Estimating Energy Conservation Potential Of Local Metal Casting Units In Uganda Using Data Envelopment Analysis

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ABSTRACT: This study sought to determine the relative energy efficiency of metal casting units in Uganda with a view of estimating the energy conservation potential. Data Envelopment Analysis (DEA) tool was used to accomplish this task. Energy consumption data was collected through interviews and field observations from the different foundries and was used as the input data for the model. Six foundries in the Central region of Uganda were surveyed following a snowball sampling technique. This consisted mainly of the annual energy consumption by the different foundries while the model outputs were annual total sales and annual total profits. Results showed that all the foundries were energy efficient with the exception of one, foundry E, as indicated by its energy efficiency score of less than unity. It can be seen that there exists potential in foundry E for energy savings and this may be accomplished by emulating energy management practices in the other units most especially foundry A and foundry D. The findings in this study can also be extended to other energy intensive industries in the country like the cement industry.

Keywords: Energy conservation, Uganda, SME foundries, Energy efficiency, Data Envelopment Analysis

INTRODUCTION

Small and Medium Enterprises (SMEs) play a major role in Uganda's economy in form of industrial production as well as generation of employment opportunities although they are frequently faced with barriers to their growth such as lack of awareness or access to clean energy efficient technologies and operating practices, research and development activities, among others. In many SMEs, energy constitutes almost 30% of their expenditure and moreover with the oil price hikes, inflation and unreliable power supply,these SMEs face a greater risk from inefficient energy consumption which can have adverse effects on the company's profits[1].Casting is the basis of the manufacturing industry but is highly polluting with tremendous energy consumption. Energy efficiency, conservation and emission reduction is related directly with the survival and development of the industry and is a key point of sustainable development of the local economy. Energy conservation in the foundry industry can be divided into two ways; direct energy saving through equipment improvements and indirect energy saving by decreasing the energy consumption per unit mass of product through improving technology level.

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Therefore it becomes necessary that the foundry industry puts into consideration environmental protection as well as energy efficiency and conservation whilst contributing to the economic development of the country.Energy efficiency improvement in foundries can have both firm level as well as macro economy level benefits. At firm level, energy intensity reduction due to efficiency improvement will reduce the cost of production of individual enterprises and at the aggregate level it will curtail the growth of industrial demand for energy. Today, foundries are under enormous pressure to minimize their energy expenditure in order to remain competitive which is crucial for their survival and growth as these energy sources are increasingly becoming more scarce and expensive[2]. Various models have been developed by researchers to predict energy conservation potential [3]; British scholars studied their national industry energy consumption and saving potential from 1970-1980 while [4] established a method to estimate the industry's energy saving potential and cost. Researcher [5] analyzed the pattern of energy use in the UK's iron and steel industry while Russian scholar [6],argued that restructuring production can lead to a 30% reduction in energy demand.Similar studies to investigate energy utilization and related efficiency requirements have been done in Sweden [7- 9]; Egypt [10]; Taiwan [11]; Germany [12], Italy[13 – 15]; Finland, France, Germany, Italy, Poland, Spain, and Sweden [16]; China [17]; among others. In the previous study [18], barriers and energy conservation issues for SME foundries in Uganda were discussed. This study therefore sought to determine the energy conservation potential that exists within the subsector in order to optimize productivity i.e. determine the relative energy efficiency of metal casting units in Uganda with a view of estimating the energy conservation potential. This was accomplished by use of the DEA tool.

2 METHODOLOGY

2.1 Collection of Data

Since there is no systematic list of SMEs operating foundries in Uganda, the research took advantage of snowball sampling technique. Two foundries known to the researchers which were visited first facilitated in generating the list of other foundry workshops. Focus was put on foundries in the Central region, because this is where the most foundry workshops are concentrated. Data was collected from six SME foundries. Interviews, observations and a checklist guided the data collection tasks. The collected data was then evaluated to determine the relative energy efficiency of the units under study. The first step was to determine the decision making units (DMUs) to be evaluated. Inputs and outputs of the respective DMUs (firms) were then determined. Open Source Data Envelopment Analysis (OSDEA) software was then used to carry out the computations.

