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Research Article

Modelling Multi-Input-Single-Output (MISO) Production Process Using Transfer Function: A Case Study of a Brewery

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Abstract: Material requirement planning in production systems usually require product explosion in order to determine the raw materials required to produce a given quantity of product in a given horizon. Product explosion can easily be done in cases when the product is a discrete item but becomes impossible in flow production processes. In this situation an appropriate method of relating input to output of processes, such as transfer function, would be used as an alternative to product explosion in material requirement planning. In this study, transfer function is used to model the relationship between the input and output of a brewery. It involved taking the inputs and outputs to the brewery for three different periods and determining the transfer functions. The determined transfer functions were compared with an equivalent model obtained using regression analysis. The results show that transfer function models performed better than regression analysis. In addition the raw materials quality variability and product variability, a key characteristics of the process industry, was effectively modeled. Transfer function is therefore recommended as the preferred tool for material requirement planning for breweries.

Keywords: Brewery, material requirement planning, modelling, multi input single output process, transfer function

INTRODUCTION

Quite regularly in production systems, it is often necessary to predict/forecast the output of a process from a given input or determine the inputs required to produce a given quantity of output. This is very desirable in production planning and control systems. In material requirement planning, when the quantity of a given product to be produced in a given period, i.e., weekly, biweekly, monthly etc as the case may be, is determined from sales forecast and demand, it is often necessary to determine the quantity of raw materials that would meet the aggregate production plan. In the manufacture of discrete items, this is often done by product explosion. In the process industry, product explosion is not possible because of the nature of the production process. Therefore, an approximate way to relate the quantity of raw materials required to produce a given product is to model the relationship between the input to a process and the output of the process.

As noted in the literature, determining the relationship between the input and output of a production process is quite complex because the input to a production process is stochastic and the output is equally stochastic (Nwobi-Okoye and Igboanugo, 2012, 2015; Nwobi-Okoye *et al*., 2015; Igboanugo and Nwobi-Okoye, 2012; Igboanugo and Nwobi-Okoye, 2011). The complexity becomes even more in the case of multi-input single-output production processes as shown in Fig. 1 in the case of a brewery.

Mathematically modelling the relationship between input and output of processes is usually done through transfer function modeling, regression analysis and its derivatives which include linear system model, Koyck-lags model, Almon-lags model etc (Lai, 1979; Nwobi-Okoye and Igboanugo, 2012; Box *et al*., 2008). Of all these mathematical modeling tools named, many authors have praised the elegance, accuracy and superiority of transfer functions in modeling the causal relationship between input and output of a process over regression analysis and its derivatives (Nwobi-Okoye and Igboanugo, 2012, 2015; Lai, 1979; Box *et al*., 2008; Kinney, 1978). Hence, our choice to investigate transfer function modeling as a tool for Material Requirement Planning (MRP) in breweries is based on sound scientific evidence backed by literature.

MRP as an operations management tool has evolved over the years. The earliest writing on the basic MRP calculations was due to Sloan (1963) who wrote about its use as far back as 1921 in his account of his years at General Motors. In the literature, it is noted that application of MRP in process industries is quite

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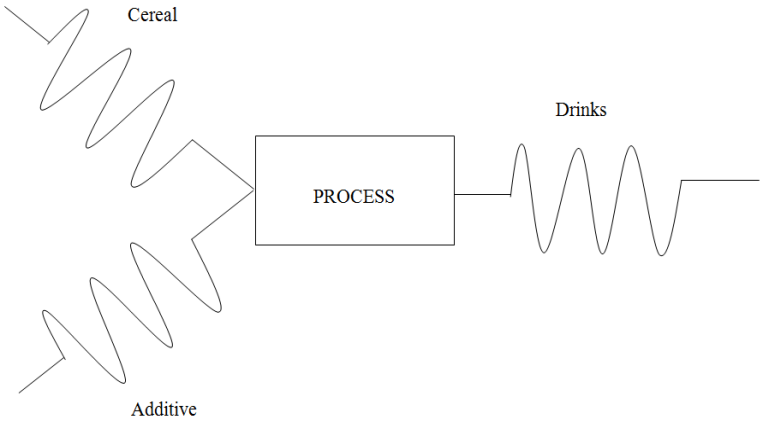

