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DECIDE

Data-driven control and prioritisation of non-EU-regulated contagious animal diseases

Deliverable 4.2

Results of loss and expenditure frontiers of causes and risk factors from all cases

WP4 – Multidimensional burden of disease metric and prioritisation of interventions

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Content

Abbreviations

Abbreviation	Description
aMPV	Avian metapneumovirus
BRSV	Bovine respiratory syncytial virus
CRS	Constant returns to scale
DEA	Data Envelope Analysis
EU	European Union
IB	Infectious bronchitis
IBD	Infectious bursal disease
MB:MC	Marginal benefit to marginal cost ratio
SE	Scale efficiency
VRS	Variable returns to scale
WP	Work Package

Partner short names

Short name	Organisation
UU	Universiteit Utrecht
UoL	The University of Liverpool
INRAE	Institut National de Recherche pour l'Agriculture, l'Alimentation et l'Environemment
NVI	Veterinærinstituttet – Norwegian Veterinary Institute
IRTA	Institut de Recerca i Tecnologia Agroalimentàries
GD	Gezondheidsdienst voor Dieren B.V.
AUSVET	Ausvet Europe (now: EpiMundi)
SLW	SLW Biolab s.c.
accelCH	accelopment Schweiz AG

Executive Summary

This Deliverable is a report on the results of Task 4.2, which explored the use of loss-expenditure frontiers to map out routes to more economically efficient disease-control for endemic disease. The aim was to determine whether the analytical frame of loss-expenditure frontiers would produce results that could be integrated into the decision-making tools being constructed within DECIDE.

Objectives:

- Development of loss-expenditure frontiers
- Description of economic efficiencies of farms and interventions
- Consideration of detrimental external impacts on wildlife and the environment for salmon aquaculture in Norway.

To meet these objectives, case studies were selected from each of the four species groups, for a specific endemic disease or disease complex. These were *Mycoplasma hyopneumoniae* infection and control in Dutch finishing pig herds; bovine respiratory disease control in French fattening cattle operations; vaccination as a means to control infections with infectious bronchitis, infectious bursal disease and avian metapneumovirus disease in broiler chickens; and salmon louse control in Norwegian salmon aquaculture.

The efficiency of units in the population was described by data-envelopment analysis or the direct calculation of marginal efficiency change with application of alternative disease-control strategies. Loss-expenditure frontiers were constructed geometrically to visualise the population level trends and identify key benchmark farms within the population which were exemplars for efficient application of disease control technologies.

Two case studies (beef, pigs) used synthetic datasets built through mechanistic models to present economic efficiency and frontier results. Two used data from real flocks or groups of animals (chickens, salmon) directly within the analysis.

The results of analysis were qualitatively different depending on data type. Model data gave clear indication as to the efficiency of interventions to control disease and identified the most efficient units within the population. The analyses based on farm data were less clear. The broiler chickens showed an increasing trend in flock performance with use of additional vaccination, but with high variability which was associated with other flock health characteristics unrelated to vaccination itself, identified through cluster analysis.

In the salmon case, the efficiency of louse control was extremely variable between farms and over time. The salmon data lacked the necessary covariates to establish decisively what separated the successful flocks or groups from those being unsuccessful in their application of control but a number of hypotheses for further analysis were developed.

The results of these analyses and the framework code written in R will be made available to the teams working on the decision tools within the DECIDE programme. The intermediate steps of the analysis may contribute to the work on Task 4.4: cost-benefit analysis of interventions.

1 Introduction

Efficiency analysis provides the means of comparing the performance of different economic units, be they farms, businesses, or people, engaged in the same economic activity. In essence, efficiency tells us how effectively a business is using resources in comparison to its peers. Efficiency analysis is therefore a means of benchmarking. In livestock production, many farmers value peer-benchmarking as a means to understanding way to improve their own farm performance (Sumner et al., 2018). With a focus on the efficient use of resources to control disease, this report explores the potential of developing benchmarking based on economic efficiency frontiers for application within DECIDE's decision-tool framework. A peer benchmark based on economic efficiency calculation and frontier analysis has the potential to answer these sorts of questions:

- Is a change in expenditure on disease control financially justified?
- Which farms are the most efficient in disease control, and therefore who should farmers look to amongst their peers for the means of improving their efficiency?
- What factors (either endogenous to the farm, or exogenous) are associated with efficient disease control?

While farm benchmarking is very widely applied for many aspects of farm management, it's use in the study of disease control is less common practically although theoretically well supported.

1.1 Efficiency analysis

Following the influential works of Debreu (1951) and Farrell (1957) on the analysis of economic efficiency, efficiency analysis has developed as a means of comparing units engaged in a similar economic activity, in order to understand their performance and identify the paths to improvement. Efficiency being a ratio of the performance of one unit against some chosen standard, is inherently a relative measure. As such, depending on how the performance of each unit is measured and against what standard it is compared, there are a variety of ways in which efficiency can be expressed. As a background to the analysis in this document, the relevant measures of efficiency and their interpretation will be described here.

To start, a population of K units produces an output or outputs (y) with input or inputs (x). Each input is denoted x_m with inputs numbered from 1 to M and outputs as y_n with outputs numbered from 1 to N. Each unit within the population converts x into y at a given rate, which is termed productivity. If a best-practice standard for productivity is known, the ratio of a unit's productivity to this standard is a measure of technical efficiency. To be more precise, Farrell (1957) describes technical efficiency in two dimensions. If we ask what the minimum possible input required to produce the observed level of output for a unit is, we are taking an input-oriented approach. If we ask what the maximum possible output for the observed level of input is, we are taking an output-oriented approach. In each case, the ratio of the ideal divided by the observed provides a measure of input efficiency (E) or output efficiency (F) respectively.

Therefore, if we term the input use of a unit in the population as x^k, and the ideal input use with best practice as x^*, then the input efficiency E is calculated as:

1.

$$E = \frac{x^*}{x^k}$$

This calculation of efficiency is based on quantities of inputs. In a situation where multiple types of input can be combined to produce y, E is defined as the maximum proportional contraction of all inputs that permits the production of y. In multi-input space this can be visualised as a linear contraction toward the origin from each unit's location in input space. The maximum proportional contraction toward the origin in such a fashion will produce a technical efficiency frontier when the population consists of multiple units. Figure 1 illustrates this for the inputs (x_1, x_2) selected by two units, denoted as x^1 and x^2. A proportional contraction to the feasible minimum input amount results in two equally technically efficient points being marked out. When prices of inputs are taken into consideration however, other forms of efficiency can be introduced to deconstruct further the overall efficiency of these units.

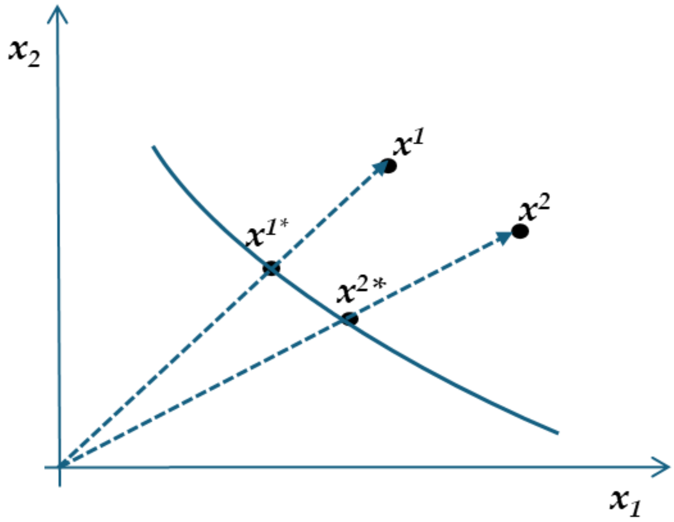

Figure 1. Technical efficiency of two units (x^1 and x^2). The solid line represents a technical efficiency frontier which is the minimum combination of inputs (x_1 and x_2) that yields a fixed level of output. The radial contraction of the input combinations used by each unit positions the technically efficient comparator on the frontier (x^{1*} and x^{2*}).

Efficiency measurement can be extended further when the prices of inputs and outputs are taken into consideration. Let w be the price vector for inputs. When each unit's choice of inputs can be considered not just by quantity, but also by cost, an efficient firm would position itself on the technically efficient frontier at a point which also minimises the total cost of x used to produce y. If we denote this point as x^{-}, then the cost-efficiency (CE) of a firm is defined as the ratio of the minimal to the actual cost of production:

2.

$$CE = \frac{wx^{-}}{wx^{k}}$$

Figure 2 illustrates this graphically. The curved frontier is an isoquant for a fixed amount of output (y). An isocost line (dashed) represents the combinations of inputs that sum to a certain price. When the prices of the two inputs are known, this line has the gradient $-\frac{w_1}{w_2}$, and therefore represents a price-weighted combination of inputs. The point at which the isocost line is tangential to the frontier is the minimum cost point (x^{-}).

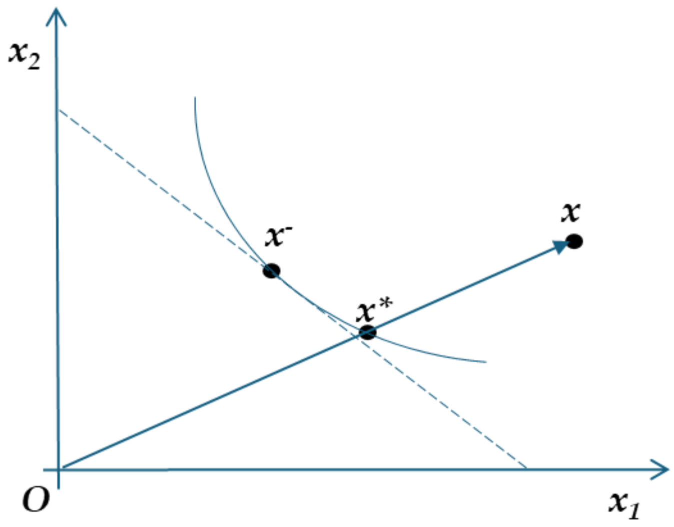

Figure 2. Isoquant illustrating constant output quantity with different combinations of two inputs (x_1, x_2). The observed unit input bundle (x) is technically inefficient. A radial contraction of its current input bundle leads to the technically efficient point, x* which lies on the isoquant. x^- is the cost-efficient input bundle on the isoquant, that is, the input bundle which is simultaneously technically efficient (lying on the frontier), and minimises the total cost (w_1x_1 + w_2x_2) where w is the price of each input. This minimum cost is illustrated by the isocost line (dashed) which is tangential to the isoquant at x^-.

The cost-efficiency estimate therefore captures two movements, firstly to a technically efficient frontier (x to x*), and then a reallocation to the least-cost optimum on that frontier (x^* to x^-). How resources are allocated to each input is an allocation problem, and the efficiency with which units address this is termed allocative efficiency (AE). Allocative efficiency is calculated as the ratio of the minimum cost input bundle x^- to the technically efficient input bundle x^*, thereby isolating the allocative contribution to cost-efficiency.

3.

$$AE = \frac{wx^-}{wx^*}$$

It may be noted from equations 2 and 3 therefore that AE is then the ratio of cost efficiency to technical efficiency.

1.2 Frontiers and benchmarking

It may have been noted that all of these efficiency measurements are contingent on being able to establish an ideal or benchmark against which to measure, whether that is the technically efficient or cost-efficient ideal. One of the primary means of using data to inform establishing a benchmark is through frontier analysis.

