Renewable Energy 92 (2016) 397–404

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Productivity and efficiency measurement of the Danish centralized biogas power sector

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ARTICLE INFO

Article history:
Received 14 February 2015
Received in revised form
8 July 2015
Accepted 7 February 2016
Available online xxx

Keywords:
Biogas energy
Data envelopment analysis
Denmark
Malmquist index
Total factor productivity

ABSTRACT

The widespread use of the renewable energy sources in the future's energy production is necessary, in order to avoid the predicted environmental, economic and social effects which can be derived from the overuse of fossil fuels. Denmark has announced to be fossil fuel independent with a renewable energy based heat and power source by 2050. Theoretically, the centralized biogas combined heat and power plants can play a determinant role in the subsequent Danish energy supply scheme, due to its feature to satisfy base load demand. The productivity and efficiency analysis of the currently operating Danish centralizes biogas CHP power plants is crucial in order to study whether there is a most efficient power plant which can be introduced as a “best practice” innovative technology for the future's Danish biogas power plants. In this paper we use the intertemporal Malmquist total factor productivity DEA method to analyze the change in the efficiency and productivity of the Danish centralized biogas power plants in the period 1992–2005.

1. Introduction

The development of the biogas power plants in Denmark has started after the first oil crisis. The purpose of the Danish energy policies at that time was to increase the share of the domestic resources against imported crude oil and to establish a more diversified energy supply scheme [28]. The environmental policies of the 1980s, intended to protect the water quality of the above- and belowground reservoirs, contributed to the wide spread of the Danish centralized biogas CHP plants [18]. However, the uncertainties caused by liberalization process of the energy market – replacing the fixed-price subsidy scheme with market determined price – resulted in no further expansion of the Danish centralized biogas sector [23,24].

In accordance with the current energy policy, Denmark announced to be fossil fuel independent with a renewable energy based heat and power source by 2050 [29]. Due to the predicted increased capacity of the intermittent sources, the based load power plants using renewable resources (e.g. biogas CHP plants) will play the key role in the new energy supply scheme. Before the further expansion of the Danish biogas sector, a productivity and efficiency analysis of the current biogas power plants is essential in order to possess benchmark for the future CHP plants. Therefore, in this paper the focus is on the productivity and efficiency measurement of the centralized Danish biogas power plants in the period 1992–2005, using intertemporal data envelopment analysis (DEA) method incorporates Malmquist index.

The paper is organized in the following way. In the next section the method is described including a literature review of applications to the energy and biogas sectors. In the subsequent section the DEA approach for dynamic productivity analysis is discussed. The case study is introduced in Section 4 while in Section 5 the results are presented. The paper ends with concluding the findings in Section 6.

2. Literature review

Efficiency and productivity measurement methods can be differentiated whether parametric econometric theory is used, or *a prior* assumptions regarding the correspondence between input and output have not been established (i.e. non-parametric methods). The previous group contains methods e.g. least square econometric models and stochastic frontier technique [2,21], while in the latter group the non-parametric data envelopment analysis (DEA) method is considered [8].

The non-parametric data envelopment analysis models (e.g. the

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http://dx.doi.org/10.1016/j.renene.2016.02.024
0960-1481/

radial CCR and BCC or the non-radial SBM) can be used to calculate technical efficiency of decision making units (DMUs). DMUs possess the highest output/input ratios of the sample frame the efficient frontier, with an assumed 100% efficient level. Those decision making units which are not lying on the frontier are considered to be inefficient. The previously mentioned basic DEA methods use static point of view, since the devised efficient frontier does not change over time.

However, when intertemporal productivity changes are studied, the technological innovation also has to be considered, besides the variations in the efficiency levels. Therefore, the expansion of the static DEA models is required, since in that dynamic environment the technological changes also contribute to the productivity changes of DMUs. The literature describes two methods which analyze changes of total factor productivity (TFP) based on Malmquist TFP index. Based on Nishimizu and Page [22]; Coelli et al. [8] introduce the Stochastic Frontier-like Methods, where the parametric stochastic production frontier theory is used in order to calculate technical change and efficiency. Total factor productivity can also be estimated by applying non-parametric DEA method to calculate the different distance functions of Malmquist TFP change indices. Once these indices are determined, technical change and technical efficiency results can be derived [8].