Fig. 1: Schematic of the input-output relationship of a brewery

difficult and less straightforward when compared to industries that manufacture discrete items (Crama *et al*., 2001; Schuster *et al*., 2000; Fransoo and Rutten, 1994; Akkerman and van Donk, 2006; Kallrath, 2002a, 2002b). One of the complexities of application of MRP to process industries is that unlike in the manufacture of discrete items, the raw materials vary for the same quantity of product and the quality of raw materials or end products could also vary considerably (Crama *et al*., 2001). This apparent complexity makes transfer function an appropriate tool for modeling the complex relationship between the input and output of a process. By doing this we would have a more accurate recipe, an important component of the MRP in the process industry.

The aim of this research is to explore transfer function modeling as possible tool for MRP in the process industry with brewery as a case study; and also to compare the tool with regression analysis, a competing tool. The hub of our investigation is a local brewery known as Consolidated Breweries PLC located at Awo Omamma, Imo State Nigeria. The company produces malt drinks and beer.

THEORETICAL BRIEF

Multiple input transfer function models: In terms of the impulse response weights $v(B)$, the transfer function can be represented as (Box *et al*., 2008):

$$Y_t = v(B)X_{t-b} + N_t \quad (1)$$

Recalling that $v(B) = \delta^{-1}(B)\omega(B)$ (Box *et al*., 2008), we obtain:

$$Y_t = \delta^{-1}(B)\omega(B)X_{t-b} + N_t \quad (2)$$

Allowing for several inputs, $X_{1,t}, X_{2,t},\ldots, X_{m,t}$ we have:

$$Y_t = v_1(B)X_{1,t} + \cdots + v_m(B)X_{m,t} + N_t \quad (3)$$

$$Y_t = \delta^{-1}(B)\omega_1(B)X_{1,t-b} + \cdots + \delta^{-1}(B)\omega_m(B)X_{m,t-b} + N_t \quad (4)$$

Here $v_j(B)$ is the generating function of the impulse response weights relating to $X_{j,t}$ to the output. Assuming differencing is applied to the input and output series we obtain:

$$y_t = v_1(B)x_{1,t} + \cdots + v_m(B)x_{m,t} + n_t \quad (5)$$

Multiplying throughout by $X_{1,t-k}$, $X_{2,t-k}$, …, $X_{m,t-k}$ in turn and taking expectations and forming the generating functions, we obtain:

$$\begin{aligned}&\gamma^{x_1y}(B) = v_1(B)\gamma^{x_1x_1}(B) + v_2(B)\gamma^{x_1x_2}(B) + \cdots + v_m(B)\gamma^{x_1x_m}(B)\\ &\gamma^{x_2y}(B) = v_1(B)\gamma^{x_2x_1}(B) + v_2(B)\gamma^{x_2x_2}(B) + \cdots + v_m(B)\gamma^{x_2x_m}(B)\\ &\gamma^{x_my}(B) = v_1(B)\gamma^{x_mx_1}(B) + v_2(B)\gamma^{x_mx_2}(B) + \cdots + v_m(B)\gamma^{x_mx_m}(B)\end{aligned} \quad (6)$$

