertility*, *longevity* and *feed efficiency*.

3. Material and Methods

DEA will be performed with a reduced set of variables from the original accounting dataset. The selection of variables is based on literature findings on functional traits and production traits chapter 2.2.1, earlier research on farm efficiency measures in Dutch dairy farms chapter 2.1.2 and previous knowledge of the dairy sector. Prior to a description of the data, variables are selected from the original dataset which contribute to cow health, fertility and longevity and furthermore relate to the production of milk from the original dataset. With this selection of variables, a sub-set will be made which will be used for the DEA. Data is processed with the help of Microsoft Excel 2016 and R Studio 1.1.414 together with R 3.5.2.

3.1. Data description

The original accounting data set that was provided by Flynth advisers & accountants, the dataset contained financial and farm specific information of 3432 unique dairy farm ID's for panel 2004-2016. Variables contained information from for example investments, financial statements or labour, but also farm specific herd information like cow age, and calving interval.

3.1.1. Data summary

Unbalanced panel data was selected for the years between 2013-2016. This means that not every year contained similar amounts of information concerning the assessed farms. Within this range, data was summarised based on several selection criteria (prior knowledge, functional traits literature and earlier research on dairy farm efficiency). Because only between 10 and 25 organic farms were found on a data panel of more than a thousand farms, organic farms were excluded from this research because of lack of data. Organic dairy farms could use different levels of inputs than conventional farms and can influence the results. Furthermore, only specialised dairy farms were selected from the provided data. This means that farms that also perform in other sectors such as arable farming are excluded from this research. Including only specialized dairy farms means that results only occur for in- and outputs that are used with the focus on milk production. Effects of other extra farm activities are therefore excluded. Specialized dairy farms that were selected all had information available on breed type that is present on the farm. Eventually, 846 farms had information available for a balanced panel of 2013-2016. Information of fixed costs and labour will not be used for further research because the focus in this study is on the relation of efficiency and functional traits. Information on variable costs will be subdivided in only relevant costs for this study. For data description, variables were subdivided into three categories containing information on variables for *Cows*, *Land* and *Costs*.

Former studies (Asmild et al., 2003; Brümmer et al., 2002; Dandi, 2017; Kovács & Emvalomatis, 2011; Lopez, 2006; Mugera, 2013; Reinhard et al., 2000, 1999; Theodoridis, 2015) emphasise besides the variable costs and feed application also on fixed costs like investments for machinery, buildings and land. Because fluctuating effects on yearly farm efficiency will appear, in this study fixed costs were not included in the selection of data variables. Furthermore, the focus in this study is on the technical efficiency explaining differences on cow level and not on investment efficiencies. Also labour can be an influencing factor of farm efficiency and is often implemented in studies that measure technical efficiencies (Mareth et al., 2016). However, because farm labour is weakly registered and mostly consists of household labour or hired labour, variables containing labour information were not included in this study for further research.

From the original accounting dataset, a set of suitable variables was selected which is shown in Appendix II. From the set of variables shown in Appendix II, the following subset was selected:

Table 3: Subset of selected variables

	Variable	Unit	Description
Cows	Number of cows	-	Average number of cows present at a farm
	Total milk production	kg	Total milk production of a year
	Average age	years	Average age of the cows
	Replacement rate	%	Average replacement rate
	Calving interval	days	Average calving interval of all cows
	Ratio of cows died	%	Percentage of died milking cows in one year
	Average culling age	years	Average age of culling
	Total concentrate application	kg	Total concentrate application
	Average SCC	cells/ml	Average Stomatic Cell Count (SCC) on a farm
Land	Area of grass	ha	Area of grass used for feed production or grazing
	Area of corn	ha	Area of corn used for feed production
	Area of other	ha	Area of other feed crops used
	Total area	ha	Total area feed crops
Costs	Concentrate costs	€	Concentrate costs per year
	Purchased roughage	€	Purchased roughage costs per year
	Total feed costs	€	Total feed costs per year
	Health costs	€	Health related costs per year
	Breeding and controlling costs	€	Costs related to breeding and controlling per year

SCC = Somatic Cell Count

The variable *Total concentrate application* is calculated from the original dataset as the product of the Number of cows and the application concentrates per cow per day for one year (365 days).

Per year summaries of the selected variables are given in the Results chapter 4.1. Of each variable, the number of data points, minimum, maximum, mean and standard deviation are given divided over the data panel for 2013-2016. To compare the heterogeneous variables, a coefficient of variation (COV) is calculated for every variable according to the following formula:

$$COV = \frac{\mu}{\sigma} \tag{3.1}$$

where:

μ = mean of the samples of one variable
σ = standard deviation of the samples of one variable

With the help of COV, a direct representation of the variance within a variable can be shown, easier interpretable than the standard deviation because COV is given in a range from 0 to 1 relative to the mean value. With the help of this parameter, highly fluctuating variables between the selected farms can be indicated directly in relation to variables that are used at a more constant rate.

3.2. Data Envelopment Analysis

The DEA methodology forms a best-practice frontier from the most efficient DMU's. DEA (and other efficiency analyses tools) can be approached with an input or an output orientation. Due to restrictions on milk production by the phosphate rights system, initiated in January 2018, an input oriented DEA will be performed. Dutch dairy farmers are assigned a given measure of phosphate rights, suitable to the dairy herd that was available on a farm at the 2nd of July 2015 (Rijksdienst voor Ondernemend Nederland, 2019). It is possible to buy phosphate rights from other farmers in the Netherlands, which allows farmers to increase their dairy herd and subsequently their milk production. Another, more sustainable, approach is to produce the same amount of milk with decreasing inputs, this latter orientation will be used in this study.

Full efficiency is attained by DMU's who are not able to improve their inputs so that outputs remain the same (concerning an input oriented approach). The best-practice frontier defines a relationship between the input and output and represents the maximum output attainable with given input(s). It reflects the current state of technology that is available at the time of assessment. Technical efficiency is determined by the DMU's that are operating on the frontier. Inefficient DMU's could attain the same output by reducing their inputs if an input-oriented approach is adopted. In this study, DEA analysis will be performed in R.

With the use of linear programming, the non-parametric surface can be derived from the selected data. The efficiency measures of the concerned DMU's can be measured relative to this surface. A DEA model can be assumed with constant or variable returns to scale (CRS and VRS respectively). By measuring both efficiency scores with CRS and VRS assumptions, scale efficiencies can be calculated which indicate the utility for farms to increase in scale concerning selected inputs and outputs. A CRS assumption can therefore be appropriate when all DMU's are operating at an optimal scale. When this is not the case, measures of technical efficiencies (TE) can be confounded with scale efficiencies (SE). Therefore, it could be better to use a VRS approach when SE's are high. SE can be calculated by examining the difference between the TE measures of both VRS and CRS (Coelli, Rao, O'Donnel, & Batesse, 2005).

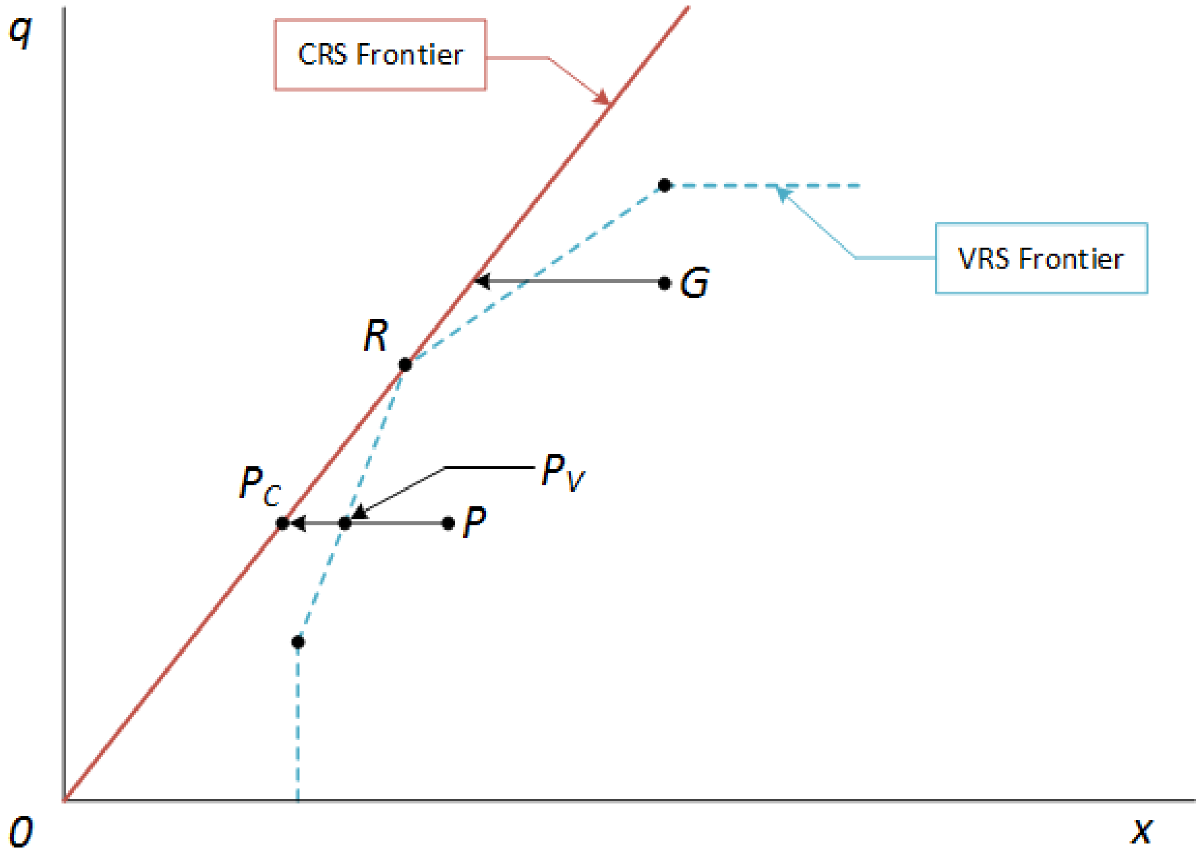

Figure 2: Visualisation of scale efficiency measurements with efficient farm R and inefficient farms G and P, q represents outputs and x represents inputs as in (Coelli et al., 2005)

With the help of Figure 2, SE can be made visible. When the farm P is concerned, it can be assumed as inefficient because it has a distance to the best-practice frontier. This distance however is unequal when a VRS approach is compared with a CRS approach. Technical inefficiency under VRS is in Figure 2 represented by PP_V, under CRS this distance is larger and represented by the distance PP_C. Visualisation of both (CRS and VRS) assumptions is done in Figure 2. Farm R is operating in a full efficient way, meaning that improvements in inputs or on scale will not lead to any progress in efficiency.