A frontier marks out the most productive firms at each level of input, with the remaining firms lying below the frontier (illustrated in Figure 3). There are multiple methods for estimating an efficiency frontier which can largely be grouped within two schools. Stochastic frontier analysis was developed within the discipline of economics and is a statistical method of fitting a frontier for efficiency based on assumptions about the distribution of data and functional form of the underlying relationship i.e. it is a parametric method (Aigner et al., 1977, Meeusen and van Den Broeck, 1977). Data envelopment analysis (DEA) has its heritage in operations and management research. This method uses numerical rather than statistical methods to describe the frontier of efficiency of units within a population in a non-parametric fashion, that is, making no distributional assumptions about the data. DEA is an application of linear programming by framing the analysis of efficiency as an optimisation problem, where each unit seeks to minimise input use for its output level, or maximise output for its chosen input bundle, with reference to the best performing of its peers (Charnes et al., 1978) under the assumption of constant returns to scale (i.e. the frontier is linear and increasing in x). This method has subsequently been significantly extended to account for variability in returns-to-scale and the estimation of cost and allocative efficiency (Banker et al., 1984, Coelli et al., 2005).

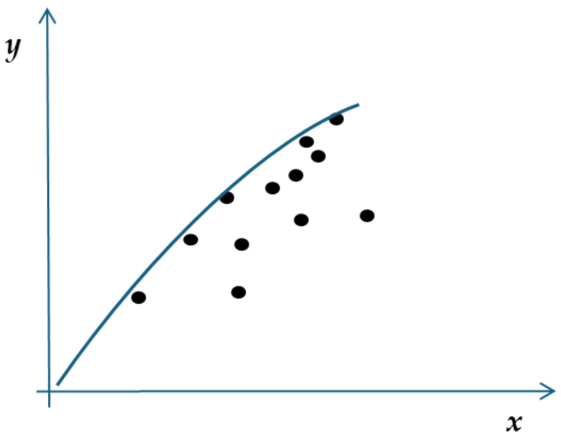

Figure 3. Illustrative diagram of a hypothetical efficiency frontier for a population of firms producing output y using input x. Those firms closest to the frontier (producing most y) at each level of x are deemed to be the most technically efficient at that level.

For input-oriented DEA, it is assumed that for each unit in the population there exists an efficiency score, θ, which represents the proportion by which current input use which would be needed under best-practice to achieve the same level of output, where θ takes values between 0 and 1. A score of θ = 1indicates full technical efficiency, while θ<1 suggests the unit could reduce its inputs proportionally by a factor of 1−θ without reducing output. This value (θ) therefore is equivalent to Farrell's E.

It is also assumed that the input-output space is continuous and convex within the range of the observed data. This means that convex combinations of observed decision-making units are feasible as production plans. The optimisation within DEA then assesses each unit against the most efficient convex combination of its peers to estimate efficiency. If variable returns to scale are also expected, then for a specific unit in the population (o) this estimates the minimum θ, such that:

4.

$$\sum_{k=1}^{K} \lambda_k x_{km} \leq \theta x_{om}$$
$$\sum_{k=1}^{K} \lambda_k y_{kn} \geq \theta y_{on}$$
$$\sum_{k=1}^{K} \lambda_k = 1$$
$$\lambda_k \geq 0 \text{ for all } k$$

Where lambda is a weight factor used to construct a composite of other best performing units. By constraining the sum of λ for each unit to be equal to 1, solutions are constrained to be weighted averages of observed data. A comparison can only be made to points within the convex hull of observed decision-making units. This allows for the possibility that efficiency varies with the scale of operation, that is, for variable returns to scale (VRS). This is then the standard specification for input-oriented DEA with variable returns to scale. In contrast, the constant returns to scale (CRS) model is simpler as it omits this constraint on λ, implying that proportional scaling of inputs and outputs is always feasible. A convex efficiency frontier can then be plotted as the upper surface of the convex hull of the observed data under VRS. In contrast, a linear efficiency frontier will be plotted under CRS, taking the form of a ray from the origin extending through the most productive population unit, irrespective of scale. This unit is the most scale efficient unit in the population, being on the frontier under both CRS and VRS. Scale efficiency (SE) for the remaining units in the population can then be calculated as:

5.

$$SE = \frac{E_{CRS}}{E_{VRS}}$$

Graphically this can be represented by plotting the two frontiers together (VRS and CRS), where scale efficiency will be maximised (i.e. equal to 1) at the point where the CRS frontier is tangent to the VRS frontier. Finally, to estimate the cost-minimal input selection necessary to calculate cost-efficiency, the problem is reframed to minimise the price-weighted input bundle given the constraints imposed by the data.

A further extension of DEA, Two-Stage DEA, consists of entering the efficiency scores into a regression analysis, usually by Tobit Regression (Hoff, 2007, Tobin, 1958), to look for factors that contribute to variation in efficiency scores. A recent review of the application of the DEA framework found 53 papers published since 1978 applying DEA to agriculture and fifteen to aquaculture to analyse economic efficiency (Camanho et al., 2024).

1.3 Frontiers and efficiency in damage control

Damage control inputs represent a special case for efficiency analysis. Damage control inputs act indirectly, that is, they do not on their own serve to increase the total output. Where a damaging effect which reduces the total output of the production process exists, damage control inputs serve to increase the proportion of the possible yield that is attained by mitigating this negative effect. This description of damage and abatement (or control) inputs was first applied to crop agriculture (Lichtenberg and Zilberman, 1986). It was later expanded to livestock farming by McInerney et al. (1992).

McInerney described a loss-expenditure frontier as a means to aid decision making in disease control. This frontier illustrates the relationship between the losses due to a disease-causing agent on the y-axis, and expenditure on control inputs on the x-axis. It has hypothesised that this will allow the efficiency of resource allocation to disease control to be calculated, thereby allowing the identification of critical points where too few or too many resources are being applied, representing lost economic efficiency. This approach stated to be a means to aid practical farm-level decision making.

McInerney's loss and expenditure framework has been revisited and extended since it was first proposed. McInerney (1996) identified areas where the loss-expenditure framework had limitations, identifying a difference between costs accrued in the prevention of disease and costs accrued as a consequence of disease, such as antibiotic treatment. This difference was expanded upon and used empirically by Chi et al. (2002), who divided costs into *ex-ante* and *ex-post*, where ex-post costs included direct losses to disease plus treatment costs, and ex-ante costs are those due to preventive action. This distinction has been further embedded by Hogeveen and Van Der Voort (2017), who proposed a loss-expenditure frontier be modified into a failure cost – preventive cost presentation, where failure costs consist of direct losses and treatment.

1.4 Application to DECIDE

While it is now more than 30 years since McInerney published this paper, there are still relatively few practical examples of loss-expenditure frontiers being used to aid decision-making in livestock disease control in the literature. The disease for which most work has been done is mastitis in dairy cows, which work has been reviewed in depth by Hogeveen et al. (2019). This review supported the loss-expenditure, or failure cost – preventive cost framework as a useful means of framing farm-level decisions in a way which appeals to farmers and their advisors.

This report presents the work done within the DECIDE programme to analyse the efficiency of expenditure on interventions targeting production diseases. Two methods were applied, the choice of which depended on the specifics of each case study. The first method was the application of DEA. DEA as a means to examine the economic efficiency of expenditure on disease prevention and control is a novel application of the method. Where the need for DEA was not supported by the available data, frontier development and efficiency analysis were examined through cost-effectiveness ratios and the fitting of frontiers by geometry alone.

Loss expenditure frontiers were used to identify intervention scenarios which show improved economic efficiency, and units which applied interventions in a technically efficient manner. A secondary objective was then to examine variation in technical efficiency to identify any farm or exogenous factors which are associated with efficiency level. Ultimately, the aim is to contribute to the further development of DECIDE's range of decision-making tools. An additional objective was to consider the economic efficiency of measures aimed at mitigating the detrimental external impacts of livestock disease on the environment, with specific reference to the salmon industry in Norway.

2 Method

The first step undertaken was to identify candidate diseases with interventions for efficiency analysis within the various activities of the DECIDE programme, with an objective set to cover each of the four species within DECIDE's remit. The four case studies were selected with reference to the animal health ontologies developed as part of WP1 (LHO) (Noor, 2024).

These candidate disease and intervention combinations were as follows:

1. Analysis of bovine respiratory disease and vaccination against bovine respiratory syncytial virus (BRSV) and *Mannheimia haemolytica* with differing management in growing cattle, using the EMULSION framework model developed within WP2 (Sorin-Dupont et al., 2023).
2. Analysis of interventions to reduce salmon lice numbers to within the legal threshold in Norwegian salmon farms, built on the analysis of Walde et al. (2023).
3. Analysis of performance of Polish broiler flocks with vaccination against infectious bronchitis (IB), avian metapneumovirus (aMPV), and Gumboro disease (IBD), based on flock performance.
4. Analysis of pig performance and management strategies for *Mycoplasma hyopneumoniae* infection using an EMULSION framework model of pig production.

2.1 General method for all case studies

For each of these four cases, the process of developing a loss-expenditure frontier followed a set of common steps with slight adjustments made to match the data and the method together on a case-by-case basis. There were four steps in common for each of the case studies analyses:

1. Description of the intervention scenarios, calculation of expenditure and loss, and preparation of data to fit the DEA structure.
2. Tailoring of the DEA method to suit the scenario hypothesis or research question.
3. Running of the DEA and estimation of economic efficiency scores.
4. Application of any second-stage analysis to be undertaken, such as Tobit regression.

The preparation of data for the DEA analysis required dividing disease-related expenditure into preventative and treatment costs. Consistent with Hogeveen and Van Der Voort (2017) disease treatment costs incurred after disease has occurred can be included within the losses to disease, while expenditure on preventive measures, such as vaccines and biosecurity are properly placed on the expenditure side of the loss-expenditure framework. With a focus on farm-level decision making, the analysis also focuses on expenditure which takes place on the farm. As such, cases where expenditure occurs outside of the farm, such as vaccination taking place before animals arrive at the study farm, are excluded from this analysis. This included, for example, vaccinations on beef breeding farms which conferred protection once calves arrived at growing units but incurred no cost to the growing farm.

The DEA analysis was performed using the Benchmarking package (Bogetoft and Otto, 2010) of R statistical software (R Core Team, 2024). Input and output matrices were constructed for each scenario. These take the form of a K x M matrix of inputs, where K is the total number of units in the sample and M is the number of different types of input used, and a K x N matrix of outputs, where N is the number of different outputs produced. This can be accompanied by a matrix of input prices of dimension K x M, allowing for cases where units pay unequal prices for the same input. Alternatively, all inputs and outputs can be entered in currency units, with a matrix of ones.

In all of this work, all DEA analysis was undertaken from the "input-oriented" perspective, since decision-making on input expenditure is the core interest of the DECIDE project. In cases where multiple inputs were distinguished, technical, allocative and cost efficiencies could be calculated. Where single inputs were considered, technical efficiency is equivalent to cost-efficiency. Scale-efficiency was only to be considered where the scale of input use in itself is considered a potential source of inefficiency.

The input-oriented DEA and cost optimising analysis were, as stated, performed in R which yielded technical and cost-efficiency scores. Allocative efficiency scores were calculated as the ratio of cost-efficiency to technical efficiency. The analysis of the lambda coefficient matrix produced by VRS DEA identifies which units in the population provide the benchmark standard for each inefficient unit.

Where used, Tobit regression was performed in R using the Applied Econometrics with R package (Kleiber and Zeileis, 2008). Marginal benefit to cost ratios were calculated as the ratio of the change in benefit (B) to the change in costs (C) between scenario (s) and baseline (b):

6.

$$MB{:}MC = \frac{B_s - B_b}{C_s - C_b}$$

2.2 Vaccination expenditure in beef rearing systems

Epidemiological and economic production model

The vaccination expenditure in beef rearing systems analysis utilised the EMULSION modelling work already conducted within DECIDE to produce performance data suitable for loss-expenditure frontier analysis. EMULSION (Picault et al., 2019) supports stochastic mechanistic epidemiological modelling in a flexible framework that allows modelling populations as individual agents through to aggregated groups or compartments. Within the context of the DECIDE project, EMULSION has provided a platform for a stochastic individual-based model of a beef rearing system, in which the spread of pathogens involved in bovine respiratory disease can be simulated (Picault et al., 2022). This model has been used to explore management interventions aimed at three pathogens involved in BRD complex: bovine respiratory syncytial virus (BRSV), *Mannheimia haemolytica* and *Myco*plasma *bovis* (Sorin-Dupont et al., 2023), and to contribute to decision-support tools and develop new strategies for improving the efficiency of antimicrobial use against infection with *Mannheimia haemolytica* (Merca et al., 2024, Sorin-Dupont et al., 2024).

