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# Input-output relations in the pig sector

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# Abstract

The objective of this paper is to investigate the scope for improving the environmental performance of pig farms in the short and the long run. In the short run, such an environmental improvement can be obtained by improving the environmental efficiency of farms relative to the currently available technology. In the long run, however, an improvement in environmental performance requires switching to new and cleaner technologies, which involves substantial investments in, *e.g.* buildings. Improvement of environmental performance in the short run is investigated by generating environmental efficiency scores for mineral excretion and ammonia emission on farm data using Data Envelopment Analysis. These environmental efficiency scores are an indication for the scope reducing excretion and emission in the short run, relative to the currently used technology.

Improvement of environmental performance in the long run is investigated in two stages. In the first stage, input-output combinations for new and cleaner technologies and new restrictions in pig farming are generated with the Technical Model Pig Feeding, developed by The Research Institute for Pig Husbandry (PV) in the Netherlands. To analyse the potential future improvements on pig firms, 60 hypothetical, but technically feasible, pig farms are generated using this model.

In the second stage, generated data are used to obtain a frontier of optimal input-output combinations. This frontier is compared with the frontier that was found using panel data from a stratified sample of specialised pig farms that participate in the LEI Farm Accountancy Data Network (FADN). These data include all expenses and revenues, as well as information on mineral excretion and ammonia emission.

Environmental performance of pig firms in the long and short run is computed as the sub-vector efficiency of the environmentally detrimental input. The shift of the frontier indicates by how much new technologies will improve the technical or environmental performance of farms.

The average efficiency score of FADN farms shows that identical output can be produced with 10% reduction in inputs. When data on new technologies are added, a further reduction of 4% in inputs is possible. The ammonia emission can be reduced with 30% (by current housing systems) conditional on output and the conventional inputs. When the technology embedded in green label housing systems is added to the data set, a total reduction of ammonia emission with 43% is possible.

# 1 Introduction and background

Recently, the Dutch government has introduced a sizeable amount of legislation in Dutch pig farming in order to decrease environmental pollution and improve animal welfare. Generally, reduction in pollution levels can be attained by more efficient use of current practices and through the use of new, more environmental friendly techniques. Two lines of research can be distinguished in the literature on the analysis of potential efficiency gains. The first line is based on the analysis of actual data, whereas the second line focuses on potential improvements by new farm practices.

To gain insight in the economic, environmental and technical efficiency of transformation processes in (pig) farming and in the potential improvements by new techniques, researchers use production functions that describe input-output relations and technological development at farm level. Dijk et al. (1998) compared the approaches used by agronomists, economists and sociologists. Thus far, these disciplines have not been integrated into one method. Agronomic and economic evidence has been combined by Kaufmann and Snell (1997) in the estimation of a production function that relates grain production per hectare to a large number of variables (fertiliser applied, weather). This approach is only suitable in case of one output, and cannot be applied if multiple outputs (good and bad) have to be modelled. Another approach followed by Van Os et al. (1993) estimates the relation between one output and one input. However, this approach requires the estimation of several input-output relations and may result in biased estimates due to the omitted variable problem. Moreover, both approaches do not incorporate future available techniques in their analysis.

Economists obtain estimates of the production functions using statistical techniques and mathematical programming. Models obtained by statistical techniques (ex post estimates) are based on observed input-output relations (*e.g.* Reinhard et al., 1999). Mathematical programming models also use observed input-output relations, but can easily incorporate technical information that is not reflected in observed input-output data (Wossink, 1993). Technical researchers use simulation models to analyse input-output relationships. The Research Institute for Pig Husbandry (PV) developed various simulation models, which compute pig production conditional on inputs and restrictions specified.

*This study aims at* integrating the economic and technical approach into one method to analyse input-output relations of the Dutch pig sector. Such a method provides performance measures of pig farms relative to the best currently available technique and relative to future available technologies.

The report is structured as follows. Chapter 2 describes the objective, which is followed by a literature review of methods towards combining technical and economic information in the analysis of input-output relations (*i.e.*, chapter 3). The Farm accountancy Data Network and the Technical Model Pig Feeding are discussed in chapter 4. Empirical results are presented in chapter 5. We conclude with conclusions and discussion (*i.e.*, chapter 6).

# 2 Objective

In order to analyse the technical, economic and environmental performance of Dutch pig farms now and in the future, it is required to have estimates of production possibilities. The standard method to compute technical and environmental performance (efficiency) is to compare the observation with a (best practice production) frontier. This frontier is estimated (or computed using mathematical programming) based on an aggregated set of inputs and outputs. This approach suffers from a few disadvantages (i) efficiency scores can only be estimated for existing data sets, new techniques cannot be evaluated (ii) a lot of technical production information is lost in the aggregation of inputs and outputs. The technical production characteristics determine to a large extent the emission of pollution.

The objective of this research is to combine the normative technical production approach and the economic (econometric) approach to construct a model that allows the computation of technical and environmental efficiency scores. The approach that is followed in this study consists of two stages. In the first stage, input-output combinations for new technologies and new restrictions in pig farming are generated with a farm technical model. In the second stage, the observed data and generated data are used to obtain a frontier of optimal input-output combinations.

# 3 Literature review of methods to combine technical and economic information

## 3.1 Introduction

This section provides a literature review of methods towards combining technical and economic information in the assessment of input-output relations. Two lines of research can be distinguished in the current literature: (i) Inefficiency measurement Data Envelopment Analysis (DEA) is used to combine different attributes of the production process and (ii) data generated in technical simulation models are used in a second stage analysis using metamodels. These methods will be discussed in section 3.3 and 3.4. Section 3.2 gives a general discussion of the literature on performance measurement.

## 3.2 Performance measurement

Efficiency scores are performance measures on the basis of which production units are evaluated. In efficiency measurement observations are compared with optimal production conditional on inputs (or outputs, depending on the definition used). Efficiency scores readily show the potential improvements. Technical efficiency measures do not need price information nor do they require the specification of any a priori weight on the environmental impacts that are being aggregated (Tyteca, 1996). The basis of standard efficiency methodology was developed by Farrell (1957). He proposed that the efficiency of a firm consists of two components: (i) technical efficiency, which reflects the ability of a firm to obtain maximum output from a given set of inputs, and (ii) allocative efficiency, which reflects the ability of a firm to use the inputs in the optimal (profit maximising) proportions, given their respective prices. These two components are then combined to provide a measure of total economic efficiency (overall efficiency). Farrell also introduced an input-oriented technical efficiency measure, defined as the ratio of minimum potential to observed input required to produce the given output. Thus the analysis of technical efficiency can have an input-conserving orientation or an output-augmenting orientation. Efficiency is a relative measure; efficiency scores depend on the firms that are compared.

Assessing the multi-attribute performance frontier for forward looking analysis is more complicated because it cannot be limited to best current practices but has to account for redesign, *i.e.,* substitution by new techniques not yet implemented in practice (MacRae et al., 1990). Including only best practice technology would be insufficient for a forward-looking analysis - under changing policy and market conditions technical change can be significant. Not only efficiently used current techniques are relevant but also experimental techniques and speculative ones not yet applied in agricultural practice. Tyteca (1996) points out this problem of the 'ideal' frontier and suggests two approaches: (1) technological definition based on the best existing techniques and expert opinions on what will become available in the next few years, and (2) metabolism approach based on fundamental principles governing the processes involved. For the current study the first approach combined with efficiency analysis seems most suitable.

