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Research Article

Comparison of GHG emissions between efficient and inefficient broiler farms in Kaduna state of Nigeria using Data Envelopment Analysis (DEA): environmental sustainability

M. S. Sadiq, I. P. Singh

Abstract

This study applied a non-parametric method in determining the efficiency of farmers, discriminating efficient farmers from inefficient ones, and identifying wasteful uses of energy in order to optimize the energy inputs for broiler production. Furthermore, the effect of energy optimization on greenhouse gas (GHG) emission was investigated and the total amount of GHG emission of efficient units was compared with inefficient units. A total sample size of 55 broiler farmers were selected from Kaduna State viz. multi-stage sampling technique. Total energy used in various operations during broiler production was 77916.14 MJ (500bird)$^{-1}$. Results revealed that 63% of producers were technically efficient, while 43 producers under PTE were identified efficient (79.6%). Additionally, it was concluded that 1.38 percent [1071.54 MJ (500birds)$^{-1}$] of overall input energies can be saved if the performance of inefficient farms rose to a high level. Finally, comparative results of GHG emissions revealed that the amount of CO_2 emissions in efficient units was less than inefficient farms.

Keywords broiler, DEA, efficient vs. inefficient, environment, GHG emission

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Introduction

The quality of environment emerged as a public discourse during the early sixties as a result of some outstanding write ups on environmental crisis. These and few other literary explosions and the almost simultaneous occurrence of several ecological disasters led many to ask: "Economic growth-at what cost?" Though few growing economies today challenge unlimited growth, their continued growth of output and population will eventually lead to environmental crisis. Man must begin to see the earth as a closed system, in contrast to the older conception that natural resources are boundless and that man can develop and exploit them without limit. Thus, conservationists have a major concern regarding the unnecessary destruction of environmental resources. Environmental resources should be viewed as essential irreplaceable social capital that must be conserved intact for future generation. The foregoing discussions amply demonstrate how agriculture and environment can come in conflict with each other. As this conflict was not recognized in time, it has led to different forms of environmental degradations; adverse effects of agriculture and its growth on environment may be more indirect than in the industry. While new technologies are immensely important for agricultural development, how much cost do we have to pay in terms of degrading environmental condition has to be considered. A pertinent question arises which invites the immediate attention of the planners that whetherl the present agricultural development would be able to sustain itself or not. These points towards an exercise of rational exploitation of the things offered to mankind by environment so that the future generations with even greater demands would be satisfied.

Evolutions of new technology brought interbreed hens, so chicks attain desirable weight in a shorter period. The intensity of energy use on broiler farms is high and studies on input-output energy pattern on broiler farms are very important. Efficient use of agricultural product energies helps to achieve increased production and contributes to the profitability and agriculture sustainability in rural areas [1]. According to literature, the only study conducted on energy optimization in broiler production using DEA was done by Heidari et al. [1]; with no effort of investigating the effect of energy optimization on GHG emission in broiler production. However, literature revealed few recent studies that used DEA to estimate GHG emissions in crops production [2-10]. In this study, the same methodology was adopted for broiler farms in Kaduna State, with the objectives to specify energy use for broiler production, segregate efficient farmers from inefficient ones, identify wasteful uses of energy inputs and investigate the effect of energy optimization on GHG emission in broiler production.

Methodology

Kaduna State is located between latitudes 9^0 08' and 11^0 07' N and longitudes 6^0 10' and 80 48'E, with a land mass of about 45,567 square kilometers; and estimated population of 6,066,562. Agriculture constitutes the largest occupation, with many people participating in small-scale farming. The State is a major region of animal husbandry. Multi-stage sampling technique was used for the study. Firstly, five LGAs viz. Kaduna North, Kaduna South, Kachia, Zaria and Makarfi were purposively selected due to high intensity of poultry production. This was; followed by the stratification of poultry producers into broilers and layers in each selected LGAs, and then, random selection of 11 respondents from boiler strata in each selected LGAs; thus, given a total sample size of 55 broiler farmers. However, only 54 valid questionnaires were retrieved and subsequently treated. Data were elicited *viz*. pre-tested questionnaire coupled with interview schedule, and subsequently subjected to DEA analytical technique.

Table 1. Equivalents for various sources of energy

Items	Unit	Equivalent MJ
Human Labour	Man-hour	1.96
Chick	Kg	4.56
Broiler	Kg	4.56
Manure	Kg	18.0
Maize	Kg	7.9
Soyabean meal	Kg	12.06
Fish meal (FA)	Kg	9
Di calcium phosphate	Kg	10
H20	m3	1.02
Petrol	L	48.23
Kerosene	L	36.7
Electric motor	Kg	64.8
Electricity	kWh	11.93

Empirical model

Data envelopment analysis

DEA method forms a linear piece wise function from empirical observations of inputs and outputs. DEA is a nonparametric methodology for estimating productive efficiency based on mathematical linear programming techniques. Unlike parametric approaches, DEA does not need a function to relate inputs and outputs. The DEA encloses the data in such a manner that all experimental data points lay on or below the efficient frontier [11]. The efficient frontier is established by efficient units from a group of observed units. Efficient units are those with the highest level of productive efficiency. In DEA, an inefficient DMU can be made efficient either by minimizing the input levels while maintaining the same level of outputs (input oriented), or, symmetrically, by maximizing the output levels while holding the inputs constant (output oriented).