Substituting $B = e^{-i2\pi f}$, the spectral equations are obtained. For the case of m = 2, the spectral equations are:

$$p_{x_1y}(f) = H_1(f)p_{x_1x_1}(f) + H_m(f)p_{x_1x_2}(f) \quad (7)$$

$$p_{x_2y}(f) = H_1(f)p_{x_2x_1}(f) + H_m(f)p_{x_2x_2}(f) \quad (8)$$

The frequency response functions $H_1(f) = v_1(e^{-i2\pi f}), H_2(f) = v_2(e^{-i2\pi f})$ can be calculated through methods outlined in the literature on spectral analysis such as Koopmans (2003) and Jenkins and Watts (1968) etc. The impulse response weights can be obtained by the inverse transformation thus:

$$v_k = \int_{-\frac{1}{2}}^{\frac{1}{2}} v(e^{-i2\pi f})e^{i2\pi f}df \quad (9)$$

METHODOLOGY

The six year data obtained from the brewery was subjected to exploratory data analysis to detect outliers and patterns in the data. After the exploratory data analysis, the transfer function model according to Eq. (4) was obtained using the input-output data for the periods 2006-2007, 2008-2009 and 2010-2011.

In order to realize the transfer function model based on Eq. (4), a plot of the 6-year input-output data was done using SPSS software. Following the plot, the data were investigated for stationarity, using the plots of the Autocorrelation Functions (ACF) and Partial Autocorrelation Functions (PACF). The inputs and output series derived from the plots were investigated for stationarity. Non stationary series were differenced to achieve stationarity. A univariate model was individually fitted to the input X_{1t} and output Y_t and input X_{2t} and output Y_t for each of the years in order to respectively estimate prewhitened input series α_{1t} and α_{2t} and pretreated output series β_{1t} and β_{2t} respectively. Calculation of the cross correlation functions, CCF (k) of $\beta_{1t}\alpha_{1t-k}$ and $\beta_{2t}\alpha_{2t-k}$ was used to identify r, s and b parameters of the transfer function model. Sequel to obtaining the nature of the transfer function models, the impulse response weights v_k, estimated with spectral analysis, were used to estimate the transfer function parameters in Eq. (4).

RESULTS

Transfer function modelling: Figure 2 shows the monthly raw materials consumption and the corresponding output (drink production) in the years 2010-2011 for Consolidated Brewery Nigeria Limited. The raw material X1 are cereals while the raw material X2 is the additive. All raw material values are in kg, while the output values are in Hecto Litre (HL).

Analysis of input 1 (X_1) and output (Y): After plotting the input series X1 as shown in Fig. 2, the data was investigated for stationarity, using the plots of the Autocorrelation Functions (ACF) and Partial Autocorrelation Functions (PACF). The input and output series derived from the plots were found not to be stationary, hence differencing was used to achieve stationarity. Stochastic regularity was achieved after the second differencing.

Examination of the ACF shown in Fig. 3, the ACF at lag 1 is significant. But examination of the PACF shown in Fig. 4, only the ACF at lag 1 repeated its significant and this is indicative that MA (1) model is the appropriate model to use.

The formula for MA (1) models (Box *et al*., 2008; DeLurgio, 1998) is given by Eq. (10):

$$X_{2t} = \mu + \theta_1 e_{2t-1} + e_{2t} \quad (10)$$

$$x_{2t} = X_{2t} - X_{2t-1} \quad (11)$$

$$x_{2t} = \theta_1 e_{2t-1} + e_{2t} \quad (12)$$

But for MA (1) models, we have:

$$ACF(1) = \rho_1 = -0.461 \quad (13)$$

But:

$$\rho_1 = \frac{-\theta_1}{1+\theta_1^2} \quad (14)$$

Therefore:

$$-0.461 = \frac{-\theta_1}{1+\theta_1^2} \quad (15)$$

$$0.461\theta_1^2 - \theta_1 + 0.461 = 0 \quad (16)$$

$$\theta_1 = -0.6128$$

Hence, fitting the coefficient θ_1 into the formula for MA (1) models, Eq. (17) is obtained:

