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Performance appraisal of gas based electric power generation system using transfer function modelling

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Abstract Gas flaring for years has been a major environmental problem in many parts of the world. One way of solving the problem of gas flaring is to effectively utilize the abundant supply of gas for power generation. To effectively utilize gas for power generation requires highly efficient gas turbines and power facilities. Traditional methods of assessing the efficiency of power generation turbines do not take into consideration the stochastic nature of gas input and power output. This is because in a power generation system, as in any typical production system, there is generally marked variability in both input (gas) and output (power) of the process. This makes the determination of the relationship between input and output quite complex. This work utilized Box-Jenkins transfer function modelling technique, an integral part of statistical principle of time series analysis to model the efficiency of a gas power plant. This improved way of determining the efficiency of gas power generation facilities involves taking input–output data from a gas power generation process over a 10-year period and developing transfer function models of the process for the ten years, which are used as performance indicators. Based on the performance indicators obtained from the models, the results show that the efficiency of the gas power generation facility was best in the years 2007–2011 with a coefficient of performance of 0.002343345. Similarly, with a coefficient of performance of 0.002073617, plant performance/efficiency was worst in the years 2002–2006. Using the traditional method of calculating efficiency the values of 0.2613 and 0.2516 were obtained for years 2002–2006 and 2007–2011 respectively. The result is remarkable because given the state of the facilities, it correctly predicted the period of expected high system performance i.e. 2002–2006 period, but the traditional efficiency measurement method failed to do so. Ordinarily, using efficiency values obtained through the traditional method as the metric, the system managers would

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assume that the period 2002–2006 was better than in the period 2007–2011 whereas the reverse is the case. The result of this study is expected to open new ways to improving maintenance effectiveness and efficiency of gas power generation facilities.

Nomenclature

k	lag variable	χ	covariance function
β_t	pretreated output series	b	transfer function lag
α_t	prewhitened input series	ω	difference equation variable for input
$v(B)$	transfer function	δ	difference equation variable for output
B	backshift operator	r	order of the output series
Y_t	process output at time t	s	order of the input series
$\mathrm{X_t}$	process input at time t	S	sample standard deviation
y_t	differenced output series	σ	population standard deviation
x_t	differenced input series	ρ	auto correlation function
$\widehat{Y}_t$	output forecast	γ	cross correlation function
$\widehat{X}_t$	input forecast	μ	mean
a_t	error term/white noise	V	voltage
υ_k	impulse response weight at lag k	I	current
h	ACF/PACF lag	T	time
q	order of moving average operator	q_g	gas consumption (m^3)
p	order of autoregressive operator	ρ_g	density of gas
d	number of differencing	C	calorific value of the gas (J/kg)
θ	autoregressive operator	MW h	megawatts hour
φ	autoregressive operator	η	efficiency
Ξ	coefficient of output variable of differential equation	ACF	auto correlation function
H	coefficient of input variable of differential equation	PACF	partial auto correlation function
		b_1	parameter of regression equation

1. Introduction

Gas flaring has been a major environmental problem in the Niger Delta region of Nigeria where most of its crude oil is produced. Effectively utilizing the abundant natural gas resources found in the Niger Delta will help in eliminating the environmental impact of gas flaring. One way of doing this is to utilize the gas in power generation to solve the problem of acute power shortages facing Nigeria. Poor electric power generation has remained a very serious problem in Nigeria ever since the 80s. The problem has hampered industrial development and contributed immensely to the poor economic state of Nigeria. Improving power generation in Nigeria has been a top priority of successive Nigerian government since 1999. Apart from insufficient number of power generation plants, existing ones are facing declining output due to ageing, neglect and ineffective maintenance. The gas powered electric power generation plant at Ughelli in Delta State, Nigeria, which started operation in 1964 is no exception to this, and has been facing declining output due to same reasons mentioned previously.

Transfer function modelling of power generation facilities will help in performance evaluation of the facilities leading to better maintenance planning, repairs, replacements and management based on the fact that transfer functions could be used as the predictor tool, with the variables serving as maintenance status and operation's efficiency indicators [1,2]. Putting the modelling results to good use would result to improved maintenance and management of power stations. Good maintenance and management of power plants in Nigeria will help improve electric power generation in Nigeria. Improved electric generation will lead to increase in gross domestic product of the country and better standard of living for the populace.