In Figure 2 an input-oriented approach is assumed. This is similar to the approach used in this study. An input-oriented approach identifies technical efficiency as a proportional reduction in input usage without changing the level of output production. A linear programming model for CRS and VRS assumptions are somewhat different to each other. Equation (3.1) represents a general equivalent form where the objective is to minimize inputs while maintaining the same output. VRS is taken into account by adding an extra constraint, $\mathrm{I}1'\lambda = 1$:

$$\begin{aligned} \min_{\theta,\lambda}\ & \theta, \\ \text{st}\ & -q_i + Q\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \\ & \mathrm{I}1'\lambda = 1 \\ & \lambda \geq 0, \end{aligned} \tag{3.1}$$

where θ is a scalar and λ is a $I * 1$ vector of constants. Data is represented by N inputs and M outputs for each of I farms. For every farm (with index i) in- and outputs are represented by column vectors x_i and q_i respectively. All I farms are subsequently represented by the $N * I$ input matrix, X, and the $M * I$ output matrix, Q. Where $\theta \leq 1$, a farm is technically efficient when a value of 1 is measured because θ is the TE score which is obtained I times. The problem in equation (3.1) uses the feasible area represented by the constraints to radially move the input vector x. This movement projects a point on the best-practice surface ($X\lambda$, $Q\lambda$). Every point represents one farm and is a linear projection of the observed data points in the production area.

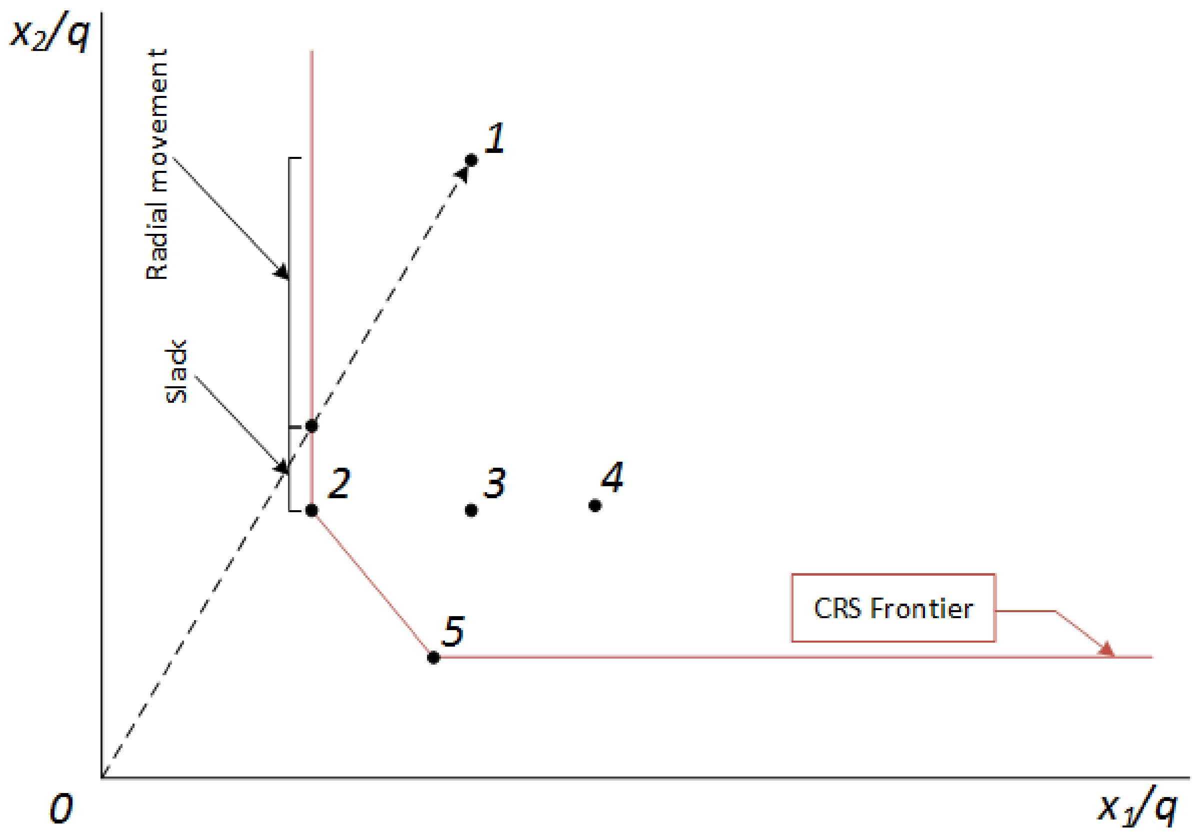

Figure 3: Constant returns to scale frontier assuming multiple inputs. Point 1 is projected on the best-practice frontier

When considering multiple inputs, slack values occur because the projected value consists of the original value, radial movement to the best practice frontier and some slack movement to efficient farms that are used as benchmarks. A multiple input situation with associated slacks are visualised in Figure 3. When concerning slacks, a farm on the best-practice frontier can therefore improve its inputs by reducing slack. This is done by projecting the observed data point to a farm on the frontier that uses less inputs and is used as a benchmark. It has no radial movement because it already operates on the frontier. Input slacks are non-occurring when $-q_i + Q\lambda = 0$. Calculating slacks can only be performed when multiple linear programs are performed additional to the original technical efficiency calculations.

Coelli et al. (2005) suggest that slacks are essentially considered as allocative efficiency. For the analysis of technical efficiency, it is suggested to concentrate on the radial movement of the first stage DEA-LP described under (3.1). In this study, only technical efficiency is considered and focus will be on the differences between farms with different efficiency scores, based on statistical analyses. Therefore slack values will not be considered in this study.

3.3 Variable selection

From the list of variables that are represented in Table 3 a final set of variables are selected with the help of selection methods in 3.2.1 and 3.2.3.

3.2.1. Correlations

To check whether there is multicollinearity and collinearity between the selected variables from the data set, a correlation matrix was built in R. With the information of the correlation matrix (Table 4) first insights are gained (together with the information from literature and the information from the descriptive statistics) on the final selection of variables for the data envelopment analysis. When strong correlations occur between several of the selected variables, multicollinearity tests can be performed. It is therefore not necessary to include all of the selected variables from the correlation matrix.

A Pearsons' correlation matrix was built to determine the correlation between the input and output variables. Because all variables are continuous from a large sample volume, this matrix can be used. The Pearson's r correlation coefficient (r) between two variables can be calculated as follows:

$$r = \frac{\sum_i (x_i - \overline{x})(y_i - \overline{y})/(n-1)}{s(x)(y)} \tag{3.2}$$

with:

r = Pearson' s r correlation coefficient
x, y = unique sample of variable x or y
$\overline{x}, \overline{y}$ = mean values of x and y
s = standard deviations with

$$s(x) = \sqrt{\frac{1}{(n-1)} \sum_{i=1}^{n} (x_i - \overline{x})^2}$$

and $s(y) = \sqrt{\frac{1}{(n-1)} \sum_{i=1}^{n} (y_i - \overline{y})^2}$

In Table 4 on the next page a correlation table is represented with variables that can be found in Table 3. The variables have correlating values based on equation 3.2 above.

Table 4: Correlation table between in- and output variables based on Pearson's r correlation coefficient. Blue coloured cells contain strongly positive correlations, red cells contain strongly negative correlations within a range between 1 and -1.

	Concentrate costs	Amount of cows	Total concentrate application	Total feed costs	Area of grass	Total area	Health costs	Purchased roughage	Area of corn	Contrate application per cow	Area of other	Replacement rate	Ratio of cows died	Average SCC	Calving interval	Average age
Total milk production	0.95	0.97	0.94	0.93	0.78	0.77	0.73	0.55	0.48	0.2	0.08	0.03	0	0	-0.1	-0.13
Concentrate costs		0.92	0.97	0.93	0.74	0.74	0.72	0.5	0.48	0.39	0.06	0.05	0.02	0	-0.06	-0.14
Amount of cows			0.92	0.9	0.82	0.82	0.67	0.53	0.46	0.08	0.08	0.02	0.04	0.08	-0.05	-0.08
Total concentrate application				0.89	0.78	0.73	0.7	0.47	0.4	0.39	0.04	0.04	0.02	0	-0.05	-0.12
Total feed costs					0.64	0.6	0.71	0.71	0.37	0.26	0.05	0.04	0.02	0	-0.08	-0.14
Area of grass						0.97	0.55	0.19	0.33	0.09	0.07	0.01	0.01	0.06	0.01	-0.03
Total area							0.54	0.15	0.57	0.03	0.13	0.03	-0.02	0.07	0.08	0
Health costs								0.39	0.36	0.26	0.04	0.04	0	-0.11	-0.12	-0.1
Purchased roughage									0.04	0.04	0.02	0	0.01	-0.04	-0.09	-0.07
Area of corn										0.04	0.09	0.11	0	0.07	-0.06	-0.12
Contrate application per cow											-0.03	0.1	-0.01	-0.15	-0.02	-0.19
Area of other												0.02	0.03	0.04	-0.01	0.01
Replacement rate													0.16	-0.03	-0.03	-0.28
Ratio of cows died														0.18	0.22	0.04
Average SCC															0.26	0.08
Calving interval																0.22

SCC = Somatic Cell Count

In Table 4 variables were ranked from having the least collinearity to having the most collinearity with other variables. The variable *Total milk production* was found with highest correlations in respect to the other variables. It is almost perfect positively correlated with the number of cows, which is no surprising result. *Total milk production* is a variable that can be classified as a production trait and therefore functions as an output for the following DEA. As shown in Figure 5 in chapter 4.1.3, *Total feed costs* consists for around 74% of *Concentrate costs.* This leads to an almost perfect positive correlation between total feed costs and costs for concentrates. It is therefore unnecessary to include both variables into the analysis. The variable *Purchased roughage* is moderately positive correlated with *Total feed costs*. *Health costs* and *Breeding controlling costs* also has strong positive correlations with *Total feed costs*, *Total milk production* and *Number of cows* in general. A higher number of cows results in a higher milk production, as expected. Furthermore, costs on feed, health and breeding increase. Higher concentrate application has a weakly positive correlation with the replacement rate and has weak negative correlation with *SCC* and *Age*. This could indicate that higher concentrate application leads to higher health issues, resulting in a lower average age. However, due to this weak correlation, this cannot be clarified based on only these results. *Total concentrate application* is almost perfectly positive correlated with *Concentrate costs*, for further analyses only one of the two variables will be selected, preferably *Total concentrate application* because this value is not affected by fluctuating concentrate prices. Only a moderately positive correlation is found between Area *of grass* is strongly positive correlated with the number of cows, which indicates the grass-based way of farming which is common in the Netherlands. *Area of corn* is moderately positive correlated with the number of cows and milk production. This finding is an indicator of the variability in feeding from own soil management by the selected farmers. *Area of other* almost has no correlation with other variables. *Culling age* is moderately correlated with *Age*, for further analyses only one of these two variables will be selected, preferably *Age* because more information is available for this variable. Both variables have a moderately negative correlation with *Replacement rate* which indicates that farms having cows with a higher average age have lower replacement rates.

