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Formulation of Linear Regression Model For Steel Production Prediction For Oil and Gas Operations in Nigeria

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Abstract

This paper focuses on the formulation of a linear regression model for steel production prediction for oil and gas operations in Nigeria. This was done by using fourteen years (**1982-1995)** production data from a company records in Nigeria. The data were analyzed and assumed that there is a linear relationship between each variable and the product. With this insight, the least square method of regression was adopted. The Formulated model (Equation 15) was tested by using Durbin Watson (D.W) model and it was found that the formulated model was adequate for steel production prediction with less than 8% error. The model was used to find the amount of liquid steel produced for a given quantity of each variable. It is clear that a sure-fire model that can maximize and predict the effect of change in any of the variables (raw materials) in steel production has been developed.

1. Introduction

Steel processes can be classified into two types: Primary and Secondary steelmaking. The primary steelmaking process turns liquid iron from a blast furnace and steel scrap into steel through melting scrap steel or direct reduced iron (DRI) in an electric arc furnace. Secondary steelmaking is a purification of the crude steel before casting and the various operations are normally done in ladles in the secondary method, alloying agents are added, gases are dissolved lower in the steel, lowering iron losses during slag removal in hot metal desulphurization without using fluoride [1]. Steel in the national economy is enormous. One cannot name an oil and gas industry where steel finds no application. The economic power of a country is determined by its output of steel, since progress in the principal economic sector, is its mining, transport, manufacturing, engineering or agriculture unthinkable without steel [2]. The demand for steel rises continually and is expected to reach the level of 1000million tonnes per year by the end of this century. Although there are many studies on steel production models, Some smart and soft computing models have been applied to a large variety of industrial processes [3], such as production, fault finding, process preparation and monitoring, machine maintenance, and quality prediction and control [4-10]. In particular, the use of these methods for machinery fault detection and product quality prediction has received increasing attention over the last years

Adly et al offered a simplified regression algorithm for precise identification of defect patterns in semiconductor wafer maps [11]. Ghorai et al established a visual examination system to confine defects on hot-rolled steel surfaces employing some kernel classifiers [12], such as the support vector machine and the vector-valued regularized kernel function approximation. Wu et al introduced a method based on the random forest for tool wear prediction and relate its performance with that of sustenance regression and feed-forward back-propagation neural networks [13]. Wang et al presented a complete survey of deep learning algorithms for smart manufacturing [14-15].

The bulk of steel to be formed and molded, as well as its elasticity, ductility, its established resistance in several uses, and its corrosion resistance, has given it a foremost place among the materials used in several sectors. In the modern world, steel is virtually indispensable in construction, infrastructure, automotive, and many other industries while also being an important determinant of economic development. Many studies have examined the role of the steel industry within the economy and have shown a positive relationship between the steel industry and economic growth [16–20].

The realization of the mathematical model highlights the essential characteristics of the modeled process/object, which determines the mathematical formalization. Formalization implies that it is possible for the characteristics of the real problem to be matched to appropriate mathematical ideas: functions, integrals, derivatives, equations, systems, inequalities, etc. [21–23].

In relationships of the scientific approach to the quality management of the research process in steel production, the mathematical models applied so far relate to the following: (a) Mathematical statistics: applications of the Poisson repartition in excellence management [24]; Pearson's coefficients [25]; the application of the study of correlation coefficients [26]; regression theory as a prediction instrument in quality management [26]; data processing [27].

(b) Probability theory: the quality loss function [28]; Six Sigma philosophy [24]; probabilistic models, i.e., [26]. Information theory: entropic models i.e., [26–32]; pseudo-entropic models, i.e., [9]. (d). Multi-criterial or multi-objective mathematical programming: optimizing product quality, [33].

At present, there are no published papers on a model that deals with the formulation and production prediction of steel. Hence there is a need for this study. A model like this is significant in steel industries in the country because (planner) which is in charge of production planning to make adequate plans for the available raw material to be utilized efficiently and economically [34].

2. Material and Methods

2.1. Plant material

The data for this study was obtained from the company production records. This is shown in Table 1 below.

Table1: Production Data from 1982-1995 (Metric tons) [34]

Year	Liquid Steel Y	Scrap X1	DRI X2	FerroAlloy X3	Coke X4	Lime X5	Lime Stone X6	Electric Stone X7	Oxygen X8	Nitrogen X9	Natural Gas X10	Air X11
1982	90237	29011.1	64068	1082	270	5775	165	65383	68489	0	0	0
1983	181957	39302.7	152844	2929	109	9097	509	115368	2547398	4821631	5032931	7338326
1984	180318	4907.08	139506	2344	162	7934	414	125502	170401	4140124	1951052	4358310
1985	243893	48534.7	24025	2926	68	12438	748	167554	2302349	4451047	568585	2916960
1986	143067	38745.1	10641	1676	213	7918	194	89771	558093	3755369	35469	5118771
1987	136552	38594.4	108719	2127	97	8831	203	81126	808926	2363841	5078667	6284083
1988	139326	37114	123738	1931	141	9303	349	96021	824056	2266030	5373933	8398586
1989	127468	21504.4	123738	1743	22	8962	323	89271	766603	1221342	3972250	8974561
1990	138950	50590.5	42741	1985	109	10445	302	101029	59772	3005313	5682738	5757670
1991	113802	36699.2	101321	1743	93	7215	325	82811	658941	2458113	4.9E+07	4715935
1992	61873	22129	53521	2950	34	3748	42	45704	266051	1336443	2530580	63991
1993	42699	20141	34574	25689	25	2673	0.4	34816	238114	405225	1746724	1769419
1994	50028	13665.4	46203	5744	31	3165	0	43228	103598	1699	2046149	2073164
1995	36041	1340.9	50339	5586	24	2275	0	30419	87331	1202	0	0

The interactions between variables are very vital aspects of steel production. The iron ores are first roasted to convert it to iron (iii) oxides mixed with coke and limestone are fed into the furnace the cup and cone charger [34]. Figure 1 shows the main reactions in the furnace and zones in which they take place.