To assess the frontier several methods can be distinguished. These methods vary according to: (1) the way the frontier function is specified (parametric or non-parametric), (2) the calculation method used to assess the function (programming techniques or econometric, *i.e.*, statistical techniques), and (3) the way in which deviations from the frontier function are interpreted: as inefficiency (deterministic methods) or as a mixture of inefficiency and noise (stochastic methods). As pointed out by Reinhard et al. (2000), the econometric approach allows hypothesis testing, whereas the DEA approach is more suitable if environmental indicators are to be taken into account. An introduction to these methods can be found in Coelli et al. (1998). Parametric methods are based on assumptions on the shape and level of the frontier function, whereas non-parametric functions are estimated by means of programming or statistical techniques. Non-parametric methods do not use a specification and employ programming techniques (Färe et al., 1994). Non-parametric methods in general are deterministic whereas parametric methods are stochastic. Moreover, parametric methods base the frontier on all observations in the sample, whereas non-parametric methods use only the most efficient observations for the frontier. The most popular non-parametric method is the Data Envelopment Analysis (DEA). DEA is based on linear programming; it truly envelops a data set. Subject to assumptions about the structure of the production technology, it envelops the data as tightly as possible.

Thrikawala et al. (1998) generated alternative field fertility distributions with a production technical model for their analysis of the optimal Management Unit Size of a simulated field. They generate a single fertility level for each cell in their analysis by varying the mean, coefficient of variation and correlation coefficient for a log normal distribution that follows an AR (1) process. In the second stage they estimate the potential efficiency gains of variation in management size units based on the generated input-output combinations.

## 3.3 DEA-analysis

Recently, the standard DEA method has been extended by several researchers in order to address issues of environmental efficiency and sustainability.

Färe and Whittaker (1995) extend the standard DEA model to fit intermediate outputs as well (*i.e.*, dairy farming is separated into crop and livestock production). Their motive for incorporating intermediate products is that it is a better representation of reality. More realistic models of production enable the analyst to examine aspects of production, which have not been available before. They studied real farm data of 137 farms from a complex survey (non-parametric estimation technique). They modelled the dairy production process as being composed of two sub-production processes, crop and livestock production. Each of these sub-processes could be decomposed into more sub-processes, and so on, down to the level of the biochemistry of crop and milk production. They model the two distinguished sub-processes in a directed network, using intensity variables. These intensity variables allow each farm to be classified as efficient in either of both sub-processes, where presence on the frontier required efficiency in both processes.

Tyteca (1997) uses DEA to integrate emissions of several pollutants by individual firms in one environmental efficiency indicator. The method is suitable to integrate a large number of pollutants and other factors. A further example of this method is provided by Callens and Tyteca (1999) who use DEA to combine economic, social and environmental efficiency indicators. A fundamental standpoint adopted is to view economic, social and environmental efficiency as a necessary (but not sufficient) step towards sustainability. They assume that they have available observations on economic, social and environmental factors for a set of Decision-Making Units (DMU). The efficiency of each DMU is computed from a set of observed data, using mathematical programming techniques. The frontier obtained from observations on existing DMU's merely reflects best practice, which as such does not imply sustainability. If past observations are used, the results obtained will be based on how industries made their choices in the past. Replacement of best practice frontier by some kind of ideal frontier reflecting sustainability goals that society may formulate for production units will provide another useful extension of the methods developed herein.

De Koeijer and Wossink (1999) present a method to quantify sustainability of arable farms based on the economic theory of productive efficiency using Data Envelopment Analysis (DEA). The deviation of observed input-per-unit-of-output ratios from the agronomic efficiency frontier is considered to be associated with agronomic inefficiency of the farms involved. The optimal point is found by weighing the inputs according to the contribution to the objective function. The environmental impacts can be used as weights (similar to prices in the computation of cost efficiency). The carrying capacity of the environment should be measured per unit of area. The weight reflecting the environmental impact is expressed per hectare. In contrast to the standard approach, they measure economic efficiency as the financial returns per unit of area. For a specific combination of environmental efficiency and economic efficiency the point farthest from the origin is the most efficient. The dominating set contains those combinations that provide maximum levels of environmental efficiency for alternative levels of economic efficiency and vice versa. In the calculations of the sustainability scores it was assumed that there are no critical minimum levels concerning the environmental and economic performance. They recommend incorporating threshold values in the measurement of the sustainability performance.

De Koeijer et al. (1999) present different definitions of the efficiency concept from economic and agronomic point of view. It is not realistic to study the effects of a change in only one input, since the efficiency of this input would be very low if the levels of the other inputs would not be adapted to the level of the concerning input. The driving force for technological change has evolved from mainly production into a multi-objective (economic and ecological) one. This shift in the direction of technological development is quite different from the earlier aim of primarily increasing production. This means that input-output relations and trends based on historical data sets are not suitable in a forward-looking analysis. De Koeijer et al. (1999) present a model (an agronomically based model that consists of four equations) that represents the relation between agricultural output, growth limiting and growth reducing factors conditional on the growth defining factors. They do not estimate this model and conclude that a model, which combines agronomic possibilities, normative economic restrictions and human behaviour, is needed for the analysis of input-output combinations.

### 3.4 Metamodels

Metamodelling is an analytical procedure that has been developed to gain insight into the behaviour of complex simulation models. A simple way to analyse the results of simulation models is to plot the input and output in a diagram. In that case a curve can be fitted and conclusions drawn to what extent a parameter has an important effect on a dependent variable. However, if more variables are taken into account metamodels are used to detect the interactions between the different variables. Metamodels often have the form of a regression analysis on input and generated output of simulation models and mathematical programming models. A simulation model is a causal model of some problem entity; this model may be deterministic or stochastic. Metamodels allow the combination of several databases in one production function (and for validation and verification). A theoretical underpinning of these 'metamodels' can be found in Kleijnen and Sargent (1999). The development of metamodels can serve different purposes (Ruben and Van Ruijven, 1999). In the first place, metamodeling is meant to simplify the outcomes of simulation models with the objective to gain better understanding of the crucial relationships within the simulation model. Secondly, metamodels are used for the validation and verification of the robustness of simulation models. Finally, metamodels are often much smaller in size and can be used to replace the original simulation model in subsequent analyses. The latter objective is especially relevant fore the purpose of our project, whereas we are looking for possibilities to integrate information derived from technical production simulation models with economic and environmental aspects of production

### 3.5 Conclusion

From the aforementioned two methodologies we selected DEA to elaborate in this study. *Data Envelopment Analysis (DEA)* is flexible and has been used before to add technical, economic and social information in one model (*e.g.,* Callens and Tyteca, 1999). De Koeijer and Wossink (1999) used DEA to compute agronomic and economic efficiency. Advantage: the standard DEA-approach is straightforward. If we succeed in analysing the standard options we can extend the analysis by incorporating more details in the DEA-model. *Metamodels* are not as accepted as DEA in (economics) literature. The capacity for this project is limited. Therefore we focus on an approach that has proven to be successful and that can be performed by our staffing.

# 4 Technical model, selection of inputs and outputs

## 4.1 Introduction

The data used in this research consist of observed and generated data on inputs and outputs of pig farms. The observed data come from a stratified sample of pig farms in the Netherlands and the generated data come from a technical model that generates input-output combinations based on future available technologies. This section describes characteristics of the observed data (section 4.2) and the Technical Model Pig Feeding used to simulate generated data (section 4.3). In addition, the choice of relevant in- and output categories that are included in the empirical analysis are discussed (section 4.4).

## 4.2 The Farm Accountancy Data Network (FADN) data

In this study we use data describing the production activities of specialised fattening pig farms (*i.e.*, more than two thirds of the production stems from fattening pigs) that were in the Dutch Farm Accountancy Data Network (FADN) for part or all of the 1994-1998 period. The FADN is a stratified random sample. Stratification is based on economic farm size, age of the farmer, region, and type of farming. We have a total of 117 observations in this unbalanced panel. However 2 farms were confronted with swine fever in 1997. Both farms were deleted from the data set. Furthermore, 19 farms were located in a region with transport restrictions due to the swine fever. Production at these farms was more or less adversely affected by this transport restriction; therefore they were all discarded from the data set in 1997. Hence, our data set consists of 96 observations on animal data of 36 pig farms and so each farm appears 2.7 times on average. The in- and outputs we specified were based upon the production process of pig farms. We distinguished the following inputs: concentrates and veterinary costs, buildings and labour. One desirable output, *i.e.*, value of pigs produced, and two undesirable outputs, *i.e.*, ammonia emission and phosphorous surplus per farm, were specialised.