2.2 Determining the Factors

According to DEA, the resources are typically referred to as ‘‘inputs’’ and the outcomes as ‘‘outputs’’. The inputs should capture resources that are required to be minimized. The outputs should reflect all useful outcomes on which it is wished to assess the DMUs. Since the selection of input and output factors is dependent upon the objectives of the survey, the factors that were used in this study were carefully selected depending on the types of energy used in the different foundry shops. The sampled firms were evaluated to determine if they are energy efficient or not. The study concentrated on the main energy consumption components and an input oriented DEA model was used to minimize these input data. The different energy sources used in the enterprises were the only input factors considered. Two output components were considered and these include Annual total sales and annual total profit. Since the foundry officials could not reveal their profits, a general mark up of 20% was used to calculate the annual profits. In summary, the factors used in this study are as follows:

Input factors:

x_1: annual used oil consumption (MJ)
x_2: annual Biomass consumption (MJ)
x_3: annual Diesel Consumption(MJ)
x_4: annual Electricity consumption (MJ)

Output factors:

y_1: annual total sales (UGX)
y_2: annual total profit (UGX)

The summaries of the factors are described in Table 1**Error! Reference source not found.**.

2.3 Modeling

DEA is a linear programming procedure for a frontier analysis of inputs and outputs. DEA assigns a score of 1 to a unit only when comparisons with other relevant units do not provide evidence of inefficiency in the use of any input or output. DEA assigns an efficiency score less than one to (relatively) inefficient units. A score less than one, means that a linear combination of other units from the sample could produce the same vector of outputs using a smaller vector of inputs. It is a useful technique because of the nature of relations between the multiple inputs and outputs involved in the many activities. The term Decision Making Unit (DMU) is used to refer to any entity that is to be

TABLE 1

SUMMARY OF FACTORS TO BE USED IN THE DEA CALCULATIONS

Factor	Factor multiplier	Values used
y1	*u1*	Annual income (UGX)
y2	*u2*	Annual profit (UGX)
x1	*v1*	Annual used oil (MJ)
x2	*v2*	Annual biomass used (MJ)
x3	*v3*	Annual diesel (MJ)
x4	*v4*	Annual electricity used (MJ)

evaluated in terms of its abilities to convert inputs into outputs. In this study, the aim was to minimize energy costs (inputs) so an input oriented Charnes, Cooper and Rhodes (CCR) model was used to evaluate the efficiency scores. The primal form of a CCR linear programming model is given as follows [19, 20]:

$$\max h_k = \frac{\sum_{r=1}^{s} u_{rk} y_{rk}}{\sum_{i=1}^{m} v_{ik} x_{ik}} \qquad (1)$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_{rk} y_{rj}}{\sum_{i}^{m} v_{ik} x_{ij}} \le 1, j = 1, \dots, n \qquad (2)$$

$$u_{rk}, v_{ik} \ge 0; r = 1, \dots s; i = 1, \dots, m \qquad (3)$$

Where

- ***k*** the branch or decision making unit (DMU) being evaluated in the set of j=1,2,...,n DMUs
- ***h_k*** the measure of productivity or efficiency of (DMU) ‘‘k’’, the (DMU) in the set of j=1,2,...,n (DMU)s rated relative to the others
- ***y_{rk}*** the amount of output ‘‘r’’ produced by (DMU) ‘‘k’’ during the period of observation (one year in this application)
- ***x_{ik}*** the amount of resource input ‘‘i’’ used by (DMU) ‘‘k’’ during the period of observation
- ***y_{rj}*** the amount of service output ‘‘r’’ produced by (DMU) ‘‘j’’ during the period of observation
- ***x_{ij}*** the amount of resource input ‘‘i’’ used by (DMU) ‘‘j’’ during the period of observation
- ***u_{rk}*** the coefficient or weight assigned to service output r computed in the solution to the DEA model
- ***v_{ik}*** the coefficient or weight assigned to resource input i computed in the solution to the DEA model
- ***m*** the number of resources or inputs used by the (DMU)s
- ***s*** the number of services or outputs produced by the (DMU)s