$$x_{2t} = -0.6128 e_{2t-1} + e_{2t} \quad (17)$$

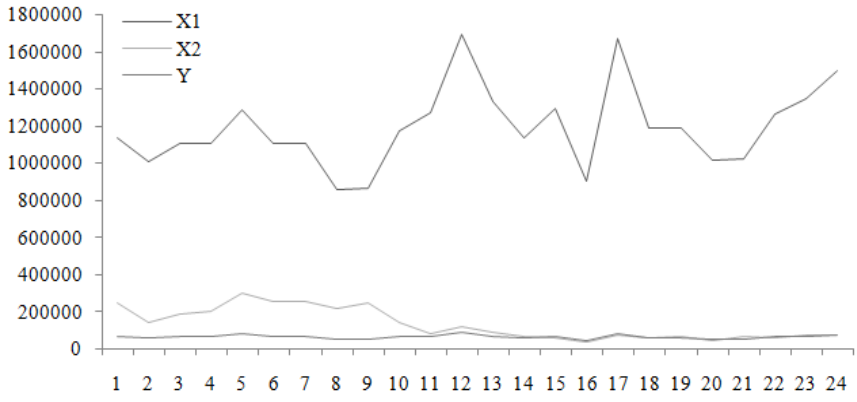

Fig. 2: Monthly raw material consumption and output

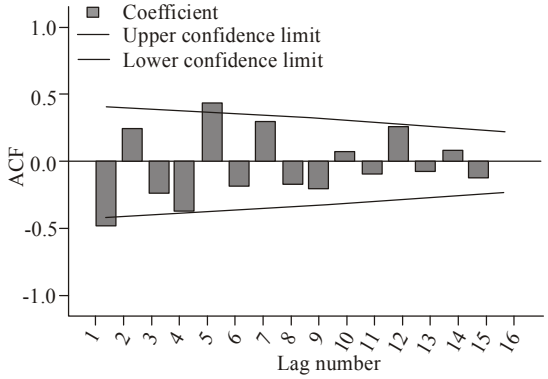

Fig. 3: ACF of the input series

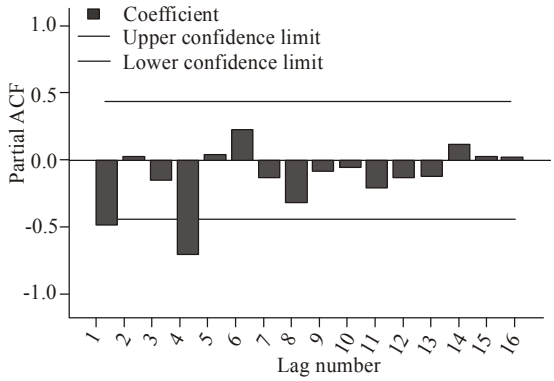

Fig. 4: PACF of the input series

Substituting Eq. (17) into Eq. (11) we obtain:

$$X_{2t} - X_{2t-1} = -0.6128e_{2t-1} + e_{2t} \quad (18)$$

$$X_{2t} = X_{2t-1} - 0.6128e_{2t-1} + e_{2t} \quad (19)$$

But:

$$e_t = \alpha_t \quad (20)$$

In forecasting form Eq. (19) is transformed to Eq. (21):

$$\hat{X}_{2t} = X_{2t-1} - 0.6128e_{2t-1} + e_{2t} \quad (21)$$

Pre-treating the output in the same way the input was transformed, we obtain:

$$Y_t = Y_{t-1} - 0.6128e_{t-1} + e_t \quad (22)$$

But:

$$e_t = \beta_t \quad (23)$$

In forecasting form Eq. (22) is transformed to Eq. (24):

$$\hat{Y}_t = Y_{t-1} - 0.6128e_{t-1} + e_t \quad (24)$$

The CCF between βt and αt is shown in Fig. 5. It has one significant CCF at lag zero (0). Hence,