In this case the EMULSION model was parameterised as follows, illustrating how technical and economic efficiency can be influenced by vaccination coverage and accompanying management. The total simulation run was for 40 days with 0.5 day increments as described in (Sorin-Dupont et al., 2023). The model simulates batches of twenty animals, with ten batches per simulation. Each simulation was repeated ten times.

Table 1. Scenario-defining factors used within the EMULSION framework.

Factor	Levels
Vaccination	Monovalent (BRSV), Bivalent (BRSV & M. haemolytica)
Vaccination coverage	0.1, 0.2, …, 1
Risk profiling of batches	Random, Sorted
Antimicrobial treatment protocol	Individual treatment, Collective treatment

Table 1 lists the variables used to define the vaccination scenarios. The scenario variables when multiplied produced 80 combinations, with the addition of a disease-free scenario against which to establish loss levels, for a total of 81 scenario runs. The Risk profiling (Sorin-Dupont et al., 2023) and treatment protocol parameterisation (Sorin-Dupont et al., 2024) have already been described. The vaccination mechanism has been developed by WP2 partners and has yet to be published publicly (Salles, 2024), the core parameters are summarised here as follows (see Table 2).

Table 2. Vaccination effects as parameterised within EMULSION.

Vaccination effects:	BRSV	M. haemolytica	Reference
Viral shedding reduction coefficient	0.4	-	Nuijten et al. (2020)
Infectious period reduction coefficient	0.8	0.8	Confidential data
Reduction coefficient for severe clinical signs	0.38	0.38	-
Spontaneous reactivation rate reduction coefficient	-	0.43	Assie et al. (2009)
Initial carrier status (low risk animals) reduction coefficient	-	0.54	-

For BRSV, vaccination reduces the shedding of virus by a factor of 2.5, which is translated into a proportional reduction in contribution to collective force of infection. The duration of infectious period for both BRSV, and *M. haemolytica* in the case of bivalent vaccine, is reduced by a factor of 1.25. The odds of developing severe clinical signs of disease is decreased by vaccination (0.38 vs non-vaccinated reference). The rate at which *M. haemolytica* spontaneously reactivates is reduced by a factor of 2.34 in animals vaccinated with the bivalent vaccine, and the rate at which carrier status is found in animals at the initial state is reduced by a factor of 1.84.

The EMULSION model results are then extrapolated linearly forward in a deterministic manner to predict economic results for calves reaching 277 days. The constant values used to perform this calculation are provided in Table 3. The economic parameters which are determined by health state and treatment strategy are summarised in Table 4.

Table 3. Production and price parameters for the beef fattening model.

Parameter	Values
Days on feed	277
Weight at purchase	330kg
Carcase sale price	Conformation U: €5.41/kg Conformation R: €5.27/kg
Dressing percentage	58%
Feed cost (per kg gain)	€0.9
Labour cost (per hour)	€16.7

In summary, the severity of clinical signs of disease classifies animals in each batch into one of four classes: healthy, mild clinical, asymptomatic and severe clinical disease. Each of these animal's conditions then results in given outcome at market after a period of 277 days based on probability of carcase classification (U or R) and sale price per kilogram. For each scenario run, representing 10 batches of 20 animals each, the total sale revenue, feed usage, cost of vaccination (dose + labour) and cost of treatment (dose + labour) was calculated. This process was repeated for the ten repetitions of all 80 scenarios, and for an additional scenario where disease and interventions were set to zero, which is the disease-free reference result.

Table 4. Disease-dependent parameters determining outcomes and costs in the economic model.

Parameter	Values
Growth rate by health status	Healthy: 1.388kg/d Asymptomatic: 1.235 kg/d Mild clinical: 1.082 kg/d Severe clinical: 0.930 kg/d
Intervention costs per head	Individual treatment: €13 Collective treatment: €13 Vaccination: €3
Intervention labour costs	Individual treatment: 0.667h Vaccination: 0.131h Collective treatment: 0.217h
Rate of conformation downgrade: U to R	Healthy: 0.2 Asymptomatic: 0.3 Mild clinical: 0.6 Severe clinical: 1

Development of frontier

The first step in the development of the frontier is the estimation of loss and expenditure for each scenario. First, an aggregate loss amount, called Net Loss was to be calculated. This was done firstly by calculating the difference between scenario values and the disease-free values for treatment expenditure, sales revenue and feed costs. The net loss. Simply put, Net Loss for each scenario was then the sum of lost revenue and treatment expenditure, less any saving on feed costs (Eq. 7.).

7.

$$Net\ loss = Treatment\ cost + Revenue\ lost - \ Feed\ cost\ saved$$

Subsequently, the ten repeats of each scenario were then used to calculate median, 5th and 95th percentiles of for the outcome measure Net Loss.

The median net loss value for each scenario was then transformed to "loss averted" by taking the maximum observed value for median net loss and subtracting the scenario value (Eq. 8.). This frames intervention effects as positive, thereby allowing the DEA to operate with the constraint that output must be maintained at or above current levels, whilst input use must be minimised.

8.

$$Loss\ averted_{Scenario} = Median\ net\ loss_{max} - Median\ net\ loss_{Scenario}$$

Loss averted was used as the output value (y-axis) for the DEA analysis. Vaccine expenditure was used as input (x-axis), which was calculated as the vaccine cost per individual, multiplied by the coverage rate and the total population. The efficiency analysis would therefore analyse the factors that affect the efficiency of vaccine application as measured by loss averted.

Given the single input-single output combination, technical efficiency was estimated by input-oriented DEA assuming the possibility of variable returns to scale. The efficiency frontier for vaccination was then plotted as the upper envelope of the convex hull that encloses all the data points in input-output space, in a piecewise fashion. The ratio of marginal costs to marginal benefits, which is the frontier gradient, was calculated for each segment across the length of frontier.

The lambda coefficient matrix of the DEA result identifies which units in the population are used to set the benchmark for the inefficient units in the population, and which units are therefore influential or provide the template for improved efficiency in other units.

Tobit regression was used to regress efficiency scores against the scenario-defining characteristics: Treatment Strategy, Valency and Risk Profiling (as in Table 1). The parameter effects for these variables are known as they are programmed in the model, however this regression was performed to illustrate the utility that could be derived from two-stage DEA analysis. Significant variables within the Tobit regression were then used to focus the presentation of results.

2.3 *Mycoplasma hyopneumoniae* control in Dutch pig fattening farms

A synthetic dataset was created by an EMULSION simulation of a batch of fattening pigs. This model is described in detail by Boeters et al. (In preparation). As this is yet to be published, a brief summary is provided here, and the results generated remain preliminary. The epidemiological-mechanistic component of the model simulated transmission dynamics and the development of clinical disease. The population is divided into 12 pens which occupy a shared airspace, allowing inter-pen transmission. Each pen houses 12 pigs which are stocked simultaneously. Pigs enter at an average weight of 25kg and are sold either at 125kg, or after 18 weeks feeding time. During this time, feed consumption is estimated based on feed conversion rate and linear daily weight gain.

The transmission of disease is determined by a five compartment SEIIR model which has the compartments: susceptible, exposed, infectious (acute), infectious (chronic) and recovered from infection (RI). During the infectious states, pigs can develop clinical signs and lung lesions. Clinical signs of disease are simulated by the movement of individual pigs through four states: healthy, subclinical, coughing and recovered, and three states with respect to lung lesion development: No lesions, Lesions, and Resolved lesions. The presence of lesions reduces the growth rate of pigs and increases feed conversion by stochastic factors.

The interventions simulated interact with these three pathways (transmission, clinical signs, lesions) in various ways. These intervention scenarios are described here. The baseline scenario (B) consisted of a no-intervention strategy. Collective treatment (CT) represents waterborne delivery of antibiotics at batch level. Individual treatment (IT) treats only individual pigs showing clinical signs rather than entire compartments. The baseline detection rate for this treatment was set at a threshold of 10% or more of the pigs detected to be coughing within a 24-hour period. Coughing sensors (CS) increase the probability of detection of clinical signs and trigger collective treatment. Vaccination (V) represents vaccination at three weeks of age against *M. hyopneumoniae.* Finally, a disease-free, no intervention scenario was run to establish a counterfactual against which losses could be measured.

Scenario specific parameter changes and intervention costs are described in Table 5.

Table 5. Scenario-specific performance and epidemiological changes, and additional costs.

Scenario	Effect	Cost
Baseline (B)	No treatment or intervention	None
Vaccination (V)	Reduces transmission during acute infection Reduces probability of developing lesions Reduces duration of coughing in clinical disease. Reduces disease effects on growth and feed conversion	€3 per pig
Individual Treatment (IT)	Applied to individual animals: Reduced transmission during acute infection Reduces probability of developing lesions Reduces duration of coughing in clinical disease. Reduces disease effects on growth and feed conversion	€1.60 per 100kg weight (€20/L antibiotics)
Collective Treatment (CT)	Applied at population level: Reduced transmission during acute infection Reduces probability of developing lesions Reduces duration of coughing in clinical disease. Reduces disease effects on growth and feed conversion	€1.60 per 100kg weight (€20/L antibiotics)
Coughing Sensors (CS)	Increased probability of detecting coughing individuals, triggering earlier application of collective treatment (CT) plan.	€3 per day for the entire batch, for 125 days not inclusive of CT costs

Disease effect on farm budget is thereby reflected in various ways when compared to a disease-free farm:

- Change in revenue at slaughter due to change in total weight.
- Change in total feed use.
- Increase in farm labour where production time extends to reach target weight.
- Increased labour applying disease control interventions.
- Additional expenditure on disease control inputs: antibiotics, coughing sensors and vaccines.

Model output for 25 runs of each of the scenarios produced. Given the discrete scenarios in terms of technology applied, DEA was not used to analyse the efficiency of units. Technical efficiency would vary only on the underlying stochasticity at herd level, rather than via any other factor of interest. Instead, a frontier was constructed in the same manner as in the DEA method, using the upper envelope of the convex hull of the data points, but without the illustrative calculation of technical efficiency as used in the cattle case study. Instead, the marginal cost to marginal benefit ratios were calculated for each intervention against the baseline (zero intervention) scenario as per Equation 6.

2.4 Comparison of loss and expenditure due to treatments against salmon lice in salmonid aquaculture in Norway

Background to Salmon case

In 1997, Norway implemented a National Action Plan against salmon lice to minimize their negative impact on farmed salmonids and mitigating the detrimental impact of salmon lice infestation pressure caused by farmed salmonids on wild salmonids (Heuch et al., 2005). Key measures included legal lice limits per farmed fish, mandatory lice reporting, coordinated regional treatments, and monitoring of lice in wild populations (Heuch et al., 2005, Myksvoll et al., 2018). The legal maximum limit is currently 0.5 adult female lice per fish per farm. This is lowered to 0.2 in spring and early summer to protect migrating wild salmon. This low threshold ensures that pathology caused by salmon lice rarely occurs in farmed salmonids. It also ensures the pressure of lice caused by farmed salmonids, to wild salmonids be kept at the lowest possible level.