Traditional methods of assessing the efficiency of power generation turbines do not take into consideration the stochastic nature of gas input and power output. This is because in a power generation system, as in any typical production system, there is generally marked variability in both input (gas) and

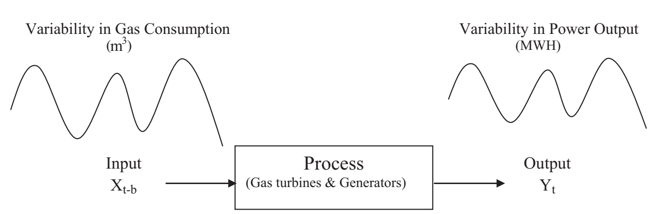

Figure 1 Schematic of the input–output relationship of a gas power generation system.

output (power) of the process as shown in Fig. 1. This makes the determination of the relationship between input and output quite complex.

Transfer function modelling, an integral part of process monitoring and control, is used to determine the causal relationship between input and output of a process. It is proposed that in order to better understand the complex relationship between the input and output to the power production system, this analytical technique known as transfer function modelling will be used.

Transfer function modelling has been used to measure transient input–output relationship of non equilibrium systems. The seminal work on transfer function modelling was done by Box and Jenkins in 1970 [3,4]. According to Lai [4], transfer function is often used to determine the causal relationship between two variables. In general, a transfer function relates two variables in a process; one of these is the cause (forcing function or input variable) and the other is the effect (response or output variable) [5].

The traditional method of measuring input–output relationship of systems is the Regression Analysis. But Regression Analysis is inappropriate in situations where the output lags the input and there exists a transient relationship between the input and output [4]. When there is a significant amount of noise in the system, transfer function modelling is superior to Regression Analysis which cannot accommodate noise in the filter [3].

Moreover, parameter estimation is determined stochastically in transfer function modelling [4]. Also, fewer parameters are required in transfer function models than in regression models, hence, models have better parsimony than regression models. This implies that transfer function models are expected to be more accurate than comparative regression models.

Since, this study requires the identification of the underlying mathematical framework that produces the relationships between the dependent and independent variables in order to achieve our result, hence, we considered the traditional statistical input–output modelling technique (Regression Analysis) and transfer function modelling. There are other mathematical methods of analysing discrete stochastic input–output systems. These include linear system model, Koyck-lags model, Almon-lags model, etc, but these have some of the deficiencies of the regression model mentioned previously [4,5].

In further reference to production systems previously described, a production system is a discrete dynamic system, and it is assumed not to be in a state of dynamic equilibrium. Hence, based on this and the facts enumerated above, transfer function modelling is the most appropriate input–output modelling for studying the behaviour of production systems.

Ever important is the efficiency of the gas turbines and power generation facilities. The literature on power generation is replete with different methods of measuring the turbine and power generation facilities efficiency. The conventional method of measuring the turbine efficiency and their applications have been extensively described [6–8]. Broadly speaking, measuring efficiency and evaluating the performance of power plants or facilities could be done by considering all the five (5) Ms of production namely: men, machines, material, method and money. Hence such measurements and evaluations could be said to be done at the Macro level. Alternatively, the efficiency measurements and performance evaluation could be done by considering one of the five (5) Ms of production, such as Machine. This is micro level efficiency measurements and performance evaluation. Techniques that belong to macro level evaluation methods include, Data Envelopment Analysis (DEA) and Analytic Network Process (ANP) [9,10]. On the other hand, techniques that belong to micro level evaluation methods include Ainley–Mathieson Method of Turbine Performance Prediction, Mean Line Prediction Method for Axial Flow Turbine Efficiency, Incidence Losses Prediction Method for Turbine Airfoils, Carnot Method, Energy/Power Input–Output Methods, Exergy Analysis, etc. [6–8,11–16]. These methods rely on the scientific principles of thermodynamics and fluid mechanics to determine or predict the efficiency of turbines/power plants. They rely solely on one of the five (5) Ms of production, i.e. machine, in order to determine efficiency or evaluate performance at micro level.

