Environmental Sustainability Assessment of Sponge Iron Industries in West Bengal using DEA

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ABSTRACT *India is the second largest producer of sponge iron in the world and had been the largest producer of sponge iron in the world till the year 2016and accounted for about 25 % of world's production. The Indian sponge iron industry sector is highly polluting because most of the units are using coal based technology and are operating in small modules. Thereforethere is urgent need to understand how the elements of 'best practice' can precisely contribute to environmental sustainability of the sector. Accordingly, this research study attempts to understand the resource consumption (raw material, energy, water, etc.) and waste generation in terms of air emission and solid waste generation. With the help of Data Envelopment Analysis (DEA), an efficient set of such industries have been identified and using the resource consumption and waste generation data of these industries, an empirical model has been evolved for assessing environmental sustainability of this industrial sector.*

Keywords: *sponge iron, DEA, waste generation, environmental performance*

Introduction

The Sponge Iron or direct reduced iron (DRI) is the main raw material for making steel through the induction furnace and arc furnace route due to less availability of high quality scrap and its increasing cost. The Sponge Iron production in India deserves special attention because India was '*the largest*' producer of Sponge iron during the period 2003-2016 and accounted for about 25 % of total world production.Also the production process is primarily coal based and therefore highly polluting in nature compared to 90% of the global DRI Plants which use natural gas.(Raja and Pal, 2006).

While the gas based DRI technologies by and large are considered to be eco friendly and energy efficient, the coal based smaller DRI modules pose serious concerns on these fronts. In India, non coking coal is extensively used for making DRI since it is easily available and very cheap fuel compared to coking coal used in blast furnace for steel making. The pollution potential of DRI industries is very high due to direct use of non coking coal in the rotary kiln and small module size. A large quantity of coal char is usually generated from the production process which causes great environmental threat. The Sponge Iron units are critically air polluting in nature emitting high concentration of particulate matter from various point sources and also from a number of secondary sources. Such industries also pose a great challenge as far as compliance with environmental norms is concerned.

In this paper an effort has been made to understand how the elements of 'best practice' can precisely contribute to environmental sustainability. (Shrivastava, 1995, Weber, 2005)Accordingly, the prime objectives of this research study is to understand the interrelation amongst resource consumption (raw material, energy, water, etc.) and generation of emission, effluent and solid waste and to evolve an empirical model for assessing the environmental performance of this industrial sector.

Tools used for Data Analysis

Data Envelopment Analysis (DEA) is a linear programming based technique to evaluate the relative performance of different homogenous units known as Decision Making Units (DMU) based on multiple inputs or outputs. DEA makes it possible to identify efficient and inefficient units in a framework where results are considered in their particular context. (J. Santos et.al 2013) In addition, DEA also enables the comparison of each inefficient unit with its "peer group", that is, a group of efficient units that are identical with the units under analysis. These role-model units can then be studied in order to identify the success factors which other comparable units can attempt to follow.

In the DEA technique, formally conceptualized by Charnes, Cooper and Rhodes (1978), efficiency is characterized as a ratio of weighted sum of outputs to a weighted sum of inputs, where the weights, structure is ascertained by methods for programming and constant return-to-scale,also known as CCR model are accepted. Later it in 1984,Banker, Charnes and Cooper built up a model known as variable return-to-scale (VRS) or BCC model devoid of the scale effect.

Data Processing

The sample sizeor the number of DMUs used in this analysis follow a thumb rule coined by different researchers. Golany and Roll (1989) framed a thumb rule that the number of units should be at least twice the number of inputs and outputs considered. Bowlin (1998) mentioned the need to have three times the number of DMUs as there are input and output variables. If N denotes the number of sample units, 's' denotes number of outputs and 'm' denotes number of inputs, then $N \geq \max\{2*m*s; 3(m + s)\}$.

Another objective of data preparation is to ensure that there is not much inequality in the data sets, this is achieved by mean normalizing the data.(Sarkis, 2002).Basic DEA models are not capable of completing an analysis with negative numbers. For eliminating the problems of non-positive values, addition of a sufficiently large positive constant to the values of the input or output is carried out for the input or output that has the non-positive number. (Bowlin 1998) has advised that in some cases the negative numbers or zero values to be converted to a smaller number in magnitude than the other numbers in the data set.

In Data Envelopment Analysis, DMU's are ranked according to efficiency score and the best performance of a DMU is indicated by an efficiency score of one. There is often more than one DMU with this efficiency score. A modified version of DEA is developed to rank and compare units with efficiency equal to 1. Among these, one is Andersen and Peterson's (1993) super-efficiency model. This technique allows efficiency to be more than one, discriminating between efficient DMUs that otherwise are all ranked equal.

Formulation for DEA

In the present study, a data envelopment analysis (DEA) is performed with the following variables given in Table 1:

Table 1: Variables Used for DEA

Symbol used	Name of Variable	Variable Type
VI1	Installed Production capacity (yearly) of a company for DRI	Input Variable
VO2	Average yearly production of DRI by a company	Output variable
VI3	Average yearly consumption of iron ore in tonnes	Input Variable
VI4	Average yearly consumption of coal in tonnes	Input Variable
VI5	Average yearly consumption of energy in MWH per year	Input Variable
VI6	Average yearly consumption of raw water in cubic metres per year	Input Variable
VO7	Average yearly generation of dolochar in tonnes	Output variable
VO8	Average yearly collection of dust from various air pollution control devices in tonnes	Output variable

The mean normalised data set for 51 DMUs is obtained by normalization of the data. Prior to this the negative values foroutput variables likedolochar generation (on a yearly basis) and dust collected from air pollution control systems (on a yearly basis) have been converted to positive non- zero values.