San Cristóbal [25] highlights the fact that the power sector related DEA literature is gathered from applications on electricity distribution and on power generation units. Zhou et al. [32] gives a detailed literature survey on DEA method used in energy and environmental related studies. As these papers show, despite the significantly increasing use of data envelopment analysis method in productivity and efficiency measurement in the power sector, the application of this theory on biogas power plant is still not widespread. Madlener et al. [20] investigates the performance (i.e. efficiency) of 41 Austrian biogas power using multi criteria (MCDA) and data envelopment analysis methods. This paper suggests the simultaneous usages of these two approaches as complementary techniques when managerial preferences are considered. While Djatkov et al. [13] uses DEA in order to analyze the efficiency of 10 biogas plants in Bavarian region, Germany, Djatkov and Effenberger [12] expands the methodology by applying the previously mentioned DEA method and the multi criteria technique to study the same plants, simultaneously. In the latter case, the conclusion is that the combined use of DEA and MCDA enables to analyze the efficiency of the biogas from all aspects, including technical, economic and environmental aspects. Djatkov et al. [14] develops a fuzzy sets theory based model in order to analyze the performance of 10 biogas power plants.

DEA methods are also used to compare the efficiency of several other types of renewable energy (RE) technologies [25] and [19]. San Cristóbal [25] considers 13 different RE technologies and compares their performance by applying multi criteria data envelopment analysis (MCDEA). On the other hand Lo Sorro & Ferruzzi [19] studies the efficiency of 21 technologies (both conventional and renewable), using DEA methods. Surprisingly, it is the large-scale wind turbine, a RE technology, which has been found to be the most efficient among the other technologies.

Based on Zhou et al. [32] several articles exist which study the intertemporal productivity of electricity generating units, using non-parametric Malmquist TFP index method. Yunos and Hawdon [31] analyzes the productivity changes of the Malaysia's National Electricity Board, considering the performance of transmission system operator of 26 other countries and 15 year timescale. Färe et al. [16] uses Malmquist input based TFP index in order to examine the productivity of 19 electricity generating utilities, between 1975 and 1981. Similarly, Chitkara [6] applies the same Malmquist TFP method to calculate the productivity changes of Indian power plants considering a five year period, and Agrell and Bogetoft [1] does a time series study of Danish district heating and cogeneration system units, in order to assess their environmental and economic efficiencies. Contrary to the previously mentioned articles, Sueyoshi and Goto [27] uses slack-adjusted data envelopment analysis (SA-DEA) method to intertemporal productivity change measurement. Applying the SA-DEA model, the efficiency and productivity of the ten electric power company is calculated on a 10 year timescale, by comparing the efficiency results to the fixed base (first) year. At the same time, Goto and Tsutsui [17] makes a bilateral comparison between Japanese and US electrical facilities, calculating with Intertemporal Efficiency Index (IEI).

For further explanation of the different (parametric and non-parametric) efficiency and productivity measurement methods see Coelli et al. [8]. Cooper et al. [10] and Cooper et al. [11] give introduction to data envelopment analysis method, while Seiford [26] and Cook and Seiford [9] make historical summary on DEA and publish a wide range of reference of literature on this field. In the next section, we will briefly introduce DEA and the Malmquist approach.

3. DEA approach for dynamic productivity analysis

The DEA method involves mathematical programming in order to determine the (in)efficiency of those DMUs, which do not belong to the efficient frontier (i.e. the border of the production possibility set, which indicate the efficient production). DEA is called non-parametric method, since it does not use fixed (pre-determined) weights for the inputs and outputs of all DMUs', but it derives variable weights from the given data. Moreover, DEA does not require the functional forms to be pre-assumed, contrary to the statistical regression (parametric) approach [10].

One basic DEA model, the CCR model [4] was based on the previous work of Farrell [15]. This model uses linear programming in order to maximize the output and input ratio of all DMUs, deriving the optimal weights of the inputs and outputs (also called multipliers) form the data set [11]. The CCR model assumes constant returns-to-scale, and it is applicable with both input- and output-orientations, severally. Banker et al. [33] published the BCC model, as an extension of the CCR model which assumes variable returns-to-scale. Both CCR and BCC models[1] are called “radial measure” model and used to calculate technical efficiency (purely technical and scale efficiencies).

Opposite the radial measure theory, non-radial DEA models combine both input- and output-orientations with focus on slack analysis (e.g. Additive model and Slacks-based measure of efficiency). These non-radial models differ from CCR and BCC theories by their translation invariance feature, since the additive [5] and slacks-based measure (SBM) models can handle semipositive input and output data [10]. The SBM model [30] has further advantages on additive model, since the previous has ability to measure efficiency with the property of unit invariance [9].