3.2.2. Multicollinearity

Multicollinearity can exist between two or more variables or a linear combination between one variable and all other variables. In this case, multicollinearity is tested with *Total milk production* as dependent variable, because this is also assumed as output in the DEA. Multicollinearity can create difficulties when linear models are built between response variable y and explanatory variables x_i. Because DEA is also a linear representation of dependent and explanatory variables, a multicollinearity test can be informative in the selection of variables. To determine if multicollinearity problems occur in the data set, Variance Inflation Factors (VIF) can be calculated after calculating a Pearson's correlation matrix, because the latter method only describes the correlations between two independent variables. VIF values measure the increase in the standard deviation in a case of multicollinearity relative to the variance in a case when no multicollinearity would occur. Large values of VIF represent the way a standard deviation is inflated and indicate the involvement of a variable to linear dependency. The threshold between large and small values for VIF is generally taken as 10, which means that variables including higher values deserve attention for inclusion because these variables can be indicators for multicollinearity problems for a data set (Alin, 2010). Values between 5 and 10 are questionable. VIF can be calculated as follows:

$$VIF_i = \frac{1}{1 - R_i^2} \text{ for } i = 1,2, \dots, k \qquad (3.3)$$

where R_i^2 is the coefficient for multiple determination of a variable x_i on the other selected explanatory variables.

Multicollinearity is shown in Table 5. Variables *Number of cows*, *Total concentrate application*, *Concentrate costs* and *Total feed costs* contain high values of VIF and require therefore attention. Total concentrate application is most informative for the concentrate use on a farm. Including also roughage costs reflect the majority of the total feed composition of a farm. Therefore, the variables *Concentrate costs* and *Total feed costs* can be eliminated. Because the number of cows is an important explanatory variable when measuring the efficiency of dairy farms, this variable will be included despite the high value of VIF. Excluding variables that give double information or result in high VIF values, reduces the mean VIF from 7.95 to 3.62. Only the variable *Number of cows* still has a value above 10.

Table 5: Multicollinearity by VIF scores

	VIF	
Mean VIF	**7.95**	**3.62**
Area of grass	4.56	4.97
Area of corn	2.23	1.78
Area of other crops	1.05	
Number of cows	17.25	15.83
Average SCC	1.20	1.19
Calving interval	1.20	1.22
Ratio of cows died	1.13	1.12
Replacement rate	1.26	1.17
Average age	1.46	1.18
Average culling age	1.53	
Total concentrate application	30.35	7.01
Concentrate costs	42.35	
Roughage costs	5.15	3.34
Total feed costs	21.92	
Health costs	2.33	2.33
Breeding and controlling costs	2.49	2.34

SSC = Somatic Cell Count

3.2.3. Best subset selection

Output of DEA results depend heavily on the amount of input and output variables that are used in the model. Choices of these variables are from importance because the extent of variable selection can have influence on the assigned weights to the in- and outputs (Wagner & Shimshak, 2007). Furthermore, in contrast to the amount of DMU's that are selected in a DEA, a higher number of variables leads to a less discerning DEA result and a higher dimensionality of the LP solution space. Eventually, more DMU's will reach a fully efficient stage and overestimation will occur (Jenkins & Anderson, 2003).

To reduce the dimensionality of the DEA model, best subset selection was used to identify a subset of variables that are related most the response of the model, which is in this case milk production. Every possible combination is used to predict milk production in a regression model, within this model, the variable *Number of cows* was always forced in. The subset containing the least residual sum of squares (RSS) can be considered as the most explanatory combination.

First, the panel data for 2013-2016 with the selected variables from the correlation analysis was divided into a training and a test dataset. Then, cross-validated prediction was performed where linear regression was performed on the training dataset and predicted on the test dataset. Finally, mean squared errors (MSE) between the regression model and the prediction model where calculated for every subset to identify which combination is most explanatory for milk production, calculated as follows:

$$MSE = \frac{1}{n}\sum_{i-1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{3.4}$$

where the mean $(\frac{1}{n}\sum_{i-1}^{n})$ of the squares of the errors $\left(Y_i - \hat{Y}_i\right)^2$ is calculated and where Y_i represents the observed values for the regression on the training dataset and $\hat{Y}_i$ represents the observed predicted values on the test dataset.

Sets of variables and outcomes of the best subset selection are summarised in Appendix III. Set 5 contains six variables which is suitable for performing a DEA. These variables are most explanatory considering the whole set of variables leading from the correlation analysis. The variables that will be selected for performing DEA are (ordered from most explanatory to least explanatory for milk production):

- Number of cows
- Calving interval
- Total concentrate application
- Health costs
- Breeding and controlling costs
- Ratio of cows died

Because these variables all declare the milk production and variables on feed are not well represented in the model by these six variables, one variable will be dropped from the selection (*Ratio of cows died*) and will be substituted with a variable which is not explanatory for milk yield but does give some information on feed intake:

- Total feed crop area (Sum of area of grass, corn and other feed crops)

With these six variables, DEA will be performed per year for the years 2013, 2014, 2015 and 2016 on the 846 DMU's. MSE's are summarized in Figure 4:

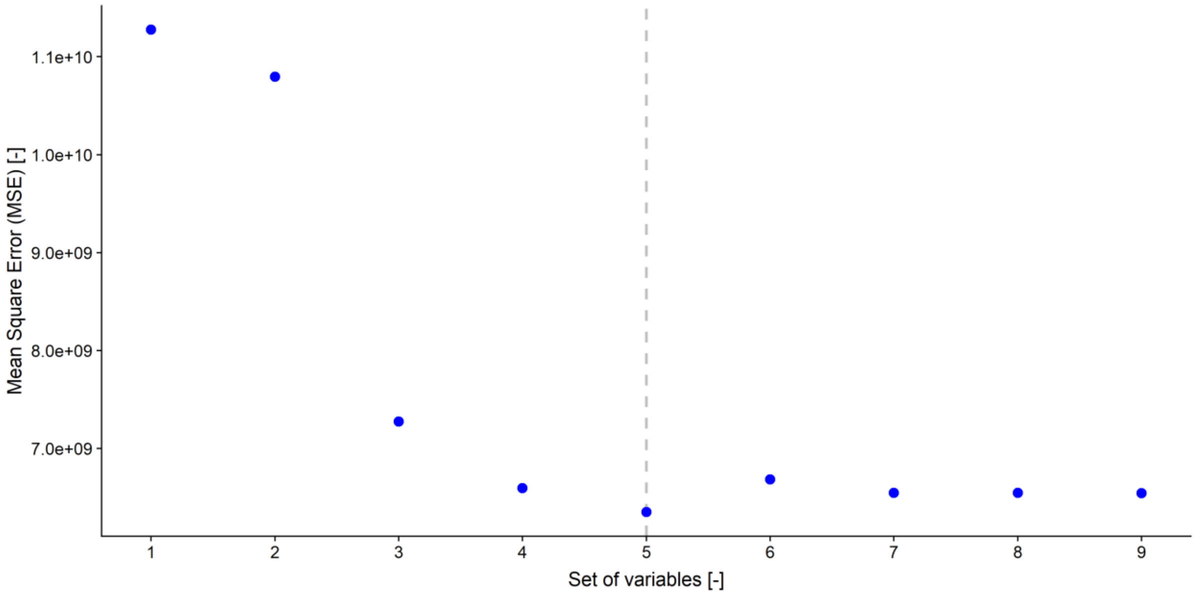

Figure 4: Summaries of Mean Squared Errors returning from the selected variables from the best subset selection with on the y-axis the MSE of each set of variables (x-axis) between the predicted and actual Milk yield). Sets of variables are shown in (Appendix III, Table 2)

In Figure 4 it is made visible that including more variables in a set of variables (Appendix III), the mean squared error (MSE) will be reduced until a given amount. Variables that were included first explain milk production the most. In this case that are the variables listed above. Including all variables will lead to a worse prediction of the milk yield than including the six variables represented by set 5 because than a larger MSE is shown.

3.4. Comparison of results

Results of the DEA are compared using several statistical tests and post-hoc tests. Comparison will be performed on different groups of efficiency levels. These groups will be based on the distribution of efficiency scores per year, shown in Table 6:

Table 6: Ranges of comparison groups based on TE score

Group	Range
1	Maximum TE score (1)
2	3rd Quartile < Maximum TE score
3	Mean < 3rd Quartile
4	1st Quartile < Mean
5	Minimum TE score < 1st Quartile

TE = Technical Efficiency

Because the group containing efficient farms could have a substantially large size, this group is taken as one separate group. Furthermore, whit this distribution of groups, it is possible to compare fully efficient farms with lower efficient farms.

Variables that were compared are a mixture of input variables, farm specific variables and derived variables from milk output. The variables that will be compared using statistical tests are shown in Table 7 which is a subset of the variables shown in Table 3. In Table 7 variables were derived per unit of output when this was found useful to compare different efficient scoring classes on their performance per output:

Table 7: Overview of variables used for statistical comparison based on TE scores

Variable	Unit	Description
Number of cows	no.	Average number of cows present at a farm
Calving interval	days	Interval between birth of a calf and a subsequent calf
Ratio of cows died	%	Percentage of cows that has died in one year at a farm
Replacement rate	%	Replacement percentage of cows at a farm
Average age	years	Average age of the production cows at a farm
Average culling age	years	Average culling age of the production cows at a farm
Milk production per total area	kg/ha	Amount of milk produced per total feeding area
Milk production per cow	kg/cow	Amount of milk produced per cow present at a farm
Concentrate application per unit of milk	kg/100 kg	Average amount of concentrates applied to a cow per 100 kg of produced kilograms of milk
Purchased roughage per unit of milk	€/100 kg	Average costs of purchased roughage per 100 kg of produced kilograms of milk
Health costs per unit of milk	€/100 kg	Average costs of health-related activities per 100 kg of produced kilograms of milk
Breeding and controlling costs per unit of milk	€/100 kg	Average costs of breeding and controlling related activities per 100 kg of produced kilograms of milk

To compare variables, they were first examined if they are normally distributed with the help of a Shapiro-Wilks test. This test assesses if the mean observations for a concerning variable are normal distributed. When variables were found normally distributed, TE scores were compared using a one-way ANOVA, divided into five TE score groups (Table 6). Variations between the groups were compared and examination of statistical difference between these groups was performed. When variables were found not normally distributed, the same procedure was performed using a non-parametric Kruskal-Wallis test. This test analyses if TE score groups are equal to each other, equal to a One-way ANOVA, however in this case non-distributed variables are assessed and makes assumptions based on median values instead of mean values. These tests indicate if there are significant differences between the assessed groups (Table 6) but do not give information for between group differences. To get this information, a post-hoc test will be performed. When a variable was normally distributed, a Tukey range test will be performed. When a variable is not normally distributed, a Wilcoxon signed rank test will be performed to compare the five groups. These post-hoc tests analyse the differences between two paired groups.