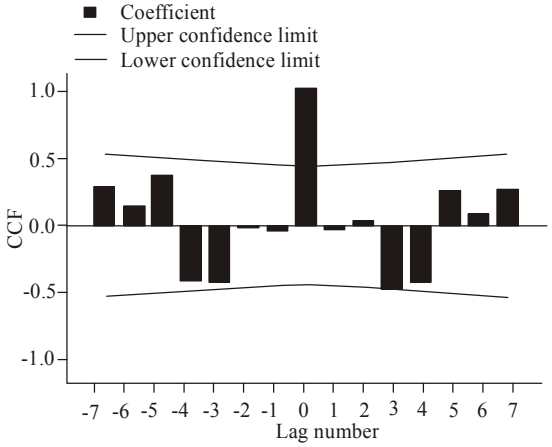

Fig. 5: CCF of the pre-whitened series

according to Box *et al*. (2008), the parameters r, s and b of the transfer function that supports such CCF pattern are 0, 0 and 0 respectively. In view of this fact, the CCF supports the following transfer function model:

$$y_t = \omega 2_0 x_{2t} + N_t \quad (25)$$

Based on Ljung-Box statistics and analysis of the residuals, the transfer function was found to have white noise residuals, hence we disregarded the noise term N_t, to obtain Eq. (26):

$$y_t = \omega 2_0 x_{2t} \quad (26)$$

As shown by Box *et al*. (2008) and DeLurgio (1998):

$$v2_0 = \omega 1_0 \quad (27)$$

$$v2_0 = \text{impulse response for } X_2$$

But:

$$X_{2t} - \mu = x_{2t} \quad (28)$$

And:

$$Y_t - \mu_y = y_t \quad (29)$$

Substituting Eq. (29) into Eq. (26), Eq. (30) is obtained:

$$Y_t = \mu_y + \omega 2_0 x_{2t} \quad (30)$$

ANALYSIS OF INPUT 2 (X_2) AND OUTPUT (Y)

The (X_2) series upon analysis was found to be stationarity, hence differencing was not used. Examination of the ACF and PACF in Fig. 6 and 7 are indicative that auto regression one (AR (1)) model is the appropriate model to use.

The formula for AR (1) models (Box *et al*., 2008; DeLurgio, 1998) is given by Eq. (31):

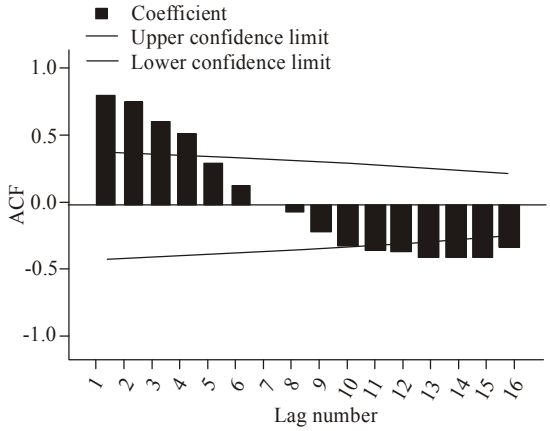

Fig. 6: ACF of the input series

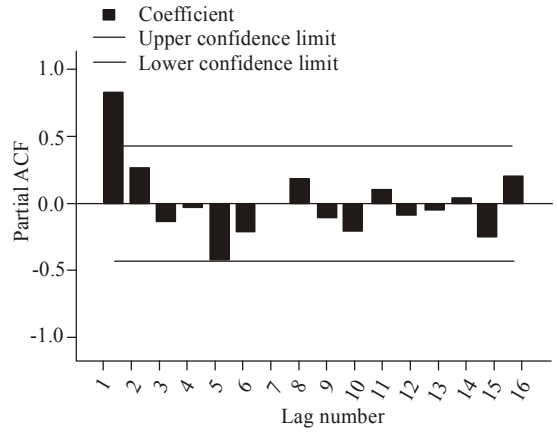

Fig. 7: PACF of the input series

$$X_{2t} = \theta_0 + \emptyset_1 X_{2t-1} + e_t \quad (31)$$

But for AR (1) models, we have:

$$ACF(1) = \emptyset_1 = 0.800 \quad (32)$$

$$\mu = 129968.9583$$
$$\theta_0 = (1 - \emptyset_1)\mu$$
$$\theta_0 = (1 - 0.800)129968.9583$$
$$\theta_0 = 25993.792 \quad (33)$$