The value of pigs produced is computed as the total of sales and growth of pigs (the pigs bought are distracted). The quantity produced (in kg slaughtered pig) does not reflect the difference in quality produced. The price that farmers receive for their pigs depends on their weight and meat percentage. Differences in prices between farmers result from differences in quality. Therefore we prefer an implicit quantity index. Implicit quantity indexes are obtained as the ratio of value to the price index and, therefore, output is in prices of a specific year, 1998 is the base year. This price index varies over the years but not over the farms, implying that differences in the composition of a netput or quality are reflected in the quantity (Cox and Wohlgenant, 1986). If prices are available at farm level in the FADN (for instance for concentrates), they are used to calculate price indexes. If prices are not present in the FADN, price indexes are taken from Statistics Netherlands/LEI (1999). The same method has been used for buildings and variable inputs (concentrates and veterinary cost). Labour input consists of total labour, measured in hours. The building costs contain interest, depreciation and maintenance costs. The phosphorous surplus is the difference between phosphorous in feed and phosphorous in pigs produced (based on the materials balance). The ammonia emission is computed from the nitrogen surplus as described in section 4.4. The nitrogen surplus is computed likewise.

*Table 4.1 Characteristics of the FADN sample variables*

| Variable | Unit | Mean | Minimum | Maximum | Std. Dev. |
|---|---|---|---|---|---|
| Concentrates | 1998 NLG | 387,833 | 117,502 | 1,598,828 | 283,347 |
| Labour | hours | 2,032 | 615 | 6,520 | 1,078 |
| Buildings | 1998 NLG | 78,019 | 9,999 | 326,656 | 65,501 |
| Veterinary costs | 1998 NLG | 20,524 | 2,026 | 130,795 | 17,390 |
| Value Pigs produced | 1998 NLG | 453,284 | 101,487 | 1,823,465 | 338,175 |
| Ammonia emission | kg $NH_3$ | 6,660 | 1,842 | 27,934 | 5,237 |
| Phosphorous Surplus | kg $P_2O_5$ | 4,332 | 1,282 | 18,429 | 3,608 |
| Pig places | number | 1,280 | 279 | 5,535 | 1,097 |

## 4.3 Simulated farm data

In addition to data from practical pig farms, simulated technical, economical and environmental data of fattening pig farms were analysed. The Technical Model Pig Feeding (TMV, Van der Peet-Schwering et al., 1999) was used to generate a set of 20 different farms, assuming new techniques such as multiphase feeding, and animals with a high genetic merit for protein deposition (see appendix 1). In addition, for each simulated pig farm, three housing systems were investigated, a standard housing system for fattening pigs and two Green Label systems (certified environmentally friendly housing systems with lower ammonia emission).

Growth and body composition of a fattening pig is influenced by many factors. The main ones are amount of feed, feed composition, genotype, sex, climate, housing system, health and stress.

*Growth and body composition according to TMV*

From the daily food intake and the dietary nutrient composition, TMV calculates the daily energy intake and the daily ileal digestible amino acid intake. Part of this daily energy and amino acid intake is required for maintenance; the rest is available for growth. Depending on the maximum capacity for protein deposition and the marginal ratio between fat and protein deposition, the daily protein, fat, ash and water deposition of the fattening pig is predicted.

Literature shows that there is a relationship between protein deposition and live weight of the pig. It is generally accepted that protein deposition increases rapidly in early life, plateau's during the growers/finishers stages and then decreases towards zero at maturity. In addition, it is assumed that there is an intrinsic upper limit to body protein deposition, which is influenced by genotype and sex. TMV assumes that the maximum capacity for protein deposition is constant during the fattening stage (20-110 kg).

The maximum capacity for protein deposition (Pdmax) depends on the genotype and sex of the fattening pig. In practice, Pdmax equals around 130 grams per day for castrates, 145 grams per day for sows and 160 grams per day for boars. In this study, additionally, a Pdmax of 175 and 190 grams per day was investigated, referring to two fictive pigs with a high genetic merit for protein deposition (see appendix 1).

The marginal ratio (MR) determines the ratio between the lipid and protein deposition from one extra MJ of energy intake when the pig has not reached Pdmax yet. So in fact, it is the ratio between the slopes of the lines describing lipid and protein deposition with increasing energy intake. When the protein deposition equals Pdmax, the extra energy is used for fat deposition. The marginal ratio depends on sex and body weight. Proposed values for castrates, sows and boars on practical pig farms are .06, .05 and .04 respectively. In this study, additionally, a MR of .03 and .35 was investigated, referring to two fictive pigs with a high genetic merit for protein deposition (see appendix 1).

The basic model is validated with experimental data that are not used for model development. This validation showed that TMV predicts protein deposition, average growth rate, feed and energy conservation ratio and percentage of meat accurately, whereas it overestimates fat deposition.

To simulate the growth, body composition, mineral excretion, indirect energy consumption and financial results for a fattening pig with the basic model of TMV, the following information has been used:

- a weight at the start of the growing period of 25 kg; from this the initial chemical body composition of the pig was computed;
- daily food and water intake (for more detailed information see appendix 1);
- nutrient composition of the various feeds: energy (MJ, ME, apparent ileal digestible - amino acids, protein, total and digestible phosphorous (see appendix 2);
- genotype and sex of the animal; which indirectly determines parameters related to efficiency of protein and fat deposition, like Pdmax and the Marginal Ratio (MR);
- a live weight of 113 kg at the end of the growing period was assumed, resulting in a growing period between 101 and 114 days.

*Additional calculations*

The housing systems, in addition to the inorganic nitrogen excretion of the pig, also determine the ammonia emission per fattening pig (see appendix 3). Ammonia in pig housing is mainly formed from the urea in the urine. The release of ammonia from its source (urea which is inorganic N) is a slow process, governed by factors such as urea concentration, pH of slurry, temperature and air velocity in the housing system. In addition to nitrogen excretion, therefore, pen design and indoor climate, therefore, influence ammonia emission per fattening pig. In this study, three different housing systems were considered: the standard housing system for fattening pigs currently in practice, and two Green Label systems, *i.e.,* a pen with separate manure channels and a pen with water and manure channel.

Technical, economical and environmental data were expressed on an annual basis and at farm level, assuming 2,000 pig places per farm.

*Table 4.2 Characteristics of the TMV sample variables*

| Variable | Unit | Mean | Minimum | Maximum | Std. Dev. |
|---|---|---|---|---|---|
| Concentrates | 1998 NLG | 533.708 | 520.267 | 576.877 | 16.621 |
| Labour | hours | 2.663 | 2.504 | 2.810 | 109 |
| Buildings | 1998 NLG | 164.254 | 155.732 | 168.769 | 6.081 |
| Veterinary costs | 1998 NLG | 31.563 | 29.687 | 33.293 | 1.288 |
| Value pigs produced | 1998 NLG | 757.128 | 701.677 | 807.045 | 15.899 |
| Ammonia emission | kg $NH_3$ | 2.959 | 2.504 | 3.752 | 340 |
| Phosphorous Surplus | kg $P_2O_5$ | 3.916 | 1.495 | 7.185 | 1.780 |

## 4.4 Choice of inputs and outputs

Before the different approaches can be used to develop the frontier function a choice should be made about the relevant in- and outputs to be taken into account. A standard approach in the agricultural economics literature is to aggregate inputs and outputs into a reasonable set and to determine the frontier function using the described methods. The disadvantage of this approach is that only limited use is made of available production technical knowledge.