When the focus is on an intertemporal economic analysis of changes in DMU's efficiency and technology, the previously introduced DEA methods can be used to calculate the distance functions for Malmquist TFP index. Fig. 1 depicts an industry with three performers (DMUs) whose productivities are studied in two successive periods; the bth (base) and the current tth periods. Every decision making units use two inputs (x_1 and x_2) in order to produce a single output (y). On the axes the standardized inputs are illustrated, thus the points indicate the amounts of the two inputs

[1] CCR is named after Charnes, Cooper and Rhodes and BCC is named after Banker, Charnes and Cooper [33].

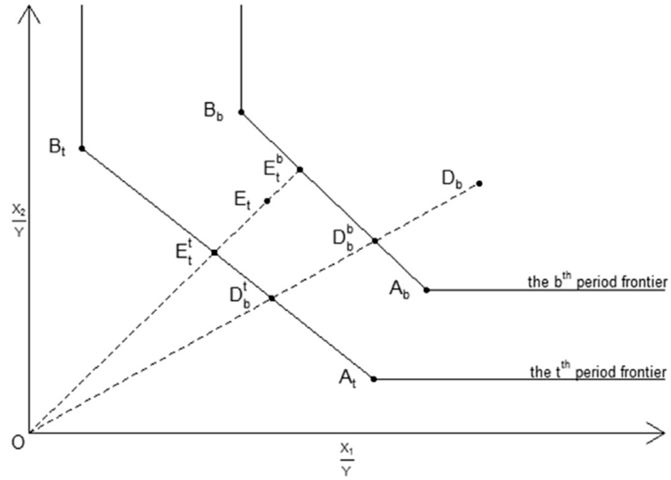

Fig. 1. The Malmquist productivity index and its components - two input one output case.

are required to generate a unit of output. As one can see, the efficiency frontier in the base period (bth) is determined by the two DMUs A_b and B_b, thus they represent the best practices for the third, inefficient decision making unit (D). In the current − second −period (tth) the same two DMUs (A_t and B_t, respectively) depict the efficiency frontier and again, the third DMU is the one whose production process is inefficient (now it is indicated by point E).

Given an input-orientation DEA approach (where one can ask by how much the inputs of a DMU can be reduced without lowering the amount of output it produces, i.e. until it reaches the frontier), the technical efficiency of the third − inefficient − DMU (D) in the base period is calculated as OD_b^b/OD. The technical efficiency of the same DMU (E) in the current period is OE_t^t/OE.

By definition, the efficiency change (also known as catch-up effect) studies the improvement of the efficiency of a DMU compared to the respective frontier. Using the DEA distance functions the technical efficiency change is calculated as follows;

$$\text{Technical Efficiency change (Catch}-\text{up)}: \quad EffCh = \frac{\overline{OE_t^t}\big/\overline{OE_t}}{\overline{OD_b^b}\big/\overline{OD_b}} \tag{1}$$

Furthermore, besides the technical efficiency, the technological innovation can also contribute to the increase in productivity; as one can see, the efficiency of the two 'best practice' DMUs could improve from the bth period to the tth period. Given all performers are rational, this development is due to the technological innovation. The technical change over periods for the third inefficient DMU is calculated as follows;

$$\text{Technical change (Frontier}-\text{shift)}: \quad TechCh = \left[\frac{\overline{OD_b^b}\big/\overline{OD_b}}{\overline{OD_b^t}\big/\overline{OD_b}} \times \frac{\overline{OE_t^b}\big/\overline{OE_t}}{\overline{OE_t^t}\big/\overline{OE_t}}\right]^{1/2} \tag{2}$$

Therefore, the total factor productivity change between the base and current periods for the inefficient DMU is the aggregation of the previously introduced two effects and calculated as;

$$\text{Malmquist TFP Index}: \quad MI = EffCh \times TechCh = \left[\frac{\overline{OE_t^t}\big/\overline{OE_t}}{\overline{OD_b^b}\big/\overline{OD_b}}\right] \times \left[\frac{\overline{OD_b^b}\big/\overline{OD_b}}{\overline{OD_b^t}\big/\overline{OD_b}} \times \frac{\overline{OE_t^b}\big/\overline{OE_t}}{\overline{OE_t^t}\big/\overline{OE_t}}\right]^{1/2} \tag{3}$$

This input-based index can be further decomposed, because changes in technical efficiency can be divided into changes in pure technical efficiency and changes in scale efficiency. Improvement of scale efficiency indicates the DMU has moved closer to the optimal scale and this is, as the other components in (3) a source of change in productivity. Here we have presented the Malmquist input-based productivity index, since similarly the biogas plants are assumed to use two inputs (animal manure and other organic waste) in order to produce a single output (biogas), which output can then be converted into heat or electricity. However, the actual empirical calculations used a Malmquist Output-based approach where one ask by how much the level of the output processed in the Danish biogas plants can be increased when the input usage stays unchanged. Either approach will give the same results [8].

