The measurement of energy performance in the agricultural sector

Stéphane Blancard, Elsa Martin*

AgroSup Dijon, CESAER

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* AGROSUP Dijon, CESAER (UMR 1041), 26 Boulevard Dr Petitjean, BP 87999, 21079 Dijon, France. Tel. +33(0)3 80 77 26 91, Fax. +33(0) 3 80 77 25 71 E-mail: elsa.martin@dijon.inra.fr

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Abstract

ADEME (the French national environmental and energy agency) develops tools in order to measure farm energy performance. The actual measurement is based on the total amount of energy consumed by farmers. The main objective of this paper is to propose an alternative method that can be used in order to improve this measurement. The alternative method that we propose is based on Data Envelopment Analysis (DEA) models. Following the procedure adopted in a cost framework by Farrell (1957) and developed by Färe et al. (1985), we propose to decompose an overall energy performance measurement into two components, namely technical and allocative performances. In order to do this, we replace prices by energy content of inputs. We show that this decomposition can considerably help policy makers to design accurate energy policies. The presence of uncertainty on data, and more particularly on energy content of inputs, leads us to recommend exploiting the methodology proposed by Camanho and Dyson (2005) in order to produce more robust results. Thus, this methodology allows deriving both upper and lower bounds for the performance measurements. A year 2007 database of French farms specialized in crops is used for empirical illustration.

Keywords Crop-farming, Data Envelopment Analysis, energy performance, uncertainty

JEL code D24, O13, Q15, Q4

1. Introduction

Energy and GHG (Greenhouse Gas) mitigation is a growing concern within the international community. As a consequence, the French government defined an energy performance plan. A part of this plan is dedicated to farms. The main idea is to measure their energy performance by ranking them with respect to their energy consumption. The aim of this ranking is to bring them to the fore their potential in energy savings.

From the farms point of view, savings can easily be made if they reflect managerial failures: two much of some inputs that are energy intensive is used with respect to what is needed in order to produce a constant amount of output. But if the savings rely on misallocation between several inputs, they are much more difficult to make since they need a reallocation of these inputs. Tools developed by the French national environmental and energy agency (ADEME) in order to measure farms energy performance fail to take both of these dimensions into account although the energy policy design can considerably suffer from this. How to derive a composite indicator that is able to take both of these dimensions into account? What are the implications in terms of policy design?

When measuring the energy performance of farms, one needs to calculate the energy content of inputs used by farms in order to produce food. ADEME chose to take a Life Cycle Assessment (LCA) perspective. LCA is a technique that allows including the energy consumed in order to produce and transport an input that is used in a production process (see EPA, 2006 for more details on the method). Nevertheless, as underlined by Huijbregts (1998), in order to achieve this aim, many parameters are used and choices are made. As a consequence, the LCA of input energy content is uncertain. How to take this uncertainty into account when measuring technical and energy performance of farms?

From the best of our knowledge, the literature on energy performance of farms is not wide. We mainly found works applied to the US (see for instance Cleveland, 1995) and to developing countries (see for instance Karkacier et al., 2006). These papers concentrated on the effect of energy factor on agricultural productivity and production. They used parametric estimations which depend on the assumptions made on the functional form of the production function.

Charnes et al. (1978) developed a non parametric estimation method especially powerful in evaluating relative performance of different decision making units (e.g. farms): Data Envelopment Analysis (DEA). DEA involves the use of linear programming methods to construct a non-parametric piece-wise surface (or frontier) over the data. Performance measurements are then calculated relative to this surface. For more details, Zhou et al. (2008) recall the basic methodology and provide a thorough literature review of data envelopment analysis in energy and environmental studies. More recently, Houshyar et al. (2010) and Nassiri and Singh (2009) determine the amount and performance of energy consumption for wheat and paddy production in Iran, by using the basic DEA method.

But the efficient targets yielded by envelopment models are not preferred when the policy-makers bear an energy reduction goal in mind. Therefore, some other targets along the efficient frontier should be considered as preferred ones. Zhu (1996) developed a set of weighted non-radial DEA models in order to construct preference structure over the proportions by which the current input levels can be changed. As a consequence, if one imposes a proper set of preferences weights for each farm under consideration, then the DEA Preference-Structure model yields energy performance measure. Energy performance can then be decomposed into managerial and allocative performance scores. For this, we rely on the same concept introduced by Farrell (1957) in the cost context and developed by Färe et al. (1985).

If one think of crop-farms, it is possible to distinguish between renewable (human power and seed) and non-renewable energy (petroleum, fertilizers and pesticides for instance). We propose to focus on the use of non-renewable energy. As a consequence, we will assume that the energy content of inputs such as land and labor is very small. Furthermore, the LCA framework adopted by ADEME allows taking into account more indirect energy consumption than the direct use of energy such as petroleum for instance. For another input like fertilizer, for instance, the LCA consists in computing all the energy consumed in order to produce and transport this input. This perspective is very similar to the cumulative exergy approach that was demonstrated as being an efficient tool for energy policy making applications by Dincer (2002). Hoang and Rao (2010) proposed a decomposition of the sustainable performance of agricultural production based on this approach. We can compare the cumulative exergy content they used for their OECD empirical study to the energy content provided by ADEME (2011) for French farms. If we look at the nitrogen input, for instance, Hoang and Rao propose to apply 32.8 MJ/kg of nitrogen and ADEME 55.57 MJ/kg. The difference is quite important. The difference is lower for oil energy: 42.8 MJ/kg in Hoang and Rao and 46.4 MJ/kg in ADEME.
The main implication of this comparison is that the energy content of input, when using a LCA framework, is uncertain. As a consequence, the energy performance measurement provided when applying the Preference-Structure framework must be adapted. Camanho and Dyson (2005) showed that DEA models can provide robust estimates of cost performance even in situation of price uncertainty. Following Kuosmanen and Post (2001), they developed a method for the estimation of upper and lower bounds for the cost performance measurement in situation of price uncertainty. This method incorporates weight restrictions of the form of input cone assurance regions that was first developed by Thompson et al (1996). Following Camanho and Dyson (2005), we will apply this method to the case of the uncertainty of energy content of input. More recently, Mostafaee and Saljooghi (2010) proposed to go further into the analysis by also considering some uncertainty on the data on inputs and outputs. Fortunately, our data were obtained from precautious surveys. It is why we will not consider this kind of uncertainty.