First it is essential to make the data of FADN and TMV comparable. Whenever possible we used price and quantity information to link the value of inputs and outputs from TMV to the FADN data set.

The average FADN feed price in 1998 corresponds well tot the feed price used in TMV, we concluded that the quality of concentrates bought in FADN does not differ from TMV. Therefore, we could simply connect the value of feed as simulated by TMV with the observed value of feed from FADN in the basis year. The veterinary costs included costs for artificial insemination. TMV did distinguish artificial insemination costs, but used a constant value for veterinary costs, *i.e.*, five guilders per slaughtered pig. We used the summation of feed cost and veterinary costs in our analysis.

The costs for capital consist of depreciation, interest and maintenance costs. Both FADN and TMV distinguished these components. However we had no information about the exact farm system in FADN; only the availability of a 'green label system' is recorded in FADN (in 1997 and 1998). None of the FADN farms selected had a 'Green label system' in 1998. In FADN digressive depreciation is applied to the book value of buildings and installations. Also interest and maintenance costs are based on the book value. We applied the FADN 1998 interest rate (3.5%) to all years. TMV only contains the new value of buildings. The mean share of depreciation, interest and maintenance in total building costs was similar in FADN and TMV. To make these data comparable we computed the mean housing costs per pig place from FADN of the 10 farms with the highest ratio of book value and new value and more than 900 pig places. These mean housing costs per pig place (NLG 77.87) are inserted in TMV.

We used the FADN meat price per kg slaughtered pig from the basis year (1998) to compute the implicit quantity indexes of meat for the TMV data too.

The ammonia emission from FADN farms was computed in an identical way as the one used for the common systems in TMV; we corrected for the feed stocks. Also the same standard animal factors used for computation of the emission in TMV are used for computation of the $NH_3$-emission in FADN (see description TMV). For the phosphorous surplus both data sets did have comparable parameters, the phosphorous surplus in TMV is converted into a phosphorus surplus (identical to FADN).

To increase the variation of selected variables, especially for TMV, all parameters are expressed per hour of labour (in the remainder of the text we use only the name of the numerator of the inputs and outputs). Table 4.3 gives the characteristics of the FADN variables and TMV variables, which are used in the analyses. The standard deviation of the TMV data is a lot smaller than that of the FADN farms.

*Table 4.3 Characteristics of the adjusted FADN and TMV variables, used in analyses*

| Variable | Unit | Mean | Minimum | Maximum | Std. Dev. |
|---|---|---|---|---|---|
| FADN data | | | | | |
| Concentrates + veterinary costs | 1998 NLG/hour | 201.45 | 57.74 | 451.48 | 79.26 |
| Buildings | 1998 NLG/hour | 37.36 | 5.36 | 121.81 | 21.12 |
| Pigs produced | 1998 NLG/hour | 221.74 | 42.00 | 491.75 | 93.80 |
| Ammonia emission | kg $NH_3$/hour | 2.11 | 0.58 | 4.35 | 0.84 |
| Phosphorous Surplus | kg $P_2$/hour | 3.24 | 0.83 | 7.26 | 1.36 |
| TMV data | | | | | |
| Concentrates + veterinary costs | 1998 NLG/hour | 212.74 | 197.02 | 236.47 | 12.98 |
| Buildings | 1998 NLG/hour | 61.78 | 55.43 | 67.40 | 3.41 |
| Pigs produced | 1998 NLG/hour | 284.20 | 273.21 | 288.66 | 4.16 |
| Ammonia emission | kg $NH_3$/hour | 1.12 | 0.89 | 1.46 | 0.16 |
| Phosphorous surplus | kg $P_2$/hour | 1.48 | 0.53 | 2.80 | 0.68 |

# 5 Empirical analysis

## 5.1 Data Envelopment Analysis (DEA) using farm data

Technical efficiency measurement using DEA is illustrated in figure 5.1, where each dot represents a combination of one input, *x* and one undesirable output, *w* of farms producing the same quantity of desirable output. In figure 5.1, the farms are labelled A, B and C. Data Envelopment Analysis creates a piecewise linear isoquant from the observations of the farms. In figure 5.1, the piecewise linear isoquant is constructed from the input combinations from farm B and C. Therefore, farms B and C are technically efficient farms. Farm A uses more of *x* and produces more *w*, while producing the same quantity of desirable output. The technical efficiency of farm A is given by the ratio 0A’/0A. Note that this measure of technical efficiency assumes that both input and undesirable output (*x* and *w*) can be contracted radially, *i.e.*, with an equal proportion given by 1-0A’/0A.

Another measure of technical efficiency that can be derived from figure 5.1 is sub-vector efficiency, which indicates the possibility for reduction of the undesirable output or the use of the input. In figure 5.1, farm A sub-vector efficiency of the undesirable output is given by the ratio 0’A”/0’A. Therefore, farm A could reduce the use of input w by a proportion given by 1-(0’A”/0A).

Figure 1. Input oriented Technical and Subvector Efficiency with DEA

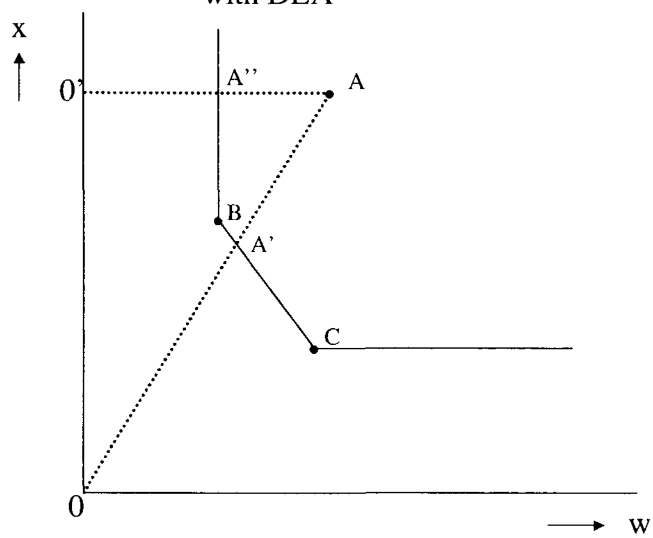


*Figure 5.1 Input oriented Technical and Sub-vector Effciency*

Another representation of the technology is given in figure 5.2, depicting the relation between input, $x$ and output, $y$ (a similar relation holds between an undesirable output $w$ and desirable output $y$).

Figure 2. Increasing, Constant and Decreasing Returns to Scale.

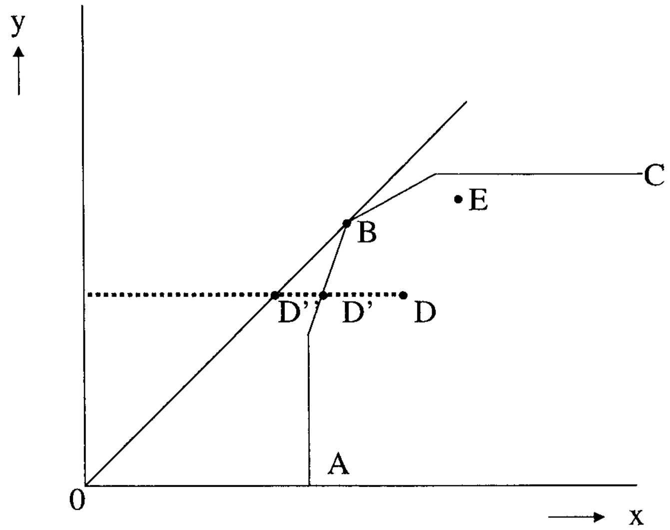


*Figure 5.2 Increasing, Constant and Decreasing Returns to Scale*

Figure 5.2 displays two frontiers, one under the assumption of constant returns to scale and one under the assumption of variable returns to scale. The line 0B is the production frontier under constant returns to scale and represents the maximum ratio of output over input. The segment ABC gives the frontier under the assumption of variable returns to scale, consisting of a region with increasing returns to scale (AB), constant returns to scale (point B) and decreasing returns to scale (BC). The frontier under representing non-increasing returns to scale is given by the lines 0BC, *i.e.*, the increasing returns to scale region from the variable returns to scale frontier is excluded.