4. Data source

In this empirical analysis the focus is on the productivity analysis of the Danish centralized biogas power plants in the period between January 1992 and December 2005.[2] During this period of time biogas production has obtained support in different ways; from the early 1990s unit based direct subsidy has been allocated for electricity produced by biogas and for biogas that has been sold to natural gas network. Furthermore, those heat plants, which have used biogas instead of fossil fuels, received indirect support through tax exemptions. While these economic incentives have been assigned during the 1990s and can be obtained since then, capital subsidy − to stimulate the installation of new biogas plants − was granted until the very beginning of 2000s. Therefore in our study we analyze the changes in productivity and efficiency of the Danish biogas sector as a result of the modified energy policy.

The monthly based biogas productions and the utilized inputs data for Denmark have been published in the quarterly released 'Dansk BioEnergi' journal [3]. Although in this time period twenty-two centralized biogas plants were in operation in Denmark, due to lack of data, only twenty power plants have been taken into account in the productivity analysis[3] and nineteen of them have been assigned for empirical research.[4]

In the study annual-based aggregated data have been calculated and used in the DEA analysis, due to the assumption that technical change (frontier-shift) can occur in long run time period (e.g. from

[2] Changes in policy in the period where we had data allowed us to analyze the impact of those changes on productivity and efficiency of the Danish biogas sector in detail. Besides the fact that there is no data available since April 2006, we can also state that as there have been no changes in energy policy for biogas in Denmark since 2005.

[3] *Helsingør* and *Skovsgård* power plants have been excluded from the productivity analysis, due to the scantly provided input data and for the short operation period – these biogas plants have been phased out in 1996.

[4] *Vegger* power plant proved to be an outlier due to its large distant from the observations of production of the other biogas power plants, thus *Vegger* power plant has also been excluded.

Table 1
Input and output categories.

Variables	Description	Unit of measurement
Input		
AM	Animal Manure	Cubic meter (m^3)
OW	Other organic waste	Cubic meter (m^3)
Output		
BP	Biogas product	Cubic meter (m^3)

5. Results

Using the Data Envelopment Analysis Computer Program (DEAP), the Malmquist TFP Indices have been calculated for the nineteen centralized Danish biogas power plants for the time period between January 1992 and December 2005 [7]. Data for 1992 has been used as benchmark, by assuming those observations to be the unit – or base – of the calculation for productivity indices year-to-year). Furthermore, a two input and single output case has been considered – variables described in Table 1, although other output results (e.g. electricity and heat production) have been published as well. The biogas which is the primary product generated in the power plant can be further used to create electricity (by running a generator) or to produce district heat (by burning it in a gas-fired plant); thus selecting only the primary product as an output for DEA keeps the model simple and doesn't let double counting on production results. One can see the summary statistics of the data set on Table 2(a–d).

Table 2a
Data summary (reactor size).

Reactor size	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
No. of PP	7	9	11	13	16	18	19	19	19	19	19	19	19	19
Overall capacity (m^3)	28950	29950	34796	43476	57276	61976	66709	66226	65476	66751	68966	69786	73765	77005
Min. capacity (m^3)	600	600	600	600	600	600	600	600	600	600	750	750	750	750
Max. capacity (m^3)	7600	7600	7600	7600	7600	7600	7600	7600	7600	9000	9000	9000	9200	9200
Avg. capacity (m^3)	3619	3328	3163	3344	3580	3443	3511	3486	3446	3513	3630	3673	3882	4053
SD of capacity (m^3)	2784	2746	2448	2567	2426	2318	2287	2301	2333	2469	2470	2450	2524	2569

Table 2b
Data summary (output).