Fitting the coefficients θ_0 and $\emptyset_1$ into the formula for AR (1) models, Eq. (34) is obtained:

$$X_{2t} = 25993.792 + 0.800X_{2t-1} + e_t \quad (34)$$

But:

$$e_t = \alpha_t \quad (35)$$

In forecasting form Eq. (34) is transformed to Eq. (36):

$$\hat{X}_{2t} = 25993.792 + 0.800X_{2t-1} \quad (36)$$

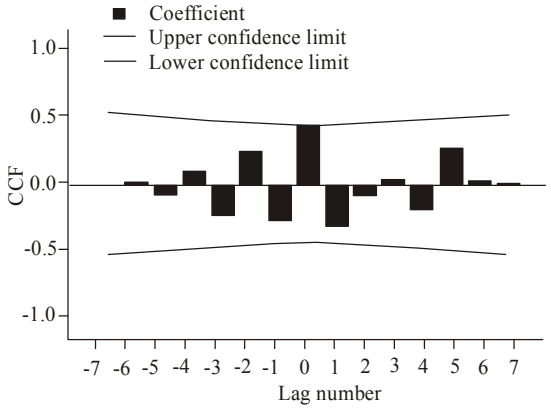

Fig. 8: CCF of the pre-whitened series

Pre-treating the output in the same way the input was transformed, we obtain:

$$\emptyset_1 = 0.800$$
$$\theta_0 = (1 - \emptyset_1)\mu$$
$$\mu = 64785.93794$$
$$\theta_0 = (1 - 0.800)64785.93794$$
$$\theta_0 = 12957.1876$$
$$Y_t = 12957.1876 + 0.800Y_{t-1} + e_t \quad (37)$$

But:

$$e_t = \beta_t \quad (38)$$

In forecasting form Eq. (37) is transformed to Eq. (39):

$$\hat{Y}_t = 12957.1876 + 0.800Y_{t-1} \quad (39)$$

The CCF between β_t and α_t is shown in Fig. 8. It has one significant CCF at lag zero (0). Hence, according to Box *et al*. (2008), the parameters r, s and b of the transfer function that supports such CCF pattern are 0, 0 and 0 respectively. In view of this fact, the CCF supports the following transfer function model:

$$y_t = \omega 2_0 x_{2t} + N_t \quad (40)$$

Based on Ljung-Box statistics and analysis of the residuals, the transfer function was found to have white noise residuals, hence we disregarded the noise term N_t, to obtain Eq. (41):

$$y_t = \omega 2_0 x_{2t} \quad (41)$$

As shown by Box *et al*. (2008) and DeLurgio (1998):

$$v2_0 = \omega 1_0 \quad (42)$$

$$v2_0 = impulse\ response\ for\ X_2$$

But:

$$X_{2t} - \mu = x_{2t} \quad (43)$$

Table 1: Transfer function models of the brewery

Year	Transfer Function Model (v(B))
2010-2011	$Y_t = 64785.938 + 0.0489805291298761(X_{1t} - \mu_1) + 0.0547027826309204\ (X_{2t} - \mu_2)$
2008-2009	$Y_t = 60639.747 + 0.0451340973377228(X_{1t} - \mu_1) + 0.0746965254718585(X_{2t} - \mu_2)$
2006-2007	$Y_t = 45447.329 + 0.048234991436449(X_{1t} - \mu_1) + 0.0601006329059601\ (X_{2t} - \mu_2)$

Table 2: Comparison of statistics of regression and transfer function models

Years	R^2 (Regression)	R^2 (Transfer Function)	MAPE (Regression)	MAPE (Transfer Function)
2010-2011	0.999	0.999	0.424816124	0.418508984
2008-2009	0.971	0.977	1.558114135	1.534790006
2006-2007	0.998	0.999	0.763015663	0.757127741