The representation of the technology in figure 5.2 allows for demonstrating different efficiency measures for the observed farm D. The variable returns to scale efficiency measure of farm D is given by the ratio D'/D and the constant returns to scale efficiency is D"/D. The scale efficiency of this farm is the ratio D"/D', and is a measure for the difference between the variable returns to scale frontier and the constant returns to scale frontier (Coelli et al., 1998). The non-increasing returns to scale efficiency measures are derived in a similar way, *i.e.*, by relating the observations to the non-increasing returns to scale frontier, 0BC. Furthermore, it can be seen that farm D is in the region of increasing returns to scale, since the horizontal line from D crosses the variable returns to scale frontier in the region of increasing returns to scale. Similarly, it can be seen that farm E is in the region of decreasing returns to scale.

## 5.2 Exploring the efficiency of new technologies using DEA

A problem associated with measuring efficiency using actual farm data is that it is a reflection of the best currently used technologies. Therefore, any technologies that are available, but not yet applied, *i.e.,* best available technologies not entailing excessive costs (BATNEEC, see Cairncross, 1993; Tyteca, 1996) are neglected. If the characteristics of these new technologies are known, *e.g.,* from experiments or from model simulations, then the efficiency of farms in a sample relative to the BATNEEC can be assessed using DEA. Figure 5.3 displays a piecewise linear isoquant representing the most efficient currently used technologies (*i.e.,* the isoquant made up of farms B and C) and an isoquant that represents the BATNEEC, which is made up of the virtual farms $M_1$ and $M_2$. The observations on the virtual farms may have been obtained from experiments or model simulations.

Technical efficiency and the sub-vector efficiency of the undesirable output of farm A relative to the currently used technologies are given, as before, by the ratios 0A'/0A and 0'A''/0'A. However, the BATNEEC frontier allows for an additional reduction of input and undesirable output, which is reflected by the frontier movement from A' to M'. This movement is an approximation for technological change that is feasible given the currently *available* technologies. The ratio between the two frontiers 0M'/0A' is an index of frontier productivity, *i.e.,* it indicates the productivity of the best *currently available technologies* relative to the best currently used technologies. The overall efficiency of farm A relative to the BATNEEC is given by the ratio 0M'/0M, whereas sub-vector efficiency of the undesirable output is given by the ratio 0'M''/0'A.

Figure 3. Input oriented Technical and Subvector Efficiency relative to new Technologies

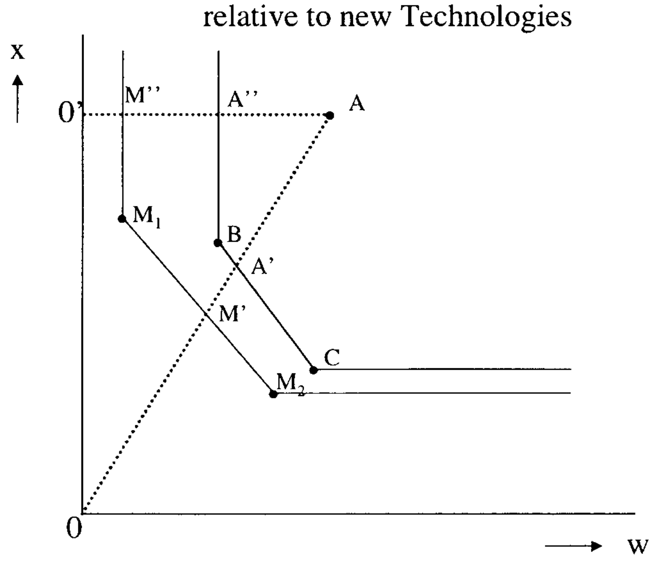


*Figure 5.3 Input oriented Technical and Sub-vector Efficiency relative to new Technologies*

## 5.3 Linear programming models for technical and sub-vector efficiency

This section discusses the linear programming models that allow for calculating the measures of technical and sub-vector efficiency given in the previous section. The discussion of the linear programming models starts from a set of observations of farms in a sample that use a *vector* of inputs ($x$) to produce *vectors* of desirable ($y$) and undesirable outputs ($w$). Input oriented technical efficiency for farm i is calculated from the following linear program: where $\theta$ is the technical efficiency score ($\theta \in [0,1]$) for the i-th firm and $\lambda$ is a vector of parameters (firm weights).

$$
\begin{aligned}
&\underset{\theta,\lambda}{Min} \quad 6 \\
&s.t. \quad -y_i + Y\lambda \geq 0 \\
&\qquad \theta x_i - X\lambda \geq 0 \\
&\qquad \theta w_i = W\lambda \qquad\qquad (1) \\
&\qquad N1'\lambda = 1 \\
&\qquad \lambda \geq 0
\end{aligned}
$$

The first and the second constraint indicate the quantities of inputs that are required to produce desirable outputs, whereas the third constraint indicates the quantity of undesirable output. The desirable outputs are strongly disposable (*i.e.,* their quantities can be reduced without costs), whereas the undesirable outputs are weakly disposable (*i.e.,* reducing the quantity involves costs). Weak disposability of the undesirable outputs is reflected by the equality constraint on undesirable outputs. The constraint $N1'\lambda=1$ implies that the sum of the lambda's equals one and allows for variable returns to scale. Note that the problem in (1) must be solved for each farm in the sample [1].

Sub-vector efficiency of the undesirable output is calculated in a similar way using:

[1] In case there are three farms, one desirable output, one undesirable output and one input, the DEA model for farm 1 becomes :

$$
\begin{aligned}
&\underset{\theta,\lambda}{Min} \quad \theta \\
&-y_1 + (y_1\lambda_1 + y_2\lambda_2 + y_3\lambda_3) \geq 0 \\
&\theta x_1 - (x_1\lambda_1 + x_2\lambda_2 + x_3\lambda_3) \geq 0 \\
&\theta w_1 - (w_1\lambda_1 + w_2\lambda_2 + w_3\lambda_3) = 0 \\
&\lambda_1 + \lambda_2 + \lambda_3 = 1
\end{aligned}
$$

$$
\begin{aligned}
&\underset{\theta,\lambda}{Min}\ \theta \\
&s.t.\quad -y_i + Y\lambda \geq 0 \\
&\qquad x_i - X\lambda \geq 0 \\
&\qquad \theta w_i = W\lambda \qquad\qquad (2) \\
&\qquad N1'\lambda = 1 \\
&\qquad \lambda \geq 0
\end{aligned}
$$

It can be seen that the sub-vector efficiency model does not scale down inputs $x$ as the technical efficiency model does. Therefore, the sub-vector efficiency model involves finding a frontier that minimises the quantity of the undesirable output.

## 5.4 Results

The FADN data set selected consists of 96 observations of 36 farms. The TMV data set contained 20 different animals (farms) and three different housing systems. Two data sets were composed for the DEA analysis. One contains FADN data only, the other contains FADN data as well as TMV data.

We model the environmentally detrimental variables as conventional inputs, rather than as an undesirable output. Cropper and Oates (1992), Ball et al. (1994) and Tyteca (1997) also followed this approach. Waste emissions are treated simply as another factor of production. Reductions in these emissions result in reduced output. Pittman (1981) also modelled pollution as input in the production function because the relation between an environmentally detrimental variable and output looks like the relation between conventional input and desirable output. We were able to measure the environmentally detrimental input usage, but we are unable to measure the environmental repercussions.