Output	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
No. of PP	7	9	11	13	16	18	19	19	19	19	19	19	19	19
Overall output (1000 m^3)	16290	20283	23934	28467	32615	40167	47685	48834	52929	55170	57894	62211	63188	64559
Min. output (1000 m^3)	326	54	330	302	226	240	282	241	325	375	342	310	367	364
Max. output (1000 m^3)	4068	4726	5401	5111	4932	5226	5842	5664	7236	6416	6663	7192	7214	6855
Avg. output (1000 m^3)	2036	2254	2176	2190	2038	2231	2510	2570	2786	2904	3047	3274	3326	3398
SD of output (1000 m^3)	1387	1764	1741	1595	1343	1489	1645	1589	1913	1732	1838	2109	2064	2167

Table 2c
Data summary (input 1 – animal manure).

Input 1 – animal manure	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
No. of PP	7	9	11	13	16	18	19	19	19	19	19	19	19	19
Overall input (1000 m^3)	396.5	466.5	498.8	589.7	762.7	911.8	992.4	1029.3	1011.4	1105.5	1186.1	1248.8	1241.0	1216.6
Min. input (1000 m^3)	10.5	1.3	8.9	8.5	4.7	2.8	7.5	9.0	9.7	10.7	11.0	10.4	10.9	6.2
Max. input (1000 m^3)	118.4	129.1	123.3	103.5	113.5	122.1	121.9	129.1	131.4	142.4	151.5	184.0	181.5	187.0
Avg. input (1000 m^3)	49.6	51.8	45.4	43.4	47.7	50.7	52.2	54.2	53.2	58.2	62.4	65.7	65.3	64.0
SD of input (1000 m^3)	40.6	52.5	43.3	37.4	36.7	43.7	41.2	40.6	40.6	44.2	47.3	52.3	49.8	50.2

As the number of centralized biogas power plants has permanently increased in the observed period so had been enlarged the overall reactor capacity – except for the period between 1998 and 2000, when power plants could not operate due to maintenance work. While the overall reactor capacity has increased by 166%, the total output has quadrupled with a simultaneous threefold increase in both – animal manure and organic waste – inputs.

The average reactor capacity has increased by ten percent, which has resulted in a 67% increase in the average output between 1992 and 2005. Moreover, a small-time increase in the average input use has been observed together with a slight rise in the dispersion of input usage.

of the further years. The cumulated productivity indices for the average unit are presented in Table 3. The same results are displayed in Fig. 2.

The results show that the average annual total factor productivity increased by 2.5% annually in the examined period. The yearly technical change was 3.6% while the technical efficiency change was annually decreasing by 1.1%. So, the driver of total factor productivity growth was technical progress, because the technical efficiency effect ("catching up effect") was negative. The pure technical efficiency was decreasing by 1.1%, while the scale efficiency was increasing by 0.1%. The scale of production was therefore improved only very slightly in the period and the reason for increased technical inefficiency was due to increasing pure technical inefficiency. This means that the production in the period on average became more and more inefficient, however only to a minor extent. The technical change mainly happened in the first 7 years when new plants entered the sector and in the later period the gain in total factor productivity was mainly due to catching up effects, as it can been seen on Fig. 3(a–e). The red frontier lines indicate the 'best practice' unit isoquant curves in the selected years, while the unit input usages of the individual DMUs are presented with an assigned color and number – e.g. in each selected year, the purple color with the number 17 next to it

Table 2d
Data summary (input 2 – organic waste).

Input 2 – other organic waste	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
No. of PP	7	9	11	13	16	18	19	19	19	19	19	19	19	19
Overall input (1000 m^3)	105.6	137.8	168.2	196.2	214.6	249.9	313.1	281.8	275.5	270.9	272.5	269.2	298.2	293.4
Min. input (1000 m^3)	0.9	0.3	1.5	1.2	1.0	0.7	0.8	1.0	0.9	1.2	1.1	1.3	1.3	0.8
Max. input (1000 m^3)	41.6	47.0	42.3	39.1	33.9	39.1	43.1	44.4	43.5	33.7	35.1	38.7	49.2	51.6
Avg. input (1000 m^3)	13.2	15.3	15.3	15.1	13.4	13.9	16.5	14.8	14.5	14.3	14.3	14.2	15.7	15.4
SD of input (1000 m^3)	13.0	14.8	14.1	13.8	11.2	11.4	12.2	11.6	11.6	9.8	9.6	9.5	11.5	13.1

Table 3
Productivity measure for the average unit (Base year 1992).