4. Results

4.1. Data summary

All variables that were selected in chapter 3.1.1 are summarized in three categories: *Cows, Land* and *Costs* for every year between 2013 and 2016.

4.1.1. Cows

From Table 8 at the next page it becomes clear that most missing values arise from the average Somatic Cell Count (SCC) variable. The variables average cow age, replacement rate, calving interval and percentage of cows died all contain between 300 and 325 missing values. From a more in-depth examination of the dataset it becomes clear that farms that miss one of the above variables, often also miss data of the others. This makes these farms less informative if one or several of these variables are selected for further research. Information on total milk production and the number of cows present at the farm is available of all the selected farms. The coefficient of variance (COV) gives information of the ratio of the variation of the data relative to the mean. With the help of the COV, variation is standardized and easier to interpret the magnitude of variation concerning the different variables. Standard deviations were found high on the percentage of cows died. Moderate variation was found in the variables average number of cows, total milk production and total concentrates applied.

Table 8: Summary of selected variables in chapter 3.1.1 in the cow related category

		N	N blank	Mean	Min	Max	Std. Dev.	COV
2013	**Number of cows [-]**	1223	0	95.7	14.4	621.1	46.4	0.5
	Total milk production [kg]	1223	0	794599	83452	4766903	397755	0.5
	Avg. age [years]	886	337	4.2	3.1	7.0	0.5	0.1
	Replacement rate [%]	872	351	25.9	6.0	73.0	7.5	0.3
	Calving interval [days]	889	334	411.9	352.0	635.0	25.5	0.1
	Ratio of cows died [%]	882	341	3.0	0.0	16.0	2.5	0.8
	Avg. Culling age [years]	874	349	5.3	3.1	10.1	0.8	0.2
	Total conc. application [kg]	1204	19	205957	27193	1926963	111504	0.5
	Average SCC [cells/ml]	282	941	172.7	67.0	409.0	54.3	0.3
2014	**Number of cows [-]**	1223	0	97.7	14.5	686.3	48.6	0.5
	Total milk production [kg]	1223	0	816585	90889	5307904	416534	0.5
	Avg. age [years]	901	322	4.2	3.1	7.0	0.4	0.1
	Replacement rate [%]	889	334	26.9	1.0	69.0	7.5	0.3
	Calving interval [days]	904	319	409.3	352.0	592.0	24.5	0.1
	Ratio of cows died [%]	899	324	3.3	0.0	25.0	2.8	0.9
	Avg. Culling age [years]	888	335	5.3	3.1	20.6	0.8	0.2
	Total conc. application [kg]	1210	13	209777	25404	2003996	117766	0.6
	Average SCC [cells/ml]	298	925	166.2	76.0	328.0	48.2	0.3
2015	**Number of cows [-]**	1223	0	102.9	16.9	879.9	55.2	0.5
	Total milk production [kg]	1223	0	872159	99125	6737981	486145	0.6
	Avg. age [years]	916	307	4.2	3.1	6.1	0.4	0.1
	Replacement rate [%]	900	323	24.0	2.0	62.0	7.0	0.3
	Calving interval [days]	917	306	409.6	356.0	594.0	24.9	0.1
	Ratio of cows died [%]	910	313	2.9	0.0	18.0	2.4	0.8
	Avg. Culling age [years]	902	321	5.3	3.1	11.0	0.9	0.2
	Total conc. application [kg]	1211	12	226854	18834	2472959	142736	0.6
	Average SCC [cells/ml]	349	874	158.5	40.0	403.0	52.4	0.3
2016	**Number of cows [-]**	1223	0	109.4	10.8	1043.9	62.2	0.6
	Total milk production [kg]	1223	0	941984	97843	8315824	557098	0.6
	Avg. age [years]	921	302	4.2	3.1	6.1	0.4	0.1
	Replacement rate [%]	909	314	26.9	2.0	89.0	7.5	0.3
	Calving interval [days]	918	305	404.9	356.0	617.0	23.8	0.1
	Ratio of cows died [%]	914	309	3.6	0.0	22.0	3.1	0.8
	Avg. Culling age [years]	904	319	5.3	3.1	10.1	0.8	0.2
	Total conc. application [kg]	1202	21	254139	11884	3810235	183716	0.7
	Average SCC [cells/ml]	308	915	159.4	40.0	351.0	52.8	0.3

SCC = Somatic Cell Count

4.1.2. Land

Selected farmers vary in cropland area. Not only because farms vary in size farmers need more land to provide their animals of feed, but also management and availability of farmland can play a role in the distribution and presence of land on farm. Furthermore, in some areas in the Netherlands it is only possible to farm grasslands. Farms can be very extensive or intensive, depending on management styles. Furthermore, rations can vary between dairy farmers in the Netherlands from very grass (protein) based to rations that include more cereals such as corn. From the Table 9, most variation is found in maize and other cropland. It is made visible that farmers almost don't cultivate other crops than maize and grass, which are also the most common components in Dutch dairy rations (Plomp et al., 2010). Availability of information on land availability on the selected farms was found for every assessed farm.

Table 9: Summary of selected variables in chapter 3.1.1 in the land related category

		N	N blank	Mean	Min	Max	Std. Dev.	COV
2013	***Area of grass [ha]***	1223	0	38.7	0.0	298.4	18.8	0.5
	Area of corn [ha]	1223	0	9.0	0.0	58.0	6.7	0.7
	Area of other crops [ha]	1223	0	0.3	0.0	21.8	1.5	5.7
2014	***Area of grass [ha]***	1223	0	40.5	0.0	345.2	20.1	0.5
	Area of corn [ha]	1223	0	7.9	0.0	58.0	6.0	0.8
	Area of other crops [ha]	1223	0	0.2	0.0	21.8	1.2	6.2
2015	***Area of grass [ha]***	1223	0	42.3	0.0	387.2	21.7	0.5
	Area of corn [ha]	1223	0	7.4	0.0	58.0	5.8	0.8
	Area of other crops [ha]	1223	0	0.1	0.0	15.7	1.0	7.0
2016	***Area of grass [ha]***	1223	0	43.5	8.1	463.5	23.9	0.6
	Area of corn [ha]	1223	0	7.5	0.0	69.4	5.9	0.8
	Area of other crops [ha]	1223	0	0.3	0.0	21.7	1.5	6.1

4.1.3. Costs

The availability of data for the selected variables on costs were found good. Variations within cost related variables was almost found similar between the variables, representing moderate variations between the farm for all costs, except for the variable *Roughage costs*. Roughage costs vary most between farms because of availability of land and crop strategies (chapter 2.2.1). Some farmers are therefore high in roughage purchases and some farmers are able to cultivate their own feeding crops. Moderate variation was found in total feed costs, which also includes the costs for concentrates. Total feed costs consist of; concentrate costs, vitamins and minerals, milk products, purchased roughage and stock change, wet by-products and grazing rents. In Figure 5 the contribution of these costs to the total feed costs are visualised.

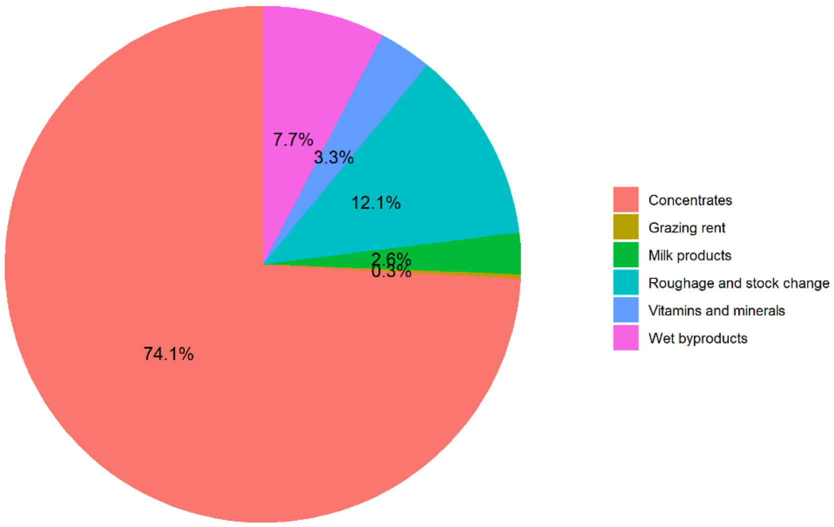

Figure 5: Overview of feeding cost structure

Total feed costs consist for almost three quarters of concentrates, which is varying moderately between farmers as seen in Table 10. It is therefore possible that some variation in efficiency can be found from concentrate use. Costs of roughage contribute to 12% of the total feed costs on average, this can vary between farms as can be observed from Table 10.

Table 10: Summary of selected variables in chapter 3.1.1 in the costs related category

		N	***N blank***	***Mean***	***Min***	***Max***	***Std. Dev.***	***COV***
2013	Concentrate costs [€]	1223	0	64066	7899	391839	33380	0.5
	Roughage costs [€]	1223	0	14404	0	136585	15392	1.1
	Total feed costs [€]	1223	0	90300	8931	483364	51503	0.6
	Health costs [€]	1223	0	7393	510	38333	4306	0.6
	Breed. and contr. costs [€]	1223	0	7171	327	30778	3563	0.5
2014	Concentrate costs [€]	1223	0	59985	6495	414017	32270	0.5
	Roughage costs [€]	1223	0	17025	0	133529	17582	1.0
	Total feed costs [€]	1223	0	84873	6639	485142	51215	0.6
	Health costs [€]	1223	0	7651	700	55202	4609	0.6
	Breed. and contr. costs [€]	1223	0	7573	188	31027	3769	0.5
2015	Concentrate costs [€]	1223	0	62558	6113	497263	36908	0.6
	Roughage costs [€]	1223	0	17301	0	199528	19368	1.1
	Total feed costs [€]	1223	0	90194	3030	590513	58832	0.7
	Health costs [€]	1223	0	8045	765	55925	5012	0.6
	Breed. and contr. costs [€]	1223	0	7553	487	35855	3978	0.5
2016	Concentrate costs [€]	1223	0	68406	3314	706013	44952	0.7
	Roughage costs [€]	1223	0	16362	0	204434	18568	1.1
	Total feed costs [€]	1223	0	95016	2701	824098	66415	0.7
	Health costs [€]	1223	0	8415	580	62369	5289	0.6
	Breed. and contr. costs [€]	1223	0	7997	150	36625	4345	0.5

4.2. Data Envelopment Analysis

4.2.1. Summary of efficiency scores

Based on the selection of the best subset variable selection method, five input variables and one output variable were selected which is explained in chapter 3.2.3. Variables that were selected for DEA are; *Number of cows, Calving interval, Total concentrate application, Breeding and Controlling costs, Health costs* and *Total area* as input variables and *Total milk production* as output variable.