The DEA has been carried out using Lingo 17 software. It is observed from the DEA analysis that the efficiency of many units is equal to one. Therefore a super efficiency analysis is carried out for the said units in order to rank and compare the units with efficiency equal to 1. According to their rank,thetop 30 DMUs as per VRSEfficiency and Super efficiency are selected for further analysis.

Development of Regression Model

A multiple regression analysis is performed for the data pertaining to the top 30 efficient sponge iron units (in order of their rank obtained as per DEA)to develop a model for predicting efficient production of DRI using optimum resources and generating minimum wastes.The predictor variables used for developing the above model arethe five raw material input variables namely:

(i) installed capacity of the plant for production of sponge iron in tonnes per year
(ii) consumption of iron ore in tonnes per year
(iii) consumption of coal in tonnesper year
(iv) consumption of energyin MWH per year

(v) consumption of raw water in cubic metres per year

The symbols used in the regression models are given in Table 1. A regression analysis is carried out for the above variables using appropriate statistical software SPSS 22.First a correlation matrix (Pearson correlation) is obtained for all the independent variables. It is observed from the above that highest pair wise correlation exists between coal consumption and energy consumption.

The statistical hypothesis test for existence of a linear relationship between Y, (in this case average yearly production of DRI, VO2) and any of the X_i , [in this case five raw material input variables which are predictor variables, namely, installed capacity of the plant for production of DRI (VI1) in tonnes per year, consumption of iron ore (VI3) in tonnes per year, consumption of coal (VI4) in tonnes per year consumption of energy (VI5) in MWH per year and consumption of raw water in cubic metres per year (VI6)] is carried out. It is concluded that there is strong evidence of linear regression relationship between the production of DRI and any one of the five raw material input variables from the ANOVA table and F test. This is further confirmed by the high coefficient of determination $R^2 = 0.997$.

The regression analysis is repeated dropping the highly correlated predictor variables one by one and finally the model with highest R^2 and adjusted R^2 is selected. The final regression equation for average yearly production of DRI is

DRI Production (MT/year) = 477.999+ 0.156 Iron Ore (MT/year) + 12.479 Energy (MWH/year)

Polynomial Regression Analysis

Often, the relationship between the dependant variable (production of DRI) and one or more of the independent variables may not be a straight line relationship but rather has some curvature to it. In such cases, polynomials of order higher than 1 provide much better fit to the data. Such polynomials in the X variableare still considered linear regression models. The general form of a polynomial regression model in one variable X is given by the following equation:

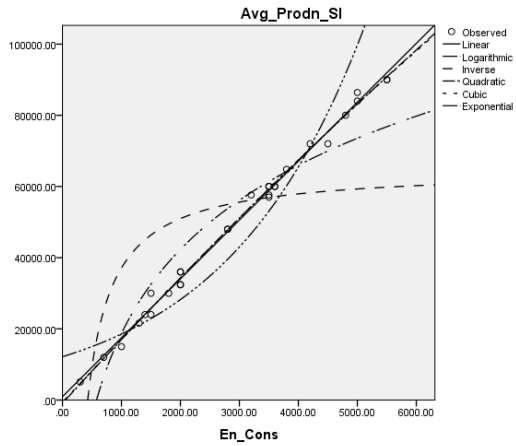
$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + BX^3 \ldots\ldots\ldots\ldots \beta_m X^m + \varepsilon$$

where m is the degree of the polynomial- the highest power of X appearing in the equation. The degree of the polynomoial is the order of the model. In this case, only quadratic and cubic equations have been considered to check whether such models provide better fit to the data. A few other models were also explored like the exponential model, logarithmic model, the reciprocal or inverse models which can be transformed into intrinsically linear models.

In the linear regression model obtained for average production of DRI, since the coefficient estimate for the independent variable consumption of energy is the highest, an analysis is carried out to find out if the data fits the one variable polynomial regression model (quadratic and cubic), logarithmic model, inverse (reciprocal) model, and exponential model. From the analysis results it is observed that the R^2 values for the linear, quadratic and cubic equations are the highest (0.994 to .995 in all cases). In case of quadratic equation, the value of b2 is zero. In case of cubic equation, the value of b2 and that of b3 is almost equal to zero. Hence both these equations are converging to linear model.

The plot of production of DRI (Y) versus consumption of energy (X) variable for all the above models considered for analysis is given in Figure 1. From Figure 1, it is concluded that the linear model is the best fit model.

Figure 1



Conclusions and Recommendations

Environmental conservation must go hand in hand with economic development because development which destroys the environment will create more poverty. DRI can be produced using gas which is a cleaner mode of operation but it is expensive and gas availability is not assured. Using DEA, a set of sponge iron industries, which have optimum efficiency have been identified in the state of West Bengal.With the existing technology, resource consumption and waste generation data of such industries an action plan has been drawn for the sector to contain it's environmental impacts. With the current capacity of production using coal as fuel, the production process can be optimised for less environmental impacts and less generation of waste using the model of DRI production derived in this study.

Minimum use of resource will lead to least generation of waste. This model of production process can be adopted by existing industries to operate in a more sustainable manner creating less negative impact on the environment. Theabove model of production needs to be followed along with other suitable environment management practices like good housekeeping, proper allocation of funds for adopting appropriate Environment Management Systems for achieving sustainable development.

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