	1992–'93	1992–'94	1992–'95	1992–'96	1992–'97	1992–'98	1992–'99	1992–2000	1992–'01	1992–'02	1992–'03	1992–'04	1992–'05
Total productivity growth	0.987	0.996	1.109	1.095	1.042	0.991	1.038	1.168	1.241	1.265	1.306	1.266	1.373
Frontier shift	1.126	1.283	1.573	1.366	1.641	1.323	1.334	1.361	1.354	1.436	1.503	1.366	1.586
Catching-up effect	0.877	0.776	0.705	0.802	0.635	0.749	0.778	0.858	0.917	0.881	0.869	0.926	0.865
Pure technical efficiency	0.916	0.918	0.914	0.937	0.798	0.853	0.879	0.867	0.918	0.925	0.948	0.951	0.854
Scale efficiency	0.958	0.846	0.772	0.856	0.796	0.878	0.886	0.990	0.999	0.954	0.917	0.976	1.016

displays the amount of inputs have been used by 'Vester Hjermitslev' biogas plant in order to produce one unit of output. Considering the chronological improvement of technical change, one can see the frontier shift to a more efficient level, where the biogas plants could produce the same unit output by utilizing less input. The improvement of technical change last until the beginning of 2000s, while the "catching up effect" has started to rise at that time due to a slight increase in the ratio of the units' efficiency measure and to the invariant technical efficiency level – i.e. the unit input utilization scores move closer to the constant frontier.

In Fig. 4 the distribution of total factor productivity across units for the period 1992–2005 is shown. Each histogram denotes a power plant and the width of the histogram is proportional to each units share from the overall capacity. As one can see from Table 4, there were six units out of the nineteen within the examined time period, who observed negative total productivity growth. This result is significant, especially if the size of these units is considered; the aggregated capacity of power plants with negative total productivity growth counts for more than forty percent of the overall capacity.

On the other hand, Lintrup biogas plant, the unit with the largest individual capacity has achieved the second highest productivity growth, more than 10%. The capacity of the six most productive units – whose productivity growth rate exceeded the five percent – add up to the 40% of the overall capacity.

The frontier productivity indices have been shown in Table 3. Although a yearly average frontier productivity growth of 3.6% has been calculated for the period 1992–2005, there occurred four years when the frontier shifted backwards. These unexpected event could happened due to the fact, that only a few number of units determined the frontier in the previous year of decline; a decrease in the efficiency score of those – previously – best practice units, assuming other units having insignificant efficiency changes, have had an effect on the frontier productivity, as well as on their own efficiency level.

As it was already stated, the average annual decrease of 1.1% in technical efficiency change has been observed. Besides the constantly weak performance of some of the units, which certainly contribute to the decline of the annual technical efficiency scores, the outstanding operation of several units enhanced this result; a prompt and considerable increase in the efficiency level of the best practice units – which unexpectedly shifted the frontier outwards – urgently raised the gap between the efficiency levels of efficient and inefficient units.

In the 2000s, a slight increase in technical efficiency change can be observed, although this improvement couldn't compensate the scant accomplishment in the 1990s.

Table 5 presents the operation period of the power plants within the examined timescale – shaded area. Furthermore, the frequency of occurrence of the units as frontier unit has also been marked in the table. As one can see, there are several units which were constantly in the reference set, thus leading the technical progress over time (e.g. Revninge, Studsgård, Vester Hjermitslev and Vaarst/Fjellerad power plants).

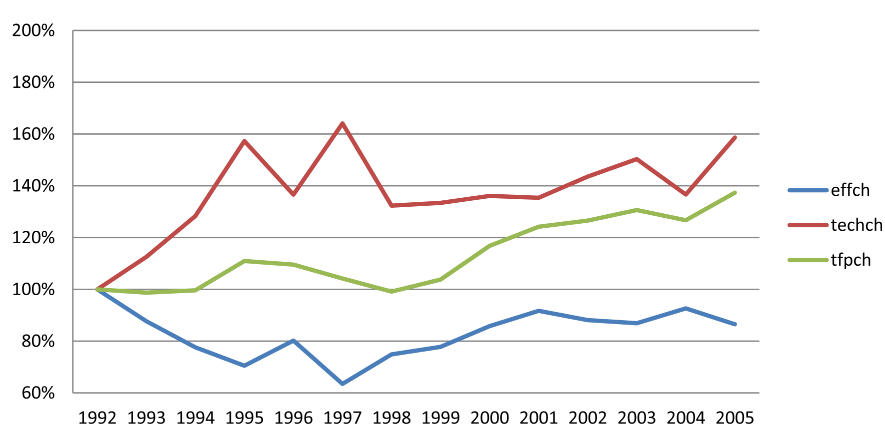

Fig. 2. Trend analysis (Changes in efficiency, technology and total factor productivity).