TE scores and their distribution resulting from the DEA, performed per year are shown in Table 11. Most efficient farms were found in the year 2014 concerning these six input variables. Mean TE scores were found to be 0.93 for all assessed years. Mean TE scores were found high and indicate that the 846 selected Dutch dairy farms operate near or on the best practice frontier. Almost no increase in mean TE was found between the assessed years (with 2013 containing the lowest and 2015 containing the highest meant TE score), however the number of efficient farms were substantially lower in the year 2016. This means that almost no improvement was made in input use relatively to the produced output on average over consequent years between 2013 and 2016.

Table 11: Summary of TE scores

	Min.	***1st Qu.***	***Median***	***Mean***	***3rd Qu.***	***Max.***
2013	0.743	0.901	0.929	0.927	0.958	1
2014	0.697	0.904	0.935	0.932	0.965	1
2015	0.705	0.905	0.935	0.933	0.966	1
2016	0.718	0.904	0.933	0.929	0.956	1

The scores are not normal distribution because many farms have a TE score of 1. Most farms have an efficiency between 0.9 and 1.

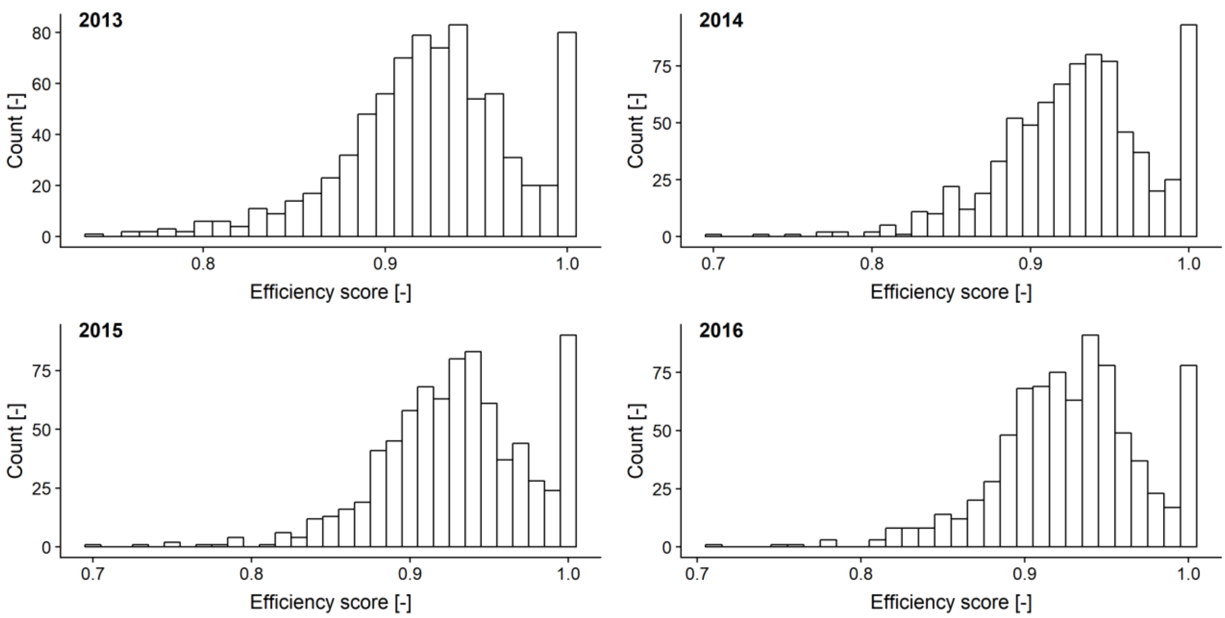

Figure 6: Histogram plots of the TE score distribution per year

The histograms in Figure 6 indicate that there are no large differences on TE scores between the years. Not many outliers were found in the lower region, but there are some farms found that have a substantially lower TE score relative to the other farms in the selected data set. This finding shows that farms are technical efficient relative to each other. Farms that have the lowest TE score, use there inputs approximately 30% less efficient than the most efficient farms in the dataset, having TE scores of 0.70.

4.2.2. TE score group dynamics through 2013-2016

To compare TE scores during the years, farms were ranked on their TE score within five groups. Groups and their group sizes are shown in Table 12**.** For further comparison, ranks are divided based on the same quartiles as in Table 11. The TE score groups can be used to compare significant differences of the selected variables that are linked to functional traits. Furthermore, a more in-depth examination of the in- and decrease of TE gives an indication of the technical level (or input/output use), which is relevant to examine if farms fluctuate a lot in TE or remain the same score every year relatively to the other farms.

Table 12: Composition of TE score groups based on the distribution per year in Table 12

TE score group	***Range***	***Rank***	***2013***	***2014***	***2015***	***2016***
1	Max.	Fully efficient	90	98	99	77
2	3rd Qu. – Max.	Highly efficient	121	114	113	134
3	Mean – 3rd Qu.	Moderately efficient	225	236	223	233
4	1st Qu. – Mean	Lower efficient	198	186	199	189
5	Min. – 1st Qu.	Low efficient	212	212	212	213

From Table 12 it can be seen that in the years 2014 and 2015 most efficient farms were found. In these years, also mean efficiency as found highest (Table 11). To analyse the in- and decrease of efficiency score, changes in ranks between groups were recorded and compared per year. Most farms maintained an equal rank between two consecutive years. In 2013-2014, more farms decreased in rank than increased, however in 2015-2016 the opposite was observed. In 2014-2015, approximately an equal number of farms decreased and increased in TE group. No farms subsequently increased in rank. There were 165 that maintained the same rank every year. Most of the farms that subsequently were in the same ranking group were found in group 5 low scoring farms. The dynamics of ranking change during the years summarised in Table 13 only give a brief overview of TE changes during the years. A more precise overview is given in Table 14.

Table 13: Dynamics of TE scores between ranking groups, brief overview

	2013-2014	***2014-2015***	***2015-2016***
Increase	219	224	210
Equal	396	402	425
Decrease	231	220	211
Constant increase		2	
Constant equal		165	
Constant decrease		3	
Other		676	

From Table 14, it can be derived that a high number of farms that are ranked in group 1 stay in group 1 in a consecutive year. Remarkable results were found in the changes from group 1 to 5 or the opposite, a minor number of farms change from the highest to the lowest ranking group (or the opposite) within one year. Most changes in ranking group were found from one rank to a rank that is one grade higher or lower.

Table 14: Dynamics of TE scores between ranking groups, elaborated overview. TE score groups overview is given in Table 12 and Table 13

	TE score groups	***2013-2014***	***2014-2015***	***2015-2016***
Increase	5 > 4	45	55	54
	5 > 3	27	21	14
	5 > 2	3	0	8
	5 > 1	1	0	0
	4 > 3	62	56	57
	4 > 2	10	8	11
	4 > 1	4	5	6
	3 > 2	45	45	40
	3 > 1	12	13	4
	2 > 1	22	17	17
Equal	5 > 5	136	136	136
	4 > 4	72	67	74
	3 > 3	92	95	116
	2 > 2	37	56	49
	1 > 1	59	64	50
Decrease	1 > 2	19	20	26
	1 > 3	7	11	10
	1 > 4	2	2	7
	1 > 5	3	1	6
	2 > 3	48	40	36
	2 > 4	11	16	8
	2 > 5	3	1	3
	3 > 4	56	59	46
	3 > 5	20	24	17
	4 > 5	50	50	51

4.2.3. In- and output variable variation between TE score groups

To indicate important influencing factors for functional traits in chapter 2.2, differences between low and high efficient farms are examined. The variables in Table 15 and Table 16 are linked to functional traits and their influence on efficiency will be explained.

Based on the grouping of farms into ranking groups it is possible to compare in- and outputs. In- and outputs that contained total recordings of costs or uses, were converted to units per kilogram output. No variables were found normally distributed; therefore, a Kruskal-Wallis test is performed for every variable together with a post-hoc Wilcoxon signed rank test to compare differences between groups.

Table 15: Variables to compare different TE score groups. Means are displayed with significant differences between groups marked with ''*

Variable	**Unit**	***2013***	***2014***	***2015***	***2016***
Number of cows	-	95.9*	97.9*	103.0	109.3*
Calving interval	days	411*	409*	409*	405*
Ratio of cows died	%	0.03*	0.03*	0.03*	0.04*
Replacement rate	%	0.26*	0.270	0.240	0.27*
Average age	years	4.24*	4.24*	4.22*	4.2*
Average culling age	years	5.25*	5.28*	5.32*	5.32*
Milk production per total area	kg/ha	17000*	17319*	17983*	18746*
Milk production per cow	kg/cow	8309*	8370*	8464*	8569*
Concentrate appl. per unit of milk	kg/kg	26.07*	25.91*	26.01*	26.95*
Purch. roughage per unit of milk	€/kg	1.72*	1.97*	1.85*	1.640
Health costs per unit of milk	€/kg	0.98*	0.98*	0.97*	0.95*
Breed. and contr. costs per unit of milk	€/kg	0.96*	0.99*	0.93*	0.92*

**P < .05*

In Table 15 differences between groups are tested with a Kruskal-Wallis test. This test indicates that differences between land area on grass, corn and other feeding crops were not found due to p-values > 0.05, suggesting that there is no significant difference between the five groups and the considered variables for land area. For the variable *Number of cows* and *Replacement rate*, not every year contained significant differences between all groups. However, there could be significant differences between some groups. All other variables contained significant differences between groups. Between group differences are shown in Table 16 at the next page.