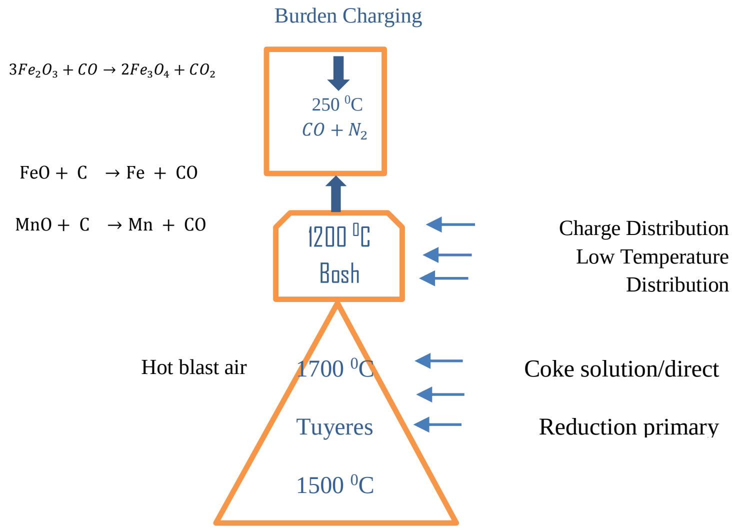

Figure 1: *Blast Furnace*

In analyzing the data collected in the graph of the product Y was plotted against each variable (x). It was assumed that there is a linear relationship between each variable and the product. With this insight, the least square method of regression was adopted [35]. The regression equation is given in equation (1) below [36].

$$Y = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + B_4X_4 + B_5X_5 + B_6X_6 + B_7X_7 + B_8X_8 + B_9X_9 + B_{10}X_{10} + B_{11}X_{11} \quad (1)$$

The normal equations for equation (1) are as follows:

$$\Sigma Y = NB_0 + B_1\Sigma X_1 + B_2\Sigma X_2 + B_3\Sigma X_3 + B_4\Sigma X_4 + B_5\Sigma X_5 + B_6\Sigma X_6 + B_7\Sigma X_7 + B_8\Sigma X_8 + B_9\Sigma X_9 + B_{10}\Sigma X_{10} + B_{11}\Sigma X_{11} \quad (2)$$

$$\Sigma YX_1 = B_0\Sigma X_1 + B_1\Sigma {X_1}^2 + B_2\Sigma X_1X_2 + B_3\Sigma X_1X_3 + B_4\Sigma X_1X_4 + B_5\Sigma X_1X_5 + B_6\Sigma X_1X_6 + B_7\Sigma X_1X_7 + B_8\Sigma X_1X_8 + B_9\Sigma X_1X_9 + B_{10}\Sigma X_1X_{10} + B_{11}\Sigma X_1X_{11} \quad (3)$$

$$\Sigma YX_2 = B_0\Sigma X_2 + B_1\Sigma X_2X_1 + B_2\Sigma {X_2}^2 + B_3\Sigma X_2X_3 + B_4\Sigma X_2X_4 + B_5\Sigma X_2X_5 + B_6\Sigma X_2X_6 + B_7\Sigma X_2X_7 + B_8\Sigma X_2X_8 + B_9\Sigma X_2X_9 + B_{10}\Sigma X_2X_{10} + B_{11}\Sigma X_2X_{11} \quad (4)$$

$$\Sigma X_3Y = B_0\Sigma X_3 + B_1\Sigma X_3X_1 + B_2\Sigma X_3X_2 + B_3\Sigma {X_3}^2 + B_4\Sigma X_3X_4 + B_5\Sigma X_3X_5 + B_6\Sigma X_3X_6 + B_7\Sigma X_3X_7 + B_8\Sigma X_3X_8 + B_9\Sigma X_3X_9 + B_{10}\Sigma X_3X_{10} + B_{11}\Sigma X_3X_{11} \quad (5)$$

$$\Sigma X_4Y = B_0\Sigma X_4 + B_1\Sigma X_4X_1 + B_2\Sigma X_4X_2 + B_3\Sigma X_4X_3 + B_4\Sigma {X_4}^2 + B_5\Sigma X_4X_5 + B_6\Sigma X_4X_6 + B_7\Sigma X_4X_7 + B_8\Sigma X_4X_8 + B_9\Sigma X_4X_9 + B_{10}\Sigma X_4X_{10} + B_{11}\Sigma X_4X_{11} \quad (6)$$

$$\Sigma X_5Y = B_0\Sigma X_5 + B_1\Sigma X_5X_1 + B_2\Sigma X_5X_2 + B_3\Sigma X_5X_3 + B_4\Sigma X_5X_4 + B_5\Sigma {X_5}^2 + B_6\Sigma X_5X_6 + B_7\Sigma X_5X_7 + B_8\Sigma X_5X_8 + B_9\Sigma X_5X_9 + B_{10}\Sigma X_5X_{10} + B_{11}\Sigma X_5X_{11} \quad (7)$$

$$\Sigma X_6Y = B_0\Sigma X_6 + B_1\Sigma X_6X_1 + B_2\Sigma X_6X_2 + B_3\Sigma X_6X_3 + B_4\Sigma X_6X_4 + B_5\Sigma X_6X_5 + B_6\Sigma {X_6}^2 + B_7\Sigma X_6X_7 + B_8\Sigma X_6X_8 + B_9\Sigma X_6X_9 + B_{10}\Sigma X_6X_{10} + B_{11}\Sigma X_6X_{11} \quad (8)$$

$$\Sigma X_7 Y = B_0 \Sigma X_7 + B_1 \Sigma X_7 X_1 + B_2 \Sigma X_7 X_2 + B_3 \Sigma X_7 X_3 + B_4 \Sigma X_7 X_4 + B_5 \Sigma X_7 X_5 + B_6 \Sigma X_7 X_6 + B_7 \Sigma X_7{}^2 + B_8 \Sigma X_7 X_8 + B_9 \Sigma X_7 X_9 + B_{10} \Sigma X_7 X_{10} + B_{11} \Sigma X_7 X_{11} \quad (9)$$