Macro level performance evaluation has extensive applications. Jha and Shrestha [9] and Jha et al. [17] used Data Envelopment Analysis (DEA) to evaluate the performance of hydropower plants in Nepal. DEA involves a holistic measure of the efficiency of Utilities where according to Berg [18], the input components would include man-hours, losses, capital (lines and transformers only), and goods and services. The output variables would include number of customers, energy delivered, length of lines, and degree of coastal exposure. Liu et al. [19] used DEA to evaluate the power-generation efficiency of major thermal power plants in Taiwan during 2004–2006. They conducted a stability test to verify the stability of the DEA model. According to the results, all power plants they studied achieved acceptable overall operational efficiencies during 2004–2006, and the combined cycle power plants were the most efficient among all plants. Sözen et al. [20] used DEA to conduct efficiency analyses of the eleven lignite-fired, one hard coal-fired and three natural gas-fired state-owned thermal power plants used for electricity generation in Turkey. They used two efficiency indexes: operational and environmental performance. In their calculation of the operational performance, main production indicators were used as input, and fuel cost per actual production (Y) was used as output (Model 1). On the other hand, in their calculation of the environmental performance, gases emitted to the environment were used as output (Model 2). They investigated the relationship between efficiency scores and input/output factors. Employing the obtained results, the power plants were evaluated with respect to both the cost of electricity generation and the environmental effects. Fallahi et al. [21] used an empirical analysis of the determinants of energy efficiency in 32 power electric generation management companies over the period 2005–2009 in India. The study uses non-parametric Data Envelopment Analysis (DEA) to estimate the relative technical efficiency and productivity change of these companies. In order to verify the stability of their DEA model and the importance of each input variable, they also conducted a stability test. The results of the study indicate that average technical efficiency of companies decreased during the study period. Nearly half of the companies (14) are below this average level of 88.7% for five years. The study equally showed that the low increase of productivity changes is more related to low efficiency rather than technology changes.

Atmaca and Basar [10] used the multi-criteria decision making technique of Analytic Network Process (ANP), a multi-criteria evaluations of six different energy plants were performed with respect to the major criteria such as technology and sustainability, economical suitability, life quality and socio-economic impacts. Nixon et al. [22], used Hierarchical Analytical Network Process (HANP) model for evaluating alternative technologies for generating electricity in India. They concluded that HANP successfully provides a structured framework for recommending which technologies to pursue in India, and the adoption of such tools is critical at a time when key investments in infrastructure were being made.

The macro level performance evaluations discussed above are still heavily dependent on the performance at the micro level. Of course micro level performance depends largely on the efficiency of the turbine and power generator. The method of measuring the gas turbine fuel efficiency according to [6,7], involves determination of the ratio of the electrical energy generated (energy output) to the energy input to the turbine. This is shown in Eq. (1).

$$\boldsymbol{\eta} = VIt/C\boldsymbol{\rho}_g q_g \tag{1}$$

As earlier stated, a common method of performance evaluation of power generation facility relies primarily on gas turbine efficiency tests [6,7]. However, the efficiency measurement methods does not take into account the stochastic nature of the forcing function, gas consumption, and the output which is the energy generated in MWH. Hence, calculated efficiency values are not statistically robust. This is because the stochastic nature of the input and the corresponding output means that efficiency is a random variable and changes from time to time, and it is a function of the particular loading conditions and state of the facilities. Hence, finding a metric to evaluate performance over a given time period requires extensive statistical analysis. Efficiency measurement is a better metric for evaluating the performance of power generation facilities. Hence, any method that measures system efficiency better would be invaluable to performance evaluation [2].

These shortcomings mentioned above, necessitate the need for a better method of performance evaluation of gas power stations. Based on their theoretical proposal in [1], Nwobi-Okoye and Igboanugo developed a highly improved and innovative method of evaluating the performance of hydropower generation systems using transfer function modelling [2]. Hence, transfer function modelling is proposed to bridge the above shortcomings previously mentioned. The aim of this work therefore is to model the transfer function of a gas power production process and to relate it to maintenance effectiveness and efficiency of gas power generation facilities based on the theory and model we previously developed (see [1,2]). This will especially be very useful in improving the efficiency and effectiveness of power generation facilities which will boost the overall power generation in Nigeria and elsewhere.

The hub of our investigation is Ughelli Electric Power PLC, Delta State, Nigeria which generates a significant quantity of electric power produced in Nigeria. A ten-year (2002–2011) monthly operations data relating to the use of gas as inputs for generation of electric power as outputs were obtained. The company's production process consists of gas turbines which generate electricity.

Ughelli Power Station uses natural gas to generate electricity. It was built and commissioned in four phases: Delta I, Delta II, Delta III and Delta IV. Delta I gas turbine power generators were commissioned in 1964 with a capacity of 72 Mega Watts (MW). Delta II power generation turbines were commissioned in 1975 with a capacity of 120 Mega Watts (MW). Delta III power generation turbines were commissioned in 1978 with a capacity of 120 Mega Watts (MW). Delta IV power generation turbines were commissioned in 1991 with a capacity of 600 Mega Watts (MW).