Until 2015, the use of pesticides was the preferred method to keep lice levels below the legal limit. However, concerns were raised about medicinal compounds creating a negative externality to the environment in being harmful to non-target species like aquatic crustaceans (Burridge et al., 2010) such as crab larvae (Gebauer et al., 2017), shrimp, and lobster (Burridge et al., 2014, Parsons et al., 2020). This led to a transition from treatment in open net cages, to use of full tarpaulin around cages, and later treatment in closed well-boats (Nilsen et al., 2008, Nilsen et al., 2010). After years of relying on pesticides to control salmon lice, salmon lice eventually developed resistance to most pesticides available. Around 2015, this led to a paradigm shift from treating medicinally to non- medicinally (Overton et al., 2019). Since then, the most frequently applied methods for immediate removal of salmon lice are non-medicinal treatments (Helgesen et al., 2023).

Soon after the shift to non-medicinal treatments, veterinarians and fish health personnel reported increasing worries about the poor health and welfare of salmon treated thermally and mechanically (Overton et al., 2019). In 2020, five years after the paradigm shift, 52 million salmon died during the on-growing phase at sea, close to 15% of the standing stock (Fish health report, 2020). It was suspected that a large part of this mortality was caused by non-medicinal treatments. The following years from 2020, mortality in the on-growing phase has been stable and high, and treatment against salmon lice is reported as one of the top five main reasons for poor welfare, mortality and reduced growth (Fish Health report, 2024).

Non-medicinal treatments mostly involve the use of heated water (thermal treatment) or brushing or flushing (mechanical treatment) the fish to remove the lice (Grøntvedt et al., 2015, Roth, 2016, Gismervik et al., 2017, Nilsen et al., 2010). Several studies have subsequently documented that thermal and mechanical treatments are associated with severe negative side-effects such as increased stress, injuries, increased mortality and reduced growth (Overton et al., 2019, Oliveira et al., 2021, Gismervik et al., 2017, Persson et al., 2022, Walde et al., 2021, Walde et al., 2022). On top of the treatment expenditures, this creates a biomass loss which results in profit loss for farmers (Walde et al., 2023).

Study design

This study examines the loss and expenditure caused by treatment for salmon lice using data collected from 609 fish groups, from 2014-2017 over 94 sites. The interventions of interest are the delousing treatments described in Table 6. These are summarized categorically as thermal, mechanical, hydrogen peroxide, freshwater bath and medicinal bath.

Table 6. Categorization of the immediate treatment operations of farmed Atlantic salmon in three Norwegian companies from 2014-2019.

Category of treatment	Description
Thermal	Non-medicinal treatment using heated seawater. Includes all treatments using: a. Optilice ® b. Thermolicer c. Heated seawater
Mechanical	Non-medicinal treatment using brushing or flushing. Includes all treatments using: a. FLS Avlusersystem b. Hydrolicer c. SkaMik d. Flushing or mechanical treatment
Hydrogen peroxide	Hydrogen peroxide (H_2O_2) bath in pen or well boat against salmon lice
Freshwater bath	Freshwater bath in pen or well boat against salmon lice
Medicinal bath	Medicinal bath in pen or well boat using one of the following active substances: a. Azametiphos b. Cypermethrin c. Deltamethrin d. Imidaclorid e. Other f. Cohorts treated with two different combinations of active substances a-f or hydrogen peroxide and one of the active substances a-f

The dataset consists of daily records at cage level describing production, consisting of identification, number and average weight of fish, feed amount and salmon lice treatments, including type and date of treatment, and fish group treated. A fish group is defined as fish within the same generation stocked at sea within the same cage traced from stocking to harvest. The dataset applied for this study is described in greater detail in Walde et al. (2021) and Walde et al. (2022). Each datapoint represents the aggregated loss and expenditure due to delousing for a single group of fish from stocking to harvest, with each having a variable number of delousing treatments sufficient to keep lice below the legal limit.

Preparation of data for analysis.

Data from one company in the original set did not fit the requirements of this analysis due to timing of production recording and was therefore excluded, leaving 333 fish groups. An additional 6 fish groups were removed due to anomalous values or untraceable movement of fish. The final dataset consisted of 327 fish groups, from four different year classes (2014-2017) and 61 sites. These fish groups were treated a total of 1, 273 times, and the number of treatments from stocking to harvest ranged from 1 to 9 per group.

Calculation of loss and expenditure

Loss in this case describes the negative side effects from treatment against salmon lice. This consists of the revenue loss due to increased mortality and decreased growth, the cost of handling dead fish and any net change in feed cost. Fish group performance was compared against a baseline of no treatment.

The baseline was set as production without treatment. The same approach was applied to simulate growth rate without treatment, including the period of fasting before treatment. Calculations of mortality are described in Walde et al. (2021) and growth rate in Walde et al. (2022). In short, this consists of comparing the average mortality and growth rate between 7 days prior and 14 days after treatment for each fish group. This was then repeated across all treatments to calculate aggregate figures for end harvest weight in addition to feed amount used, and biomass of dead fish.

The treatment expenditure was the sum of each individual treatment, costed as a price per unit of live biomass at the date of treatment. The economic input parameters are summarized in Table 7. Additional information can be found in Walde et al. (2023).

Table 7. Economic input parameters.

Economic input parameter	Value applied in model	Source
Feed prices	14.60 NOK/ kg dry feed	Intrafish.no/Ilaks.no
Handling dead	2.12 NOK/kg round weight	Pettersen et al., 2015
Sales price per weight class:	NOK/kg	https://fishpool.eu/nasdaq-salmon-index/
1-2	72.34	
2-3	81.54	
3-4	87.08	
4-5	89.37	
5-6	91.94	
6-7	93.15	
7-8	96.54	
8-9	98.82	
9+	101.86	
Treatment expenditure:	NOK/kg round weight treated	Iversen et al. (2017)
Thermal	0.37	
Mechanical	0.26	
Hydrogen peroxide	0.50	
Freshwater bath	1.33	
Medicinal bath	0.37	

Analysis

In this case study, the output of interest was the number of lice per fish being maintained below the target level, thus each sample unit was assumed to achieve the same output, with variation in the efficiency with which this was achieved. It was hypothesized that this variation would be associated with increased number of treatments, as each treatment incurs an additional loss and expenditure, but also by treatment method. To represent the fact that a loss of fish biomass and an amount of expenditure are the necessary cost of reaching a fixed level of lice (as output), a single input, input-oriented DEA was performed on the aggregated loss and expenditure value as input, with a dummy variable, value 1, for all units as output.

Table 8. Number of treatments per treatment category per year class.

Treatment method	2014	2015	2016	2017	Total
Thermal	10	62	111	391	574
Mechanical	0	0	1	78	79
Hydrogen peroxide	159	34		35	228
Freshwater bath	1			16	17
Medicinal bath	144	20	3	41	208
Hydrogen peroxide AGD	63	42			105
Freshwater AGD	6	4	4	38	62
Total	**383**	**162**	**119**	**609**	**1 273**

2.5 Vaccination in Broiler chickens in Poland

Study background

Within the context of the DECIDE project, a dataset was compiled by the project partners from 59 pseudo-anonymised poultry farms that grew Ross308 broilers in the northeast region of Poland between 2018 and 2022. The dataset is the result of a collaboration between farms who provided production information, including vaccine and antibiotic treatments, and a veterinary laboratory that screened a selection of the flocks using a comprehensive dataset. The dataset is fully described in Delavenne et al. (In preparation).

Poland is the largest producer of poultry in Europe, however, little is known about the economic impact and burden of endemic disease on Polish producers. Three viral diseases were selected by the partners as having the potential to be a major influence on the health of broilers: Infectious bronchitis (IB), Gumboro disease (IBD), and avian metapneumovirus disease (aMPV). Flocks are commonly vaccinated against those diseases, but there are many brands, strains and programmes of vaccination available from which producers can choose. This has led to the possibility that vaccine expenditure is variable across the population, and that vaccines are not being applied in the most efficient manner. Benchmarking is proposed to be a means to analysing the use of vaccination, identifying the flocks that are performing better than others and determining if change in current vaccination expenditure is justified by building a loss-expenditure frontier.

Calculation of loss

The production parameters which were considered to be affected by disease were:

- Total chicken weight to be paid out to the farmer (after the weight of condemnation and weight lost during transport are removed)
- Total weight of feed given to the flock throughout the production. This weight is also linked to an estimated amount of water consumed by the birds
- Number of chicks placed in the chicken house
- Number of days of production

Determining loss required setting of a zero-loss baseline, this is referred to as the “ideal scenario”. No pre-existing model of broiler production was available from which the baseline could be calculated, so this became part of the analysis performed here. This required estimating some key production parameters which were not included in the original dataset, such as stocking density and floor space for each flock. This in turn requires taking into consideration regulations on production which limit the maximum stocking density in Europe to no more 39kg/m^2 or 42kg/m^2 with special derogation. Under ideal conditions flocks were assumed to undergo a single thinning event when birds were 1.8kg to maximise the use of available housing, with clearance at an average weight of 2.7kg per bird (ADAS and AVEC, 2024). Mortality was assumed to be zero in a disease-free case, and feed consumption was based on breed standards (Aviagen, 2022). In addition, carcase condemnation was assumed to be zero in a disease-free case.

Floor space was estimated by two methods, the midpoint of which was used as the value in the calculation. These methods were:

Division of reported chicks placed, assumption of 21.98 chicks placed per m^2 of floor space and 39kg/m^2 (ADAS and AVEC, 2024). This is referred to as the ADAS method.

The second method calculated a number of chicks placed per m^2 of floor based on an estimated mortality rate, and other parameters. The mortality rate was estimated based on the hypothesis that in the first week of production half of the mortality and the remaining week was mortality. The remaining parameters for the calculation were setting thinning at 1.8kg and finish at 2.7kg and the growth rates described in the Ross 308 performance objectives (Aviagen, 2022), with a maximum limit of 42kg/m^2. In short, this maximises the number of chicks placed per metre based on those constraints. Again, this number was used as a denominator to divide the reported chicks placed. This is referred to as the "Legal Limit" method.

Estimates of house size were then calculated for all units in the sample, and this house size estimate was used in the calculation of number of chicks placed, total output and input use in the ideal scenario.

Calculation of costs and control expenditure

Concerning the costs associated with vaccination and antibiotic inputs, these were based on the product given to the flock for vaccination and on the product given to the flocks for antibiotics, the length of treatments and the usual dosage for each product as defined in the official product characteristics. Prices for these inputs were not included in the dataset, so an online search was used to estimate product prices. If no comparable prices for a product could be found, a standard price of €0.01 per dose was used for four doses, with a total price of €0.04 per bird (ADAS and AVEC, 2024). All prices were converted to Euros.

Production costs for broilers were retrieved from Agridata (EC, 2025) and from ADAS and AVEC (2024) (Table 9).

Table 9. Input costs for broiler production in Poland used to estimate flock gross margins.

Description	Price in Euro	Source
Chicken per kg	1.87	Minimum of the selling price of the whole carcass broiler (65%) April 2023 (EC, 2025)
Feed per kg	0.460	Minimum feed price (ADAS and AVEC, 2024)
Water-based feed kg	0.15 * 1.7 = 0.255	Price from the Polish authorities of water prices * coefficient of water consumption per feed (ADAS and AVEC, 2024).
Labour per day	69.6	8.70 euro/h (ADAS and AVEC, 2024)
Day old chick (per chick)	0.04	(ADAS and AVEC, 2024)

As for the beef case, antibiotics were considered a reaction the occurrence of disease and included with loss. Loss was then calculated via two gross margin calculations as follows:

$$Gross\ Margin = Sales\ - \sum (cost\ of: feed, water, chicks, antibiotics, casual\ labour)$$

This calculation was repeated for both the observed and ideal health scenarios. As there was considerable difference in scale between the various units in the population, a net change (observed – ideal) would have produced results that were heavily influenced by scale of enterprise. Instead, losses were quantified by a ratio of the two scenarios. Specifically:

$$Margin\ ratio = \frac{Observed\ gross\ margin}{Ideal\ gross\ margin}$$

The expenditure side of the loss-expenditure space was defined by expenditure on vaccinations for the three diseases of interest. A cost per dose was calculated as the sum of all vaccines for a disease divided by the number of products given to a flock. The input used for the DEA was defined as the total number of vaccine products given to the flock.