$$\Sigma X_8 Y = B_0 \Sigma X_8 + B_1 \Sigma X_8 X_1 + B_2 \Sigma X_8 X_2 + B_3 \Sigma X_8 X_3 + B_4 \Sigma X_8 X_4 + B_5 \Sigma X_8 X_5 + B_6 \Sigma X_8 X_6 + B_7 \Sigma X_8 X_7 + B_8 \Sigma X_8{}^2 + B_9 \Sigma X_8 X_9 + B_{10} \Sigma X_8 X_{10} + B_{11} \Sigma X_8 X_{11} \quad (10)$$

$$\Sigma X_9 Y = B_0 \Sigma X_9 + B_1 \Sigma X_9 X_1 + B_2 \Sigma X_9 X_2 + B_3 \Sigma X_9 X_3 + B_4 \Sigma X_9 X_4 + B_5 \Sigma X_9 X_5 + B_6 \Sigma X_9 X_6 + B_7 \Sigma X_9 X_7 + B_8 \Sigma X_9 X_8 + B_9 \Sigma X_9{}^2 + B_{10} \Sigma X_9 X_{10} + B_{11} \Sigma X_9 X_{11} \quad (11)$$

$$\Sigma X_{10} Y = B_0 \Sigma X_{10} + B_1 \Sigma X_{10} X_1 + B_2 \Sigma X_{10} X_2 + B_3 \Sigma X_{10} X_3 + B_4 \Sigma X_{10} X_4 + B_5 \Sigma X_{10} X_5 + B_6 \Sigma X_{10} X_6 + B_7 \Sigma X_{10} X_7 + B_8 \Sigma X_{10} X_8 + B_9 \Sigma X_{10} X_9 + B_{10} \Sigma X_{10}{}^2 + B_{11} \Sigma X_{10} X_{11} \quad (12)$$

$$\Sigma X_{11} Y = B_0 \Sigma X_{11} + B_1 \Sigma X_{11} X_1 + B_2 \Sigma X_{11} X_2 + B_3 \Sigma X_{11} X_3 + B_4 \Sigma X_{11} X_4 + B_5 \Sigma X_{11} X_5 + B_6 \Sigma X_{11} X_6 + B_7 \Sigma X_{11} X_7 + B_8 \Sigma X_{11} X_8 + B_9 \Sigma X_{11} X_9 + B_{10} \Sigma X_{11} X_{10} + B_{11} \Sigma X_{11}{}^2 \quad (13)$$

Computed data are fixed into the normal equations generated from equation 1 above. The resulting equations were reduced to a matrix form as shown below in Table 2.

Table 2: Matrix form of data generated from equation 1

12	414347.9	108097.6.9	60455	1418	99779	3574	11680.03	9460122	30197379	82573560	57969776	B0	1618621
414348	1.48E+10	3.08E+10	1.46E+09	4.54E+09	3.36E+09	1.27E+09	3.81E+10	3.55E+11	1.05E+12	2.91E+12	1.93E+12	B1	5.58E+10
1080977	3.08E+10	1.12E+11	3.48E+09	1.12E+08	8.25E+09	3.23E+08	9.64E+10	8.68E+11	2.62E+12	8.24E+12	5.63E+12	B2	1.41E+11
60455	1.46E+09	3.48E+09	777707919	3518778	297443788	8122408.6	3.65E+09	2.95E+09	7.93E+10	2.09E+11	1.72E+11	B3	5.00E+09
2.00E+05	6.78E+09	1.58E+09	3.52E+06	2.26E+05	1.10E+07	4.03E+05	1.29E+08	9.00E+08	3.48E+09	7.58E+09	5.97E+09	B4	1.90E+08
99779	3.36E+09	8.25E+09	2.97E+08	1.10E+07	8.39E+08	3.33E+06	9.75E+09	8.72E+10	2.70E+11	6.29E+11	4.99E+11	B5	1.00E+10
3574	1.27E+08	3.21E+08	8.12E+06	4.03E+05	3.33E+06	1.52E+06	4.02E+08	4.15E+09	1.17E+10	2.56E+10	1.91E+10	B6	5.91E+08
1168003	3.81E+10	9.64E+10	3.65E+10	1.29E+08	9.75E+09	4.02E+08	1.16E+11	1.06E+12	3.26E+12	7.07E+12	5.59E+12	B7	1.70E+11
9460122	3.55E+11	8.68E+11	2.59E+09	9.00E+08	8.72E+10	4.15E+09	1.06E+12	1.46E+13	3.23E+13	5.98E+13	5.21E+13	B8	1.58E+12
3E+07	1.05E+12	2.62E+12	7.93E+10	3.48E+09	2.70E+11	1.17E+10	3.26E+12	3.23E+13	1.03E+14	2.05E+14	1.60E+14	B9	4.80E+12
8.3E+07	2.91E+12	8.24E+12	2.09E+11	7.58E+09	6.29E+11	2.56E+10	7.07E+12	5.98E+13	2.05E+14	2.50E+15	4.30E+14	B10	1.00E+13
5796976	1.93E+12	5.63E+12	1.72E+11	5.97E+09	4.99E+11	1.91E+10	5.59E+12	5.21E+13	1.60E+14	4.30E+14	3.61E+14	B11	8.27E+12

The regression parameters ($B_0 - B_{11}$) were obtained by using Excel [37].

2.2 Model Testing

Equation 14 below is the Durbin Watson (D.W) model used to test the model developed. Using a model developed to generate values given by y this is the estimated value. Also, the difference between y and actual observation Y was obtained and called error function, e_1. Moreover, the difference between the nearest neighborhood residuals was obtained.

$$D.W = \frac{\Sigma(e_t - e_{t-1})^2}{\Sigma\, e_1^2} \quad (14)$$

The Durbin Watson test for significance was accepted at P<0.5 significance or (probability).