Delta II and Delta III gas turbines were replaced in 2002 and 2005 respectively with new turbines each with a capacity to generate 150 Mega Watts (MW). Delta I gas turbines were retired in 2006 due to obsolence. Currently Ughelli Power Station has the capacity to generate 900 MW of electricity. The current output capacity of 900MW is never met in practice due to complex interplay of factors ranging from poor gas availability, ageing, government neglect and poor maintenance of the power generation facilities.

Transfer function approach was used to appraise the efficiency and performance of Ughelli Electric Power generation facilities for ten years between 2002 and 2011 inclusive. The transfer function model developed has intuitive and theoretical appeal. It was developed based on the assumption that the time series was generated by a stochastic process.

2. Theoretical brief

The modelling done in this work relies on the theory of transfer functions. Transfer function modelling is one of the major areas where time series analysis is applied.

Mathematically, in its simplest form, a linear transfer function model could be represented by [2]:

$$Y_\infty = gX \tag{2}$$

Here Y_∞ represents the steady state output

g represents the steady state gain

X represents the steady state input

There are two types of transfer function models. They are discrete and continuous transfer function models. Continuous transfer function models are usually represented by differential equations which could be first order equations, second order equations or higher order equations, while discrete models are often represented by difference equations [3]. Continuous transfer function models assume that transfer function observation are taken at continuous time intervals. What this means is that the period in between observation is so small that the time is assumed to be continuous. Continuous transfer function models are usually represented by differential equations which could be first order equations, second order equations or higher order equations [3,23]. According to Box et al. [3], the general method for representing continuous dynamic systems is through the use of differential equations:

$$(1+\Xi_1 D+\ldots+\Xi_R D^r)Y_t = g(1+H_1 D+\ldots+H_s D^s)X_{t-b} \tag{3}$$

On the other hand, discrete transfer function models assume that the time series of transfer function observations are taken at discrete time intervals. Discrete transfer function models are usually represented by difference equations which could be first order equations, second order equations or higher order equations [3]. Box et al. [3] gave the general method for representing discrete dynamic systems in difference equation form as:

$$(1+\xi_1\nabla+\ldots+\xi_r\nabla^r)Y_t=g(1+m_1\nabla+\ldots+m_s\nabla^s)X_{t-b} \tag{4}$$

Using the backward shift operator on Eqs. (4) and (5) is obtained.

$$(1-\delta_1B-\ldots-\delta_rB^r)Y_t=(\omega_0-\omega_1B-\ldots-\omega_sB^s)X_{t-b} \tag{5}$$

$$\delta(B)Y_t=\omega(B)X_{t-b} \tag{6}$$

$$Y_t=\delta^{-1}(B)\omega(B)X_{t-b} \tag{7}$$

The ratio $\delta^{-1}(B)\omega(B)$ in Eq. (7) is called the transfer function of the system. The concept of a transfer function model is like passing the input series through a stochastic–dynamic filter to generate the output series [3,4]. In this situation the stochastic–dynamic filter is the turbine-generator system shown in Fig. 1.

In terms of the impulse response weights, $\boldsymbol{\upsilon}$, the transfer function model could be represented by Eq. (8).

$$Y_t=v_0X_t+v_1X_{t-1}+v_2X_{t-2}+\ldots \tag{8}$$

In terms of the B operator, Eq. (8) is transformed to Eq. (9).

$$Y_t=(v_0+v_1B+v_2B^2+\ldots)X_t \tag{9}$$

$$Y_t=v(B)X_t \tag{10}$$

Assuming the series Y_t and X_t are modelled as an autoregressive integrated moving average (ARIMA) process, Eqs. (11) and (12) are obtained.

$$X_t=\frac{\theta(B)}{\phi(B)}\alpha_t \tag{11}$$

Similarly,

$$Y_t=\frac{\theta(B)}{\phi(B)}\beta_t \tag{12}$$

Hence, substituting Eqs. (11) and (12) into Eq. (10), Eq. (13) is obtained:

$$\frac{\theta(B)}{\phi(B)}\beta_t=v(B)\frac{\theta(B)}{\phi(B)}\alpha_t \tag{13}$$

The implication of Eq. (13) is that before the input series X_t could be correlated to the output series Y_t both input and output series must be transformed to α_t and β_t respectively.