It is assumed that there are n DMUs and that the DMUs under consideration convert m inputs to s outputs. In particular, let the k_{th} DMU produce outputs y_{rk} using x_{ik} inputs. To measure the efficiency of this conversion process by a DMU, a fractional mathematical programming model, denoted as relation (2), is proposed. The objective function of the model maximizes the ratio of weighted outputs to weighted inputs for the DMU under consideration subject to the condition that the similar ratios for all be less than or equal to one. The k_{th} DMU is the base DMU in the above model. The optimal value of the objective function of the model is the DEA efficiency score assigned to the k_{th} DMU. If the efficiency score is 1 (or 100%), the k_{th} DMU satisfies the necessary condition to be efficient; otherwise, it is inefficient. Note that the inefficiency is relative to the performance of the other DMUs under consideration. It is difficult to solve the above model because of its fractional objective function. However, if either the denominator or numerator of the ratio is forced to be equal to one, then the objective function will become linear, and a linear programming problem can be obtained [21]. A linear form of a CCR model is given as follows [20]

$$\max h_k = \sum_{r=1}^{s} u_{rk}\, y_{rk} \tag{4}$$

Subject to:

$$\sum_{i=1}^{m} v_{ik}\, x_{ik} = 1 \tag{5}$$

$$\sum_{r=1}^{s} u_{rk}\, y_{rj} - \sum_{i=1}^{m} v_{ik}\, x_{ij} \le 0 \; j = 1, \dots, n \tag{6}$$

$$\boldsymbol{u_{rk,} v_{ik} \ge \varepsilon, r = 1, \dots, s; i = 1, \dots, m}$$

εis an infinitesimal positive number, which constrains the input and output coefficients to be positive, eliminating the possibility that they will be given a zero relative value in the DEA results. The objective function of this model maximizes the productivity or efficiency rating h_k for DMU k. This is subject to the constraint that when the same set of u and $v$coefficients are applied to all DMU being compared, no DMU will be more than 100 percent efficient, and the coefficients values are positive and non-zero [20]. DEA produces an efficiency score for each DMU relative to the other DMUs in the database that demonstrates who the ''best practice'' DMUs are and by how much the less efficient DMUs fall short.In the case of inefficient DMUs, DEA models also identify target input–output levels, which would render them inefficient, and efficient peers they could emulate to improve their performance. For inefficient DMUs, the optimal inputs and output values are calculated as follows [21].

$$\boldsymbol{x_i^t = \sum_{j \in E_0} x_{ij}\, \lambda_j^* = \theta_k^* x_{ik} - s_{ik}^{-*}} \tag{7}$$

$$y_r^t = \sum_{j \in E_0} y_{rj}\, \lambda_j^* = y_{rk} + s_{rk}^{+*} \tag{8}$$

The superscript * is used to denote the optimal value of a variable. The input and output levels $(x_i^t, i = 1,2, \dots, m, y_r^t, r = 1,2, \dots, s)$ are the coordinates of the point on the efficient frontier used as a bench mark for evaluating DMU k. These levels are often referred to as a projection point of DMU k on the efficient boundary or simply targets of DMU k. When a DMU is inefficient, the new input–output levels can be used as the basis for setting its targets so that it can improve its performance. There are generally infinite input–output level combinations that would render any given DMU efficient. The specific combination in Eqns. (8) and (9) corresponds to giving pre-emptive priority to the radial contraction of the input levels of DMU k. This means that the targets in Eqns. (8) and (9) preserve, in large measure, the mix of inputs and outputs of DMU k, though if any slack values are positive, the mix of the target input–output levels differs from that of DMU k. If $\theta_k^* = 1$ and$s_{ik}^{-*} = 0, i = 1,2, \dots m$ and $s_{rk}^{+*} = 0, r = 1,2, \dots s$, then the k_{th}DMU is efficient because the Model has been unable to identify some feasible production point that can improve on some input or output level of DMU k without detriment to some other input or output level. Note that if one feasible value of θ_k is 1, then$\lambda_k = 1, \lambda_j = 0, \forall \ne k$, otherwise if $\theta_k^* < 1$ then, $\lambda_j = 0, \forall \ne k$, Also, these$\lambda_j = 0$, values constitute inefficient DMUs' reference set [21]. DEA produces an efficiency score for each DMU relative to the other DMUs in the database that demonstrates who the ''best practice'' DMUs are and by how much the less efficient DMUs fall short. In the case of inefficient DMUs, DEA models also identify target input–output levels, which would render them efficient, and efficient peers they could emulate to improve their performance.

3.0 Results and Discussions

Six foundry shops referred to as Foundry A, B, C, D, E, and F for the purposes of this study were used in the computation of the relative energy efficiency.