The remainder of the paper is structured as follows. In the following section, we describe the methodology. The section 3 provides a description of data set and retained variables. Section 4 is devoted to our results that will be presented as policy implications. Finally, section 5 concludes.

2. Methods: Energy performance measurement with uncertainty on energy content of input

The notion of Energy performance (EP) indicates the extent to which a production unit minimizes the energy to produce a given output vector, given the energy content of input it faces. In other words, it assesses the ability to produce current outputs at minimal energy. After Farrell (1957) who introduced this concept, Färe et al. (1985) formulated a programming model for EP assessment. This model requires input and output quantity as well as energy content of inputs at each DMU. In next subsection, we recall the basic model DEA-like to measure EP. In the subsection 2.2, we also presented the weight-restricted DEA model for measuring energy performance when energy contents of inputs are uncertain that can be adopted in line of Camanho and Dyson (2005).

2.1. The decomposition of energy performance into technical and allocative performance within a basic envelopment model

2.1.1. Graphical illustration

To graphically illustrate the energy, technical and allocative performance concepts, suppose in the Figure 1, seven DMUs (**A** to **G**) which produce y with two inputs x_1 and x_2. The segments linking DMUs **A**, **B**, **C** and **D** form the efficient frontier. We use DMU **F** to illustrate the performance concepts. The ratio 0**f**/0**F** gives the technical performance. This means that it is possible to find another DMU or to build a composite DMU (**f** in our case) which produce the same output level with the less input level. Note that the value is equivalent to the ratio between the technically efficient plan (E^T) and the observed plan ($E^{\mathbf{F}}$) i.e. $E^T / E^{\mathbf{F}}$. Let us introduce some information on the energy content of input (w_1 and w_2). Assume now that DMU **F** has eliminated its lack of technical performance by moving to point **f**. However, this point is not energy efficient when compared to DMU **C** which is less energy-intensive production plan. Thus, given the energy contents of inputs, the composite DMU **f** and thus the allocative performance of **F** appears less high than the one of **C**. The ratio 0**f'**/0**f** gives the allocative performance score which measures the extent to which a technically efficient point falls short of achieving minimum energy contents because it fails to make the substitutions (or reallocations) involved in moving from **f'** to **C**. The allocative performance measurement can also be expressed in terms of a ratio between the minimum energy at point **C** and the used energy at the technically efficient point **f**: $E^{\min} / E^T$. Finally, we have the relationship:

0**f'**/0**F** = (0**f**/0**F**) × (0**f'**/0**f**)

or

Energy performance = Technical performance × Allocative performance

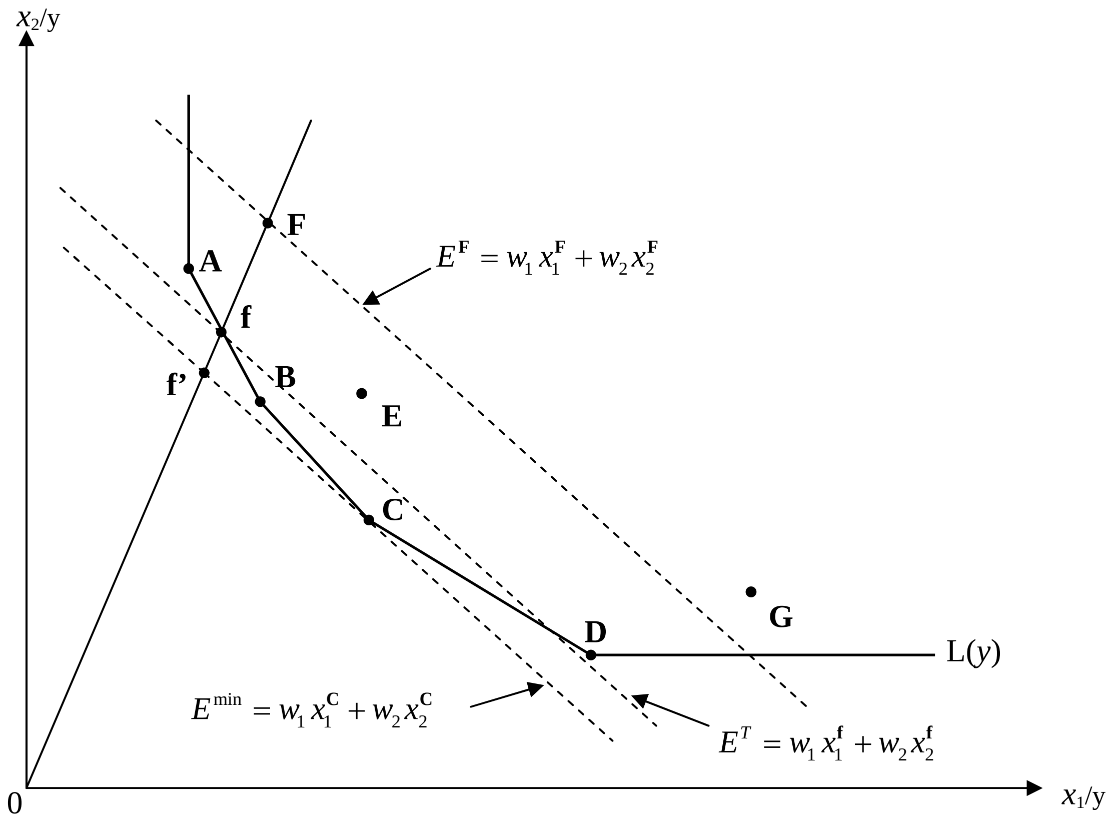

Figure 1: Energy, allocative and technical performance measurement in the input space