For the white noise series α_t in Eq. (13), the variance is given by:

$$\chi_{\alpha\alpha}(0)=\sigma_\alpha^2 \tag{14}$$

Therefore covariance of the series α_t and β_t at lag k is given by:

$$\chi_{\alpha\beta}(k)=v_k\sigma_\alpha^2 \tag{15}$$

But

$$\gamma_{\alpha\beta}(k)=\frac{\chi_{\alpha\beta}(k)}{\sigma_\alpha\sigma_\beta} \tag{16}$$

Substituting Eq. (15) into Eq. (16), Eq. (17) is obtained:

$$\gamma_{\alpha\beta}(k)=\frac{v_k\sigma_\alpha}{\sigma_\beta} \tag{17}$$

Eq. (17) shows that the impulse response weight, υ_j is related to the cross-correlation between the pre-whitened series α_t and β_t.

In continuation, transfer function modelling involves three distinct steps namely: identification, estimation and diagnosis. For full treatment of transfer function modelling see [1–4,24–27].

3. Methodology

A 10-year daily input–output data were obtained from Ughelli Electric Power PLC, Ughelli, Delta State, Nigeria. The company generates a significant quantity of electricity consumed in Nigeria. The data were used to model the electric power generation/production process transfer function.

A discrete transfer function model applicable to a production process has been developed by Box et al. [3]. We shall assume the model as stated in Eq. (7), and incorporating the noise term, Eq. (18) is obtained:

$$Y_t=\delta^{-1}(B)\omega(B)X_{t-b}+N_t \tag{18}$$

The noise term, N_t, is represented by an ARIMA (p,d,q) process such that:

$$N_t=\varphi^{-1}(B)\theta(B)a_t \tag{19}$$

Here a_t is the white noise. Substituting Eq. (19) into Eq. (18), gives

$$Y_t=\delta^{-1}(B)\omega(B)X_{t-b}+\varphi^{-1}(B)\theta(B)a_t \tag{20}$$

In order to realize the transfer function model based on Eq. (18), a plot of the 10-year input–output data was done using SPSS software. After the plot, the data were 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 to be stationary, hence differencing was not used to achieve stationarity. A univariate model was individually fitted to the input X_t and output Y_t in order to respectively estimate prewhitened input and pretreated output series namely α_t and β_t

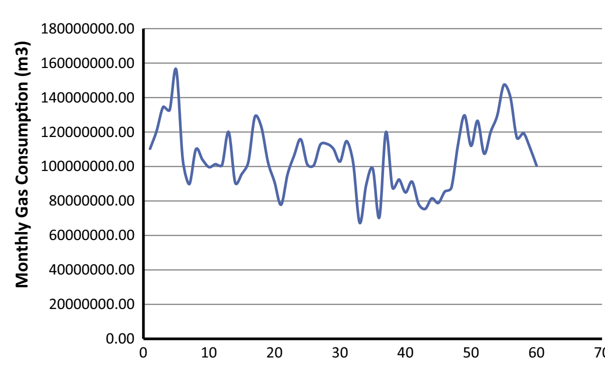

Figure 2 Input series for 2002–2006.

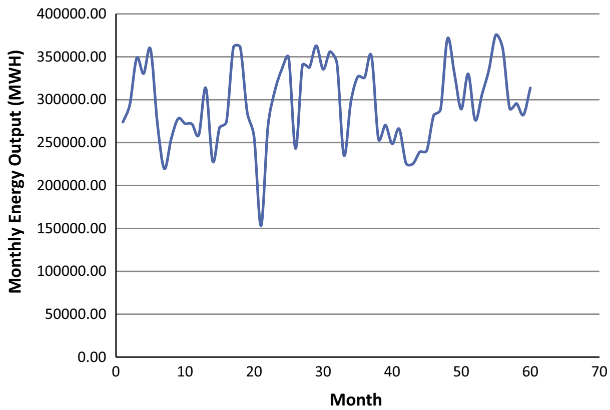

Figure 3 Output series for 2002–2006.

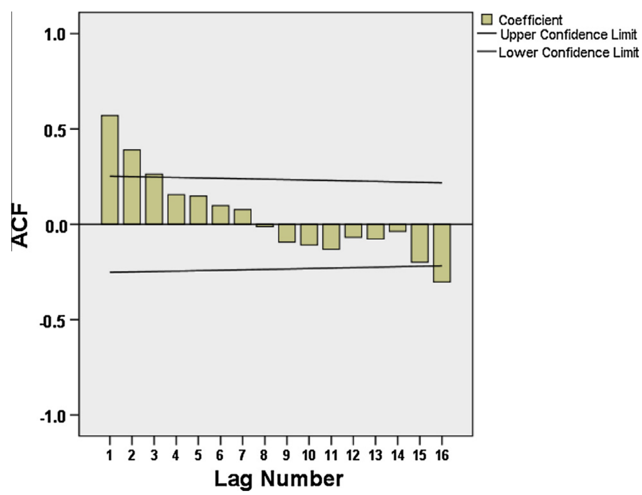

Figure 4 ACF of the input series.