2.3 **Hypothesis**

To test the model using the Durbin Watson model, there are certain ranges of D.W values for which we need to consider.

H_0 There exists no correlation among residual

H_1 There exists correlation among residual

2.4 **Decision**

If computed D.W. $\geq d_L$ reject, H_0

If computed D.W. $\leq$ du accept H_1

If $d_L \geq$ D.W.$\leq$ du then test is indecisive

3. Results and discussion

The values of regression parameters B_0 $B_1 - B_{11}$ are shown in Table 3 at the last right column.

Table 3: Regression Parameters

											Constants		Solution
12	414347.91	108097.6.9	60455	1418	99779	3574	11680.03	9460122	30197379	82573560	1618621	B_0 =	262295.198
414347.9	1.476E+10	3.08E+10	1.46E+09	4.54E+09	3.36E+09	1.27E+09	3.81E+10	3.55E+11	1.05E+12	2.91E+12	5.58E+10	B_1 =	-6.996
1080977	3.08E+10	1.12E+11	3.48E+09	1.12E+08	8.25E+09	3.23E+08	9.64E+10	8.68E+11	2.62E+12	8.24E+12	1.41E+11	B_2 =	-3.529
60455	1.46E+09	3.48E+09	777707919	3518778	297443788	8122408.6	3.65E+09	2.95E+09	7.93E+10	2.09E+11	5.00E+09	B_3 =	19.365
2.00E+05	6.78E+09	1.58E+09	3.52E+06	2.26E+05	1.10E+07	4.03E+05	1.29E+08	9.00E+08	3.48E+09	7.58E+09	1.90E+08	B_4 =	4398.826
99779	3.36E+09	8.25E+09	2.97E+08	1.10E+07	8.39E+08	3.33E+06	9.75E+09	8.72E+10	2.70E+11	6.29E+11	1.00e+10	B_5 =	-3.813
3574	1.27E+08	3.21E+08	8.12E+06	4.03E+05	3.33E+06	1.52E+06	4.02E+08	4.15E+09	1.17E+10	2.56E+10	5.91E+08	B_6 =	138.017
1168003	3.81E+10	9.64E+10	3.65E+10	1.29E+08	9.75E+09	4.02E+08	1.16E+11	1.06E+12	3.26E+12	7.07E+12	1.70E+11	B_7 =	-8.064
9460122	3.55E+11	8.68E+11	2.59E+09	9.00E+08	8.72E+10	4.15E+09	1.06E+12	1.46E+13	3.23E+13	5.98E+13	1.58E+12	B_8 =	0.417
30197379	1.05E+12	2.62E+12	7.93E+10	3.48E+09	2.70E+11	1.17E+10	3.26E+12	3.23E+13	1.03E+14	2.05E+14	4.80E+12	B_9 =	0.006
82573560	2.91E+12	8.24E+12	2.09E+11	7.58E+09	6.29E+11	2.56E+10	7.07E+12	5.98E+13	2.05E+14	2.50E+15	1.00E+13	B_{10} =	0.004
5796976	1.93E+12	5.63E+12	1.72E+11	5.97E+09	4.99E+11	1.91E+10	5.59E+12	5.21E+13	1.60E+14	4.30E+14	8.27E+12	B_{11} =	0.047

These are then plugged into equation 1 to obtain multivariate regression model given as:

$$\boldsymbol{Y = 262295.198 - 6.996X_1 - 3.529X_2 + 19.365X_3 + 4398.826X_4 - 3.813X_5 + 138.017X_6 + 8.064X_7 + 0.417X_8 + 0.006X_9 + 0.004X_{10} + 0.047X_{11} + \varepsilon_{in}} \quad (15)$$

Where $\boldsymbol{\varepsilon_{in} = standard\ error}$

Equation 15 was then used to generate values for Durbin Watson test and these presented in Table 4

Table 4 Computation of Durbin Watson Test

YEAR	**Steel Produced**	**Estimated Steel Produced**	**e_1**	**e_{t-1}**	**e_t-e_{t-1}**	**$(e_t-e_{t-1})^2$**	**e_t^2**
1982	90237	90229.32	7.68		7.68	58.9824	58.9824
1983	181957	181949.3	7.7	7.68	0.02	0.0004	59.29
1984	130318	130310.3	7.7	7.7	0	0	59.29
1985	243893	243885.3	7.7	7.7	0	0	59.29
1986	143067	143059.3	7.7	7.7	0	0	59.29
1987	136552	136544.3	7.7	7.7	0	0	59.29
1988	139326	139318.3	7.7	7.7	0	0	59.29
1989	127648	127640.3	7.7	7.7	0	0	0
1990	138950	138942.3	7.7	7.7	0	0	0
1991	113802	113794.3	7.7	7.7	0	0	0
1992	61873	61865.32	7.68	7.7	-0.02	0.0004	58.9824
1993	42699	42691.32	7.68	7.68	0	0	58.9824
1994	50028	50020.32	7.68	7.68	0	0	58.9824
1995	36041	36033.32	7.68	7.68	0	0	58.9824
						58.9832	**828.522**

$$D.W = \frac{\sum(e_t - e_{t-1})^2}{\sum e_1^2} = D.W = \frac{58.9832}{828.522} = 0.071191$$

Note:

H_o There exist no correlation among residual

H_1 There exists correlation among residual

From the table

d_L = 0.1.05

d_u = 3.053

Hence D.W lies in an indecisive region, where it is not possible either to reject or fail to reject the null hypothesis. Table 3 and Figure 2 illustrate the steel produced and estimated steel produced using the model developed. From the figure, the model was able to predict steel production with less than 8% error.