2.1.2. The energy, allocative and technical performance models

Let us consider that K DMUs are observed and we denote $\mathfrak{K} = \{1,\ldots,K\}$ by the associated index set. We assume that DMUs face a production process with M outputs and N inputs where $y = (y_1,\ldots,y_M) \in R_+^M$ is the vector of outputs and $x = (x_1,\ldots,x_N) \in R_+^N$ is the vector of inputs. We also define the respective index sets of outputs and inputs as $\mathfrak{M} = \{1,\ldots,M\}$ and $\mathfrak{N} = \{1,\ldots,N\}$. Following Färe et al. (1985), the model is defined by the production possibility set:

$$T = \left\{ (x,y) : \sum_{k\in\mathfrak{K}} \lambda^k y_m^k \geq y_m \ \ \forall m \in \mathfrak{M}, \sum_{k\in\mathfrak{K}} \lambda^k x_i^k \leq x_i \ \ \forall i \in \mathfrak{N}, \sum_{k\in\mathfrak{K}} \lambda^k = 1,\ \lambda^k \geq 0 \ \ \forall k \in \mathfrak{K} \right\} \qquad (1)$$

For a DMU j with a production plan (x^j, y^j), the minimum energy E is calculated via the following program:

$$
\begin{aligned}
& E = \min \sum_{i \in \mathfrak{N}} w_i \, x_i \\
& \text{subject to:} \\
& \sum_{k \in \mathfrak{K}} \lambda^k y_m^k \geq y_m^j \quad \forall m \in \mathfrak{M} \\
& \sum_{k \in \mathfrak{K}} \lambda^k x_i^k \leq x_i \quad \forall i \in \mathfrak{N} \\
& \sum_{k \in \mathfrak{K}} \lambda^k = 1 \\
& \lambda^k \geq 0 \quad \forall k \in \mathfrak{K}
\end{aligned}
\qquad (2)
$$

where w_i is the weight (here, the energy content) of input *i* faced by DMU *j* and therefore *E* corresponds to the minimum energy required to produce output vector *y* at energy content of inputs *w*. If we denote E^j the total energy content of the current input levels of DMU *j*, then its energy performance is measured as the ratio of minimum energy to the current energy: $\frac{E}{E^j} = \frac{\sum_{i \in \mathfrak{N}} w_i \, x_i^{j*}}{\sum_{i \in \mathfrak{N}} w_i \, x_i^j}$,

in which "*" indicates the optimality. $\left[\left(1 - \text{energy efficiency} \right) \times 100 \right]$ indicates the percentage of total wasting energy.

In the same spirit of cost performance developed by Färe et al. (1985), the energy performance incorporates two sources of performance viz. technical performance and allocative performance. Bad technical performance score reflects managerial failures while bad allocative performance score reflects an input misallocation. Consequently, a DMU will only be energy efficcient if it is both technically and allocatively efficient.

In order to obtain a decomposition of energy performance, we need to measure technical performance by the traditional input-oriented DEA model. Since our work is based on the dual linear programming problems to the envelopment models (called multiplier models), we propose here to recall this form of the traditional input-oriented DEA model:

$$
\begin{aligned}
& \max \sum_{m \in \mathfrak{M}} u_m y_m^j \\
& \text{subject to:} \\
& \sum_{i \in \mathfrak{N}} v_i \, x_i^j = 1 \\
& \sum_{m \in \mathfrak{M}} u_m y_m^k - \sum_{i \in \mathfrak{N}} v_i \, x_i^k \leq 0 \quad \forall k \in \mathfrak{K} \\
& u_m \geq \varepsilon \quad \forall m \in \mathfrak{M} \\
& v_i \geq \varepsilon \quad \forall i \in \mathfrak{N}
\end{aligned}
\qquad (3)
$$

As demonstrated by Schaffnit et al. (1997) and reemphasized by Camanho and Dyson (2005) in cost context, we can also demonstrate that the measure of energy performance (EP) can be alternatively obtained with the inclusion of weight restrictions in the standard DEA models. They also noted the relevance of the relative energy contents of inputs for the EP measurement. Also, the restrictions imposed to the weights underlying the assessment are that the relative value of the energy content of input observed at each DMU, such that: $\frac{v_{i^a}}{v_{i^b}} = \frac{E_{i^a}}{E_{i^b}}, \quad i^a, i^b = 1, \ldots, N$ where *a* and *b* are for example two inputs among the set $\mathfrak{N}$.

For the DMU *j*, the resulting energy performance model based on the DEA model with the addition of weights restrictions is as follows:

$$
\begin{aligned}
& \max \sum_{m \in \mathfrak{M}} u_m y_m^j \\
& \text{subject to:} \\
& \sum_{i \in \mathfrak{N}} v_i x_i^j = 1 \\
& \sum_{m \in \mathfrak{M}} u_m y_m^k - \sum_{i \in \mathfrak{N}} v_i x_i^k \leq 0 \quad \forall k \in \mathfrak{K} \\
& v_{i^a} - \frac{E_{i^a}}{E_{i^b}} v_{i^b} = 0 \\
& i^a < i^b, \quad i^a, i^b = 1, \ldots, N \\
& u_m \geq \varepsilon \quad \forall m \in \mathfrak{M}
\end{aligned} \tag{4}
$$

2.2. An extension with uncertainty on energy content of inputs

With uncertainty on energy content of input, we can adopt two perspectives viz. optimistic and pessimistic and thus assess two EP: one with the most favorable energy content scenario (the energy content is minimal) and one other with the least favorable energy content (the energy content is maximal).