Table 16: Between group differences for both input and output variables for the panel 2013-2016

2013

TE score group	Unit	1	2	3	4	5
Cows	no.	116.9 ^{ab}	92.4 ^{ab}	99.6 ^{a}	93.7 ^{ab}	87.0 ^{b}
Calving int.	days	403 ^{ab}	396 ^{a}	403 ^{b}	410 ^{c}	434 ^{d}
Cows died.	%	0.03 ^{a}	0.03 ^{a}	0.02 ^{a}	0.03 ^{a}	0.04 ^{b}
Repl. rate	%	0.26 ^{ab}	0.27 ^{a}	0.26 ^{ab}	0.26 ^{ab}	0.25 ^{b}
Age	years	4.16 ^{a}	4.17 ^{a}	4.19 ^{a}	4.25 ^{ac}	4.35 ^{c}
Culling age	years	5.02 ^{a}	5.09 ^{ab}	5.15 ^{ab}	5.28 ^{bc}	5.5 ^{c}
Milk p. area	kg/ha	20531 ^{ab}	18775 ^{a}	17475 ^{bc}	16329 ^{c}	14610 ^{d}
Milk p. cow	kg/cow	8630 ^{ab}	8865 ^{a}	8548 ^{b}	8230 ^{c}	7676 ^{d}
Concentrate	kg/100kg	23.56 ^{a}	24.17 ^{a}	25.65 ^{b}	26.68 ^{c}	28.1 ^{d}
Roughage	€/100kg	1.80 ^{ab}	2.09 ^{a}	1.71 ^{ab}	1.71 ^{ab}	1.50 ^{b}
Health	€/100kg	0.77 ^{a}	0.95 ^{ab}	0.95 ^{b}	1.02 ^{bc}	1.09 ^{c}
Breeding	€/100kg	0.80 ^{a}	0.91 ^{ab}	0.97 ^{bc}	0.98 ^{bc}	1.04 ^{c}

2014

TE score group	Unit	1	2	3	4	5
Cows	no.	122.3 ^{a}	95.5 ^{ab}	97.2 ^{ab}	97.7 ^{ab}	88.8 ^{b}
Calving int.	days	403 ^{a}	396 ^{a}	399 ^{a}	408 ^{b}	431 ^{c}
Cows died.	%	0.04 ^{ab}	0.02 ^{a}	0.03 ^{a}	0.03 ^{a}	0.04 ^{b}
Repl. rate	%	0.28 ^{a}	0.27 ^{a}	0.27 ^{a}	0.27 ^{a}	0.27 ^{a}
Age	years	4.23 ^{ab}	4.16 ^{ab}	4.15 ^{b}	4.29 ^{ac}	4.35 ^{c}
Culling age	years	5.2 ^{ab}	5.15 ^{a}	5.14 ^{a}	5.39 ^{b}	5.46 ^{b}
Milk p. area	kg/ha	20941 ^{a}	18177 ^{a}	18272 ^{a}	16504 ^{b}	14838 ^{c}
Milk p. cow	kg/cow	8644 ^{ab}	8867 ^{a}	8622 ^{a}	8362 ^{b}	7703 ^{c}
Concentrate	kg/100kg	23.74 ^{a}	23.61 ^{a}	25.52 ^{b}	26.33 ^{b}	28.21 ^{c}
Roughage	€/100kg	2.18 ^{ab}	2.19 ^{ab}	2.16 ^{a}	1.78 ^{ab}	1.70 ^{b}
Health	€/100kg	0.79 ^{a}	0.94 ^{b}	1.01 ^{b}	0.99 ^{b}	1.06 ^{b}
Breeding	€/100kg	0.79 ^{a}	0.93 ^{b}	0.97 ^{bc}	1.05 ^{cd}	1.08 ^{d}

2015

TE score group	Unit	1	2	3	4	5
Cows	no.	128.4 ^{a}	102.9 ^{a}	102.7 ^{a}	98.9 ^{a}	95.4 ^{a}
Calving int.	days	401 ^{ab}	393 ^{a}	400 ^{b}	409 ^{c}	431 ^{d}
Cows died.	%	0.03 ^{ab}	0.02 ^{b}	0.03 ^{b}	0.03 ^{ab}	0.03 ^{a}
Repl. rate	%	0.25 ^{a}	0.24 ^{a}	0.24 ^{a}	0.24 ^{a}	0.23 ^{a}
Age	years	4.15 ^{ab}	4.16 ^{b}	4.17 ^{b}	4.23 ^{bc}	4.33 ^{c}
Culling age	years	5.15 ^{a}	5.07 ^{ab}	5.38 ^{bc}	5.3 ^{ac}	5.49 ^{c}
Milk p. area	kg/ha	22550 ^{a}	19566 ^{a}	18473 ^{a}	16797 ^{b}	15604 ^{c}
Milk p. cow	kg/cow	8719 ^{ab}	8906 ^{a}	8737 ^{a}	8442 ^{b}	7844 ^{c}
Concentrate	kg/100kg	24.63 ^{a}	24.63 ^{a}	25.47 ^{ab}	26.31 ^{b}	27.69 ^{c}
Roughage	€/100kg	2.02 ^{a}	2.04 ^{a}	1.99 ^{a}	1.72 ^{a}	1.66 ^{a}
Health	€/100kg	0.80 ^{a}	0.84 ^{a}	0.96 ^{b}	1.03 ^{bc}	1.07 ^{c}
Breeding	€/100kg	0.78 ^{a}	0.84 ^{a}	0.96 ^{b}	0.97 ^{b}	1.00 ^{b}

2016

TE score group	Unit	1	2	3	4	5
Cows	no.	131.6 ^{ab}	118.4 ^{a}	108.6 ^{ab}	110.5 ^{a}	95.4 ^{b}
Calving int.	days	398 ^{ab}	389 ^{a}	395 ^{b}	405 ^{c}	427 ^{d}
Cows died.	%	0.04 ^{ab}	0.03 ^{b}	0.03 ^{b}	0.04 ^{b}	0.05 ^{a}
Repl. rate	%	0.3 ^{a}	0.27 ^{b}	0.26 ^{b}	0.27 ^{ab}	0.27 ^{ab}
Age	years	4.16 ^{a}	4.12 ^{a}	4.19 ^{a}	4.18 ^{a}	4.3 ^{b}
Culling age	years	5.2 ^{ab}	5.18 ^{a}	5.31 ^{ab}	5.3 ^{ab}	5.49 ^{b}
Milk p. area	kg/ha	22975 ^{ab}	20326 ^{a}	19061 ^{ab}	18514 ^{b}	16085 ^{c}
Milk p. cow	kg/cow	8853 ^{ab}	8915 ^{a}	8806 ^{a}	8600 ^{b}	7964 ^{c}
Concentrate	kg/100kg	25.35 ^{a}	25.44 ^{a}	26.14 ^{a}	27.66 ^{b}	28.72 ^{c}
Roughage	€/100kg	1.79 ^{a}	1.71 ^{a}	1.74 ^{a}	1.67 ^{a}	1.40 ^{a}
Health	€/100kg	0.68 ^{a}	0.93 ^{b}	0.96 ^{bc}	0.98 ^{bc}	1.03 ^{c}
Breeding	€/100kg	0.72 ^{a}	0.86 ^{b}	0.94 ^{c}	0.94 ^{bc}	0.99 ^{c}

a-d within row significant differences between TE score groups occur with different superscripts (P < .05)

Differences between the groups of high and low efficient farms are significant for all variables except the variables *Number of cows* (except for 2014), *Ratio of cows died*, *Replacement rate* and *Purchased roughage*. The number of cows differs a lot within group 1, with a standard deviation from 80 to 97 cows during the panel of years. The variable *Replacement rate* was relatively lower in 2015 than in the other years, but not varying between the groups in general. The variable *Ratio of cows died* also does not vary between the first four groups and remains equal over the years. Also, no significant differences were found between fully efficient farms (group 1) and low efficient farms (group 5) for every year except 2013. Also, significant differences between efficiency groups for *Purchased roughage* were not found in general.

The variable *Total concentrate application* has significant differences between fully efficient farms (group 1) and lower efficient groups (4 and 5) for every year. Also, highly efficient farms (group 2) has significant differences with lower efficient groups (4 and 5) for every year. Highly efficient farms do not differ significantly from fully efficient farms for every assessed year. For the output variable *Milk production per total area* and *Milk production per cow*, significant differences between highly efficient groups (1 and 2) and low efficient group 5 were found every year. For both output variables, the first two groups do not differ from each other significantly during all the assessed years. Also, no significant differences between groups 1 and 3 were found, however group 3 significantly differs from group 2 and 4 for some years. Group 3 differs from group 5 significantly for every year for both output variables. From these results, efficient farms are represented by farms that are significantly more area intensive and use significantly less concentrates than farms with lower efficiency. Furthermore, the efficient farms have also significantly higher milk yields per cow which could indicate that these farms have cows that perform significantly better for *feed efficiency*, a functional trait which was selected in chapter 2.2.

For *Health* and *Breeding and controlling costs* significant differences were found between the highly efficient groups. The group containing fully efficient farms did differ significantly from groups 3, 4 and 5 in every assessed year. For these two variables, no significant differences were found between lower efficient groups (4 and 5) and for some years (depending on the variable health or breeding and controlling costs). For the variable *Calving interval* significant differences were found between groups containing lower and moderate efficient scores (2, 3, 4, 5), but also between fully efficient farms (group 1) and lower efficient groups (4 and 5). In every year that was assessed, fully efficient, highly efficient and moderately efficient farms (groups 1, 2 and 3) differed significantly from lower and low efficient farms (groups 4 and 5). Both relating to functional traits *health* and *fertility* these results indicate that efficient farms could have significantly healthier and fertile cows than cows that are present on lower efficient farms due to lower costs that are spend on health and fertility related costs. Furthermore, efficient farms have a significant lower calving interval which could indicate that cows at efficient farms have higher success rates of inseminations and gestation.

For the variable *Age*, shows significant differences between fully efficient farms (group 1) and low efficient farms for every year, age of cows is significantly higher at lower efficient farms. The fully efficient farms do not differ significant from other groups. Between groups 2, 3 and 4 there is some variation between significant differences with other groups. Concerning the variable *Culling age*, significant differences highly vary between the assessed years. For every year, group 2 differs significantly from group 5. Furthermore, no significant differences were found between groups 1 and 2, groups 2 and 3 and between groups 4 and 5 for every year. For the functional trait *longevity*, farms that have lower efficiency contain cows that have a higher average age than the cows that are present on high efficient farms. Also, lower culling ages were found at fully efficient farms in comparison with lower efficient farms, however this was not found significant.

5. Discussion

In economics, efficiency analysis can be performed by applying different methods. Also, in dairy farming, several methods were performed to measure or estimate technical efficiency. An overview of methods that are used in the past is given in the review of Mareth et al. (2016). Studies on Dutch dairy farming are given in chapter 2.1.2. Technical efficiency is always a relative measure between DMU's and it is therefore difficult to compare various studies with each other. Not only variations in performed method occur, within these various methods the amount and type of in- and outputs could be approached differently. Inputs that are used to measure or estimate technical efficiency consist mostly of land, herd size, labour, capital and variable inputs, however based on the focus of a study (for example animal welfare or environmental impact) a set of chosen in- and output variables can change. The selection of variables depends on the goal of the study, for example determining the impact of environmental inputs like in Reinhard et al. (2000). In this study, focus was set on the performance of an individual cow influencing farm performance. With the help of a literature study, influencing factors were found and selected from the used accounting dataset.