To better understand the created frontiers, different vaccination scenarios were defined based on when vaccination occurred for each of the three diseases at the start of production (hatchery or first day in the flock) or later in the production flock. accordingly. Twelve main scenarios were defined, which are illustrated in Table 10.

Table 10. Vaccination scenarios present in the Polish broiler dataset for inclusion in loss-expenditure analysis.

Name	IB start	IB later	IBD start	IBD later	aMPV start	aMPV later	Number of flocks
IBV12IBDV2aMPV	X	X		X			17
IBV12IBDV1aMPV2	X	X	X			X	19
IBV1IBDV2aMPV2	X			X		X	10
IBV12IBDV2aMPV2	X	X		X		X	11
IBV1IBDV2aMPV	X			X			6
IBV12IBDVaMPV	X	X					4
IBV12IBDV12aMPV2	X	X	X	X		X	7
IBV1IBDV12aMPV	X		X	X			6
IBV12IBDV12aMPV	X	X	X	X			4
IBV1IBDV1aMPV	X		X				5
IBV12IBDV2aMPV1	X	X		X	X		3
Other	-	-	-	-	-	-	7

A multifactor and cluster analysis of these flocks had already been performed (Delavenne et al., *In preparation*). The clusters identified in analysis were overlayed on the current loss-expenditure analysis to describe the characteristics of the flocks. The clusters were defined as follows:

- Cluster 1 was characterised by the presence of fibrinous lesions in the liver, cardiovascular, respiratory, and celomic cavities. This cluster presented no specificities regarding economic performance (European Production Efficiency Factor - EPEF) but showed a higher condemnation rate. *Escherichia Coli was the o*nly aetiological agent significantly more present in this cluster.

- Cluster 2 can be defined as a cluster of high-performing flocks associated with a low FC', high EPEF, and high weight at slaughter. These flocks also had better health performances, including fewer necropsy lesions. However, necrosis or ulcers of the musculoskeletal system were more common in this cluster than in the other. In terms of the presence of an aetiological agent, *Eimeria* infestation was less often observed.
- Cluster 3 can be defined as a cluster with older flocks with low production and health performance. These flocks had a higher FCR, lower EPEF, and higher age at slaughter and mortality rate than the others. Particularly, three necrotic lesions were more frequent: changes in the composition of the liver, cardiovascular thinning and vascular congestion in the kidneys or ureters. Among the aetiological agents, the cluster showed signs of infestation by *Eimeria* and presented more signs of circulation of aMPV.

3 Results

3.1 Beef cattle analysis

The results of the epidemiological component of the model have already been reported by WP2 and are not the focus of this work. The economic model showed a net loss per animal sold of between €92.08 and €350.74 per animal sold across the range of intervention scenarios modelled. Losses displayed an inverse relationship with vaccine coverage, and with collective treatment of sick animals (Figure 4).

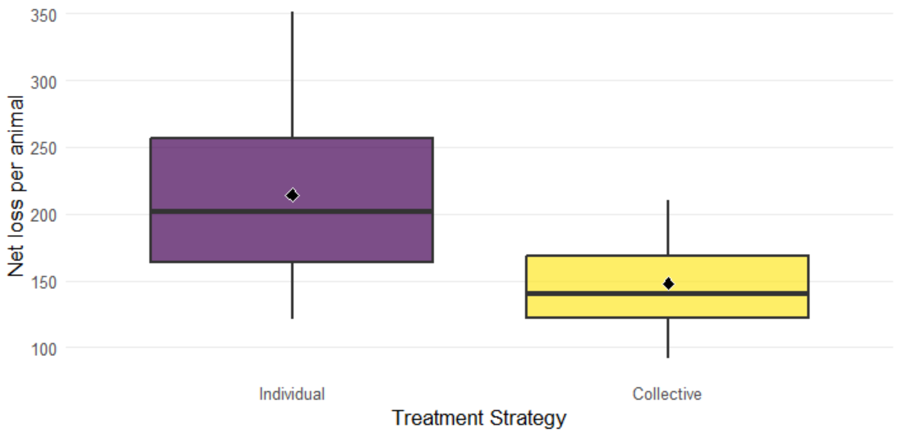

Figure 4. Distribution of median net loss per animal (lost revenue + treatment expenditure – feed cost saved) across each scenario, grouped by treatment strategy.

The technical efficiency scores for vaccine use within units ranged from 0.143 to 1 (Figure 5). Improved technical efficiency was significantly associated with treatment strategy by Tobit regression, with a large effect size (Table 11). The effects of vaccine valency were on the boundary of statistical significance, but the apparent effect size was considerably smaller. Risk profiling appeared to bear no association with the efficiency of vaccine use.

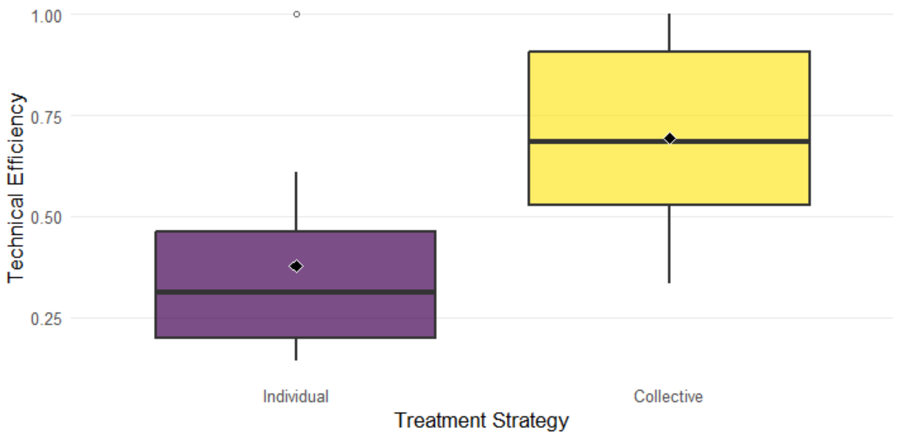

Figure 5. Distribution of technical efficiency by treatment strategy category.

The lambda weighting coefficients for each target unit, which identify which of the units are the key benchmarks for the rest of the population were aggregated to determine the most influential units, and the influence of those units marked illustrated by bar chart Figure 6. The three units which set the benchmark for the population were 3, 19 and 45, which corresponded to:

3: Bivalent vaccine, sorted risk groups, collective treatment, 100% coverage.

19: Bivalent vaccine, sorted risk groups, collective treatment, 40% coverage.

45: Monovalent vaccine, random risk groups, collective treatment, 10% coverage.

Table 11. Results of Tobit regression on technical efficiency.

	Category	Coefficient	P-value
Valency	Bivalent	0.089	0.121
Treatment	Collective	0.328	<0.0001
Risk Profiling	Sorted	0.001	0.991

The efficiency frontier for vaccine expenditure is then illustrated in Figure 7. The increasing trend in loss-averted with vaccination coverage (which is proportional to expenditure since all units are of the same population size) can clearly be seen. Additionally, the effect of employing a collective treatment strategy on the efficiency of vaccine use can clearly be seen with those units using the collective strategy lying in closer proximity to the frontier.

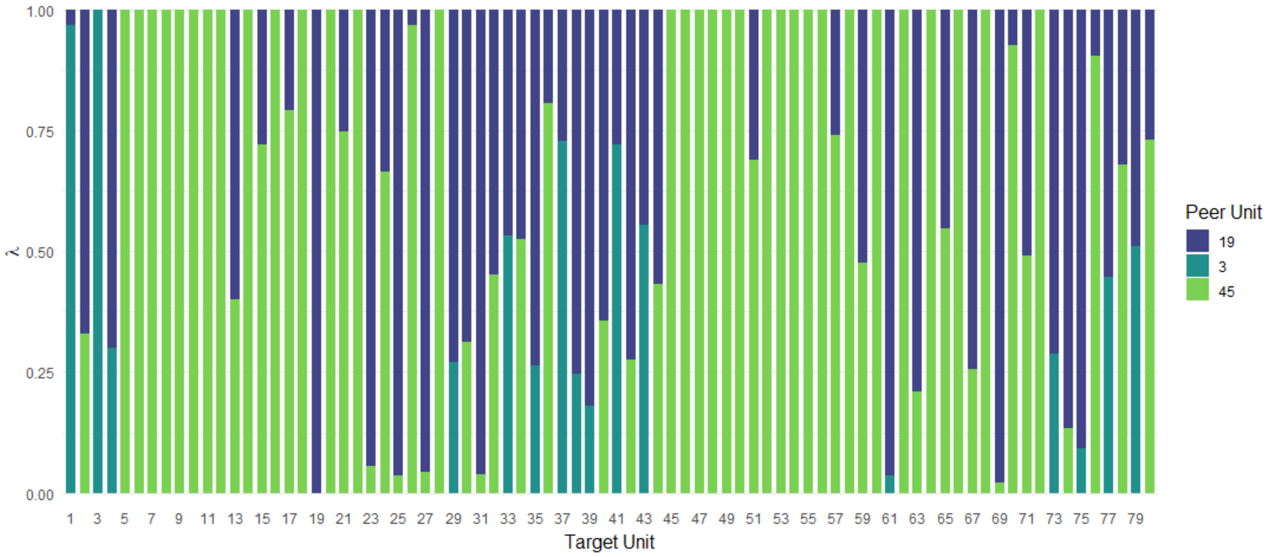

Figure 6. Lambda weighting coefficient analysis for units with lambda scores > 0 in VRS DEA analysis, indicating which unit numbers (legend: 3, 19, 45) are most influential as benchmarks, and to which targe units (x axis), the strength of influence being expressed on the y-axis.

The gradient of each segment of the frontier is equal to a marginal cost (MC) to marginal benefit (MB) ratio. It can be seen that expenditure on vaccination is strongly beneficial, with the minimal gradient at the frontier being equivalent to an expenditure of €0.15 for each €1 in loss averted. The influential units, those that set the benchmark, are identified by their identity number.

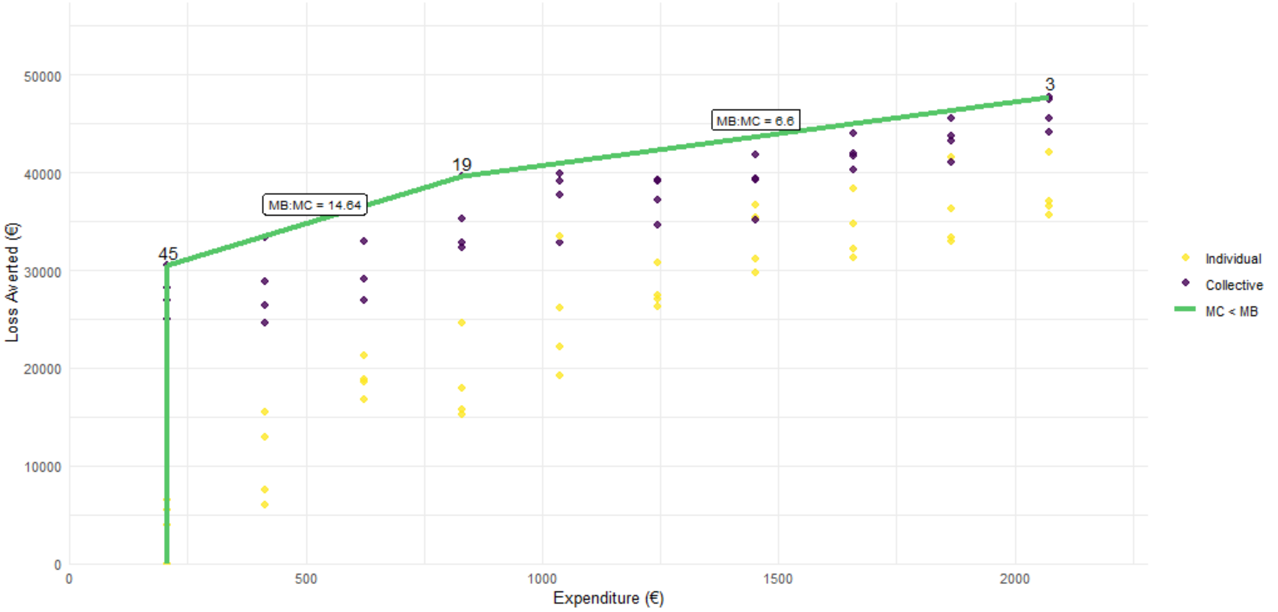

Figure 7. Loss-averted to expenditure frontier for use of vaccination against BRD. Frontier segments are colour-coded to benefit to cost ratio, where a marginal benefit to marginal cost ratio above 1 indicates more than €1 benefit per euro spent. Each unit represents the median of 10 simulations, colour-coded by disease treatment strategy. Influential benchmark units are identified by ID number.