Technical efficiency (TE)

TE can be defined as the ability of a DMU (e.g. a farm) to produce maximum output given a set of inputs and technology level. The TE score (θ) in the presence of multiple-input and output factor can be calculated by the ratio of sum of weighted outputs to the sum of weighted inputs or in a mathematical expression given below [12]:

$$\theta = \frac{U_1Y_{1j} + U_2Y_{2j} + U_sY_{sj}}{V_1X_{1j} + V_2X_{2j} + V_mX_{mj}} = \frac{\sum_{r=1}^{s} UrYrj}{\sum_{i=1}^{m} ViXij} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

Let the DMUj to be evaluated on any trial be designated as DMUo (o = 1, 2 . . . n). To measure the relative efficiency of a DMUo based on a series of n DMUs, the model is structured as a fractional programming problem, and specified as follows [12]:

$$Max\ \ \theta = \frac{\sum_{r=1}^{s} UrYr0}{\sum_{i=1}^{m} ViXi0} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$Subject\ to: \frac{\sum_{r=1}^{s} UrYrj}{\sum_{i=1}^{m} ViXij} \le 1 \qquad j=1,\ 2 \ldots\ldots\ldots\ldots n$$

$$U_r \ge 0, \quad V_i \ge 0$$

where n is the number of DMUs in the comparison, s the number of outputs, m the number of inputs, Ur (r = 1, 2, …, s) the weighting of output Yr in the comparison, Vi (i = 1, 2, …, m) the weighting of input Xi, and Yrj and Xij represent the values of the outputs and inputs Yj and Xi for DMUj, respectively. Equation (2) can equivalently be written as a linear programming (LP) problem as follows:

$$Max:\ \theta = \sum_{r=1}^{s} UrYro \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$Subject\ to: \sum_{r=1}^{s} UrYrj - \sum_{i=1}^{m} ViXij \le 0 \quad J=1,\ 2\ldots\ldots\ldots n$$

$$\sum_{i=1}^{m} UiXio = 1$$

$$U_r \ge 0,\ V_i \ge 0$$

The dual linear programming (DLP) problem is simpler to solve than Equation (3) due to fewer constraints. Mathematically, the DLP problem is written in vector–matrix notation as follows:

$$Min:\ \theta \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

$$Subject\ to:\ \ Y\lambda \ge y_0$$

$$X\lambda - \theta X_0 \le 0$$

$$\lambda \ge 0$$

Where Y_o is the s x 1 vector of the value of original outputs produced and X_o is the m x1vector of the value of original inputs used by the o^{th} DMU. Y is the s x n matrix of outputs and X is the m x n matrix of inputs of all n units included in the sample. λ is a n x 1 vector of weights and Θ is a scalar with boundaries of one and zero which determines the technical efficiency score of each DMU. Model (4) is known as the input-oriented CCR DEA model. It assumes constant returns to scale (CRS), implying that a given increase in inputs would result in a proportionate increase in outputs.

Pure technical efficiency (PTE)

The TE derived from CCR model, comprehend both the technical and scale efficiencies. So, Banker et al. [13] developed a model in DEA, which was called BCC model to calculate the PTE of DMUs. The BCC model is provided by adding a restriction on λ (λ =1) in the model (4), resulted to no condition on the allowable returns to scale. This model assumes variable returns to scale (VRS), indicating that a change in inputs is expected to result in a disproportionate change in outputs.

Scale efficiency (SE)

SE relates to the most efficient scale of operations in the sense of maximizing the average productivity. A scale efficient farmer has the same level of technical and pure technical efficiency scores. It can be calculated as follow:

$$SE = \frac{TE}{PTE} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; (5)$$

SE gives the quantitative information of scale characteristics. It is the potential productivity gained from achieving optimum size of a DMU. However, scale inefficiency can be due to the existence of either IRS or DRS. A shortcoming of the SE score is that it does not indicate if a DMU is operating under IRS or DRS conditions. This problem is resolvable by solving a non-increasing returns of scale (NIRS) DEA model, which is obtained by substituting the VRS constraint of λ =1 in the BCC model with λ ≤ 1. IRS and DRS can be determined by comparing the efficiency scores obtained by the BCC and NIRS models; so that, if the two efficiency scores are equal, then DRS apply, else IRS prevail. The information on whether a farmer operates at IRS, CRS or DRS status is particularly helpful in indicating the potential redistribution of resources between the farmers, thus, enables them to achieve higher output.