DEA uses a non-parametric approach and is therefore not restricted by parametrical assumptions and needs functional forms to relate the inputs to the outputs. DEA is a useful method when multiple inputs are handled with a single output, but it does not account for random noise in these variables. This means that assumptions are made in relation to statistical noise or measurement errors. DEA is in contrast to SFA more sensible for outliers, however this effect will be reduced when sample sizes are enlarged. DEA does treat all variables equal, it is therefore easily possible to include various variables which do not have to be in an equal range or have the same probabilistic behaviour. Because technical efficiency scores are approached completely different besides the two methods, results are likely to be different and both methods have their advantages and disadvantages. However, in Resti (1999) no clear advantages were found using one method above the other. In this study, only the non-parametrical deterministic approach (DEA) was performed, due to its advantage of approaching all variables equally by not adding any weights to the variables.

The variables that were selected in this study are different from other studies. For example, the variables labour and capital were not included. All variables except *Total area land* were found explainable for milk production. Because DEA makes no difference between variable weights, *Total area land* was chosen as a variable not explainable for milk production and included in the set of chosen inputs. The variable is however an indicator for roughage feed input and therefore for importance for this study. Furthermore, because land area is a common selected variable in efficiency analysis in dairy farming according to the assessed literature, this variable was chosen with a higher priority relative to *Purchased roughage*. This will result in other results, because the selected variables are not similar to other studies. The focus of this study is not to compare the TE scores with other studies, however studies found in literature with similar approaches give an indication of the TE level of Dutch dairy farming.

To explain functional traits in the DEA, variables have been chosen that include information of the traits *health*, *fertility*, *longevity* and *feed efficiency.* The set of variables that was chosen include *Total land area* and *Total concentrate application* concerning the functional trait *Feed efficiency*, variables *Calving interval* and *Breeding and controlling costs* concerning the functional trait *Fertility* and the variable *Health costs* concerning the functional trait *Health*. Furthermore, the variable *Number of cows* was included to measure the farm production performance explanatory for the output variable *Total milk production*. Within this set of in- and output variables, no variables explaining the functional trait

Longevity were included. Because the variables *Age* and *Replacement rate* were not found explanatory for *Total milk production* and only a limited set of variables could be selected, the variables *Age* and *Replacement rate were* excluded from the DEA analysis. They were however included in the comparison study.

Besides selecting the right set of in- and output variables, the amount of variables that will be chosen heavily depend the output of DEA results (Wagner & Shimshak, 2007). Selecting too many variables will lead to overestimation of the TE scores and lead to a shift of the mean TE score. When too many variables are chosen, the possibility for a DMU to be efficient in some way will be enlarged. Therefore, in this study a maximum of six input variables and one output variable was restricted. A balance between information loss and overestimation was found sufficient with this set of variables because the variables explaining milk yield and variables in relation with functional traits were included, having a mean TE score of all years of 0.93. The set of six variables was eventually found best from a selection of several sets that differed in variable size and composition.

This mean TE score is higher than that was found in literature about Dutch dairy farming (Brümmer et al., 2002; Dandi, 2017; Kovács & Emvalomatis, 2011; Reinhard et al., 2000, 1999) performed in the past. Scores between 0.78 and 0.92 were found from the performed literature study where different methods with different sets of variables were used. It is therefore not assumable to compare these scores with each other. However, relatively to each other, Dutch dairy farmers are very efficient in input use, not regarding which set of variables are used. The conclusion that Dutch dairy farmers are relatively very efficient to each other was found both in literature and in this study. However different methods were used to find TE scores.

From the dataset, information onwards 2004 was available. This study only gives results for the years between 2013 and 2016. A similar approach (four year panel) was found in literature (Brümmer et al., 2002; Dandi, 2017; Kovács & Emvalomatis, 2011; Reinhard et al., 2000, 1999). It was chosen to only include the most recent years that were made available and to exclude all other years. For these four years the panel was balanced, including multiple years would lead to loss in data because not all farms have data available for multiple years. For dairy farmers in the Netherlands farm characteristics could be somewhat affected during the years that were assessed due to the abortion of milk quota in 2014 and preparations for the initiation of the phosphate regulation in 2018. The average number of cows present on a farm does not stagnate from 2015 (reference year for phosphate regulation), however the replacement rate is lower in 2015 relative to the other years. Also, average milk production per cow increased substantially which could indicate that farmers focus on a reduced feed use per kilogram of milk, however the application of concentrates per cow have also increased during the years. This could indicate that farmers are more focussing on functional traits like in this finding *feed efficiency* instead of increasing their dairy herd.

In the review of Mareth et al. (2016) on efficiency analysis in dairy farming it was found that mean TE scores varied according to herd size and that it did not vary according to land size. In this study, no significant differences according herd size were found between efficient and lower efficient farms. However, farms that were efficient used a rather intensive land management, having significantly higher milk yields per hectare of land. From the results it can be seen that farms which have high production levels per cow, are found in the group with farms which are highly efficient. Fully efficient farms have still a significant higher milk yield than lower efficient farms, however do not contain the cows which reach the highest production levels on average. Subsequent to these somewhat lower milk yields, these farms use significantly less concentrates per cow than farms with moderate and low(er) efficiency and less concentrates per cow than on farms which are highly efficient. Also, farms that are fully efficient use less health and breeding and controlling costs than the highly efficient farms, resulting in 2016 with significant lower costs on health and breeding and controlling. Concerning age and culling age, fully and highly efficient farms do not differ significantly. Farms that have low(er) TE scores do have significant differences concerning the two variables on age. These farms have cows present that reach a higher age on average. Reasons for having a herd with on average lower age could not be found in this study, however it could be suggested that farms only want to keep their most productive cows due to phosphate production restrictions. Also calving intervals were found significantly higher on the lower performing farms which could indicate that cows that are present there are less fertile, having higher insemination failures, having increased gestation failures, or that cows are held in lactation for a longer period, resulting in a lower year-round milk yield. This indicates that fully efficient farms perform slightly lower in production performance than highly efficient farms, however focussing on functional traits fully efficient farms perform better than lower efficient farms relating to *feed efficiency*, *health* and *fertility*. In comparison with low(er) efficient farms, fully efficient farms perform worse for the functional trait *longevity*.

Results were compared based on the distribution of the technical efficiency scores for every year. Similar patterns were found for all variables between the farms with the highest and the farms containing the lowest efficiency scores. There were differences found between the other groups concerning the assessed years. It was chosen to compare groups based on their distributions above comparing various clusters. Cluster analyses were performed per year, but it was not made clear how many clusters should be assessed. Furthermore, no clear patterns were found between the various years. Cluster analysis was performed based on the in- and output variables, however the composition of clusters and farms varied highly between the years. Comparison was therefore performed based on the distribution of efficiency scores and results of the cluster analyses were excluded from the report. From Figure 6 it is made visible that similar patterns occur, but only change in magnitude. This is not a remarkable result because on average farms will only slightly change their in- and output levels between the years. From Table 12 it becomes clear that group sizes remain approximately equal over the years, but looking into Table 13 and Table 14 it is also observed that technical efficiency scores can be highly dynamic for a farm relatively to the other assessed farms. Because the farms are classified based on their distribution, it makes it however possible to compare the farm characteristics (based on the variables in Table 3) of various years, other than for example a cluster analysis.

DEA was found as an applicable method to relate farm performance to functional traits because significant differences could be found between high and low efficient farms in relation to functional traits. These functional traits are related to individual cows and a farmer could reduce the use of inputs by selecting for cows that have suitable characteristics for the important functional traits. Efficient farms only perform less on longevity; however, this could also be affected by the initiation of the phosphate regulation. Within farm differences could not be indicated with the help of the dataset that was used for this study, however the dataset was found sufficient with indicators for the most important functional traits found in literature (Egger-Danner et al., 2012; Fuerst-Waltl & Baumung, 2010; Groen et al., 1997; Pritchard et al., 2013). Because efficiency analysis methods like DEA are restricted to only a limited set of in- and output variables, it is found difficult to include every aspect of functional traits. In the subsequent comparison study between the various TE score groups, it however became clear that some significant differences were found between efficient and low efficient farms in relation to the indicators for functional traits. Based on this information, DEA was found as an appropriate tool for this study. With the help of the results of this study, future studies could focus on the within farm differences relating to the indicators for functional traits that were selected in this study and could examine if cows on efficient farms have significantly different characteristics than cows on low(er) efficient farms. It could be possible that characteristics at farm level could influence the functional and productive characteristics of an individual cow.

6. Conclusion

From literature study it became clear that Dutch dairy farmers are relatively efficient. Studies concluded high TE scores, between 0.78 and 0.92 with multiple methods and orientations (both input and output orientated studies). In this study, a mean TE score of around 0.93 was found for every assessed year. What can be concluded by both the found literature and this study is that Dutch dairy farms are efficient relative to each other. Between 7 and 99 fully efficient farms were found, which represents that approximately 10% of the assessed farms use their inputs at an optimal level.

Difference in TE score between Dutch dairy farms was found for every year. Concerning one consecutive year, it is shown that most farms remain in the same TE score group and approximately the same number of farms increase or decrease to one or more groups containing a higher or lower efficiency score. Almost no farms constantly in- or decrease in TE score group subsequently between the years 2013-2016. However, this is also affected by the cause that only farms that are in the highest or lowest groups could perform a constant in- or decrease. Around 23% of all farms remain in the same TE score group every year. Furthermore, it becomes clear that farms mostly switch between one group which is higher or lower in efficiency.

To answer the question of which indicators of farm level efficiency can influence the performance of individual cows and therefore change the expression of traits related to farm performance, functional traits were classified into four groups; *health, fertility, longevity* and *feed efficiency.* From DEA analysis, significant differences in TE were found for variables which are all related to traits of an individual cow. From an accountancy dataset, it was possible to find variables that had significant differences between various TE score groups and are indicators for functional traits. These variables are *Calving interval, Age, Culling age, Concentrate application, Health costs* and *Breeding and controlling costs* also for production traits like *Milk production per area* and *Milk production per cow* significant differences between efficient and low efficient farms were found. Farm level efficiency differences could therefore be explained by cows that are healthy and fertile, having both low health and breeding and controlling costs. Furthermore, cows at efficient farms were found feed efficient, using significantly lower amounts of concentrates to reach a given quantity of milk output. On the other hand, cows on efficient farms have on average a significantly lower age, and lower calving intervals which could indicate that old cows are replaced earlier at a given age or after a certain number of lactations. The same trend was found for every assessed year from 2013 to 2016. Concerning productivity, fully efficient farms produce a lower milk yield per cow than highly efficient farms. It can be concluded that fully efficient farms perform well on the functional traits *health*, *fertility*, and *feed efficiency* but perform worse on the functional trait *longevity*.