To graphically illustrate these notions, consider the case where only the maximal and the minimal energy content for all DMUs can be identified, e.g. for two inputs we have $E_1^{\min}, E_2^{\min}, E_1^{\max}$ and $E_2^{\max}$. The energy content (or weight) ratios underlying the energy performance evaluation would be restricted to the following range: $\frac{E_1^{\min}}{E_2^{\max}} \leq \frac{v_{i^a}}{v_{i^b}} \leq \frac{E_1^{\max}}{E_2^{\min}}$.

The slope of the iso-energy underlying the evaluation of CP could vary between the slope of $E_\beta E_{\beta'}$ i.e., $-\frac{E_1^{\max}}{E_2^{\min}}$ and the slope $E_\alpha E_{\alpha'}$ i.e., $-\frac{E_1^{\min}}{E_2^{\max}}$. The optimistic EP measurement assesses each DMU by comparison to the most favorable iso-energy line. In Figure 2, the optimistic EP frontier corresponds to the segments linking $E_\beta, \mathbf{B}, \mathbf{C}$ and $E_{\alpha'}$ (the energy content ratio of the iso-energy line is as close as possible to the marginal rate of substitution between the inputs). Conversely, the pessimistic frontier measurement assesses each DMU by comparison to the least favorable energy content scenario. It corresponds to the segment linking

E_{α}, ω and $E_{\beta'}$ for the pessimistic frontier. In the case of DMU **F** the optimistic EP is measured by 0**f''**/0**F** whereas pessimistic EP is measured by 0**f'**/0**F**.

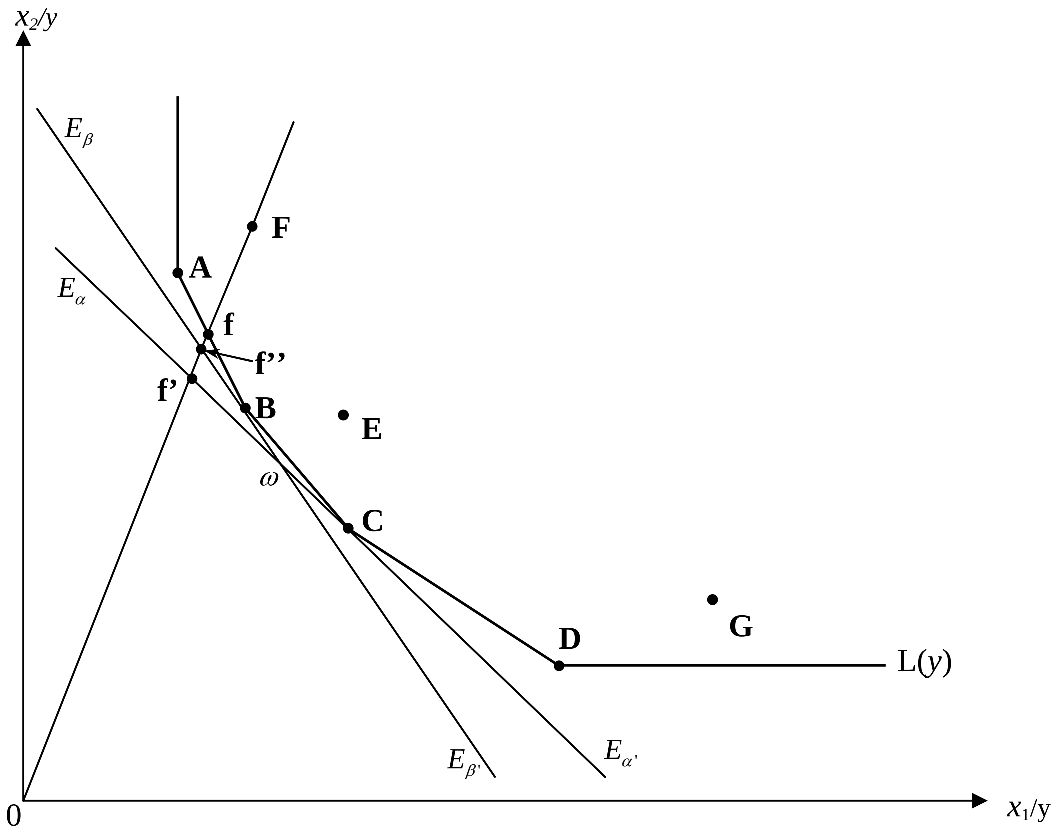

Figure 2: Optimistic and Pessimistic EP measurement in the input space

As mentioned above, for the optimistic EP model, we focus our attention on the most favorable energy content scenario. Optimistic EP model can be written as follows:

$$\max \sum_{m \in \mathfrak{M}} u_m y_m^j$$

subject to:

$$\sum_{i \in \mathfrak{N}} v_i x_i^j = 1$$

$$\sum_{m \in \mathfrak{M}} u_m y_m^k - \sum_{i \in \mathfrak{N}} v_i x_i^k \leq 0 \; \forall k \in \mathfrak{K} \tag{5}$$

$$\frac{E_{i^a}^{\min}}{E_{i^b}^{\max}} \leq \frac{v_{i^a}}{v_{i^b}} \leq \frac{E_{i^a}^{\max}}{E_{i^b}^{\min}}$$

$$i^a < i^b, i^a, i^b = 1, \ldots, N$$

$$u_m \geq \varepsilon \quad \forall m \in \mathfrak{M}$$

The constraints $\frac{E_{i^a}^{\min}}{E_{i^b}^{\max}} \le \frac{v_{i^a}}{v_{i^b}} \le \frac{E_{i^a}^{\max}}{E_{i^b}^{\min}}, \quad i^a < i^b, i^a, i^b = 1,\ldots,N$ provide inequality bounds for multipliers that are reasonable from an energy point of view (see Thompson et al., 1990 for economically reasonable bounds). Thus, the assurance region is specified by this input cone. Finally, optimistic CP model can be rewritten in linear form as follows:

$$\max \sum_{m\in\mathfrak{M}} u_m y_m^j$$

subject to:

$$\sum_{i\in\mathfrak{N}} v_i x_i^j = 1$$

$$\sum_{m\in\mathfrak{M}} u_m y_m^k - \sum_{i\in\mathfrak{N}} v_i x_i^k \le 0 \quad \forall k \in \mathfrak{K} \qquad (6)$$

$$v_{i^a} - \frac{E_{i^a}^{\max}}{E_{i^b}^{\min}} v_{i^b} \le 0$$

$$v_{i^a} - \frac{E_{i^a}^{\min}}{E_{i^b}^{\max}} v_{i^b} \le 0$$

$$i^a < i^b, \quad i^a, i^b = 1,\ldots,N$$

$$u_m \ge \varepsilon \quad \forall m \in \mathfrak{M}$$

Since the DMU's evaluation is based on *n* inputs, there are C_2^N different ratios between two inputs, which give a total of $2\times C_2^N$ linear inequality constraints.