The results of standard DEA models divide the DMUs into two sets of efficient and inefficient units. The inefficient units can be ranked according to their efficiency scores; while, DEA lacks the capacity to discriminate between efficient units; number of methods are in use to enhance the discriminating capacity of DEA. In this study, the benchmarking method was applied to overcome this problem. In this method, an efficient unit which was chosen as the useful target for many inefficient DMUs and so appears frequently in the referent sets is highly ranked.

In the analysis of efficient and inefficient DMUs, the energy saving target ratio (ESTR) was used to specify the inefficiency level of energy usage for the DMUs under consideration. Following Sadiq et al. [9-10], the formula is given below:

$$ESTR\ (\%) = \frac{(Energy\ saving\ target)}{(Actual\ energy\ input)} \times 100 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; (6)$$

Where energy saving target is the total amount of energy inputs reduced, which could be saved without reducing the output level. A higher ESTR percentage implies higher energy use inefficiency, and thus, a higher energy saving amount.

GHG emissions

CO2 emission coefficients of inputs were used to quantifying GHG emissions in broiler production. GHG emission was calculated by multiplying the input application rate by its corresponding emission coefficient (Table 2).

Table 2. GHG emission coefficients of inputs

Items	Unit	GHG coefficient (kg CO_2eq. unit-1)
Petrol	L	1.85
Kerosene	L	1.85
Electric motor	MJ	0.071
Electricity	kWh	0.608

Results and Discussion

Energy use pattern in broiler production

Table 3 presents the amount of inputs, output and their energy equivalents for broiler production. The total energy consumption was 77916.14MJ $(500\text{birds})^{-1}$. Feed with approximate share of 72.7% was the most energy consumed, followed by electricity. The main reason for high feeds energy consumption was that farmers did not have appropriate knowledge about the proper time and the amount of feeds usage. Contribution of human labor, machinery (electric motor) and H2O in comparison with other inputs in the total input energy is negligible. However, total output energy observed in the studied area was 142458.26 MJ $(500\text{birds})^{-1}$; average output of broiler and manure were 816.86Kg and 7707.41 Kg, respectively, per 500 birds.

Table 3. Physicochemical parameters

Inputs	Quantity (500birds)-1	Total energy equivalent [MJ$(500\text{birds})^{-1}$]	(%)
Chicks (kg)	222.33	1013.84	1.3
Human labour (mhr)	78.83	154.5	0.2
Feeds (kg)			
Maize	1434.076	11329.20	14.5
Soyabean meal	1878.806	22658.40	29.1
Fatty meal (FA)	2014.079	18126.71	23.3
Di-calcium phosphate	453.168	4531.68	5.8
H2O (m3)	0.1028	0.1049	0
Petrol (L)	44.63	2152.49	2.8
Kerosene (L)	13.704	502.93	0.7
Electric motor (kg)	3.045	197.32	0.2
Electricity (kWh)	1445.847	17248.96	22.1
Total energy input		**77916.14**	**100**
Output			
Broiler (kg)	816.86	3724.88	
Manure (kg)	7707.41	138733.38	
Total energy output		**142458.26**	

Source: Field survey, 2015

Efficiency measurement of broiler farmers

Results of farmers' distribution based on the efficiency score obtained by the application of CCR and BCC DEA models are shown in Figure 1. Evidently, 63 percent (34farmers) and 79.6 percent (43 farmers) from total farmers were identified as efficient farmers under constant and variable returns to scale assumptions, respectively; implying these farms could shift on CCR and BCC frontier. Furthermore, approximately 25.9 percent and 20.4 percent of TE and PTE respectively, had efficiency scores between 0.99 and 1.00. However, if the BCC model is assumed, only 11.1 percent had efficiency scores of less than 0.89; whereas, if the CCR model is considered, none had efficiency score of less than 0.89. The results of returns to scale estimation indicated that all of the technically efficient farmers (based on the CCR model) were operating at CRS, indicating optimum scale of their practices.