3.1 **Application f The Model**

To predict amount of steel produced using the model developed (equation 15), each quantity of variable (x_1---------x_{11}) are substituted in equation 15. For example, x_1=300tonnes, x_2=350tonnes, x_3=70tonnes, x_4=100tonnes, x_5=150tonnes, x_6=200 tonnes, x_7=400 tonnes,

x_8=400tonnes, x_9=100tonnes, x_{10}=125tonnes, x_{11}=440tonnes.Using equation 15, gives=Steel = 730637.3 Metric tonnes.

Comparison of Steel Produced and Estimated Steel Produced

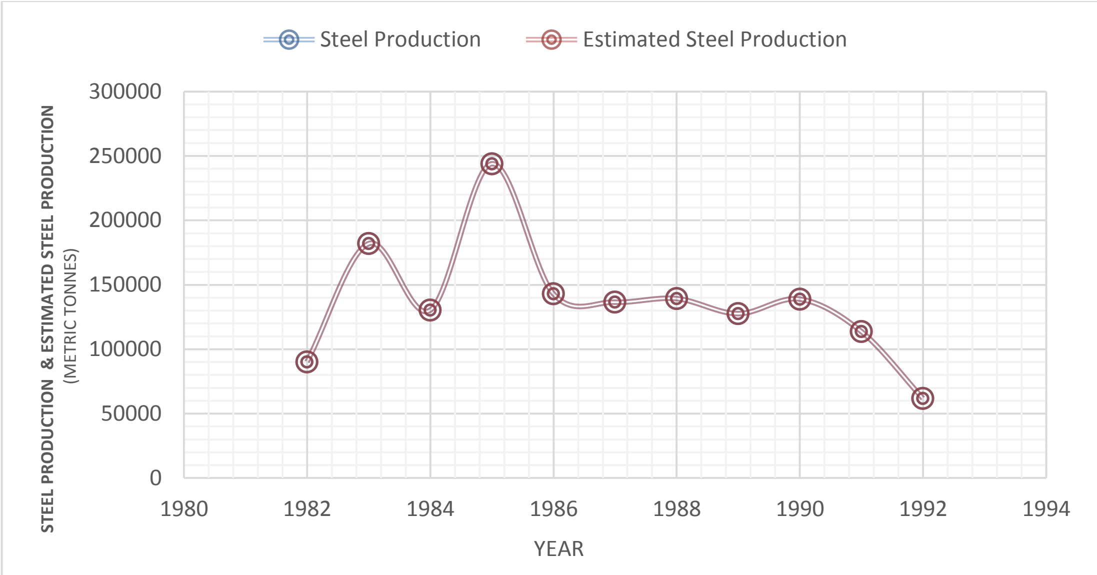

Figure 2: *Comparison of Steel Produced and Estimated Steel Produced*

3.2 **Effect of Raw Materials on Product (Liquid Steel)**
The effect of some raw materials was looked at and their results are presented graphically in Figure 3.

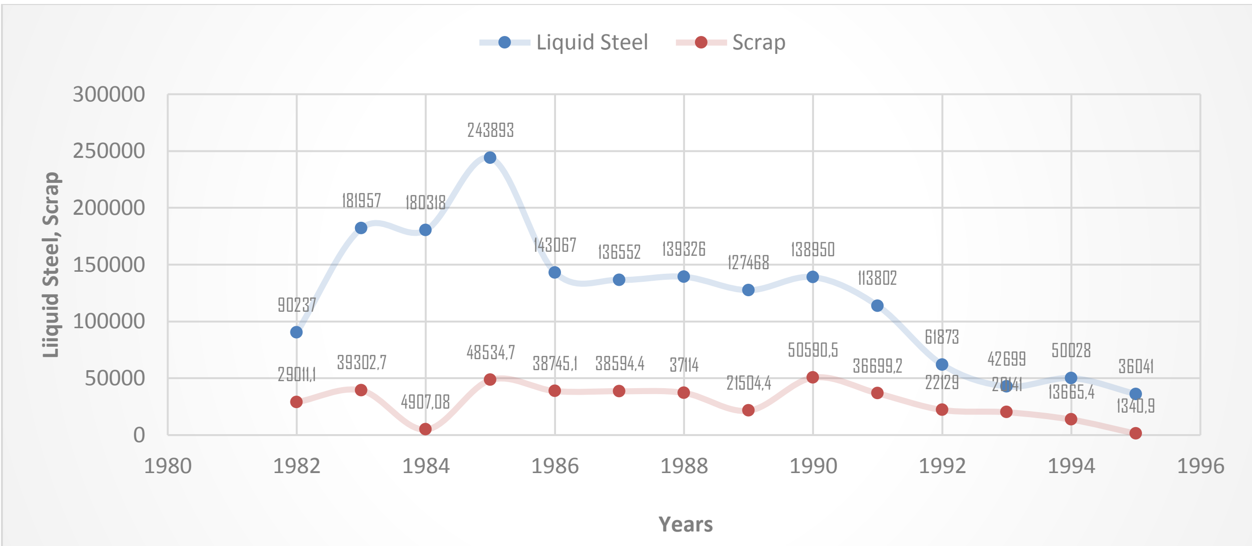

Figure 3*:* *Effect of Scrap on Liquid Steel*

An important process in the steel industry is melting. The melting rate is directly connected to energy consumption and furnace productivity. Electric-arc furnace steelmaking, about 60% of the total energy requirement is consumed in heating and melting scrap, and more than 50% of the time required for one heat is used for melting [38]. Several studies have been carried out to investigate the scrap melting in a liquid steel bath [39-45]. The effect of scrap on liquid is shown in Figure 3 The addition of 35.5% scrap brings about 100% increase in liquid steel.