Table 3: Raw materials requirements for 50,000 HL of product for different periods

Year	Product Requirement (HL)	Cereal Requirement (Kg)	Additive (Kg)
2010-2011	50, 000	752773	82199
2008-2009	50, 000	869557	154001
2006-2007	50, 000	895598	91700

And:

$$Y_t - \mu_y = y_t \quad (44)$$

Substituting Eq. (41) into Eq. (44), Eq. (45) is obtained:

$$Y_t = \mu_y + \omega 2_0 x_{2t} \quad (45)$$

The analysis above revealed that transfer function is of the form:

$$y_t = \omega 1_0 x_{1t} + \omega 2_0 x_{2t} \quad (46)$$

Since:

$$y_t = Y_t - \mu_y,\ x_{1t} = X_{1t} - \mu_1 \text{ and } x_{2t} = X_{2t} - \mu_2$$
$$Y_t = \mu_y + \omega 1_0 (X_{1t} - \mu_1) + \omega 2_0 (X_{2t} - \mu_2) \quad (47)$$

Since:

$$v1_0 = \omega 1_0 \text{ and } v2_0 = \omega 2_0$$

where, $v1_0 = impulse\ response\ for\ X_1$ and $v2_0 = impulse\ response\ for\ X_2$:

$$Y_t = \mu_y + v1_0 (X_{1t} - \mu_1) + v2_0 (X_{2t} - \mu_2) \quad (48)$$

$v1_0$ and $v2_0$ were obtained by spectral analysis. After spectral analysis and parameter optimization using genetic algorithm the values of $v1_0$ and $v2_0$ obtained were:

$$v1_0 = 0.0489805291298761$$
and $v2_0$= 0.0547027826309204

Therefore for 2010-2011 operation of the brewery, the transfer function is given by:

$$Y_t = \mu_y + 0.0489805291298761(X_{1t} - \mu 1) + 0.0547027826309204(X2t - \mu 2) \quad (49)$$

Table 1 shows the transfer function models obtained for the three years operation of the brewery.

But from Table 2, a comparison of the two models from statistical point of view indicates that the transfer function model performed better than the regression model. This is because the coefficient of determination R^2 is higher and Mean Absolute Percentage Error (MAPE) lower in the transfer function models. This confirms our earlier assertion that transfer function models are better statistically than regression models. This also confirms the findings of Kinney (1978), as well as Nwobi-Okoye and Igboanugo (2015) that ARIMA based univariate transfer function models which requires the largest information set and the greatest computation effort yields the smallest mean absolute error and as well as the smallest prediction bias in comparison to regression based models.

DISCUSSION

Assuming 50,000 HL of product required in a particular month in the period 2006-2007, by back casting, using a computer program written with C++, we discover that to produce that quantity we require 895598 kg of cereal and 91700 kg of additives through transfer function modeling. Also, assuming the same 50,000 HL of product is required in a particular month in the period 2008-2009, by back casting we discover that to produce that quantity we require 869557 kg of cereal and 154001 kg of additives. Similarly, if 50,000 HL of product is required in a particular month in the period 2010-2011, by back casting we discover that to produce that quantity we require 752773 kg of cereal and 82199 kg of additives.

The raw material requirements for producing 50,000 (HL) of product for various periods are shown in Table 3. Figure 9 shows the flow chart for the C++ program used in calculating the raw materials requirement for any required quantity of product. Once this is known, the managers could plan for raw material procurement. Of course from the results, material requirement planning based on transfer function modeling is more accurate and statistically better than that based on regression analysis.