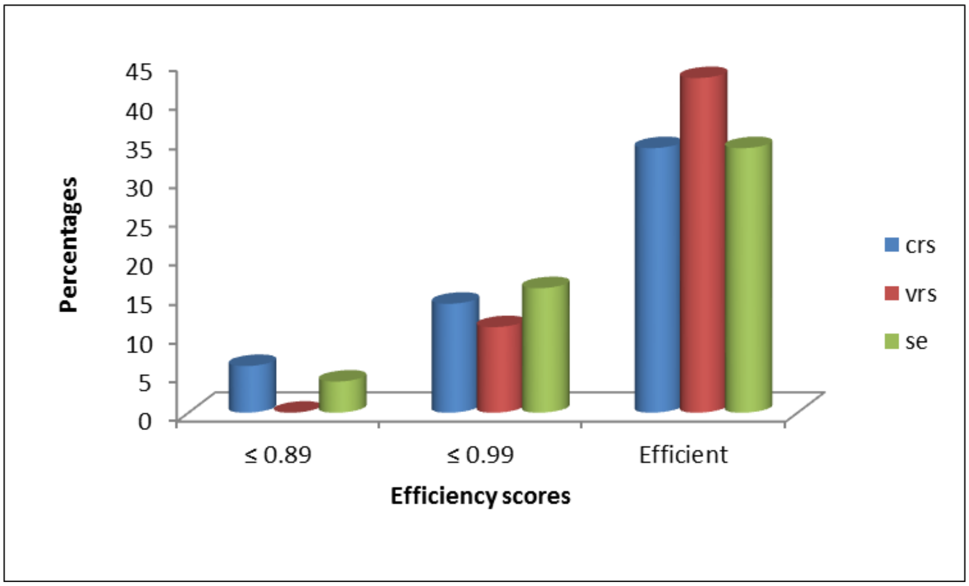

Figure 1. % Distribution of efficiency scores

Summarized statistics for the three estimated measures of efficiency are given in Table 4. Results revealed that the average values of technical and pure technical efficiency scores were 0.976 and 0.993, respectively. The technical efficiency scores varied from 0.814 – 1.00; while pure technical efficiency scores ranged from 0.904-1.00. The small variation in the technical efficiency implies that all the farmers were fully aware of the right production techniques but did not apply them properly; while mild variation in pure technical efficiency indicates that the farmers were almost rational in allocation of resources at their disposal. Average PTE provides information about the potential resource savings that could be achieved while maintaining the same output level.

Table 4. Deciles frequency distributions of efficiency scores

Efficiency level	TE	PTE	SE
≤ 0.89	6 (11.1)	0	4 (7.4)
≤ 0.99	14 (25.9)	11 (20.4)	16 (29.6)
1.00	34 (63)	43 (79.6)	34 (63)
Total	54	54	54
Minimum	0.814	0.904	0.814
Maximum	1.00	1.00	1.00
Mode	1.00	1.00	1.00
Mean	0.976	0.993	0.983
SD	0.047	0.021	0.040

Source: Computed from DEAP 2.1 computer print-out

In the case of TE, farmers with efficiency scores of less than one are technologically inefficient in energy use; while for PTE, farmers with less than one efficiency scores are wasting energy resources than required, indicating ample scope for target farmers to improve their operational practices in enhancing their energy use efficiency for adjustment strategy. If technical efficiency is assumed, average farmers need to increase their efficiency scores by 2.4 percent; worst inefficient farmers require TE adjustment scores of approximately 18.6 percent, and best inefficient farmers require approximately 0.7 percent adjustment, respectively, to be on the frontier surface. However, if an adjustment for pure technical efficiency scores is assumed, average farmers need to reduce their energy inputs by 0.7 percent; worst inefficient farmers' need approximately 9.6 percent input reduction, and best inefficient farmers require 0.2 percent input reduction, respectively, to be on the frontier surface. Based on pure technical efficiency, 34 farmers were globally efficient and operating at the most productive scale sizes of production, while 9 farmers were locally efficient entities operating at an inferior scale size. The average scale efficiency score was relatively low (0.983), showing the disadvantageous conditions of scale size. This indicates that if all of the inefficient farmers operated at the most productive scale size, about 1.7 percent savings in energy use from different sources would be possible without affecting the output level.

Returns to scale properties in broiler production

The BCC model includes both IRS and DRS, while NIRS model gives DRS. To determine whether a DMU has IRS or DRS, an additional test is required. The values of TE for both BCC and NIRS were calculated and their values were compared. The same values of TE for NIRS and BCC models show that the DMU has DRS, while different values imply that the farm has IRS. Results of RTS for some selected DMUs revealed that 34 DMUs had CRS; 12 DMUs had DRS, while 8 DMUs were found to be operating at IRS (Table 5). Therefore, a proportionate increase in all inputs leads to more proportionate increase in outputs; and for considerable changes in yield, technological changes in practices are required. The information on whether a farmer operates at IRS, CRS or DRS is particularly helpful in indicating the potential redistribution of resources between the farmers, thus, enables them to achieve higher output.