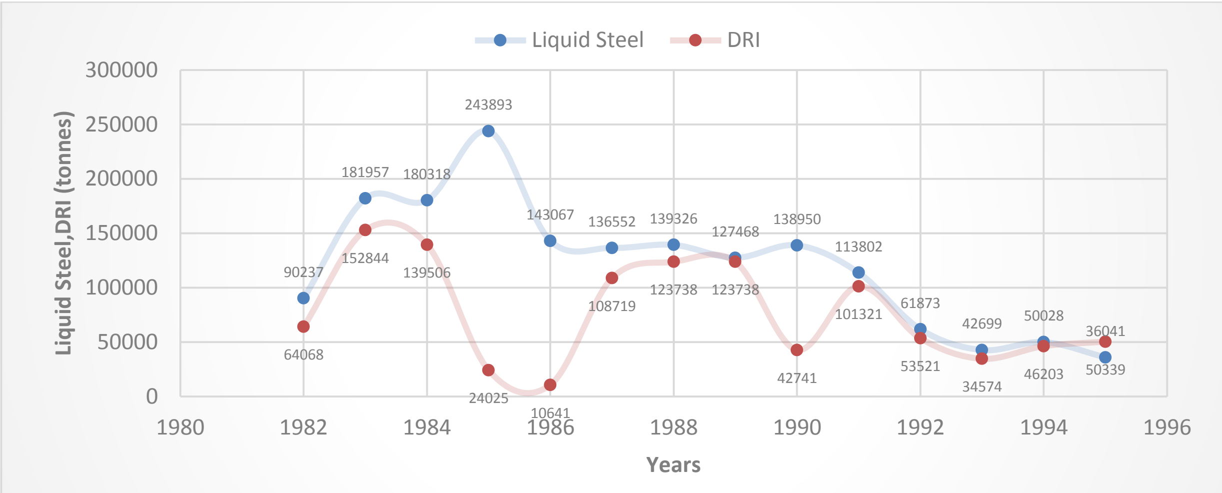

Figure 4: *Effect of DRI on Liquid Steel*

The effect of direct reduced iron (DRI) addition on dephosphorization of molten steel by electric arc furnace (EAF) slag at 1550 ^{0}C Thermodynamic behaviors of phosphorus, oxygen, and carbon was strongly reliant on DRI content. When using DRI in the EAF process, it is very important to control the basicity of slag. Figure 4 shows that 139% addition of DRI brings about 100% improvement in the properties of liquid steel.DRI contains a relatively high level of phosphorus, which adversely affects the properties of steels [46]. The use of DRI is to produce high-quality steels in an EAF also increases the possibility of phosphorus pollution of steel. Thus, phosphorus should be completely controlled in the EAF process. Though, because there are various types of oxides (*e.g.*, Fe_tO, SiO_2, Al_2O_3, CaO) as well as carbon present in DRI, a complete understanding of the consequence of DRI on slag formation behavior, and thus dephosphorization efficiency in the EAF process, is essential.

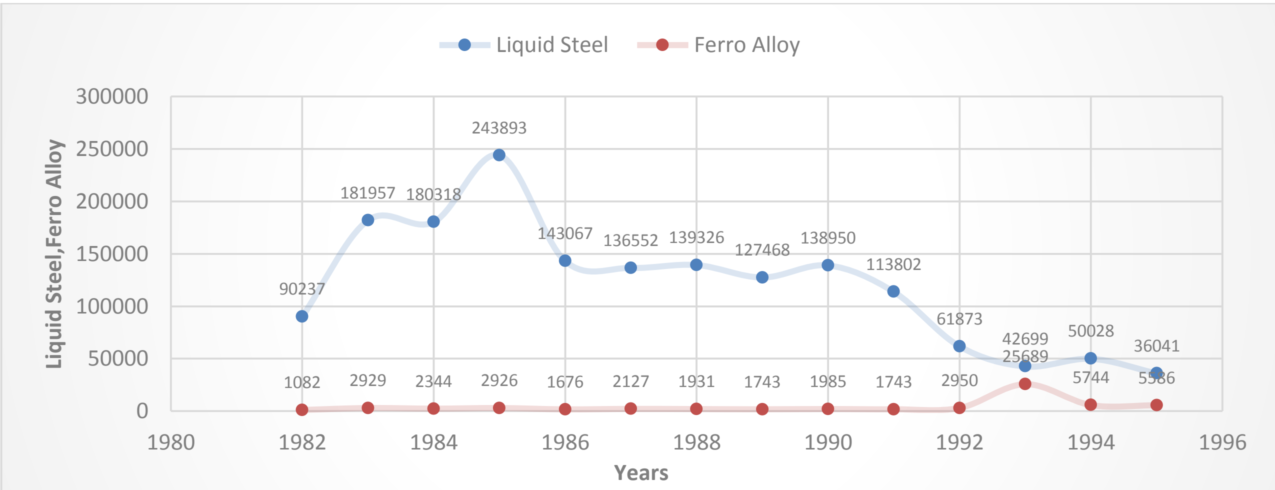

Figure 5: *Effect of Ferro Alloy on Liquid Steel*

Figure 5 shows the effect of Ferro Alloy on liquid steel. Ferroalloy influences the reproducibility of steel properties from heat to heat. Ferroalloys is one of the costliest inputs to steelmaking [47]. Coke is injected to increase the melt-down effectiveness by providing extra energy from the combustion process aided by oxygen injection and to form foaming slag with CO produced from the carbon combustion to cover the electric arc and hence reduce energy losses by radiation. The effect is shown in figure 6 [48].