3.1 Technology employed and related causes of energy inefficiencies

The melting technology employed is mainly tilt, pit and in a few cases, rotary furnaces. This kind of technology dictates regular and routine maintenance of the furnace walls which is not well followed. There is need for better housekeeping, behavioral changes, preventive maintenance, and installation of energy efficient equipment. At 69% of the total energy consumed in the foundries, the melting process consumes the biggest part of the energy used in foundry shops, and this is where serious attention should be put.The specific energy consumption of the foundries ranged from 7.35 – 14.61 MJ/kg, with an average of 10 MJ/kg which is above the benchmark of 8.62 MJ/kg in developed countries. Accordingly, the major causes of energy inefficiencies, as also indicated in the previous study [18] include: Insufficient metering of the energy consumption of main production processes like melting and baking of the molds. Design flaws, insufficient insulation and poor maintenance of the production units were noted in the foundries surveyed. Poor quality scrap input into the furnace was another major problem. This scrap is normally charged with no proper sorting in relation to size and cleanliness. Very large pieces create gaps and spaces within the crucible and affect heat conduction and distribution tremendously. Employing energy inefficient technology. The technology employed is not energy efficient, besides it is not well maintained. Because of poor refractory materials, the linings wear very fast leading to colossal energy losses. Energy losses are also attributed to poor operational and maintenance practices.

3.2 Annual Energy Consumption Estimation

In order to estimate the annual energy utilisation, the estimated number of castings per week was used and a year was assumed to have 52 weeks. Holidays and public days were assumed not to affect the number of castings per week. The consumption of the different sources of energy per casting process was obtained in differing units as shown in Table 2.This necessitated converting the differing units to one common unit and the MJ was chosen for this purpose. Energy content of the different sources used in converting to MJis as shown in Table 2.

3.3 Annual Income and Profit Estimation

In computing the annual income per firm, the selling price per kg of cast metal and the estimated annual cast metal production per unit were used. A year was assumed to have 52 weeks. Holidays and public days were assumed not to affect the number of castings per week. Since the foundry officials could not reveal their profits, a general mark up of 20% was used to calculate the annual profits as shown in Table 2. The input and output values used in the DEA model were calculated and are as presented in Table 2.Substituting the values of the inputs and outputs in the linear form of CCR model (equations 5, 6, and 7) and foundry A, we get the following;

$$Max\ h_A = (525{,}000{,}000u_1 + 50{,}400{,}400u_2)$$

Subject to

$$(461{,}229v_1 + 86{,}400v_2 + 1{,}934v_3) = 1$$

$$(525{,}000{,}000u_1 + 50{,}400{,}400u_2) - (461{,}229v_1 + 86{,}400v_2 + 1{,}934v_3) \leq 0$$

$$(537{,}600{,}000u_1 + 107{,}520{,}000u_2) - (860{,}961v_1 + 345{,}600v_2 + 34{,}368v_3) \leq 0$$

$$(480{,}000{,}000u_1 + 96{,}000{,}000u_2) - (737{,}967v_1 + 345{,}600v_2 + 17{,}184v_3) \leq 0$$

$$(540{,}000{,}000u_1 + 108{,}000{,}000u_2) - (922{,}458v_1 + 108{,}000v_2 + 17{,}403v_3) \leq 0$$

$$u_1 \geq 0$$
$$u_2 \geq 0$$
$$v_1 \geq 0$$
$$v_2 \geq 0$$
$$v_3 \geq 0$$

Where;

$\boldsymbol{h_A}$is the efficiency of foundry A (expressed as a fraction)

$\boldsymbol{u_1}$isthe coefficient or weight assigned to service output $y_1$computed in the solution to the DEA model

$\boldsymbol{u_2}$is the coefficient or weight assigned to service output y_2 computed in the solution to the DEA model

$\boldsymbol{v_1}$ isthe coefficient or weight assigned to resource input x_1 computed in the solution to the DEA model

$\boldsymbol{v_2}$is the coefficient or weight assigned to resource input x_2 computed in the solution to the DEA model

$\boldsymbol{v_3}$is the coefficient or weight assigned to resource input x_3 computed in the solution to the DEA model.

The objective function of this model maximizes the productivity or efficiency rating $h_A$for foundry A. This is subject to the constraint that when the same set of u and v coefficients are applied to all DMU being compared, no DMU will be more than 100 percent efficient, and the coefficient values are positive and non-zero. A complete DEA exercise involves solution of *N* such models, each for a base DMU (j=1, 2... *N*), yielding N different sets of weights (v_{ik},u_{rk}). In each model, the constraints are the same while the ratio to be maximized is changed. Computation of an efficiency score is usually done with the dual of primal model. The dual constructs a piecewise linear approximation to the true frontier by minimizing the quantities of the different inputs to meet the stated levels of the different outputs.