To obtain the EP model under a pessimistic perspective, as noted by Camanho and Dyson (2005), it is necessary to develop an alternative method. It requires solving more than one linear program. The assessment consists of running a set of linear programming models, where each DMU in the set is considered in turn as a potential peer for evaluated DMU. This kind of models has the following structure:

$$\max \psi_j^p = \sum_{m \in \mathfrak{M}} u_m y_m^j$$

subject to:

$$\sum_{i \in \mathfrak{N}} v_i x_i^j = 1$$

$$\sum_{m \in \mathfrak{M}} u_m y_m^p - \sum_{i \in \mathfrak{N}} v_i x_i^p = 0 \tag{7}$$

$$\sum_{m \in \mathfrak{M}} v_m y_m^k - \sum_{i \in \mathfrak{N}} v_i x_i^k \leq 0 \quad \forall k \in \mathfrak{K}$$

$$v_i \geq \varepsilon \quad \forall i \in \mathfrak{N}$$

$$u_{\mathrm{m}} \geq \varepsilon \quad \forall m \in \mathfrak{M}$$

where the index *p* represents the peer DMU underlying the performance assessment of DMU *j*. The second constraint forces the performance of the peer *p* to be equal to one in the assessment of DMU *j*. If not, model (7) has no solution which indicates that DMU *p* is not suitable as a peer of DMU *j*. Moreover, model (7) is only feasible if the peer used for DMU *j* is located on the frontier. For large problems, the set of peer DMUs can be reduced to efficient DMUs (belonging to the frontier) By introducing the constraints of model (5) i.e. $\frac{E_{i^a}^{\min}}{E_{i^b}^{\max}} \leq \frac{v_{i^a}}{v_{i^b}} \leq \frac{E_{i^a}^{\max}}{E_{i^b}^{\min}}, \quad i^a < i^b, i^a, i^b = 1, \ldots, N$ in (7) we have the deterministic CP.

Finally, to obtain the pessimistic EP model, we replace the restrictions of model (5) in model (7) and change the objective function of (7) from maximization to minimization (the pessimistic CP measurement is obtained choosing the minimal score ψ_j^p). The model is written as follows:

$$\min \psi_j^p = \sum_{m \in \mathfrak{M}} u_m y_m^j$$

subject to:

$$\sum_{i \in \mathfrak{N}} v_i x_i^j = 1$$

$$\sum_{m \in \mathfrak{M}} u_m y_m^p - \sum_{i \in \mathfrak{N}} v_i x_i^p = 0 \tag{8}$$

$$\sum_{m \in \mathfrak{M}} u_m y_m^k - \sum_{i \in \mathfrak{N}} v_i x_i^k \leq 0 \quad \forall k \in \mathfrak{K}$$

$$\frac{E_{i^a}^{\min}}{E_{i^b}^{\max}} \leq \frac{v_{i^a}}{v_{i^b}} \leq \frac{E_{i^a}^{\max}}{E_{i^b}^{\min}}$$

$$i^a < i^b, \quad i^a, i^b = 1, \ldots, N$$

$$u_m \geq \varepsilon \quad \forall m \in \mathfrak{M}$$

3. Data and variables

This study is based on data collected by a French group of agronomists (named PLANETE and created in the 90s) and centralized by SOLAGRO, a French non-governmental organization established to promote sustainable energy and agriculture, and respect for the natural environment. The members of PLANETE worked for ADEME in order to supply software computing an energy assessment of farms. Bochu (2002) summarized the results of this study. A consequence is that, for each farm, we have at our disposal the details on both all the outputs produced but also all the inputs used for this production. Entering these data for each farm, the software is able to calculate the energy performance of each one, basically computing the ratio between outputs and inputs. In order to do so, it applies coefficients that convert carefully inputs and outputs into a common energy unit: the joule. Currently, the software has evolved to a more modern one named DIATERRE that does not consider the energy content of output anymore because of the difficulties of leading a LCA related to them. The conversion coefficients have been actualized and are summarized in a guide available upon request. We will use those coefficients.

SOLAGRO provided us a data set of 151 farms investigated during the year 2007. Our main request was to have homogeneous farms. As a consequence,

- they all grow the same culture: cereals;
- they are all facing the same pedo-climatic conditions by being located in the same area: west-center of France;
- they are characterized by the same production system: there is no organic farm.

This sample of farms cannot be a representative one since the energy assessment made by PLANETE was not an obligation and only voluntary farms made it. It is not a problem since our aim is not to provide a general analysis of the energy performance of some farms: it is to investigate what is the best model to be used in order to decompose farms energy performance.

For the same reason, we decided to concentrate on major inputs. The output under consideration will be an aggregated value of the mass of cereals produced. Concerning the inputs, we first selected the following one: area, units of labor, petroleum, nitrogen, seeds and pesticides.[1] We then ran some correlation tests in order to check that the selected inputs are correlated to the output. Unsurprisingly, we found no correlation between pesticides and the amount of cereals produced: the contribution of damage control agents to production differs fundamentally from that of standard inputs. We did not find any correlation between seeds and the output also. The explanation relies on the fact that only seeds bought are considered[2]. We do not know the amount of seeds produce by the farm. As a consequence, we decided not to consider those inputs in our analysis. These choices concerning the production technology do not change our main results since our main aim is not to measure farms performance: it is to compare different models. As a consequence, if one model is inexact, the other will also be and our results in terms of comparisons will remain true.