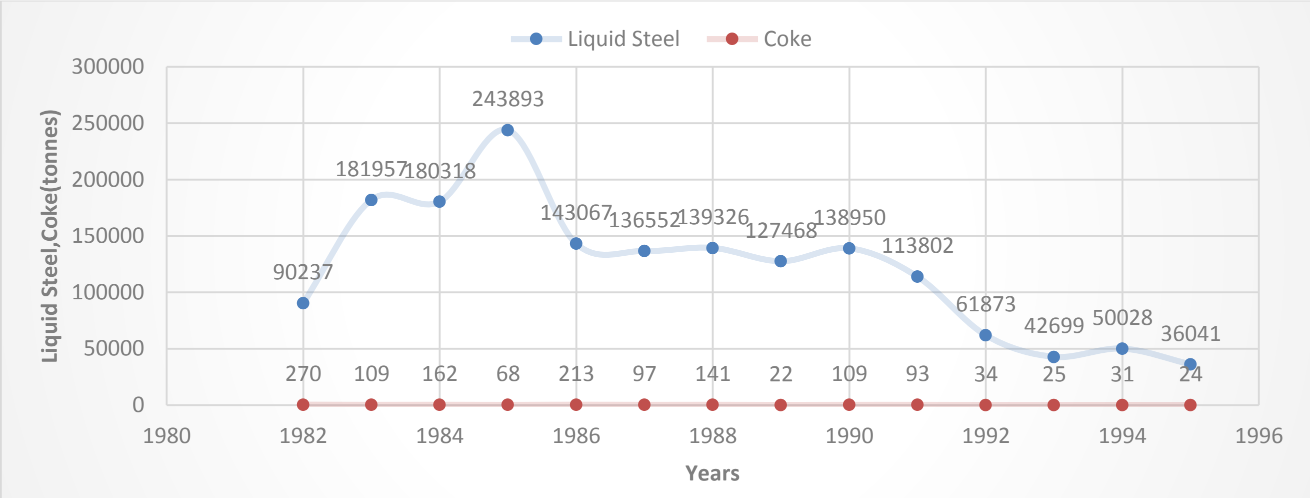

Figure 6: *Effect of Coke on Liquid Steel*

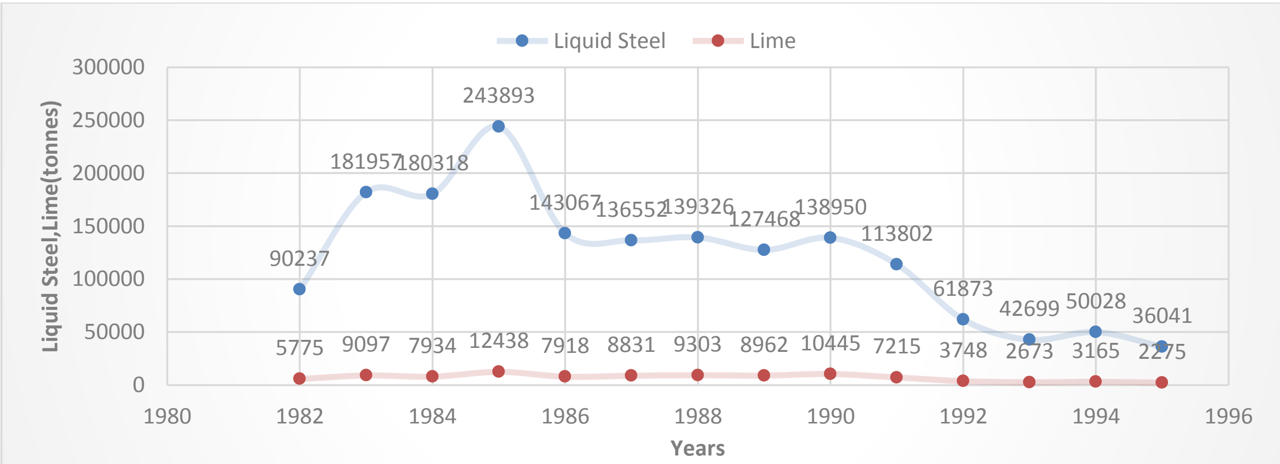

Figure 7: Effect of Lime on Liquid Steel

Figure 7 shows the effect of Lime on Liquid Steel Lime has a serious role at different steps of the steelmaking process, and specially to make a good slag simplifying the removal of sulphur and phosphorus, Lime quality and quantity has a direct effect on slag quality, which affects metallurgical results, headstrong life, liquid metal yield, and productivity, and therefore the total cost of the steel production. Lime quality and quantity have a direct effect on slag quality, which affects metallurgical results, refractory life, and productivity, and therefore the total cost of steel production [49-50]. Oxygen is injected by manipulators to aid the formation of foaming slag in combination with carbon injections or to achieve a blowing process similar to that of the oxygen steelmaking process. Manual lances are used to clear the deslagging gate, residual scrap or blocked tap holes as well as to intensify the meltdown of the charge [51]. Figure 8 shows that as the quantity of oxygen into the system, there will be a high yield of liquid Steel. Figure 9 shows that as the quantity of Nitrogen into the system, there will be a high yield of liquid Steel. Figure 10 shows that as the quantity of Natural gas into the system, there will be a high yield of liquid Steel. Natural gas is a major source of electricity generation through the use of cogeneration, gas turbines and steam_turbines. Natural gas is also well suitable for combined use in association with renewable energy sources such as wind or solar. An important point to draw from this study is that multivariate models have definite advantages since they combine the characteristic of multiple regression and univariate Box Jenkins. It can capture and measure the effect of raw materials on steel production and these are shown from Figure 3 through to Figure 10.