For the analyses we used the program Onfront. Onfront 2.0 (we used a beta version) offers the possibility to compute sub-vector efficiency scores. The model contains 4 inputs (Feed including veterinary costs, capital, phosphorous surplus and ammonia emission). We use the input-oriented approach because we are interested in minimisation of the environmentally detrimental inputs conditional on the desirable output.

First, the FADN data are analysed, we compute the three distinguished returns to scale models (see section 5.2). Consistent with the theory we find that the constant returns to scale (CRS) input oriented efficiency scores are smaller than the non-increasing returns to scale (NIRS) and the variable returns to scale (VRS) scores (see table 5.1 for the FADN farms). The latter contains the largest number of efficient farms. The average efficiency score is about 0.9, suggesting that identical output can be produced with 10% radial reduction of inputs. The scale efficiency is computed as the ratio of the CRS score and the VRS score (table 5.1). Nine farms are scale efficient. Seventy-one farms operate in the Increasing Returns to Scale segment of the frontier. The remaining 16 farms are located in the decreasing returns to scale portion of the frontier.

*Table 5.1 Results of analyses with FADN data only*

| | CRS | NIRS | VRS | Scale efficiency |
|---|---|---|---|---|
| Mean efficiency | 0.886 | 0.888 | 0.902 | 0.982 |
| Standard deviation | 0.081 | 0.083 | 0.073 | 0.049 |
| # efficient farms | 9 | 12 | 16 | 9 |
| Efficiency minimum | 0.546 | 0.546 | 0.681 | 0.546 |

Second the entire data set (FADN and TMV data) is analysed. The mean VRS efficiency score of the FADN farms decreases 4% when the data set is expanded with the TMV data (see table 5.2). Thus the technology represented by the TMV data enables another 4% reduction in inputs on average for the FADN-farms.

*Table 5.2 Results of the analyses with TMV and FADN data combined*

| | CRS | NIRS | VRS | Scale efficiency |
|---|---|---|---|---|
| Mean efficiency FADN farms | 0.840 | 0.848 | 0.864 | 0.974 |
| # efficient FADN farms | 6 | 10 | 12 | 6 |
| # efficient TMV data | 3 | 3 | 3 | 4 |
| # farms δ efficiency | 90 | 86 | 84 | 89 |
| Avg. change vs. FADN | 0.048 | 0.045 | 0.044 | 0.008 |
| Min. efficiency FADN farms | 0.499 | 0.499 | 0.651 | 0.499 |
| Min. efficiency TMV data | 0.800 | 0.800 | 0.800 | 0.994 |

The number of efficient FADN-observations decreases if TMV data are added. The frontier is now also defined by three TMV data points. Thus the frontier has changed due to the TMV-data. However, the majority of the efficient farms in the FADN data (12 out of 16) remain on the frontier when the TMV data are added. This result suggests that the TMV data only affect a portion of the frontier. The input-oriented efficiency is to a small extent affected by the inclusion of new techniques. The input-efficiency score of all inefficient FADN-observations (in the entire data set) is effected by the inclusion of TMV-data (denoted in table 5.2 by '# farms δ efficiency).

We want to discriminate between potential efficiency gains due to improved management practice, and efficiency gains due to investments in green label pig housing. Therefore we deleted the 40 TMV data points based on improved housing systems, the TMV data based on the current housing system remain in the data set. The frontier determined by this data set could be attained by improved management. Now only one TMV data is located on the frontier. The change in efficiency scores (compared with the efficiency scores based on FADN data only) is only marginally smaller than in the case 60 TMV data were used. However the one efficient TMV data point is a pig with a very large protein deposition, such a large protein deposition is not feasible in practice yet.

*Table 5.3 Results of analyses with current housing systems using FADN data and part of TMV data*

| | CRS | NIRS | VRS | Scale efficiency |
|---|---|---|---|---|
| Mean efficiency FADN farms | 0.841 | 0.849 | 0.865 | 0.973 |
| # efficient FADN farms | 6 | 10 | 12 | 6 |
| # efficient TMV farms | 1 | 1 | 1 | 2 |
| # farms δ efficiency | 90 | 86 | 84 | 89 |
| Avg. change vs. FADN | 0.047 | 0.044 | 0.043 | 0.009 |
| Min. efficiency FADN farms | 0.499 | 0.499 | 0.651 | 0.499 |
| Min. efficiency TMV farms | 0.811 | 0.811 | 0.811 | 0.999 |

We are mainly interested whether the new technology, put forward by TMV, change the best practice frontier with respect to the environmentally detrimental variables (conditional on the output). In the previous analyses the four inputs were reduced equiproportionally. Therefore, we now compute sub-vector efficiencies by keeping the conventional input (feed and housing costs) fixed and reducing the ammonia emission and the phosphorous surplus, conditional on the desirable output. Thereafter, we minimise the environmentally detrimental variables separately conditional on the other environmentally detrimental variable, the conventional inputs and the desirable output. We analysed sub-vector efficiencies in variable returns to scale context, because the data are most closely enveloped by the frontier in that case. Farms that are located on the frontier (compare the input-oriented efficiency scores in table 5.1) remain all efficient when sub-vector efficiency is computed (irrespectively of the dimension of the frontier).

*Table 5.4 Results of the sub-vector analyses (VRS) with FADN data only*

| | P-surplus and $NH_3$ | P-surplus | $NH_3$ |
|---|---|---|---|
| Avg. efficiency | 0.882 | 0.861 | 0.868 |
| Standard deviation | 0.085 | 0.098 | 0.088 |
| # efficient farms | 16 | 16 | 16 |
| Efficiency minimum | 0.675 | 0.628 | 0.675 |

Consistent with the theory the sub-vector efficiency scores in the FADN sample are smaller than the corresponding VRS input-oriented efficiency scores (table 5.1). However they are only to a small extent (2-4%) smaller than the comprehensive input-oriented efficiency scores, indicating that the environmentally detrimental inputs are not utilised very inefficiently compared with the conventional inputs; condition on the current best practice technology. The sub-vector efficiency of phosphorous surplus and ammonia emission is almost identical.

*Table 5.5 Results of the sub-vector analyses with TMV and FADN data combined*

| | P-surplus and $NH_3$ | P-surplus | $NH_3$ |
|---|---|---|---|
| Avg. eff. FADN farms | 0.657 | 0.644 | 0.571 |
| # eff. FADN farms | 12 | 12 | 12 |
| # eff. TMV data | 3 | 3 | 2 |
| # farms δ efficiency | 84 | 84 | 84 |
| Avg. change vs. FADN | 0.257 | 0.248 | 0.339 |
| Min. efficiency FADN farms | 0.332 | 0.329 | 0.127 |
| Min. efficiency TMV data | 0.598 | 0.598 | 0.190 |

When the entire data set (FADN and TMV) is analysed we find more pronounced differences between the input-oriented efficiency scores and the corresponding sub-vector efficiency scores. This result indicates that the TMV data move the frontier in the direction of minimisation of the environmentally detrimental inputs. The ammonia emission can be reduced with 43% if the frontier TMV technology is implemented in practice (table 5.5). This large potential reduction is due to the different housing systems in TMV. Two out of three TMV efficient data stem from green label housing systems.

The potential reduction in phosphorous surplus is not as large (35%) for the FADN farms. The variation in phosphorous efficiency scores within the TMV data is smaller than in the ammonia efficiency scores (the different housing systems do not affect the phosphorous surplus). The combined phosphorous and ammonia sub-vector efficiency is almost totally determined by the phosphorous surplus inefficiencies (table 5.5).

To assess the potential reduction of the environmentally detrimental inputs by improved management, we focus on the possibilities offered by the current housing system (defined by FADN and 20 TMV data). We find that the phosphorous sub-vector inefficiency is identical to the corresponding inefficiency scores of the total TMV data (the housing system does not affect the phosphorous surplus). However the ammonia emission can now only be reduced with about 30% by current housing systems (table 5.6). The combined environmental efficiency score is now determined by the ammonia inefficiency. The environmental performance of farms can increase with 30%, based on improved management.