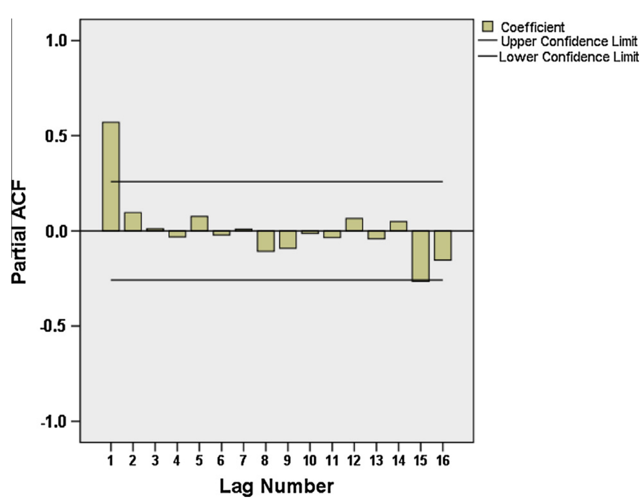

Figure 5 PACF of the input series.

respectively. Calculation of the cross correlation function, CCF (k) of $\beta_t\alpha_{t-k}$ was used to identify r, s and b parameters of the transfer function model.

Furthermore, the transfer function was estimated using Y_t and X_t. The residual of the transfer function was used to identify the noise term N_t of the transfer function model. Later model diagnostics was carried out to ensure that the coefficients are significant and non redundant.

4. Results

The graphs of the input and output series of the data obtained from Ughelli Electric Power PLC for the years 2002–2006 are shown in Figs. 2 and 3 respectively. The graphs for other years while not shown here follows similar pattern.

The abscissa of Figs. 2 and 3 are in months-of-the year (12). The station uses natural gas as fuel to run the turbines. Shell Petroleum Development Company (SPDC)'s Ughelli east field in Delta State, Nigeria supply natural gas to Delta II and III units, while Nigeria Gas Company (NGC)'s Uturogun gas plant supplies gas to Delta IV. However, a tripartite gas line valve is installed to enable both supply inlets to complement short falls in times of emergency. The gas consumption depends on availability and demand. Thus as shown in Fig. 2, the gas supply does not follow any particular pattern. The output time series of Fig. 3 follow the pattern described in the foregoing.

4.1. Analysis of input series

The input series upon analysis was found to be stationarity, hence differencing was not used. Examination of the ACF and PACF in Figs. 4 and 5 is indicative that auto regression one (AR (1)) model is the appropriate model to use.

The formula for AR (1) models [3,26,28] is given by Eq. (21):

$$X_t = \theta_0 + \phi_1 X_{t-1} + e_t \tag{21}$$

But for AR (1) models, we have:

$$\mathrm{ACF}(1) = \phi_1 = 0.570 \tag{22}$$

$$\theta_0 = (1 - \phi_1)\mu \tag{23}$$

$$\theta_0 = (1 - 0.570)105546409.83 \tag{24}$$

$$\theta_0 = 45384956.2269 \tag{25}$$

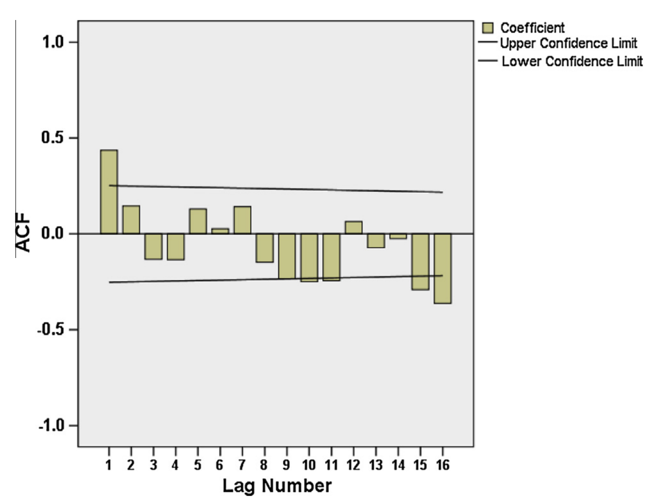

Figure 6 ACF of the output series.