TABLE 2
DEA INPUTS AND OUTPUTS

DMU	Foundry	Inputs (MJ) Used Oil (x_1)	Biomass (x_2)	Diesel (x_3)	Electricity (x_4)	Outputs (UGX) y_1	y_2
DMU1	A	499,200	93,600	0	2,095	252,000,000	50,400,000
DMU2	B	931,840	374,400	37,232	37,232	537,600,000	107,520,000
DMU3	C	798,720	374,400	18,616	18,616	480,000,000	96,000,000
DMU4	D	998,400	117,000	0	18,853	540,000,000	108,000,000
DMU5	E	332,800	93,600	0	2,246	108,000,000	21,600,000
DMU6	F	728,000	0	814,450	31,422	765,000,000	153,000,000

Note, 1 US $ ≈ UGX 2900

TABLE 3
RELATIVE ENERGY EFFICIENCIES OF THE FOUNDRIES UNDER EVALUATION

DMU Name	Objective Value	Efficient
DMU1	1	Yes
DMU2	1	Yes
DMU3	1	Yes
DMU4	1	Yes
DMU5	0.635	
DMU6	1	Yes

OSDEA software was employed to evaluate the firms under study. The input oriented CCR model was used. The values that were obtained are presented in Table 3. The objective value is the efficiency score for each DMU relative to the other DMUs under study and it demonstrates who the best practice DMUs are and by how much the less efficient DMU can improve. From the results, DMU5 has an efficiency score that is less than one implying that there is room for improvement. This does not automatically mean that foundry E (DMU5) is inefficient but rather the efficiencies here are taken as indicative of the fact that other DMUs are adopting practices and procedures which, if foundry E was to adopt, would enable it to reduce its energy consumption. The target input–output levels, which would render the inefficient DMUs efficient were also calculated in the model and presented in Table 4.

TABLE 4
TARGET INPUT-OUTPUT LEVELS THAT WILL MAKE THE INEFFICIENT DMUS EFFICIENT

DMU Name	x_1	x_2	x_3	x_4	y_1	y_2
DMU1	499200	93600	0	2095	252,000,000	50,400,000
DMU2	931840	374400	37232	0	537,600,000	107,520,000
DMU3	798720	374400	18616	0	480,000,000	96,000,000
DMU4	998400	117000	0	18853	540,000,000	108,000,000
DMU5	**211320	**37041	0	**1426	108,000,000	21,600,000
DMU6	728000	0	814450	31422	765,000,000	153,000,000

*** indicates the target value of inputs that would render DMU5 (foundry E) efficient. The model indicates that there is need for foundry E to reduce the consumption of all the energy sources employed in the firm in order to be as efficient as other firms under study. This translates into a 42% reduction. The efficient peers that DMU5 could emulate to improve its performance are as presented in Table 5.*

TABLE 5
PEERS THAT THE INEFFICIENT DMU SHOULD EMULATE

DMU Name	Peer Group
DMU1	DMU1
DMU2	DMU2
DMU3	DMU3
DMU4	DMU4
DMU5	DMU1, DMU4
DMU6	DMU6

4. Conclusion and Remarks
Energy inefficiencies in the Ugandan SME foundry units is attributed to the technology employed, poor operations and maintenance practices, and the poor quality scrap inputs. There is need for improvement of technology, which could give better yields and energy efficiencies. Foundry employees should get acquaintance with better operation and management practices which embrace efficient energy management. Comparing the inputs and outputs of the foundries understudy using the DEA method indicate that the energyimprovement potentialfor the SME metal casting units in Ugandais about 42%.Various energy conservation measures need to be applied in order to reduce energy use, as indicated in the previous study [18].The model also highlights DMU1 (foundry A) and DMU4 (foundry D) as the foundries that can be emulated by foundry E. This study could be extended to other energy intensive industries like the processing industries and also benchmark energy conservation practices used in the developed countries to enable the Ugandan industries increase their productivity and competitiveness.

Conflict of Interests
Authors declare that there is no conflict of interests regarding the publication of this paper.

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