*Table 5.6 Results of sub-vector analyses with current TMV systems and FADN data combined*

| | P-surplus and $NH_3$ | P-surplus | $NH_3$ |
|---|---|---|---|
| Avg. eff. FADN farms | 0.708 | 0.644 | 0.705 |
| # eff. FADN farms | 12 | 12 | 12 |
| # eff. TMV data | 1 | 1 | 1 |
| # farms δ efficiency | 84 | 84 | 84 |
| Avg. change vs. FADN | 0.174 | 0.248 | 0.186 |
| Min. efficiency FADN farms | 0.434 | 0.329 | 0.434 |
| Min. efficiency TMV data | 0.645 | 0.598 | 0.645 |

In a second stage analysis Tobit is used to explain the efficiency scores (see appendix 4). A significant relation between the magnitude of the input-oriented efficiency scores and farm size and feed costs per pig place is found. An increase in the number of pig places has a significant positive effect on the efficiency score. Higher feed costs, related to a higher feed quality, are positively related to the efficiency score. Capital costs per pig place are negatively related to the ammonia sub-vector efficiency scores [1]. Feed per pig place and labour per pig place have a positive (marginal) impact on the ammonia sub-vector efficiency scores. Further analysis is needed to analyse the possible relation between inefficiency scores and farm characteristics (management aspects).

[1] The ammonia emission is calculated without considering the type of buildings used.

# 6 Conclusions and discussion

## 6.1 From a scientific perspective

For a correct interpretation of results with respect to the pig production sector, we should realise that data on, *e.g.*, pig welfare and meat quality, were not included in this analyses. Data analyses included technical data and a few environmental parameters, *i.e.*, N and P surplus per farm and $NH_3$ emission per farm. FADN data, however, show only limited variation in $NH_3$ emission per farm because only standard housing systems were present in the data set.

FADN farms can decrease their input costs on average by 10%. Hence, possibilities for technical improvement on practical pig farms are limited. The ammonia emission of FADN farms, however, can be reduced by 43%, due to both genetic selection and multi-phase feeding (30%) and introduction of green-label housing systems (13%). As expected, the potential reduction in P-surplus was smaller than the reduction in $NH_3$ emission, *i.e.*, 35% for FADN farms. The TMV feedmix and housing system minimise the nitrogen input, but are less effective in minimising phosphorous input.

Simulated data used to determine the available technology not implemented yet in practical farms (BATNEEC) frontier focuses on measurements for ammonia emission reduction. Hence, determination of the BATNEEC frontier is a very important phase in a DEA analysed including but practical and simulated data. Further improvements of technical and environmental efficiency for pig farms requires development of new innovative pig production systems. Technical, environmental, and societal performance of these innovative systems should be used to determine the BATNEEC frontier.

Different procedures can been applied to assess the possibilities for improving economic performance and reducing environmental emissions in agricultural production (see section 3). Models based on statistical techniques, mathematical programming methods and simulation procedures differ with respect to (i) the type of input-output data that are used (i.e. currently available and/or potential 'best practice' technologies), (ii) the specification of behavioural and technical parameters (i.e. management practices and investment decisions) and (iii) the relationship between economic and environmental criteria (*i.e.* trade-offs and externalities).

Programming methods have been widely used in agricultural policy analysis to identify trade-offs between economic and environmental objectives at farm and regional level (Van Rheenen, 1995; Schipper, 1996). These models provide adequate insights into optimal land use patterns and the potential conflicts between income and environmental effects forthcoming from different technically efficient production systems. Within this framework, actual production techniques are combined with simulated technologies to construct different scenarios for simulation purposes (Rabbinge et al., 1994; Van Keulen and Veeneklaas, 1992).

Econometric procedures are usually applied for the analysis of the performance of economic systems, taking into account actual farm household behaviour. Therefore, production functions can be estimated that includes primary inputs, environmental externalities and relevant farm household characteristics (Mausolff and Farber, 1995; Heerink and Ruben, 1996). The latter variables can be subsequently used to explain efficiency deviations from the frontier function, making use of Tobit analysis.

Data Envelopment Analysis (DEA) is recently proposed as an approach that permits to identify potential options for cost-efficient improvement of farm environmental performance. While original DEA analyses are based on the estimation of the efficiency frontier with actual farm data, the standard approach has been extended to include data derived from simulation models.

Finally, meta-modelling offers an alternative framework for the simultaneous analysis of technical and economic efficiency of actual and simulated production systems, identifying dynamic trade-offs between income objectives and environmental effects. This procedure is used to fit continuous production functions from discrete data sets that are subsequently linked to decisions-support models at higher aggregation levels, including the usual price effects. Table 6.1 provides a comparative overview of the four methods and indicates the type of parameters and procedures that are applied within each framework.

*Table 6.1 Different analytical methods to assess economic-environmental information*

| | Production functions | Programming methods | Data Envelopment Analysis (DEA) | Meta-modelling |
|---|---|---|---|---|
| Actual technologies | + | + | + | + |
| Simulated technologies | | + | + | + |
| Environmental trade-offs | | + | | + |
| Environmental externalities | + | | + | |
| Price endogeneity | | + | | + |
| Adoption behaviour | + | | + | + |

Compared to other procedures used for the appraisal of economic and technical data, DEA exhibits a number of clear advantages. Whereas programming and metamodels only identify static trade-offs between economic and environmental objectives, DEA enables a simultaneous assessment of economic efficiency and environmental externalities. Furthermore, DEA yields direct insight into the costs associated with the reduction of environmental effects (undesirable outputs). Finally, DEA permits to compare economic and environmental implications of different options for technology change and/or improved farm management practices (*i.e.* sub vector efficiency).

The DEA application to the Dutch pig sector reveals that input efficiency scores of most current production techniques (FADN farms) are only slightly below best practices as derived from the (TMV) simulation model. However, the latter data include an additional segment of the production frontier. This is especially true for ammonia emissions that require substantial fixed investments for the establishment of low-emission housing systems.

This points to the fact that DEA is especially suitable as a procedure for the analysis of investment options, while (marginal) adjustments in farm management practices that offer minor efficiency gains are easily outweighed.

Even while the DEA methodology enables in principle a sound analysis of the interactions between economic and environmental criteria, aspects of factor substitution are not explicitly addressed. Therefore, DEA tends to be most appropriate for capturing long-term effects of technological change (i.e. shifts of the production frontier) but cannot be directly used to assess short-term adjustments. In principle, parametric models and meta-modelling procedures offer suitable alternatives for the analysis of factor substitution effects.

DEA analysis might be reinforced through the application of a number of additional procedures. First, empirical proof regarding the possibility for 'pooling' currently available and potential 'best practice' technologies into a single analytical procedure is required (Pindyck and Rubinfeld, 1991:223-231). Meta-modelling procedures can be helpful to determine whether both data sets can be combined. Second, it might be useful to make a clear separation between (short run) input use and (long run) investment decisions, since the latter require usually a substantial higher benefit-cost ratio for being adopted. Third, dynamic applications of DEA are required to assess the pathways of transition from current towards potential technologies.

## 6.2 From a policy perspective

Information about improving economic performance and reducing environmental emissions simultaneously contributes to the development of integral policy instruments. The process of developing environmental policies is directed by public and private interests, information about environmental and economic possibilities and consequences, and power mechanisms. Environmental policy making is therefore a complex process in which high quality information on what can be possibly achieved by individual farmers will be highly valued.

Extended DEA is attractive when potential 'best practice' technologies and relevant behavioural parameters are specified. The spectrum of actual and potential efficiency scores is highly relevant from a policy perspective. Therefore, a sufficient 'time horizon' of potential technologies should be taken into account by DEA to enable support of long term policy decisions. Integrating farm management parameters in the proposed approach requires information on the presence of suboptimal practices. Therefore, future FADN activities should include farm management parameters.