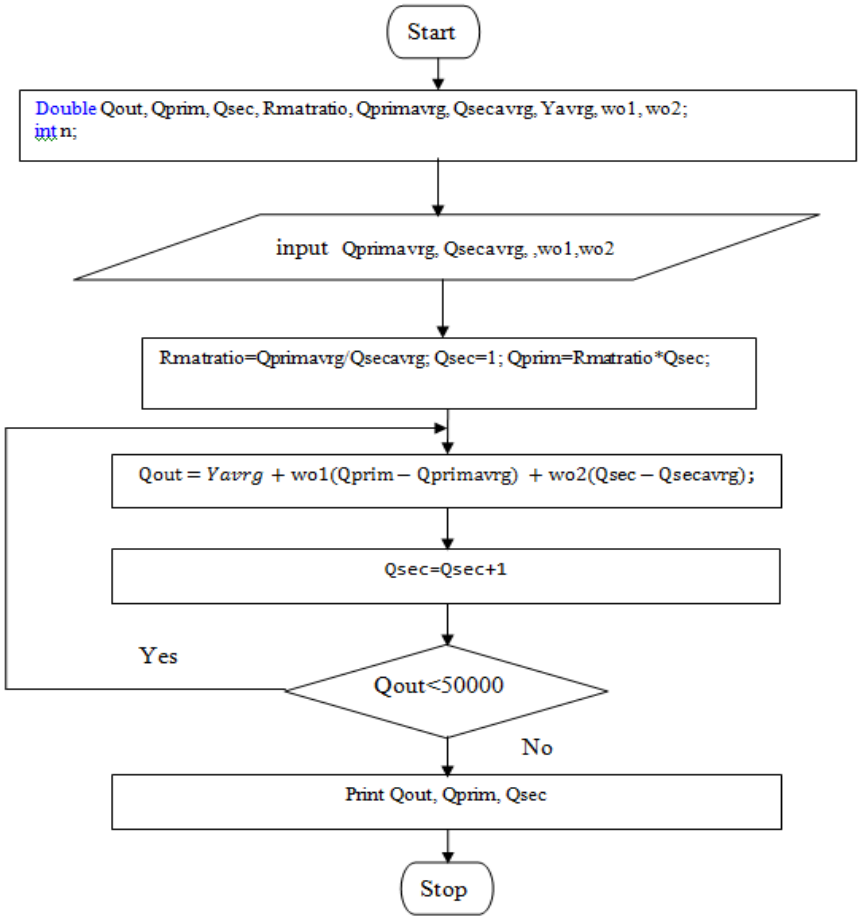

Fig. 9: Flowchart for computation of quantities of primary and secondary raw materials

Table 3 confirms the fact that in the process industry, raw materials vary for the same quantity of product and the quality of raw materials or end products could also vary considerably (Crama *et al*., 2001).

CONCLUSION

Proper planning is critical to the successful operation of any production system. Effective planning for raw materia l procurement is very important for the success of MRP and production planning and control system in general. With transfer function modeling system engineers could effectively obtain the approximate quantities of raw materials required in meeting the master production schedule for a given production horizon in process industries.

Nomenclature, symbols and notations:

k = Lag variable
β_t = Pretreated output series
α_t = Prewhitened input series
$v(B)$ = Transfer function
B = Backshift operator
Y_t = Process output at time t
X_t = Process input at time t
y_t = Differenced output series
x_t = Differenced input series
$\hat{Y}_t$ = Output forecast
$\hat{X}_t$ = Input forecast
a_t = Error term/white noise
υ_k = Impulse response weight at lag k
h = ACF/PACF lag
q = Order of moving average operator
p = Order of autoregressive operator
d = Number of differencing
θ = Autoregressive operator
φ = Autoregressive operator
Ξ = Coefficient of output variable of differential equation
H = Coefficient of input variable of differential equation
χ = Covariance function
b = Transfer function lag
ω = Difference equation variable for input
δ = Difference equation variable for output
r = Order of the output series
s = Order of the input series
S = Sample standard deviation

σ = Population standard deviation
ρ = Auto correlation function
γ = Cross correlation function
μ = Mean
ACF = Auto Correlation Function
PACF = Partial Auto Correlation Function

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