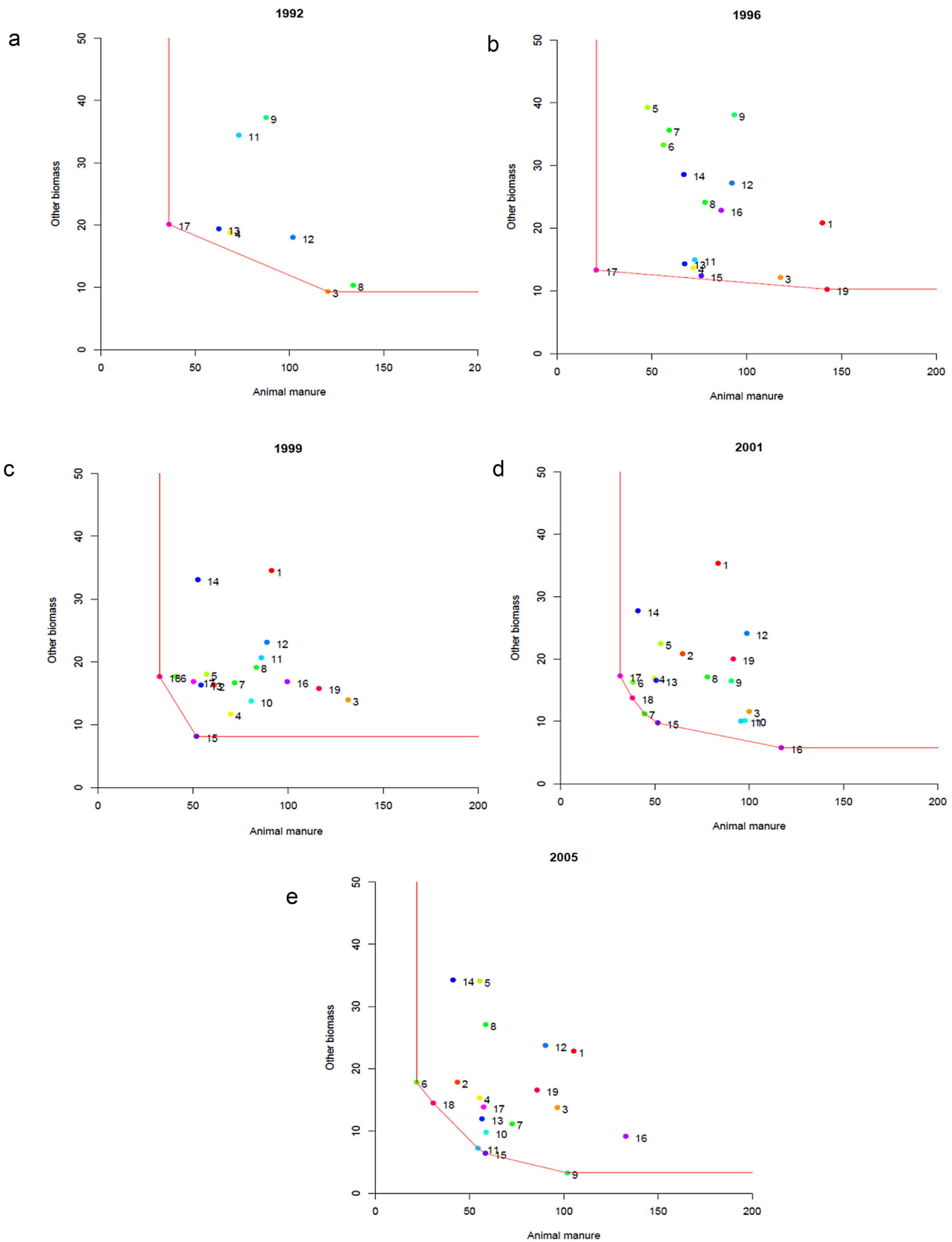

Fig. 3. Unit isoquant curves with unit input usage scores. a Unit Isoquant curve (1992). b Unit Isoquant curve (1996). c Unit Isoquant curve (1999). d Unit Isoquant Curve (2001). e Unit Isoquant Curve (2005).