It can be concluded that with using DEA it is possible to include cow specific traits to examine farm performances. However, with the dataset that was used for this study, results are still on farm level but give insights in cow specific characteristics which need further consideration on cow level. Significant differences between fully efficient and low(er) efficient farms were found and indicate where low(er) efficient farms could improve in relation to functional traits.

7. Recommendations

This study only contains results based on data of Dutch dairy farming. It would be interesting to also apply the same study on other countries using the same way of farming to examine if the same findings occur for other countries. In the Netherlands, dairy farmers are relatively efficient to each other, however what would be the case for countries where differences in TE scores are much higher? Furthermore, can the findings of this study be validated by applying the same study for similar countries or will other significant differences be found. Countries in similar regions could be compared on management and differences between regions could be indicated. When differences between countries are made visible, it could be possible for farmers or breeders to focus on the indicators that need attention by learning from countries that perform well on similar indicators. However, climate and geographical and income differences should always be considered.

Furthermore, in this study only DEA is concerned, and no other efficiency analysis methods were performed. It would be interesting do examine the results of a similar study in SFA and to compare the differences between the two methods. In literature, no clear advantages were found using the one method over the other, however, there were differences found which would be interesting to validate the findings in this study.

These recommendations relate to the validation of this study. Another recommendation is to investigate farm data and compare herd efficiencies to indicate the high and low performing cows. By combining the information of this study, and examination of individual cow traits and performances, correction factors could be created for high performing cows on low efficient farms or vice versa so that the comparison of cows is not affected by the TE level of a farm.

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Appendices

Appendix I: Elaborated overview of Dutch efficiency analyses in dairy farming

Table I: Overview of studies on technical efficiency in Dutch dairy farming.

Authors	***Year***	***Panel***	***Method(s)***	***Orientation***	***MTE***	***Sample size***	***Variables***	***In- output***	***Unit***
Reinhard, Lovell, & Thijssen	1999	1991 - 1994	Stochastic translog production frontier	Input	0.903	613	Dairy farm output (aggregated)	Output	NLG
							Labour	Input	hours
							Capital	Input	NLG
				Output	0.894		Variable inputs	Input	NLG
							Nitrogen surplus	Input	kg N
Reinhard, Knox Lovell, & Thijssen	2000	1991 - 1994	SFA	Input	0.889	613	Dairy farm output (aggregated)	Output	NLG
							Labour	Input	hours
			SFA	Output	0.899		Capital	Input	NLG
							Variable inputs	Input	NLG
			DEA (VRS)	Input	0.811		Nitrogen surplus	Input	kg N
							Phosphorus surplus	Input	kg P
			DEA (VRS)	Output	0.784		Energy	Input	Gigajoule
Brümmer, Glauben, & Thijssen	2002	1991-1994	TFP	Output	0.896	141	Milk output	Output	*1000 DM
							Other outputs	Output	*1000 DM
							Intermediate inputs	Input	*1000 DM
							Labour	Input	hours
							Capital	Input	*1000 DM
							Land	Input	hectares
Kovács & Emvalomatis	2011	2001-2005	DEA (CRS)	Output	0.89	178	Milk revenues	Output	€
							Other revenues	Output	€

Dandi & Rao	2017	2011-2014	DEA (VRS)	Output	0.92	2046	Capital	Input	€
							Labour	Input	AWU
							Land	Input	UAA
							Material inputs	Input	€
							Livestock	Input	amount
			SFA	Output	0.91		Purchased feed	Output	€
							Milk income	Output	€
							Labour cost	Input	€
							Capital	Input	€
							Other costs	Input	€
							Intensification	Input	€
							AFC	Input	years
							Age	Input	years
							Concentrate	Input	€
							Pasture size	Input	hectares
							Milking robot	Input	dummy

MTE = Mean Technical Efficiency, SFA = Stochastic Frontier Analysis, DEA = Data Envelopment Analysis, VRS = Variable Returns to Scale, CRS = Constant Returns to Scale, TFP = Total Factor Productivity, AFC = Age at First Calving, NLG = Dutch Guilders, N = Nitrogen, P = Phosphorus, DM = German Mark, AWU = Annual Working Unit, UAA = Utilised Agricultural Area.

Appendix II: Selected variables from original dataset (Dutch)

Table II: Selected variables from original dataset

	Eenheid	***Type***	***Soort***	***Noodzakelijk***	***Interessant***	***Misschien***	***Niet noodzakelijk***
Boekjaar begin	Jaar	Discrete	Filter	-	-	-	-
Periode begin	Maand	Discrete	Filter	-	-	-	-
Boekjaar einde	Jaar	Discrete	Filter	-	-	-	-
Periode einde	Maand	Discrete	Filter	-	-	-	-
gemengd of zuiver	-	Dichotomous	Filter	-	-	-	-
biologisch	-	Dichotomous	Input			x	
melkrobot aanwezig ja / nee 0 = nee 1 = ja	-	Dichotomous	Input			x	
ligplaatsen per melkkoe	-	Continuous	Input		x		
beweinden koeien 0=nee 1=ja blank=NB	-	Nominal	Input			x	
veeslag	-	Nominal	Input	x			
oppervlakte grasland in ha	ha	Continuous	Input	x			
voederoppervlakte mais in ha	ha	Continuous	Input	x			
oppervlakte overige voedergewassen in ha	ha	Continuous	Input	x			
Kg melk totaal bedrijf	kg/jaar	Discrete	Output	x			
melkkoeien	-	Continuous	Input	x			
gemiddeld aanwezig vrl. jongvee 1-2 jaar	-	Continuous	Input				x
gemiddeld aanwezig vrl. jongvee 0-1 jaar	-	Continuous	Input				x
gemiddeld aanwezig mnl. jongvee 0-1 jaar	-	Continuous	Input				x
kg melk per koe	kg/jaar	Discrete	Output				x
vetgehalte in %	%	Continuous	Input			x	
eiwitgehalte in %	%	Continuous	Input			x	
meetmelk FPCM geproduceerd/koe	kg/jaar	Discrete	Output				x
celgetal	cellen/ml	Discrete	Input		x		
gemiddelde tussenkalftijd	dagen	Discrete	Input		x		
percentage gestorv kalv <14 dagen	%	Continuous	Input				x

percentage gestorv kalv <1 jaar	%	Continuous	Input				x
% gestorven melkkoeien	%	Continuous	Input		x		
Vervangingspercentage melkkoeien	%	Continuous	Input	x			
Leeftijd bij eerste keer afkalven	jaar	Continuous	Input				x
Leeftijd melkkoeien (rollend jaar)	jaar	Continuous	Input	x			
Leeftijd melkkoeien bij uitstoot	jaar	Continuous	Input		x		
levensproductie in kg melk per melkkoe	kg/koe	Discrete	Output				x
kg krachtvoer per dag per koe	kg/koe/dag	Continuous	Input		x		
Melkopbrengst	€	Discrete	Output				x
verkopen vee	€	Discrete	Input				x
aankopen vee	€	Discrete	Input				x
aanwas melkvee	€	Discrete	Input				x
Omzet en aanwas	€	Discrete	Input				x
Totaal opbrengsten	€	Discrete	Output				x
Krachtvoer	€	Discrete	Input		x		
Vitaminen en mineralen	€	Discrete	Input		x		
Melkproducten	€	Discrete	Input		x		
Natte bijproducten	€	Discrete	Input		x		
Aangekocht ruwvoer	€	Discrete	Input		x		
Totaal voerkosten	€	Discrete	Input	x			
Bemesting	€	Discrete	Input				x
Zaaizaad en gewasbescherming	€	Discrete	Input				x
Gezondheidskosten	€	Discrete	Input	x			
KI- fokkerij en melkcontrole samen	€	Discrete	Input	x			
Opfokkosten jongvee bij derden	€	Discrete	Input				x
Strooisel	€	Discrete	Input			x	
Overige directe kosten	€	Discrete	Input			x	
Betaalde arbeid	€	Discrete	Input				x
Werk door derden	€	Discrete	Input				x
Bedrijfsresultaat	€	Discrete	Output				x

code beweiding voorjaar	-	Nominal	Input	x
code beweiding zomer	-	Nominal	Input	x
code beweiding najaar	-	Nominal	Input	x
pinken op stal in zomer	-	Nominal	Input	x
kalveren op stal in zomer	-	Nominal	Input	x
Resultaat na belasting	€	Discrete	Input	x
gebruik van diepstrooisel ligboxen	-	Nominal	Input	x
kalverdrinkautomaat aanwezig	-	Nominal	Input	x
mestschuif aanwezig?	-	Nominal	Input	x
mestrobot aanwezig?	-	Nominal	Input	x
voermengwagen aanwezig?	-	Nominal	Input	x
wordt er droge mest als boxvulling gebruikt?	-	Nominal	Input	x
melkkoeien emissiearme huisvesting?	-	Nominal	Input	x
emissiearme vloer aanwezig?	-	Nominal	Input	x

Appendix III: Best subset selection

Table III: Variables included in the best subset selection. Variable Cows is forced in, which means that this variable will always be included

	Forced in	**Forced out**
Calving_int	FALSE	FALSE
Area_total	FALSE	FALSE
Cows	TRUE	FALSE
Cows_died	FALSE	FALSE
Repl_rate	FALSE	FALSE
Age	FALSE	FALSE
Total_concentrate	FALSE	FALSE
Roughage_costs	FALSE	FALSE
Health_costs	FALSE	FALSE
Breeding_controlling_costs	FALSE	FALSE

Table IV: Best subset composition with set numbers indicating which variables will be included in the designated set

Set	***Cows***	***Calv. int.***	***Conc.***	***BC***	***Healt h***	***Cows died***	***Roug hage***	***Age***	***Area total***	***Repl. rate***
1	"*"	"*"	" "	" "	" "	" "	" "	" "	" "	" "
2	"*"	"*"	"*"	" "	" "	" "	" "	" "	" "	" "
3	"*"	"*"	"*"	"*"	" "	" "	" "	" "	" "	" "
4	"*"	"*"	"*"	"*"	"*"	" "	" "	" "	" "	" "
5	"*"	"*"	"*"	"*"	"*"	"*"	" "	" "	" "	" "
6	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "	" "	" "
7	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "	" "