Once these choices were made, we deleted the observations with missing values on the crucial variables of interest and we calculated the productivity of each input in order to check

[1] We were unable to consider the capital because of a lack of data.

[2] This choice is consistent with the seminal aim of the data set that is to lead a LCA on all inputs used by the farms.

consistency of data. Finally, 145 observations were left. Table 1 provides some descriptive statistics of these variables.

Table 1: Descriptive statistics of inputs and output

	Mean	Standard deviation	Min	Max
Area (hectare)	193	111	33	568
Labor (unit of labor)	1.7	1.1	0.5	6.5
Nitrogen (kg)	27 247	18 723	2 103	95 705
Petroleum (Liter)	18 143	14 619	2 193	91 279
Cereals (Quintal)	10 282	6 606	585	33 528

In order to calculate the energy content of inputs, we used the same conversation coefficients as ADEME (2011). These coefficients are based on the LCA guidance provided by ECOINVENT, a Non-Profit Swiss Centre for Life Cycle Inventories and were adapted to the French case by ADEME. As explained in the introduction, we decided to focus on non-renewable energy. It is why area and labor have a small (10^{-6}) and determinist conversion coefficient. We also explained that conversion coefficients based on a LCA are characterized by a high level of uncertainty. We do not have access to the minima and the maxima provided by ECOINVENT since ADEME only based its adaptation to the French case on mean data. As a consequence, in order to illustrate our view, we propose to base our analysis on the coefficient provided by Hoang and Rao (2010). We will use these coefficients as the minimum value and we will derive the potential maximum by applying the same difference to the mean. All the coefficients used are summarized in Table 2. We again remind here that our aim is not to provide a careful empirical analysis of farms energy performance. It is to formulate some policy implications for the measurement of farms energy performance when the energy content of input is uncertain.

Table 2: Energy contents of inputs (in MJ/unit)

	Mean	Min	Max
Nitrogen	55.57	32.8	78.34
Petroleum	46.4	42.8	50

4. Results and policy implications

The subsection 4.1 will be dedicated to the results and policy implication in the deterministic setting and the subsection 4.2 to the one in the uncertain case.

4.1. The decomposition of energy performance in the deterministic case

To examine energy performance (EP) and its components (technical and allocative performance) in the deterministic case, we first run the linear programming models (3) and (4)[3]. At this stage we applied the mean of the energy content of inputs (see table 2). The allocative performance (AP) scores were directly deduced from the other performance scores. Table 3 provides the scores obtained.

[3] The linear programs previously described were implemented by using the solver function of Excel. All files are available upon request to the authors.

Table 3: Energy, technical and allocative performance scores

	Mean	Standard Deviation	Min	Max	Number of efficient farms
Energy performance	0.4756	0.1080	0.2282	1	1
Technical Performance	0.7181	0.1535	0.2953	1	9
Allocative Performance	0.6721	0.1135	0.3318	1	1
ADEME	0.4756	0.1080	0.2282	1	1

The results for EP indicate us that, on average, farms could reduce all the inputs used and thus minimize their energy use by 53% (i.e. 1-EP). We also calculated what we named an ADEME score that corresponds to the score actually used by ADEME through the implementation of the French energy performance plan. It is simply obtained by dividing the sum of the energy consumed (through input use) in Joule by the output (cereals) in quintal. We then normalized the minimum to one (it will be the efficient farm) in order to obtain a performance score that can be compared with the DEA one. We can observe that, on average, the performance scores obtained with the ADEME methods are very close to the EP scores. Checking more precisely, we can observe that the rankings are exactly the same one. A remark follows.

Remark: *When the energy content of inputs is known, the DEA method confirms the results obtained by the ADEME method.*

An energy policy based on EP (or equivalently ADEME) scores will consist in helping farms with low scores to moderate input use where the energy content is high and, as a consequence, in reducing energy use, explicit energy performance policies may need to be designed toward farms whose performance is low.

Furthermore, table 3, shows that, some farms could minimize their energy use by increasing technical and allocative performance scores. By only eliminating mismanagement of resources (TE), farms could reduce all the inputs used by 29% without reducing the amount of output produced. Finally, by making reallocation on input or changing input-mix, farms can reduce their energy use to 33%.

To illustrate the insights gained from a decomposition of the EP scores into TP and AP scores, we propose to consider three cases of three farms (**20**, **39** and **43**) as shown in Table 4.

Table 4: Input and output data for three illustrative farms

	Farm 20	Farm 39	Farm 43
Area (hectare)	226	152	160
Labor (unit of labor)	1	0.8	1
Nitrogen (kg)	31 200	15 844	5 940
Petroleum (liter)	17 517	11 460	11 273
Cereals (quintal)	12 122	10 542	8 046

Table 5 provides the potential reduction of energy used on each component of these three farms.

Table 5: Performance results and potential reduction of energy in MJ for illustrative farms

	Farm 20	**Farm 39**	**Farm 43**
Energy performance	0.5048	0.7916	1
Potential reduction in energy	*1 261 063*	*294 322*	*0*
Technical Performance	0.8284	1	1
Potential reduction in energy	*447 178*	*0*	0
Allocative Performance	0.6123	0.7916	1
Potential reduction in energy	*813 885*	*294 322*	0

For example, farm **39** can benefit from energy saving by eliminating only the lack of allocative performance that corresponds to 21% of observed energy i.e. 294 322 MJ. Compared to farm **39**, farm **20** suffers both an input mismanagement and misallocation and can reduce its energy used by two ways. The potential energy saving is about to 1.261 millions of MJ. The energy gains would come from mainly the elimination of the lack of technical performance. We also have the case of farm **43** which cannot benefit from energy saving. Finally, note that the case of farms which only suffer of input misallocation is not found in our sample. The decomposition proposed helps to go further into the design of an energy policy.