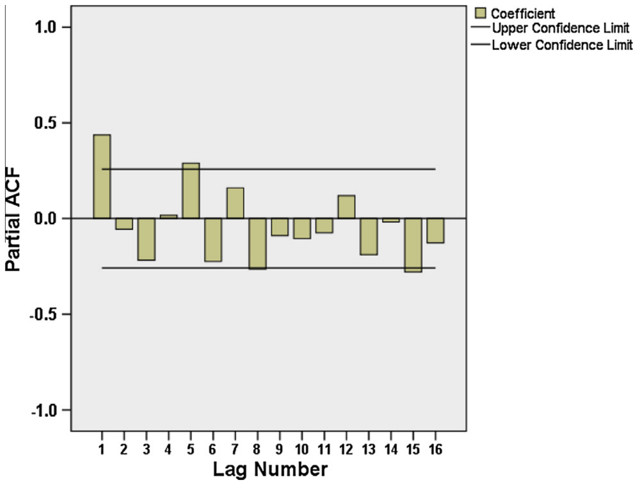

Figure 7 PACF of the output series.

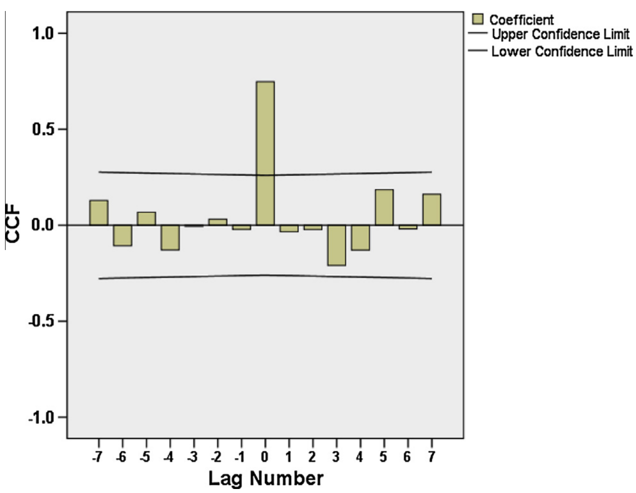

Figure 8 CCF of the pre-whitened series.

Fitting the coefficients θ_0 and ϕ_1 into the formula for AR (1) models, Eq. (26) is obtained.

$$X_t = 45384956.2269 + 0.570 X_{t-1} + e_t \tag{26}$$

But

$$e_t = \alpha_t \tag{27}$$

In forecasting form Eq. (26) is transformed to Eq. (28):

$$\widehat{X}_t = 45384956.2269 + 0.570 X_{t-1} \tag{28}$$

4.2. Analysis of output series

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

The formula for AR (1) models [3,26] and [28] is given by Eq. (29):

$$Y_t = \theta_0 + \phi_1 Y_{t-1} + e_t \tag{29}$$

But for AR (1) models, we have:

$$\mathrm{ACF}(1) = \phi_1 = 0.570 \tag{30}$$

$$\theta_0 = (1 - \phi_1)\mu \tag{31}$$

$$\theta_0 = (1 - 0.570)295761.51 \tag{32}$$

$$\theta_0 = 127177.4493 \tag{33}$$

Fitting the coefficients θ_0 and ϕ_1 into the formula for AR (1) models, Eq. (34) is obtained.

$$Y_t = 45384956.2269 + 0.570 Y_{t-1} + e_t \tag{34}$$

But

$$e_t = \beta_t \tag{35}$$

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

$$\widehat{Y}_t = 45384956.2269 + 0.570 Y_{t-1} \tag{36}$$

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 [26], 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:

$$y_t = \omega_0 x_t + N_t \tag{37}$$

Based on Ljung-Box statistics shown in Table 1 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. (38).

$$y_t = \omega_0 x_t \tag{38}$$

As shown by [3,26],

$$v_0 = \omega_0 \tag{39}$$

But

$$v_0 = \frac{\gamma_{\alpha\beta}(0) S_\beta}{S_\alpha} \tag{40}$$

$\gamma_{\alpha\beta}(0)$ is the cross correlation between α and β at lag zero (0).

But

$$X_t - \mu_x = x_t \tag{41}$$

And

$$Y_t - \mu_y = y_t \tag{42}$$

Substituting Eq. (42) into Eq. (38), Eq. (43) is obtained.

$$Y_t = \mu_y + \omega_0 x_t \tag{43}$$

Table 1 Model Statistics 2002–2006.