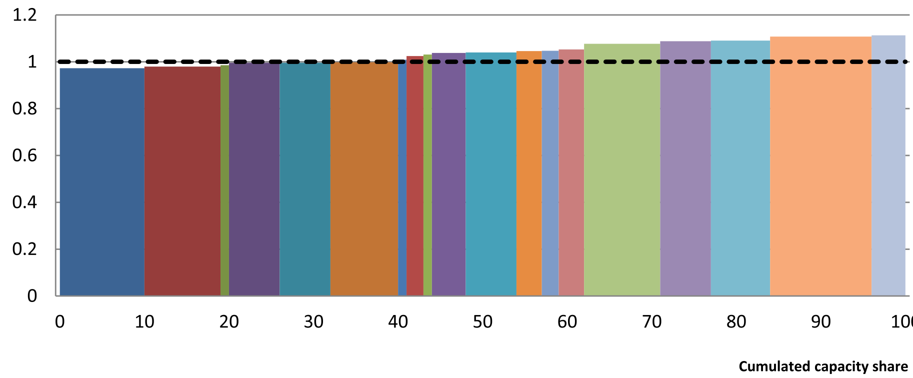

Fig. 4. The distribution of Malmquist productivity measure – average unit.

Table 4
Total productivity growth by firms means.

Unit	Catching-up effect	Frontier shift	Pure technical efficiency	Scale efficiency	Total productivity growth
Blaabjerg	1.004	0.992	0.966	1.040	0.996
Blåhøj	1.008	1.038	1.000	1.009	1.047
Davinde	0.946	1.041	0.948	0.999	0.985
Fangel	0.983	1.057	0.983	1.001	1.040
Filskov	1.025	1.006	1.002	1.023	1.031
Hashøj	1.085	0.992	1.029	1.054	1.077
Hodsager	1.010	0.999	1.013	0.997	1.009
Lemvig	0.963	1.018	0.988	0.974	0.980
Lintrup	1.049	1.056	1.000	1.049	1.108
Nysted	1.032	1.057	1.033	0.999	1.090
Revninge	1.045	1.065	1.044	1.001	1.113
Ribe	0.965	1.033	0.995	0.969	0.996
Sinding-Ørre	1.007	1.045	1.000	1.007	1.053
Snertinge	1.057	0.989	1.005	1.051	1.046
Studsgård	1.000	0.998	1.000	1.000	0.998
Thorsø	1.059	1.027	1.003	1.056	1.088
Vester Hjermitslev	1.000	1.038	1.000	1.000	1.038
Vaarst/Fjellerad	1.000	1.025	1.000	1.000	1.025
Århus Nord	0.937	1.037	0.945	0.992	0.973

Table 5
The establishment of units and their occurrence on the frontier.

	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Blaabjerg														
Blåhøj														
Davinde	X	X					X							
Fangel		X												
Filskov														
Hashøj												X	X	X
Hodsager										X				
Lemvig														
Lintrup														X
Nysted							X		X					
Revninge											X		X	X
Ribe														
Sinding-Ørre									X					
Snertinge														
Studsgård						X		X	X	X	X	X	X	X
Thorsø										X				
Vester Hjermitslev	X	X	X	X	X	X	X		X	X	X			
Vaarst/Fjellerad							X	X	X	X	X	X		X
Århus Nord				X	X									

The benchmark firms are diverse. One firm (e.g. Lintrup biogas plant) didn't experienced technical progress, but had high technical efficiency scores, meaning that this firm optimized its production. Another firm (e.g. Studsgård or Vaarst Fjellerad centralized power plants) was entering after some years and it "went" directly to the frontier and stayed there. A third firm (e.g. Vester Hjermitslev biogas power plant) determined in many years the frontier in the beginning of the period and therefore it had a relative high technical progress. A fourth firm (e.g. Revninge) entered in 1998 using less of one of the inputs than other firms and by induced technical progress it "moved" the frontier.

6. Conclusion

The energy policy in early 90'ties was supporting and subsidizing investments in biogas plants including feed-in tariff prices, while in the later part of period there was no specific support or subsidies. This change in policy can be seen directly in the results of our study. There is no enlargement of the biogas sector after the determination of support scheme and the productivity growth in this period is mainly due to catching up effects with improvements in both pure technical efficiency and scale efficiency. This shows that the biogas plants have optimized their production in the period, with very few investments and hence technical progress is absent. Therefore a future energy policy for biogas, if the focus is on technical progress, might focus on investment subsidies – at least this is what this study shows.

From an economic point of view biogas might be able to play a determining role in the future Danish energy system. It depends on the relatively cost and benefits of the different energy sources, but also how the different sources interact. While biogas is not cost-efficient today, it might play a role as a base-load source.

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