Table 5. Characteristics of farms with respect to return to scale

Scale	No. of farms	Mean energy output	
		Broiler	Manure
Sub-optimal	8	3438.38	128025
Optimal	34	3753.48	144158.82
Super-optimal	12	3834.87	130500

Source: Computed from DEAP 2.1 computer print-out

Ranking analysis of broiler production

Identifying efficient operating practices and their dissemination will help to improve efficiency not only in the case of inefficient farmers, but also for relatively efficient ones, because efficient farmers obviously follow good operational practices. However, among the efficient farmers, some show better operational practices than others, therefore, discrimination need to be made among the efficient farmers while seeking the best operational practices. In order to have the efficient farmers ranked, the number of times an efficient DMU appears in a referent set was counted (Table 6). Only efficient farms serve as peers for the inefficient farms and in this instance farms 1-2, 15-16, 17-20, 21-24, 25-26, 28-29, 31-33, 37-39, 40-41, 44-45, 47-48, 49-50, 51 and 52 are the peers. Farm 24, for example, was a peer for 7 farms making it the most comparator used farm. These efficient farms can be selected by inefficient DMUs as best practice DMUs, making them a composite DMU instead of using a single DMU as a benchmark. While the referent set is composed of the efficient units which are similar to the input and output levels of inefficient units, efficient DMUs with more appearance in referent set are known as superior unit/spark plug in the ranking. Results of such analysis would be beneficial to inefficient farmers to manage their energy sources usage in order to attain the best performance of energy use efficiency. However, these superior units/spark plugs can be use as reference means of dissemination of farm improvement by extension delivery services.

Table 6. Benchmarking of efficient DMUs

DMUs	Frequency in referent set	Ranking	DMU (farm)	Frequency in referent set	Ranking
F24	7	1	**F51**	2	5
F01	5	2	**F02**	1	6
F39	5	2	**F16**	1	6
F44	5	2	**F31**	1	6
F26	4	3	**F33**	1	6
F40	4	3	**F37**	1	6
F20	3	4	**F45**	1	6
F41	3	4	**F47**	1	6
F15	2	5	**F48**	1	6
F17	2	5	**F49**	1	6
F21	2	5	**F50**	1	6
F25	2	5	**F52**	1	6
F28	2	5			
F29	2	5			

Source: Computed from DEAP 2.1 computer print-out

Performance assessment of broiler farms

Table 7 shows the peers for each farm and the weights that these peers account for. For each inefficient farm there are peers which serve as comparators against which the farm is measured. Efficient farms do not have any peers other than themselves as they are on the efficient frontier, thus defining the efficiency. It stands to reason that the weight will be unity in the case of efficient farms. The higher the weight the more important that particular farm is as a peer for the inefficient farm in question. This means that the inefficient farm is better off comparing itself to the peer with the highest weight in order to improve its efficiency by emulating its peers. The identification of peers is important in that the peers' production technology, in this case pollution minimizing technology, can be studied and implemented by the inefficient farms. Result shows the worst inefficient DMU (DMU22) and the best inefficient DMU (DMU12). For instance, in the case of DMU22 the composite DMU that represents the best practice or reference composite benchmark DMU is formed by combination of DMU40, DMU51, DMU17, DMU1 and DMU5.

This means DMU22 is close to the efficient frontier segment formed by these efficient DMUs, represented in the composite DMU. The selection of these efficient DMUs is made on the basis of their comparable level of inputs and output to DMU22. The benchmark DMU for DMU22 is expressed as 40(0.484); 51(0.127); 17(0.099); 1(0.267) and 5(0.024), where 40, 51, 17, 1 and 5 are the DMU numbers while the values in the brackets are the intensity vector λ for the respective DMUs. The higher value of the intensity vector λ for DMU40 (0.484) indicates that its level of inputs and output is closer to DMU22 compared to the other DMUs.

Table 7. Performance assessment of broiler farms

DMUs	PTE score (%)	Benchmarks
F22	90.4	40(0.484) 51(0.127) 17(0.099) 1(0.267) 5(0.024)
F11	91.6	28(0.212) 24(0.276) 40(0.194) 26(0.068) 39(0.250)
F13	99.5	24(0.143) 48(0.004) 1(0.190) 41(0.459) 49(0.034) 29(0.059) 20(0.111)
F35	99.5	24(0.011) 20(0.094) 29(0.122) 44(0.205) 39(0.469) 1(0.099)
F12	99.8	20(0.041) 1(0.507) 44(0.392) 24(0.060)

Source: Computed from DEAP 2.1 computer print-out

Setting realistic input levels for inefficient broiler farmers

A pure technical efficiency score of less than unity for a farmer indicates that, at present conditions, he is using energy values more than required. Therefore, it is desirable to suggest realistic levels of energy to be used from each source for every inefficient farmer in order to avert energy wastage. Results in Table 8 presents the average energy usage in actual and optimum conditions [MJ (500 birds)$^{-1}$], possible energy savings and ESTR percentage for different energy sources. It is evident that, total energy input could be reduced to 76844.60 MJ (500 birds)$^{-1}$; while, maintaining the current production levels and also assuming no other constraining factors. Required energies for petrol, kerosene, machinery (electric motor) and electricity were 2086, 495.55, 192.43and 16922.59 MJ (500 birds)$^{-1}$, respectively; while chicks, human labour, feeds and H20 energies required were 1003.28, 151.72, 55992.3 and 0.1046MJ (500 birds)$^{-1}$, respectively.