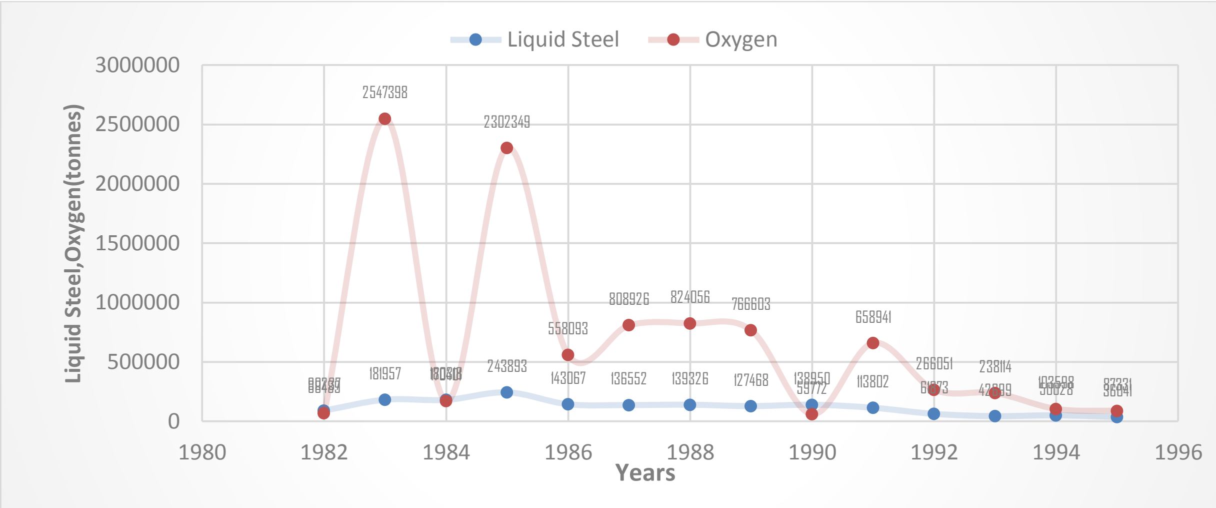

Figure 8: *Effect of oxygen on Liquid Steel*

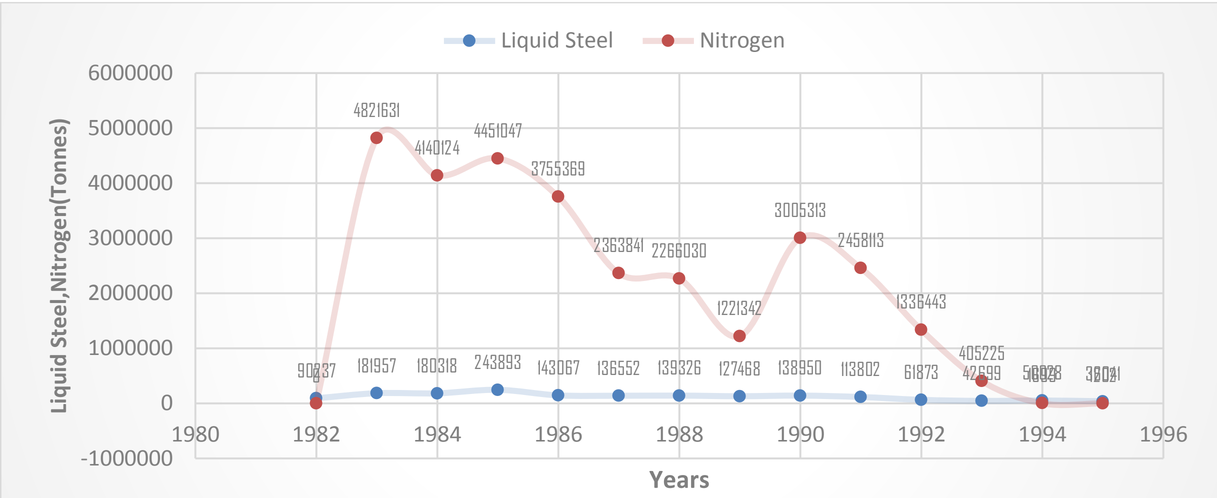

Figure 9: *Effect of Nitrogen on Liquid Steel*

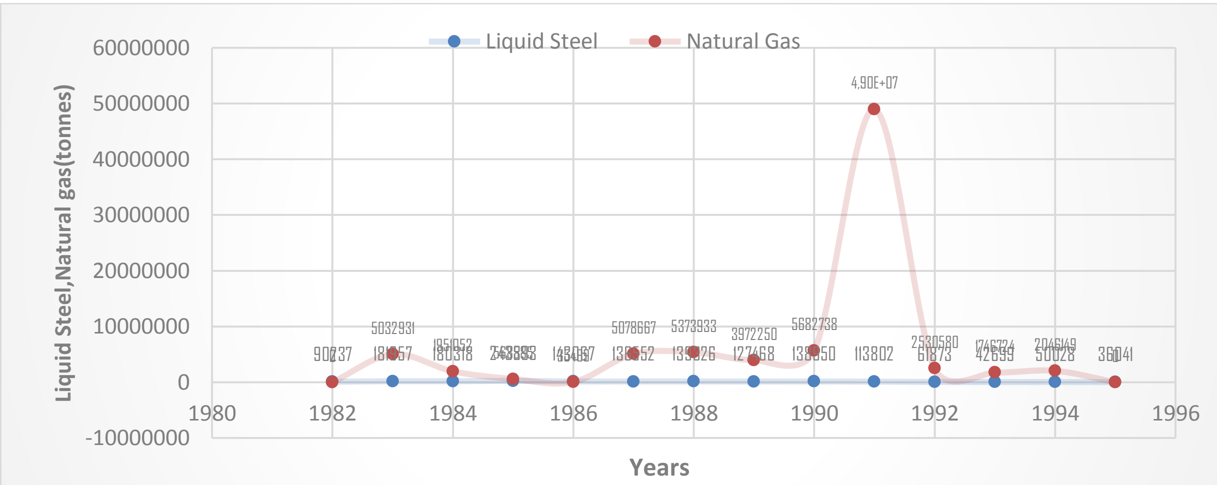

Figure 10: *Effect of Natural gas on Liquid Steel*

Durbin Watson's test for significance carried out suggests that the model developed is robust and reliable. This is because the residual values obtained are so insignificant that the probability of having values greater than the observed would be less than 10%. Using equation 15 (Model equation) as object function and considering some constraints steel optimization can be carried out and effect of change of any of the variables to the overall yield of steel when other variables are constant [52].

Conclusion

Based on the analysis carried out above and the subsequent discussion, it is clear that a sure-fire Model that can maximize and predict the effect of change in any of the variables (raw materials) in steel production has been developed. Such a model can provide the steel industries in the country important information about the sensitivity of the optimal solution.

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