3.2 Loss-expenditure frontier for interventions to control Mycoplasma hyopneumoniae infection

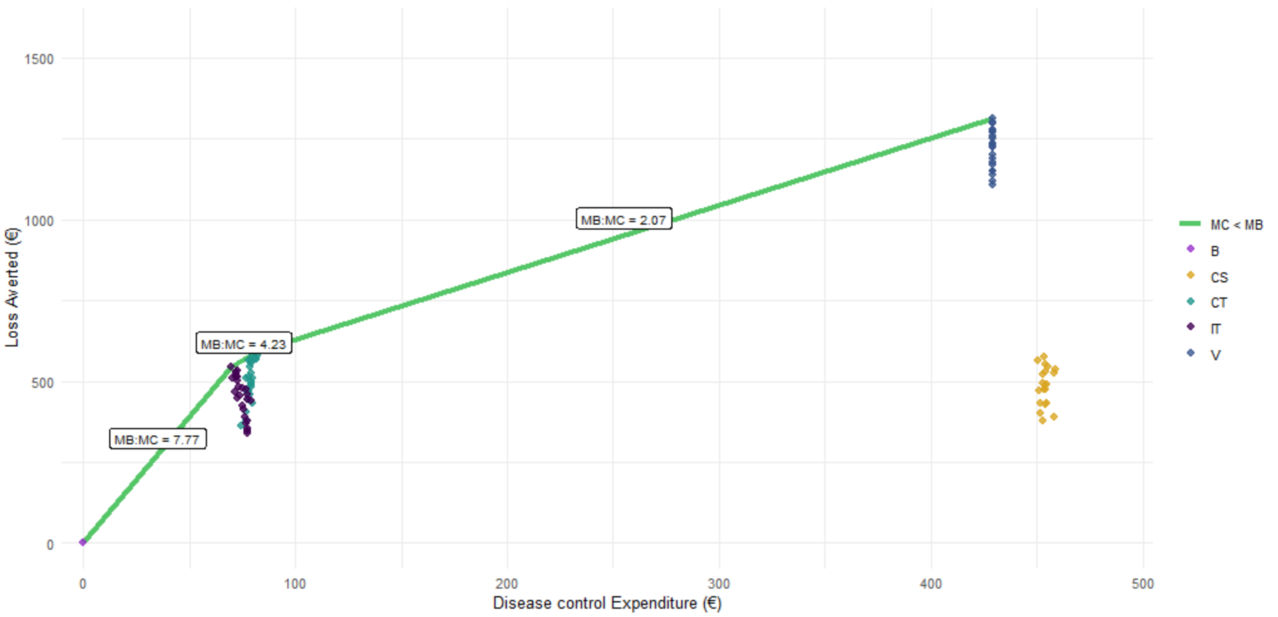

Figure 8. Loss expenditure frontier for *Mycoplasma hyopneumonia* control. Scenarios are B = Baseline, CS = Coughing sensors, CT = Collective treatment, IT = Individual treatment, V = Vaccination. Frontier gradient is equal to the ratio of marginal benefit to cost. A MB:MC ratio greater than one indicates more than €1 benefit per €1 spent.

The marginal cost to benefit ratios (Table 12) showed that CT, IT and V were beneficial relative to the baseline of no treatment, and that vaccine remained beneficial as additional expenditure beyond the two different antibiotic treatment options (IT and CT). This is indicated by the MC/MB ratio being 0.48 at the frontier between CT and V (Figure 8). With the current parameterisation, coughing sensors (CS) appears to be dominated by every other strategy, being more expensive and at best equally effective. Furthermore, the 95% range of the marginal benefit: cost ratio overlapped with 1, indicating a significant probability that the benefit of coughing sensors would not be recovered in losses averted.

Table 12. Marginal cost to marginal benefit ratios, with 95% range. Scores greater than 1 indicate less more than €1 gained per euro spent.

Scenario	Mean marginal cost: marginal benefit ratio	95% Range (2.5 – 97.5th percentiles)
CS	1.07	0.84 – 1.26
CT	6.29	4.70 – -7.24
IT	6.10	4.47 – 7.49
V	2.85	2.59 – 3.04

3.3 Salmon case study

The results shows that losses and expenditures increase with increasing number of treatments of one fish group. This result is presented graphically and can be visualised when loss and expenditure are stratified by treatment number and colour coded by type of treatment employed (Figure 9). The losses incurred from the negative side effects of treatment are on average 9.4 times higher compared to the expenditures themselves, ranging from minimum 0.1 to maximum 32.7 times higher. The variability in loss increased with increasing treatment number. The largest loss experienced by a single fish group was in excess of NOK 22 million (€1.9 million).

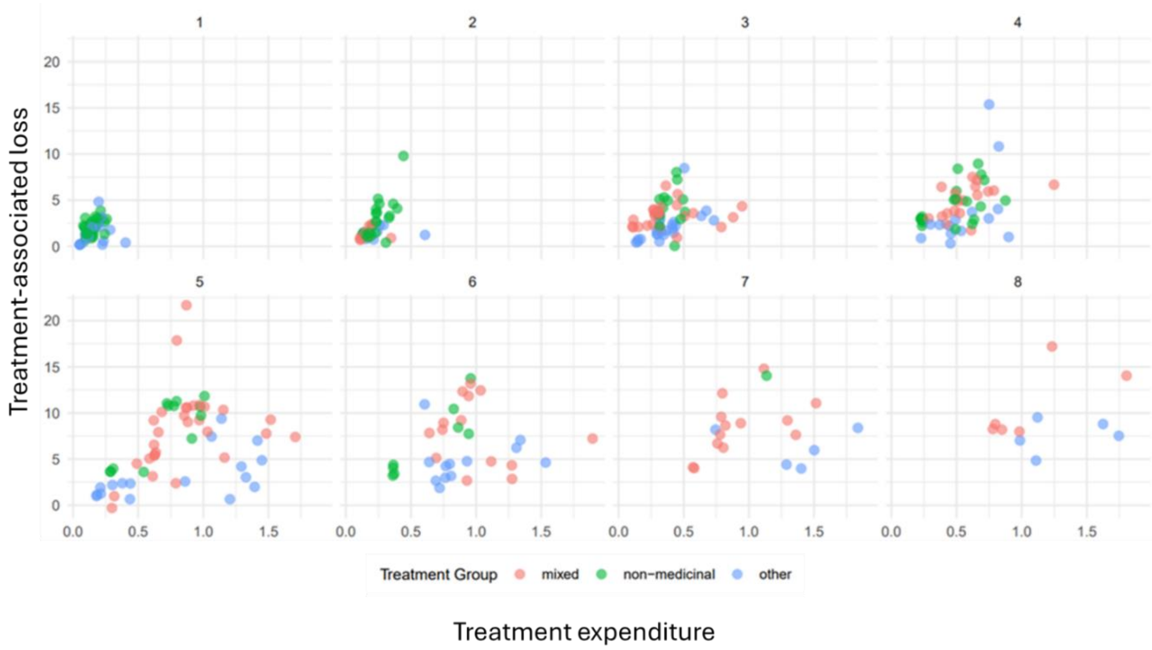

Figure 9. Losses due to treatment (y-axis) and expenditure on treatment (x-axis) stratified by number of treatments during production at sea expressed in 1 000 000 NOK (1€=11.58NOK). Non-medicinal treatment(s) (green) are thermal and/or mechanical treatment. Other treatment(s) (blue): medicinal, hydrogen peroxide, and/or freshwater treatment. Mixed treatments (red): combination of non-medicinal (green) and medicinal (blue) treatments.

The DEA produced technical efficiency estimates for each fish group, and a Tobit regression was applied on the efficiency scores against treatment type, but no significant relationship was found between treatment type and efficiency of louse control.

3.4 Polish broiler study

The DEA analysis was run on 99 flocks from 52 farms produced between January 2022 and February 2023. The median number of flocks per chicken house in the study was two (min = 1 and max = 2) and per farm is two (min = 1 and max = 6), with sixteen farms having only one flock in the analysis and 31 farms with two flocks. Amongst the flocks used in the analysis, five were not screened and were therefore not part of the cluster analysis. A more extensive description of the performance of flocks included in the analysis is given in Table 13.

Table 13 Descriptive statistics for the performance of broiler flocks included in the analysis.

Performance or health and welfare indicators	Mean	SD	Median	Min	Max
Flocks in the DEA (n = 99)					
European Efficiency Factor (EEF)	395.63	45.56	399.19	255.01	487.84
Mortality**	5.21	3.37	4.58	0.620	21.55
Mean weight at slaughter	2.54	0.15	2.55	2.13	2.93
Mean age at slaughter	38.91	1.25	38.87	35.82	42.03
Feed conversion rate (FCR)	1.57	0.11	1.57	1.29	2.00
Recorded flocks (n = 1,697)					
European Efficiency Factor (EEF)	403.68	51.56	405.52	84.59	771.57
Mortality*	4.45	3.42	3.93	-18.15	40.69
Mean weight at slaughter*	2.57	0.16	2.58	1.70	3.00
Mean age at slaughter	39.10	1.61	39.00	30.00	46.00
Feed conversion rate (FCR)	1.57	0.13	1.57	0.81	3.19

The table also describes all the recorded flocks provided by farms, including the ones that were not screened or for which treatment and vaccination were not provided or that had to be excluded from the DEA analysis. The comparison underlines issues in provided data and highlights that the flock production performance used in the DEA are not representative of the all the recorded flocks available. Furthermore, this table also highlights the data quality issues as the data were re-used and not produced for a research output.

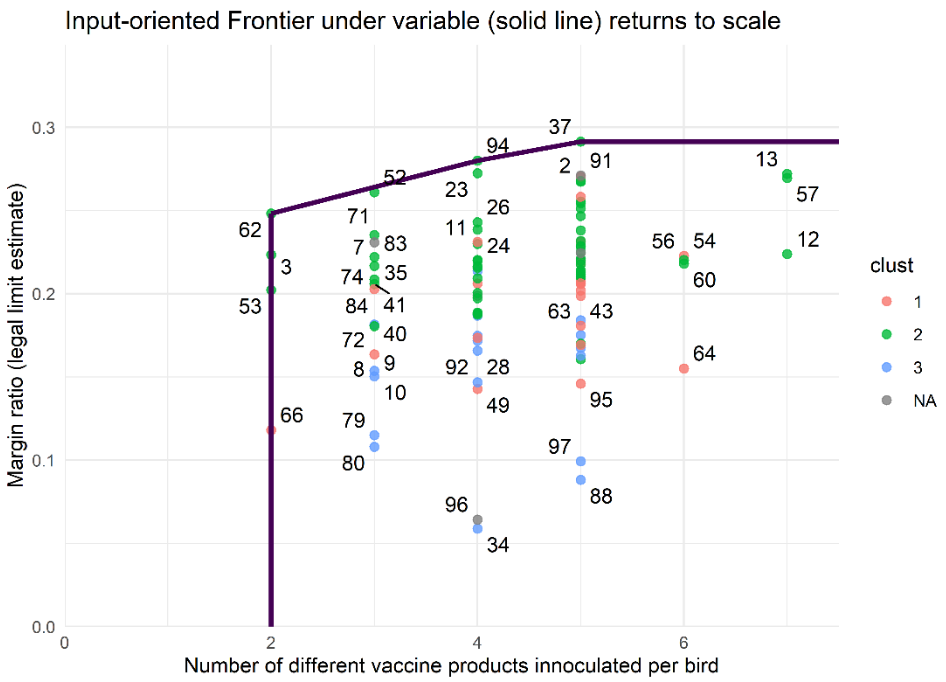

Figure 10. Proportion of ideal output achieved (y-axis) with number of vaccines administered (x-axis), each point is annotated with its flock number.