Not only the spectrum of actual and potential efficiency scores is relevant from a policy perspective. Given adequate assessments on 'best practices', information on the dynamics of this spectrum over time contributes to improved assessment of policy alternatives.

The approach contributes both to private and public environmental policy making. Public policies have a more generic character. The approach supports the process of determining generic emission values (i.e. forfeits). From a private policy perspective, the approach can help determining valuable 'best practices'.

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# Appendix 1 Parameter values for 20 alternative simulated pig farms

| Animal on farm | Geno-Type | Pdmax | Marginal Ratio | Efficiency Protein deposition | Feeding strategy* | Feed intake of various feeds (kg/produced pig) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | S98 | S99 | V98 | NMR | NMA |
| 1 | Castrate | 130 | .06 | .45 | 2 | 44.84 | - | 207.1 | - | - |
| 2 | Castrate | 130 | .06 | .45 | M | 44.84 | - | - | 47 | 160.1 |
| 3 | Castrate | 130 | .06 | .54 | 2 | 44.84 | - | 190.11 | - | - |
| 4 | Castrate | 130 | .06 | .54 | M | 44.84 | - | - | 44.87 | 147.78 |
| 5 | Boar | 145 | .05 | .45 | 2 | 41.05 | - | 206.15 | - | - |
| 6 | Boar | 145 | .05 | .45 | M | 41.05 | - | - | 58.92 | 147.23 |
| 7 | Boar | 145 | .05 | .54 | 2 | 41.05 | - | 187.28 | - | - |
| 8 | Boar | 145 | .05 | .54 | M | 41.05 | - | - | 58.48 | 128.8 |
| 9 | Sow | 160 | .04 | .45 | 2 | 41.05 | - | 194.15 | - | - |
| 10 | Sow | 160 | .04 | .45 | M | 41.05 | - | - | 58.92 | 135.23 |
| 11 | Sow | 160 | .04 | .54 | 2 | 41.05 | - | 178.91 | - | - |
| 12 | Sow | 160 | .04 | .54 | M | - | 41.05 | - | 78.2 | 97.82 |
| 13 | Fictive | 175 | .035 | .54 | 2 | - | 41.05 | 173.18 | - | - |
| 14 | Fictive | 175 | .035 | .54 | M | - | 41.05 | | 95.27 | 75.08 |
| 15 | Fictive | 175 | .035 | .6 | 2 | - | 41.05 | 167.51 | - | - |
| 16 | Fictive | 175 | .035 | .6 | M | - | 41.05 | - | 94.13 | 70.53 |
| 17 | Fictive | 190 | .03 | .54 | 2 | - | 41.05 | 170.34 | - | - |
| 18 | Fictive | 190 | .03 | .54 | M | - | 41.05 | - | 94.7 | 72.8 |
| 19 | Fictive | 190 | .03 | .6 | 2 | - | 41.05 | 164.67 | - | - |
| 20 | Fictive | 190 | .03 | .6 | M | - | 41.05 | - | 94.13 | 70.53 |

* 2 = two-phase feeding; m = multi-phase feeding

# Appendix 2 Nutrient composition of various possible feeds in the diet

| | S98 | S99 | V98 | NMR | NMA |
|---|---|---|---|---|---|
| Price (excl. VAT) (*f*/100 kg) | 42.64 | 44.50 | 36.51 | 37.00 | 35.50 |
| DM-content (g/kg) | 880 | 880 | 880 | 880 | 880 |
| Metabolic energy (EW) (*f*/kg) | 1.070 | 1.070 | 1.050 | 1.050 | 1.050 |
| Output analyses | g/kg | g/kg | g/kg | g/kg | g/kg |
| Amino acids (apparent ileal digestible) | | | | | |
| - Lysine | 8.90 | 10.20 | 7.00 | 8.00 | 6.00 |
| - Methionine | 2.90 | 3.40 | 2.40 | 2.54 | 1.90 |
| - Methionine + Cystine | 5.30 | 6.10 | 4.40 | 4.70 | 3.60 |
| - Threonin | 5.70 | 6.50 | 4.50 | 5.10 | 3.80 |
| - Tryptophane | 1.70 | 2.00 | 1.40 | 1.50 | 1.20 |
| - Isoleucine | 5.70 | 6.50 | 4.50 | 5.10 | 3.80 |
| Crude protein (CP) | 180.0 | 185.0 | 160.0 | 165.0 | 140.0 |
| Digestible CP | 144.0 | 148.0 | 128.0 | 132.0 | 112.0 |
| Phosphorus | 5.50 | 5.50 | 4.60 | 5.00 | 4.34 |
| Apparent digestible P | 3.00 | 3.00 | 2.00 | 2.20 | 1.60 |
| Ash | 71.0 | 71.0 | 69.0 | 68.0 | 61.0 |
| Crude fat (Cfat) | 50.0 | 50.0 | 54.0 | 56.0 | 58.0 |
| Digestible Cfat | 3.6 | 3.6 | 43.0 | 45.0 | 46.0 |
| Crude fiber (Cfiber) | 55.0 | 55.0 | 65.0 | 53.0 | 57.0 |
| Digestible Cfiber | 22.0 | 22.0 | 26.0 | 21.0 | 23.0 |
| Nitrogen free extract (NFE) | 524.0 | 519.0 | 532.0 | 538.0 | 564.0 |
| Digestible NFE | 462.0 | 462.0 | 485.0 | 470.0 | 491.0 |

# Appendix 3 Computation of ammonia emission per pig per year

For each pig farm simulated, three different housing systems were considered. Ammonia emission/animal place/year for these three systems are taken from Staatscourant (1999, 139: pg. 16). Annual emission of $NH_3$/animal place in the standard housing system was 3.5 kg for an average Dutch pig (which is in this study 0.5 x standard castrate (animal 1) + 0.5 x standard sow (animal 9). An average Dutch pig excretes 8.87 kg of inorganic N per year. Hence, ammonia emission expressed as percentage of inorganic N excretion is 32% and was used in all other alternative situations. In this way, a reduction in N intake of a fattening pig directly resulted in a reduction in inorganic N excretion and therefore in ammonia emission.

Similarly, two Green Label systems were considered, in which the emission of $NH_3$ was either 2.5 or 1 kg per animal place.

# Appendix 4 Tobit estimation results of the second stage analysis of efficiency scores

*Table A4.1 Tobit parameter estimates of the second stage analysis of the input-oriented efficiency scores of the FADN farms*

| Variable | Parameter estimate | Standard error | T-value |
|---|---|---|---|
| Number of pigs | - 0.000167 | 0.000104 | - 1.594 |
| Capital per pig | - 0.000459 | 0.000487 | - 0.941 |
| Labour per pig | 0.0448 | 0.0193 | 2.323 |
| Feed per pig | 0.00189 | 0.000184 | 10.299 |
| Veterinary costs per pig | - 0.00186 | 0.00183 | - 1.018 |
| Output per pig | 0.0000007 | 0.0000003 | 2.193 |

*Table A4.2 Tobit parameter estimates of the second stage analysis of the Ammonia sub-vector efficiency scores of the FADN farms*

| Variable | Parameter estimate | Standard error | T-value |
|---|---|---|---|
| Number of pigs | - 0.000268 | 0.000210 | - 1.278 |
| Capital per pig | - 0.00434 | 0.000986 | - 4.397 |
| Labour per pig | 0.0847 | 0.0389 | 2.173 |
| Feed per pig | 0.00180 | 0.000362 | 4.971 |
| Veterinary costs per pig | - 0.00108 | 0.00371 | - 0.291 |
| Output per pig | 0.0000009 | 0.0000006 | 1.541 |