Furthermore, ESTR results showed that if all farmers operated efficiently, reduction in petrol and machinery energy inputs, with respect, by 3.06 percent and 2.48 percent would be possible without affecting the output level. These energy inputs had the highest inefficiency which owed mainly to lightening of poultry huts. Artificial lighting is important in raising the production of chickens; if the housing is lit in the cooler hours before sunrise or after sunset, the chickens are able to eat more and grow well. However, day length must not be increased during the growing period of the young chicks until just before four weeks. In order to improve the farms environment as well as reduction in consumption of petrol fuel, it is strongly suggested that the heating system efficiency be raise or replace with alternative sources of energy such as biogas, solar energy, wind etc. Moreover, the ESTR percentage for total energy input was 1.38 percent, indicating that by adopting the recommendations obtained from this study, on average, about 1.3 percent [1071.54MJ(500 birds)$^{-1}$] from total input energy in broiler production could be saved without affecting the output level.

Table 8. Energy saving [MJ (500birds)$^{-1}$] from different sources if recommendations of study are followed

Input	Actual energy used [MJ(500birds)$^{-1}$]	Optimum energy requirement [MJ(500birds)$^{-1}$]	Energy saving	ESTR (%)
Chicks	1013.84	1003.28	10.56(0.99)	1.04
Human labour	154.5	151.72	2.78(0.26)	1.8
Feeds	56645.99	55992.3	653.69(61)	1.15
H2O	0.1049	0.1046	0.0003(0)	0.29
Petrol	2152.49	2086.62	65.87(6.15)	3.06
Kerosene	502.93	495.55	7.38(0.68)	1.47
Electric motor	197.32	192.43	4.89(0.46)	2.48
Electricity	17248.96	16922.59	326.37(30.46)	1.89
Total energy input	77916.14	76844.60	1071.54	1.38

Source: Computation from DEAP 2.1 computer print-out

Figure 2 shows distribution of saving energy from different sources for broiler production. It is evident that the maximum contribution to total saving energy is 61 percent from human labour. However, human labour and electricity energy inputs contributed to the total saving energy by about 91.46 percent. From these results it is strongly suggested that improving the usage pattern of these inputs be considered as priorities providing significant improvement in energy productivity for broiler production in the study area. Improving energy use efficiency of human labour *viz*. channeling of its excess to other sectors is suggested to prevent wastage by inefficient farmers. Applying alternatives sources of energy such as biogas, solar energy, wind etc is suggested to prevent electrical energy wastage by inefficient farmers.

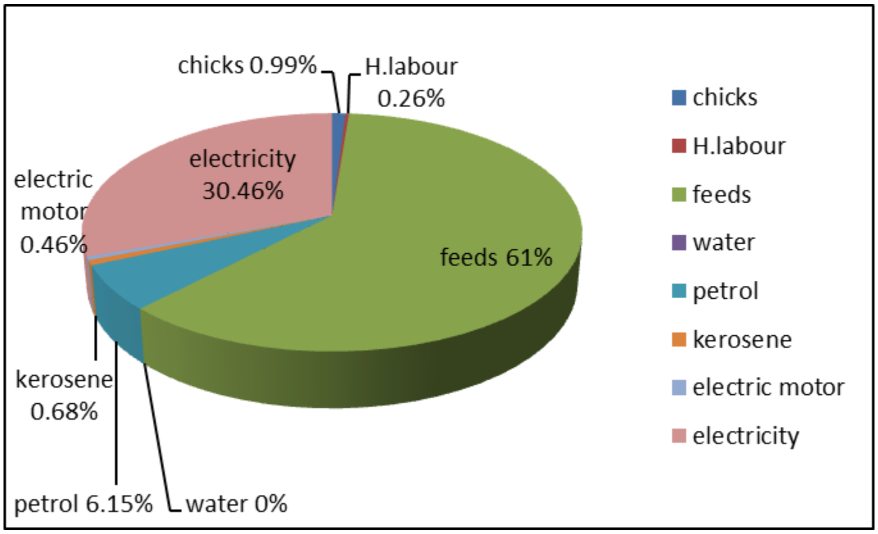

Figure 2. Total saving energy [1071.54MJ(500 birds)$^{-1}$]