An increase in margin ratio, that is, improvement in performance, can be seen with the number of vaccinations in the range 2 to 5. The number of flocks who were administered more than 5 vaccines is too small to make any significant observations. Four key influential flocks define the frontier (66, 62, 94 and 37).

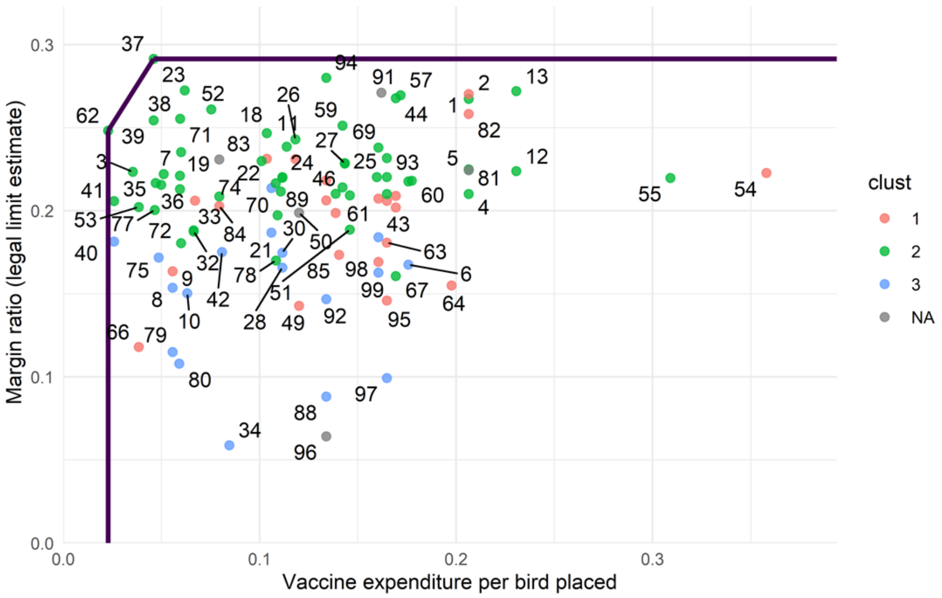

Figure 11. Input oriented DEA under variable returns to scale plotting efficiency of expenditure on vaccine against proportion of ideal outcome achieved. Colour-coding indicates clustering on health and performance related variables.

The cost-efficiency frontier for vaccine expenditure is illustrated in Figure 11. The figure is different from the technical efficiency for input use (Figure 10) as the different vaccine products can vary in price. In this context, the cost-efficient frontier is not as informative as expected for a minimum expense of 0.05 euro per bird; no relationship between efficacy and cost is observed (efficacy doesn't increase with cost). Indeed, flocks 54 and

55 who respectively administered 4 and 5 different vaccine products used a vaccine that was more expensive than the others but didn't ensure a gross margin ratio above 0.25. Furthermore, the frontier is defined by only two significant flocks that were already identified highlighted in the technical efficiency frontier (62 and 37). They are described below:

- Flock number 37 is the most efficient flock. Its production performance reflects this result as it has the second best EEF (n = 477), an FCR below the standard error (1.37), and no ATB was used during production. The flock was screened but no viral infection was confirmed and only bacteria were found (*Staphylococcus spp*., Clostridium *perfringens*, *Enterococcus cecorum*). The flock was held in a large chicken house estimated to be between 2390 and 2490m^2.
- Flock number 62 is the flock with the less expenditure as only two cheaper vaccines were administered to the flock. The production performance is closer to the sample mean presented in Table 13, with an EEF of 414.14 slightly above the mean and an FCR of equal to the sample mean (1.54). The flock presented a few health issues as ATB were used. Indeed, during screening in addition to common bacteria, IB was circulating in the flock and signs of low levels of *Eimeria spp.* infestation were found. The flock was held in a small chicken house estimated to be 1120 and 1180m^2.

Despite the absence of a cost-efficient frontier reflecting the relation between cost and efficiency, plotting the result of the cluster analysis from Delavenne et al (in preparation) does provides some additional insight for the analysis. Indeed, most of the flock classified in cluster two have a gross margin above 0.2 (mean of 0.23) and 25% of the flocks with a gross margin above 0.240. In contrast, flocks from cluster 3, have a higher frequency of health issues have a gross margin mean of 0.150 and a range (0.06-0.21). Similarly, flocks from cluster 1 which is defined by an old infectious episode resulting in high level of condemnation, but no explicit impact on production performance present the highest variability in terms of gross margin with a mean of 0.2 and a range of 0.12-0.27.

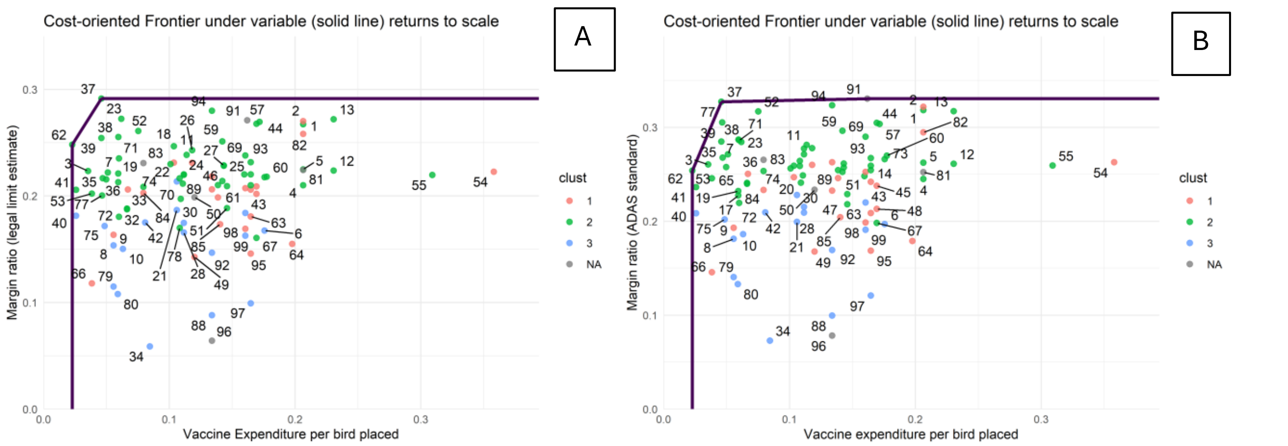

Figure 12: Input oriented DEA under variable returns to scale plotting efficiency of expenditure on vaccine against proportion of ideal outcome achieved with A based on the chicken house 'legal limit' estimate and B the 'ADAS' estimate. Colour-coding indicates clustering on health and performance related variables.

Figure 12 highlights the impact of the chicken house estimate using the 'legal limit or the 'ADAS' method. Slight changes are observed. Specifically, the margin ratio was overall slightly larger, and an additional flock defined the DEA frontier when the ADAS method is used. However, they were no significant changes to the frontier profile. Unfortunately, considering this new flock, no screening of health state was available. However, concerning its production performance, its 'EEF' was high (451.62) and FCR low (1.47) despite a high cumulative mortality (9.16%) and the use of ATB. The difference in the gross margin can be explained by the large difference in the chicken house estimate between the two methods for this flock which was housed in a large chicken house of 3260m^2 according to the 'legal limit' method or 2680m^2 according to one of 'ADAS'.

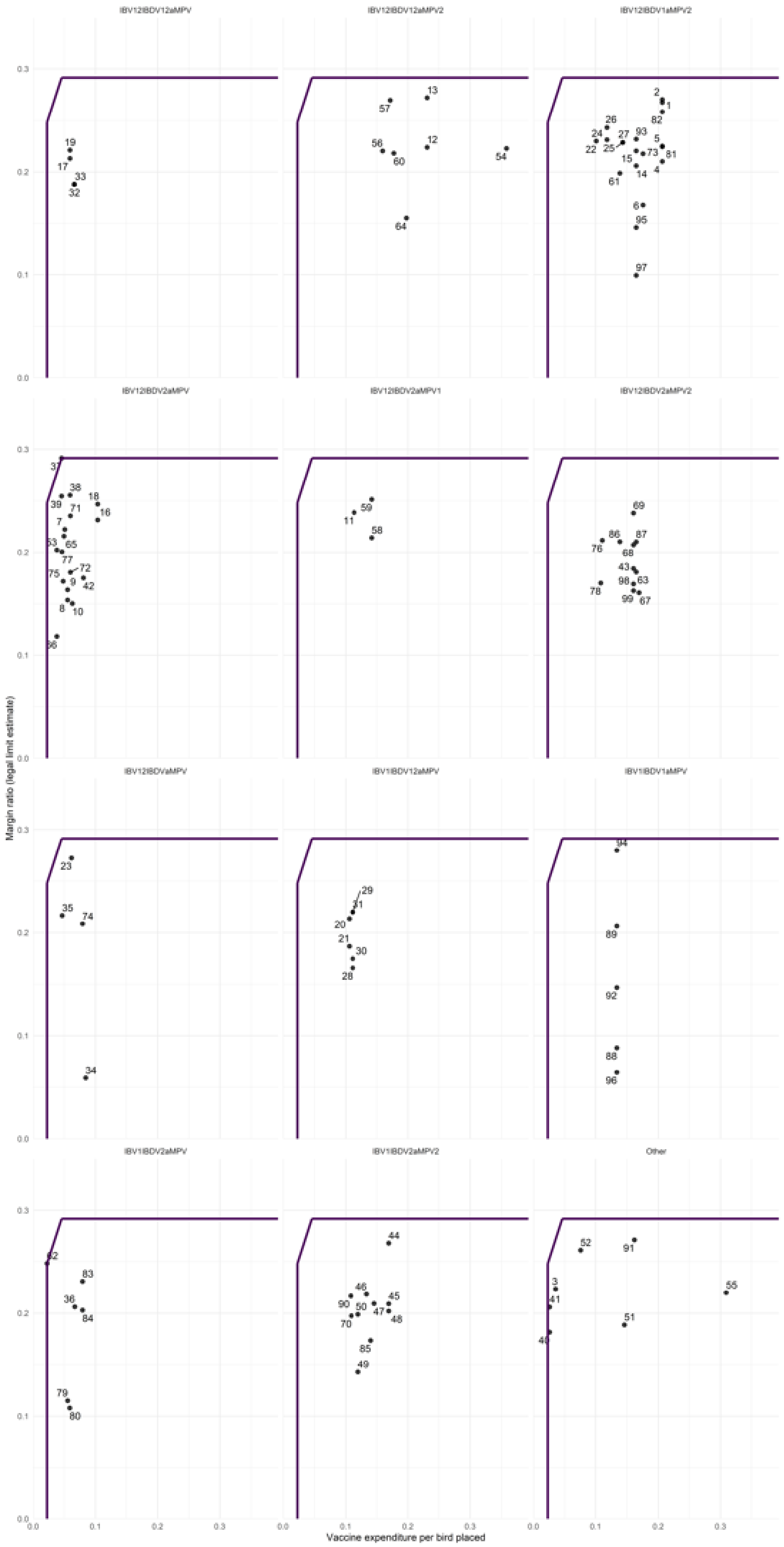

Figure 13: Input oriented DEA under variable returns to scale plotting efficiency of expenditure on vaccine against proportion of ideal outcome achieved. Each facet represents flocks following a specific vaccination program (see Table 10 for scenario descriptions).