For instance, an energy policy designed toward farm **39** will more precisely consist in giving it incentives to reallocate its inputs in a way corresponding more to energy-extensive farms. Such a policy aim is to induce an evolution of farms towards more energy-extensive systems. As a consequence, our method helps to identify both farms characterized by an energy-extensive system (like farm **43**) and farms characterized by an energy-intensive system. Studying the differences between both will help the policy maker to design an appropriate energy policy.

We know from the environmental economics theory that a policy aiming to reduce the energy used by farmers must be designed in order to modify the price system if the farm is cost-efficient. More specifically, if one adds classical iso-cost lines in Figure 1, they will certainly have a different slope from the iso-energy one since the price ratio must be different from the energy content of inputs one. The intersection of the lowest iso-cost line with the isoquant curve gives the equilibrium spontaneously chosen by a cost-efficient farm without any energy policy. As a consequence, an energy policy aiming at reducing the energy use of cost-efficient farms must be designed in order to induce that the farmers choose the equilibrium corresponding to a lower energy use, exogenously chosen by the policy maker. More operationally, such energy policy will consist in subsidizing or taxing the input use in such a way that the slope of the iso-cost lines equals the one of the iso-energy one.

If we now turn back to our examples (Table 5), an energy policy designed toward farm **20** will be more complex than one designed toward farm **39** since it will consist both in giving incentives to reallocate inputs like energy-extensive farms but also to reduce the use of input. The interesting thing here is that this reduction will generate some gains for the farm since it will allow it to produce the same amount of output with less input and hence at a lower cost. As a consequence, a policy specifically designed in order to induce this reduction will not have to pass throw the price system but more throw agricultural advice.

As a consequence, the decomposition of energy performance into technical and allocative performance offers different ways of reducing the lack of performance for unit managers or policy makers. Furthermore we see in Table 3 that, in our sample, by mean, the lack of energy performance is mainly due to the allocative performance scores (rather than to the technical performance scores). The policy implication is that, within the framework of our sample, it is more important to put money into policies aiming at increasing the allocative performance score, i.e. policies based on incentives rather than on advices.

To go further, we propose to calculate some correlation tests between EP, TP and AP rankings using the Spearman's procedure. The results are summarized in Table 6.

Table 6: Spearman rank correlation tests between the different performance scores.

	Energy Performance	**Technical Performance**	**Allocative Performance**
Energy performance	1.0000*		
Technical Performance	0.6797*	1.0000*	
Allocative Performance	0.3045*	-0.3837*	1.0000*

*: statistically significant test at 5% level.

The relatively high correlation between EP and TP means that EP can be a good approximation of TP and that technical and energy goals are quite consistent in our sample. As a consequence, public policies designed in order to help farms with a low rank with respect to EP (resp. TE) can also help them to improve their TP (resp. EP). In a different perspective, public policies designed in order to reward farms with a high rank with respect to EP (resp. TE) can also reward farms with a high TP score (resp. EP). From an even more general point of view, we can conclude that energy and food production goals can be consistent in the short-run in our sample.

In contrast, the low rank correlation coefficient between EP and AP rankings reveals the relevance of decomposition. For instance, in our sample, public policies designed in order to help only farms with a low EP could reduce the amount of output produced and would not be directed towards farms able to reallocate inputs, that can only be the case if AP is also used in order to design an energy policy.

From all of this, a first result follows.

Result 1: *Considering only the EP can hide the existing disparities on each component (technical and allocative). Therefore, by dissociating the energy performance scores into each component, policy makers can better target their policies toward farmers. For example, policies should help to move towards less intensive-energy farm systems by a reallocation of inputs.*

4.2. Extension with energy content uncertainty

We then extended the previous analysis to a framework in which the energy content of inputs is uncertain. In order to do so, following Camanho and Dyson (2005), we consider two scenarios: an optimistic and a pessimistic one. The optimistic scenario corresponds to the most favorable scenario: the energy contents of inputs are minimal (see Table 2). In the pessimistic scenario, they are maximal. We used the linear programming models (6) and (8) in order to obtain EP in the pessimistic case and in the optimistic one. Optimistic and pessimistic AP are directly obtained by respectively calculating optimistic EP/TE and pessimistic EP/TE. In the uncertain case, only AP and thus EP varied (TE was unchanged). The results are summed up in Table 7. We recall some statistics from the deterministic case in order to compare with the uncertain case.

Table 7: Performance Scores with and without uncertainty

	Mean	Standard deviation	Min	Max	Number of Efficient farms
Optimistic EP	0.5565	0.1294	0.2381	1	1
EP	0.4756	0.1080	0.2282	1	1
Pessimistic EP	0.2873	0.0956	0.0917	1	1
Optimistic AP	0.7858	0.1372	0.3535	1	1
AP	0.6721	0.1135	0.3318	1	1
Pessimistic AP	0.4032	0.0971	0.1506	1	1

A first and direct implication is that the deterministic AP and EP scores are upper and lower bounded respectively by the optimistic and pessimistic scores. Even in the optimistic scenario, the lack of performance exists. This confirms the interest of policy intervention. This can be checked once more with Table 8 that relates the specific results for our three illustrative farms.