Improvement of energy indices for broiler farms

Comparison between energy indices in the actual and optimum energy use showed improvements of these indices (Table 8). Obviously, by optimization of energy use, both energy ratio and energy productivity indicators can improve by 1.09 percent and 1.84 percent, respectively. Also, in optimum consumption of energy inputs, the net energy indicator by improvement of 1.66 percent would increase to 65613.66MJ (500birds)$^{-1}$. In otherwords, energy ratio, energy productivity, specific energy and net energy were 1.83; 0.109 Kg MJ(500birds)$^{-1}$; 9.14MJ(500birds)$^{-1}$ and 64542.12MJ(500birds)$^{-1}$, respectively, and they can be improved to 1.85; 0.111 Kg MJ(500bird)$^{-1}$; 9.02 MJ(500birds)$^{-1}$ and 65613.66MJ(500birds)$^{-1}$.Therefore, it is obvious that broiler production had relatively high requirements for nonrenewable energy resources and to certain extent feeds energy (renewable energy); its electrical energy requirement is high and need high amount of petrol fuel consumption in situation of power outage. In the case of feeds, farmers mainly don't have enough knowledge on more efficient input use and there is a common belief that increased use of feed energy resource will increase output. These situations occur simply because the farmers mainly don't have enough knowledge on more efficient input use. Methods presented in this study demonstrate how energy use efficiency in broiler production may improve by applying the operational management tools to assess the performance of farmers. On an average, considerable savings in energy inputs may be obtained by adopting the best practices of benchmarking/ high-performing DMUs in broiler production process. Adoption of more energy-efficient poultry systems would help in energy conservation and better resource allocation. Strategies such as providing better extension and training programs for farmers and use of advanced technologies should be developed in order to increase the energy efficiency of broiler productions in the studied area.

Table 9. Improvement of energy indices for broiler farms

Items	Unit	Qty in Actual use	Qty in optimum use	Change (%)
Energy ratio	-	1.83	1.85	1.09
Energy productivity	KgMJ-1	0.109	0.111	1.84
Specific energy	MJKg-1	9.14	9.02	-1.3
Net energy	MJ(500birds)-1	64542.12	65613.66	1.66
Total input energy	**MJ(500birds)-1**	**77916.14**	**76844.60**	**-1.38**

Source: authors computation, 2015

The farmers should be trained with regard to the optimal use of inputs, especially, electricity, petrol and feeds as well as employing the new production technologies. Therefore, agricultural institutes in the state have an important role in this case to establish the more energy efficient and environmentally healthy broiler production systems in the studied area.

Comparison of input use pattern of efficient and inefficient farms

The quantity of source wise physical inputs and output for 3 truly most efficient and inefficient broiler farms based on CCR model were compared (Table 10). Results revealed that the use of all inputs by efficient farmers were less than that of inefficient farmers. However, use of petrol fuel caused the main difference between efficient farmers and inefficient ones; efficient farmers used approximately 30.6 percent less petrol fuel than inefficient farmers. Furthermore, inefficient farmers had lower broiler (1.02%) and manure (22.84%) productions, respectively, than the efficient ones.

Table 10. Input use [MJ (500 Birds)$^{-1}$] for efficient and inefficient broiler production farms

Inputs	Inefficient farms (A)	3 Top Efficient farms (B)	Difference (%) [(A-B)/A]*100
Chicks	1008.78	988	2.06
Human labour	156.89	130.33	16.9
Feed	55471.9	53754.13	3.1
H2O	0.1036	0.095	8.6
Petrol	2083.78	1446.9	30.6
Kerosene	424.22	354.77	16.4
Electric motor	198.19	179.33	9.5
Electricity	16386.73	14634.33	10.7
Outputs			
Broiler	3742.93	3781	-1.02
Manure	130418.2	160200	-22.84

Source: Computation from DEAP 2.1 computer print-out

Comparison of GHG emissions of efficient and inefficient broiler farms

GHG emission of efficient and inefficient DMUs was investigated to determine the role of energy optimization in environmental condition of broiler production in the studied area (Table 11). Results indicated the GHG emissions of 3 truly most efficient and inefficient broiler farms to be 831.94kgCO2eq and 950.53kgCO2eq, respectively. It is obvious that the total GHG emissions of inefficient units were more than 3 truly most efficient broiler farms by approximately 12.48%.; petrol fuel accounted for the major difference (30.57%). Therefore, consumption of inefficient units should be close to 3 truly most efficient farms. Furthermore, alternative environmental friendly energy sources viz. biogas, solar and wind energies are the best option.