Figure 13 shows how the flock performed for each of the main vaccination scenarios on the DEA analysis. A specific program can concern between 3 to 21 flocks, which is too little to make any significant inferences. However, the different scenarios seem to be associated to specific patterns, with means ranging from 0.16-0.23 and standard error ranging from 0.02-0.09.

4 Discussion

This Task within the DECIDE programme set out to produce a set of results centred around calculations of efficiency, and the use frontiers as an interpretation tool. DEA was applied where possible as it simultaneously examines efficiency and plots frontiers. In so doing, four datasets were explored to be used with this method, two of which were synthetic farm of herd data generated by modelling.

The beef case allowed a demonstration of the basics of analysis by DEA, with the frontier approach illustrating the variation in outcomes when applying a single intervention (vaccination) across a population due to underlying factors. Although this is analysis of synthetic data produced by the EMULSION model, the utility of the approach for empirical farm data can be easily envisioned if a broad dataset were available containing farm-level and exogenous factors with the potential to influence successful intervention against disease. In this case, the synthetic dataset simplified the analysis and allowed DEA with a clear result on very few input parameters, and economies of scale were removed by all farms being of the same size. The real data (salmon and poultry) showed clearly the increase in complexity in trying to understand loss-expenditure frontiers with the many interacting factors which contribute to successful application of disease control interventions.

The datasets used here showed that extensive data are required to connect different aspects of farm efficiency: the health state of the animal, its performance in terms of economically desirable activity which in this case would be growth and feed conversion, the actions of the farmer in terms of any interventions taken, and the farm-economic datasets describing those actions and their consequences (expenditure, revenue). Integrating these data, often segregated, is not an easy process and as WP1 showed, re-using data requires strong data management and more specifically rich metadata including description of the data structure and quality. Furthermore, integrating data from different sources often requires connecting similar concept scattered in the data sources, in that case, animal health ontologies, such as the one created by WP1, could be a solution to support this process.

As a method DEA has the capacity to analyse production for complex processes where there are multiple inputs and outputs. In the cases illustrated here, the poultry and salmon case studies did not successfully identify any underlying factors which associated with efficiency (salmon case) or in the poultry case any clear trend in performance with increasing expenditure (number of vaccinations multiplied by price) on vaccination, although a trend was noted with an increasing number of vaccines. The difference observed in the gross-margin ratio for broiler flocks could be due to differences in vaccination efficiency of the products, flock health factors other than the three diseases of study or other flock management issues (for example an issue in feed or environment). With only 99 flocks for which health and production data were connected, and with some candidate explanatory variables not collected, the possibility for analysis was limited. If a larger flock sample were available, the DEA could offer better insight into understanding the different vaccination programs and the interaction with health state.

This points to a clear limitation in the current cases, that the datasets used were not collected with DEA in mind rather as available data against which DEA and loss-expenditure frontiers were tested as a possible method to guide decision-making. The poultry dataset was not connected to any price data with respect to inputs, and both datasets lacked any description of fixed-cost infrastructure which can be critical to preventive disease control and a direct substitute for veterinary intervention. The need for investments in data collection and data infrastructure leading to datasets with the right combination of variables describing farm characteristics was identified as a key recommendation in a recent literature review of DEA-use in agriculture (Kyrgiakos et al., 2023).

The DEA capacity of disaggregating efficiency into technical, cost and allocative components, as described in the introduction was not utilised in this case because the difficulty in distinguishing different inputs in a manner suitable to use in a DEA input matrix. This would be another advantage to having more comprehensive datasets not limited to loss and expenditure but to assessing the efficiency of the enterprise as a whole and the health of animals as a component contributing to that efficiency.

The pig case study illustrated a case where DEA was not needed to analyse the efficiency of economic units, as there was either little overlap between the different options (two treatment classes versus coughing sensors versus vaccination). In this case, the underlying model structure meant between farm variation was essentially nullified as a core factor in the analysis, despite a small random stochastic component being incorporated within the model. As a result, marginal benefit to cost (MB:MC) ratios were used to perform a stepwise analysis of increasing expenditure. In calculation to the inverse of a marginal cost-effectiveness ratio, where the denominator is in currency rather than another unit of effectiveness. If multiple dimensions of intervention effectiveness were to be incorporated in a single presentation of efficiency shift, cost-effectiveness ratios would be one means of doing this. One intervention, the coughing sensor, showed little to no marginal benefit over the application of collective treatment alone and was dominated by the other strategies as currently parameterised within the EMULSION model.

The vaccine strategy in the pig study had a less attractive MB:MC ratio when compared to the use of antibiotics. This illustrates an important point. The application of vaccine is likely to bring non-monetary benefits in terms of both reduced use of antimicrobials and improved animal welfare as animals where animals are prevented from becoming ill, rather than becoming ill and being treated. This supports the need for the presentation of the different facets of disease burden simultaneously, as is the focus of Task 4.4. Even where treatment is effective and cheap, the benefits of prevention can be underestimated when only the financials are considered.

Similarly, in the cattle study, without vaccination the clearest way to improve results was by employing a collective treatment strategy. This has implications for the use of antimicrobials on farm; some healthy animals will receive antibiotic treatment. Farms with 10% vaccination coverage and collective treatment achieved were exceeded in performance by all farms vaccinating with 70% or more coverage. The true cost of achieving vaccination coverage as high as this is currently not well described, since farmers may try to source stock that are vaccinated prior to movement and the cost of this search is not known. This will be the subject of a paper being drafted by WP2 colleagues. As well as this, the labour cost of collective treatment is significantly lower than individual treatment. This creates a combination of incentives for increased use of antimicrobials and possibly less use of vaccine. This should be examined in greater detail in future.

DEA as a method has been shown in the literature to be quite adaptable and extendible to fit specific circumstances or research interests (for an overview, see Panwar et al. (2022)). In particular extensions such as Window DEA allow for the analysis of time-series data by treating each unit as a separate entity at different time points, so efficiency can be tracked over time. In the current study, the Salmon case tracked the application changing technology over time would be useful to explore how farms adapted to the new control methods available. Furthermore, a method which allows tracking efficiency overtime has wider application in the analysis of disease control programmes.

Over time DEA has also been adapted to fit more diverse circumstances, for example where some outputs of production are undesirable (Seiford and Zhu, 2002). This type of adaptation of the DEA method has been used extensively to examine the production of negative environmental externalities, such as pollution and environmental degradation. However, this would require examining the production process as a whole, with both desirable and undesirable outputs. This would not have fit within the objectives described in Task 4.2, which required specifically a loss-expenditure space be described, but would be an alternative approach that could be explored in future.

Lambda weights were used to show which combination of efficient units on the frontier provide a benchmark for each inefficient unit. The use of lambda coefficients to identify influential units may have useful application where populations under study are diverse on any number of underlying dimensions. Lambda is a weighting coefficient and can be used as a way to group farms working sharing some common input base (for example, in terms of farm size or scale). The application of this method in the beef case was illustrative of how lambda coefficients might be used to perform this identification with a real rather than synthetic dataset. It is proposed that there may be circumstances in which this has application is establishing peer-to-peer knowledge exchange mechanisms through farmers being able to see like-for-like comparisons being made.

The application of Tobit regression showed that the key step for farm-level improvement after vaccination was to employ collective treatment upon detection of a threshold of clinical cases. The discussion of the detection mechanism and threshold effects programmed into the EMULSION model are not within the remit of WP4, rather it is noted that when simulation runs were aggregated by scenario, such that the data was reduced from 800 data points to 80, the Tobit regression was unable to identify a statistically significant relationship between technical efficiency and two of the interventions as parameterised: risk profiling and valency of vaccination, despite the fact these were known to be having an effect in the model code. This perhaps indicates that sample size should be a careful consideration when working with real data, which are likely to be considerably noisier than the modelled data used here.

The salmon case study shows some farmers compared to others have lower costs associated with immediate treatments to control salmon lice reducing negative spill-over to environment. It highlights that they manage this with fewer immediate treatments, and although applying the same number of treatments and even within same treatment category, have lower losses (Figure 9). Importantly, the study also shows that the treatment associated losses are on average nine times higher compared to the expenses, highlighting the large cost of negative side effects from treatments, and potential economic incentive for preventing or reducing these side effects. While the rate at which lice spillover to wild populations has not been precisely quantified, the cost of mitigating this risk in both financial and animal welfare burden is clearly of considerable magnitude.

One of the hypothesised reasons for the large variability in losses even when the same number of treatments were applied was treatment method. Differences in treatment associated mortality and growth reduction and possible reasons for this are discussed in greater detail in (Walde et al., 2021, Walde et al., 2022). Several studies show high mortality associated with non-medicinal treatments, and comparing non-medicinal treatments to medicinal shows a significant higher growth reduction associated with non-medicinal treatments (Walde et al., 2021, Walde et al., 2022, Oliveira et al., 2021, Persson et al., 2022). It is also discussed that non-medicinal treatments improve in effectiveness over time due to improvements in labour skills and since this dataset stretches from 2014-2019 this could also be part of the explanation for the variability within the “mixed” and “non-medicinal” treatment category. In previous analysis the variability in treatment effect on growth has been discussed to be linked to factors like treatment rig, experience of personnel, holding time in treatment chamber and time between treatments for the fish to recover. Including these parameters in future dataset could make it possible to investigate factors contributing to success of some farmers in keeping treatment associated losses low.

The study made it possible for farmers to benchmark their treatment strategy regarding immediate treatments if their position in the data were communicated to them but does not identify the most cost-effective overall treatment strategy. In addition, some other investments or expenditure which could moderate the efficiency of control were not included in the data. For example, the data set does not contain information on the use and cost of other means of controlling salmon lice level, for instance use of cleaner fish, semi closed cages or other preventative measures. In that sense, it does not show if farmers investing in preventative measures are more efficient compared to the ones applying higher number of immediate treatments to keep below the legal threshold.

In this case, significant relationships between efficiency of control and potential causes of variation were not found. This may be a limitation of the dataset, rather than a true rejection of a hypothesis. As previously discussed, the spread over time opens the door to inconsistency within the data due to farmers becoming more familiar with new interventions. The incomplete description of the enterprise within the available data, particularly in the fixed-cost infrastructure, illustrates the importance of being able to account for farm-endogenous factors which may explain variability in efficiency.

It is proposed that were a fuller dataset available, this would give the possibility not only to identify successful cases but allow a successful two-stage DEA to be conducted associating efficiency to underlying endogenous and exogenous causal candidate variables. This could include variables describing environmental conditions such as temperature and daylight hours and regional farm density, as well as additional farm-level biotic and abiotic factors such as pre-treatment louse intensity, capital expenditure on equipment and infrastructure, and labour expertise. The need to build datasets capable of enumerating the many interacting factors influencing disease control efficiency.

In conclusion, analysis performed on the efficiency of endemic disease management has used a different set of data for cattle, pigs, salmon and broiler chickens. The former examples were based on simulation of the systems and highlighted key trigger points for disease management. The salmon and chicken datasets were less conclusive and demonstrate the difference between empirical versus simulated systems. In particular, the lack of data on farm fixed-cost infrastructure and alternative preventive treatments (houses, ventilation systems, nets, other investments with significant disease-preventative impact) made it difficult to control for farm or house level effects that might explain variation in the effectiveness with which vaccinations and other interventions are applied. These conclusions highlight the need for data collection as important indicators of efficiency and to validate and improve the modelling systems used.

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