Table 8: Performance results and potential reduction of energy in MJ for illustrative farms with uncertainty

	Farm 20	Farm 39	Farm 43
Optimistic EP	0.6017	0.9095	1
Potential reduction in energy	*706 221*	*91 389*	*0*
Pessimistic EP	0.2868	0.4912	1
Potential reduction in energy	*2 367 865*	*923 026*	0
Optimistic TP	0.8244	1	1
Potential reduction in energy	*311 354*	*0*	*0*
Pessimistic TP	0.8244	1	1
Potential reduction in energy	*583 002*	*0*	*0*
Optimistic AP	0.7299	0.9095	1
Potential reduction in energy	*394 867*	*91 389*	*0*
Pessimistic AP	0.3479	0.4912	1
Potential reduction in energy	*1 784 863*	*923 026*	0

In Table 8, we see that the potential reduction in energy of farm **39** can be multiplied by ten from the optimistic case to the pessimistic case. This is quite different for farm **20** for whom it is multiplied by more than three. Nevertheless, the difference in MJ between the optimistic case and the pessimistic case is higher for farm **20** than for farm **39**: 1.662 millions of MJ with respect to 831 637 MJ. In both cases, the difference is quite high. As a consequence, it is important to bear these boundaries in mind when designing a public policy. We furthermore see in Table 8 that, for farm **39**, the uncertainty relies only on the effect of input reallocation. It is not the case for farm **20** that can also reduce the inputs used: the uncertainty of the potential reduction in energy of this farm is equal to 271 648 MJ for the potential due to the reduction of input use and it is equal to 1 3896 996 MJ for the potential due to the reallocation of inputs.

As a consequence, this extension of the basic energy performance decomposition allows policy makers to design their policies according to their risk preferences. Indeed, a risk-neutral policy-maker will base its policy on the deterministic rankings. But a risk-averse policy maker will use the pessimistic rankings and a risk-lover one, the optimistic one.

Furthermore, the extension proposed allows leading a robust sensibility analysis of the deterministic EP scores. We ran some rank correlation tests in order to check the consistency between the rankings obtained in the deterministic setting and the one obtained when the energy content of inputs is uncertain in our sample. Again, we cannot accept the null hypothesis of independence. Table 9 summarizes the correlation coefficients calculated for EP rankings.[4]

Table 9: Rank correlation coefficients of energy performance and allocative performance rankings

	EP rankings	**optimistic EP rankings**	**pessimistic EP rankings**
EP rankings	1.0000*		
optimistic EP rankings	0.9729*	1.0000*	
pessimistic EP rankings	0.7662*	0.6298*	1.0000*

*: statistically significant test at 5% level.

	AP rankings	**optimistic AP rankings**	**pessimistic AP rankings**
AP rankings	1.0000*		
optimistic AP rankings	0.9534*	1.0000*	
pessimistic AP rankings	0.6637*	0.4679*	1.0000*

*: statistically significant test at 5% level.

From Table 9, we see that, in our sample, the deterministic method is a good approximation of the EP rankings in the most favorable scenario with respect to the energy content of inputs (optimistic case): the correlation coefficient is close to one. It is not so obvious for the least favorable scenario: the correlation coefficient is lower. This means that an energy policy designed with respect to the deterministic rankings of farms is more appropriate if the energy content of inputs is lower than the mean than if the energy content of inputs is higher than the mean. As a consequence an energy policy designed towards particular firms can not have the expected effects if the energy content of inputs is lower than the mean. Concerning the correlation coefficients calculated for AP rankings, one can observe that the correlation coefficients are lower than for the EP rankings. As a consequence, in our sample, an energy policy based on input reallocation will be more sensible to the uncertainty of the energy content of inputs.

A second result follows.

[4] We ran the same tests with AP rankings and the results are the same one.

Result 2: *When the energy content of inputs is considered as uncertain but the min and the max are available, policy makers cannot based their policies on an average. DEA methods allow deriving upper and lower bounds for the energy performance and allocative performance through the incorporation of weight restrictions. And the regulator can choose to base its policy on the rankings corresponding to its risk preferences.*

5. Conclusion and extensions

To conclude, within the framework of our sample, on average, a policy designed in order to induce farms moving towards the less intensive-energy farms will save up to 52% of energy. We showed how DEA methods could be used in order to design more accurate energy policies in the agricultural sector than the one designed with current indicators. First, DEA methods provide information on energy performance of farms that can help policy makers to target energy policy toward specific farms that need it. Secondly, results indicate that the lack of energy performance in the agricultural sector can be driven either by mismanagement of input or by a bad choice of input mix. DEA methods allow policy makers to design the policies differently depending on the type of inefficiencies that characterizes a farm. If a farm is characterized by bad technical performance score, the energy policy will consist in giving farms some advices in order to reduce the amount of inputs used in order to produce the same amount of outputs; if it is characterized by a bad allocative performance score, it will be helpful to study energy-extensive agricultural systems in more details and to compare them to energy-intensive agricultural system in order to implement the accurate energy policy. Thirdly, we showed that DEA methods allow to lead a robust sensibility analysis of the basic results other the uncertainty of energy content of inputs, and thus to test the need for policy intervention in different contexts.

Nevertheless, the data used to build the technology can be subjected to uncertainty. Indeed, the 52% of energy savings can be included between 44% and 71%. In this paper, we proposed to remove the problems of imprecise data by adopting the Camanho and Dyson (2005) procedure to derive both upper and lower bounds for energy performance. Other problems remain to be solved as the fact that our results are based on estimated technology and not on true technology. Therefore, some additional analysis could be relevant to achieve more robust results. Bootstrap procedure as proposed by Simar and Wilson (1998, 2008) and detecting outlier methods (Wilson, 1993; Simar, 2003) could help. Some other approaches like robust alternatives to DEA models (Cazals et al, 2002; Daraio and Simar, 2006) could also be considered.

Furthermore, in order to check the cost of the policies discussed, it would be interesting to calculate the difference between the costs of energy-optimal and cost-optimal input use. In the certain case, the cost-optimal input use can be obtained in the same way as the energy-optimal input use with primal programs, the only difference being that one need to use the inputs price system. In order to follow Camanho and Dyson (2005) methods, we chose a dual approach. It does not allow computing the cost of the policies in the uncertain case. Mostafaee and Saljooghi (2010) method would be more appropriate. It would also be interesting to compare the results obtained with each methodology. Nevertheless this would consist in a new and different work from this one. It is why it is left for a future work.

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