Table 11. GHG emissions of 3 truly efficient and inefficient broiler farms

Inputs	Inefficient farms (kgCO2eq) (C)	Efficient farms (kgCO2eq) (D)	Difference (%) [(C-D)/D]*100
Petrol	79.94	55.5	30.57
Kerosene	21.39	17.89	16.36
Electric motor	14.07	12.73	9.52
Electricity	835.13	745.82	10.69
Total GHG emissions	950.53	831.94	12.48

Source: computation from DEAP 2.1 computer print-out

Figure 3 displays the amount of each input for 3 truly most efficient and inefficient units from GHG emissions point of view. Results indicted GHG emissions of petrol fuel to be highest; followed by kerosene fuel, electricity and electric motor. It's obvious, that petrol fuel consumption of inefficient units was much more than efficient units. Accordingly, the main inputs of GHG creator were identical for efficient and inefficient. As such, the researchers opined that the consumption of all these inputs should be reduced.

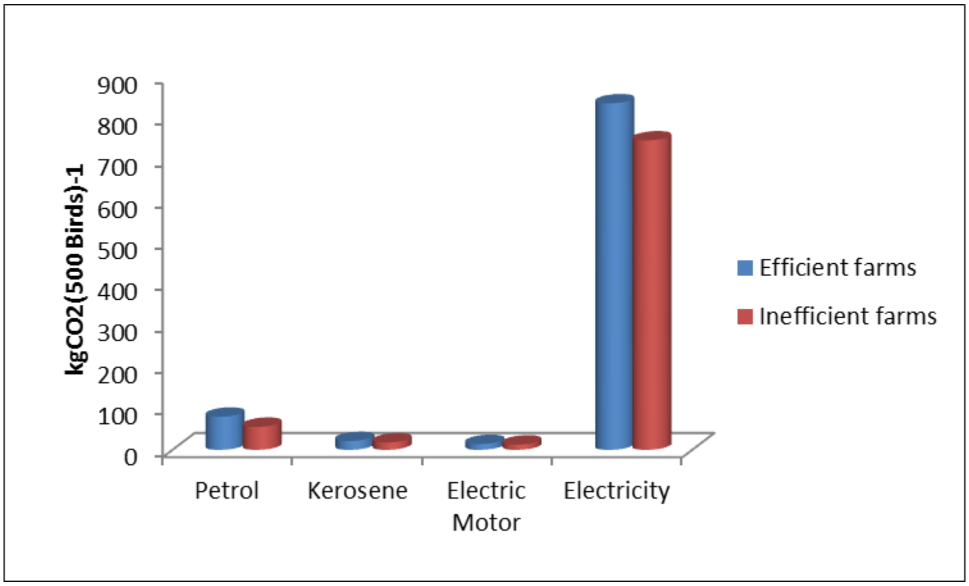

Figure 3. Quantity of GHG for 3 efficient and inefficient broiler farms

Conclusion

This study determines the possibilities of energy use improvement in broiler production using DEA approach. This method helped to identify the impact of energy use from different inputs on output, measure efficiency scores of farmers, segregate efficient farmers from inefficient farmers, ranking efficient farmers, identifying wasteful energy uses by inefficient farmers, compare GHG emission of 3 most efficient farms and inefficient farms aimed at determining the role of energy optimization in environmental condition of broiler production in the studied area. Results indicated that there were substantial production inefficiencies by farmers; such that, potential of 1.38 percent reduction in total energy input use may be achieved if all farmers operated efficiently and assuming no other constraints on this adjustment. In other words, the total energy input could be reduced by 1.38 percent without reducing the present output level by adopting study based recommendations. Average broiler outputs were 820.82 and 829.17 kg per 500birds for efficient and inefficient broiler farms, respectively. Thus, about 1.02 percent of broiler output declined in inefficient broiler farms. Comparative results of GHG emissions revealed that the amount of CO_2 emissions in efficient units was less than inefficient farms. Moreover, results revealed that broiler production in the studied area showed a high sensitivity to non-renewable energy sources which may result in both the environmental deterioration and rapid rate of depletion of these energetic resources. Therefore, policies should emphasize on development of new technologies to substitute fossil fuels with renewable energy sources aiming efficient use of energy and lowering the environmental footprints; limited fossil fuels sources implies that policy makers need to come up with best management in productivity improvement of broiler production in the studied area. Development of renewable energy usage technologies such as lightening systems using biogas, wind or solar power, using better management techniques, utilization of alternative sources of energy such as biogas, wind and solar energy are suggested to reduce the environmental footprints of energy inputs and to obtain sustainable broiler production systems. However, modern and well established scientific practices should be used to obtain higher technical efficiency in broiler production viz. having good knowledge of broiler feeds consumption; specifically the quantity of required feeds per meat Kg (feed conversion ratio); capacity training of poultry farmers and processors to enable them cope with the present challenges of modern poultry farming and commercialization of the poultry sub-sector in the state in particular and the country in generally. Also, losses at the farmers' level can be minimized through opening and strengthening of Agricultural Technology Information Centre (ATIC) in agricultural institution. Further, local level extension systems needs to be strengthened for effective transfer of technology.

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