Model	Number of predictors	Model fit statistics	Ljung-Box Q(18)			Number of outliers
		Stationary R-squared	Statistics	DF	Sig.	
Transfer Function Model	1	.628	35.403	17	.006	0

Table 2 Model fit 2002–2006.

Fit statistic	Value
Stationary R-squared	0.628
R-squared	0.628
RMSE	2.925E4
MAPE	7.881
MaxAPE	56.609
MAE	2.196E4
MaxAE	8.665E4
Normalized BIC	20.772

Table 3 Transfer function models of Ughelli Power Station.

Years	Transfer function model ($v(B)$)
2002–2006	$\widehat{Y}_t = \mu_y + 0.002073617x_t$
2007–2011	$\widehat{Y}_t = \mu_y + 0.002343345x_t$

In forecasting form Eq. (43) is transformed to Eq. (44).

$$\widehat{Y}_t = \mu_y + \omega_0 x_t \tag{44}$$

The lag of 0 in the transfer function model shows that the average gas flow in the month is used for generation the same month. The model has intuitive and theoretical appeal. The model statistics and fit are good as shown for the years 2002–2006 in Tables 1 and 2 respectively.

For 2002–2006 operations at Ughelli Power Station we obtained:

$$\gamma_{\alpha\beta}(0) = 0.748$$

$$S_\beta = 43098.51$$

$$S_\alpha = 15546595.64$$

Hence,

$$v_0 = \frac{0.748 \times 43098.51}{15546595.64}$$

$$v_0 = 0.002073617$$

$$\omega_0 = 0.002073617$$

Hence from Eq. (23)

$$y_t = 0.002073617x_t$$

Since $\omega_0 = 0.002073617$ for the 2002–2006 operation of Ughelli Power Plant, the transfer function is given by:

$$\widehat{Y}_t = \mu_y + 0.002073617x_t \tag{45}$$

Similarly, for the 2007–2011 operation $\omega_0 = 0.002343345$ was obtained. Hence, the transfer function for 2006–2011 is given by:

$$\widehat{Y}_t = \mu_y + 0.002343345x_t \tag{46}$$

Table 3 shows the transfer function models for the ten-year operation of Ughelli Power Station. The transfer function parameter ω_0 is a measure of how effective the available gas is converted to electric energy, and could be regarded as the coefficient of performance of the Power Station's yearly operations. The higher the value of ω_0, the more efficient is the power generation facility and the lower the value of ω_0, the power generation facility is less effective in converting available gas to electrical energy. Hence, ω_0 is analogous to the in slope **m** of the equation of a straight-line.

Table 4 depicts the total annual gas supply and energy generated together with the corresponding coefficient of performance of Ughelli Power Station computed on annual basis. The results indicate that the years 2007–2011 had the highest coefficient of performance (COP) in the 10-year sample studied. On the other hand the years 2002–2006 had the least COP.

As shown in Table 4, the value of ω_0 in the years 2002–2006 was 0.002073617 while the value was 0.002343345 in the years 2007–2011. This shows that the system performance was more effective in the years 2007–2011 than in the years 2002–2006. This is in conformity with the theoretical proposal in [1], that the transfer function parameters could be used as performance indicators. This theory was first put into use by Nwobi-Okoye and Igboanugo when they used it to evaluate the performance of a hydropower generation system [2]. The low energy generation in the years 2007–2011 was because gas supply was poorer in those years when compared to the years 2002–2006, which was probably due to the disruption of oil and gas production by Niger Delta militants who were very active in this period.

Applying regression modelling/analysis to the same problem, we obtained the values as shown in Table 5. As shown in Table 5, the coefficient of performance increased in the years 2007–2011, just like the coefficient of performance obtained from the transfer function model. But from Table 6, a comparison of the two models from statistical point of view indicates that the transfer function model performed better than the

Table 4 Energy generated Vs coefficient of performance of Ughelli Power Station.

Years	Total gas supply (m^3)	Total energy generated (MW h)	Coefficient of performance ω_0
2002–2006	6,332,784,590	17,745,690.80	0.002073617
2007–2011	3,464,616,305	9,234,419.30	0.002343345

Table 5 Comparison of coefficients of performances obtained from regression and transfer function models.

Years	Coefficient of performance (regression) b_1	Coefficient of performance (transfer function) ω_0
2002–2006	0.001814167	0.002073617
2007–2011	0.002201413	0.002343345

Table 6 Comparison of statistics of regression and transfer function models.

Years	R^2 (regression)	R^2 (transfer function)	MAPE (regression)	MAPE (transfer function)
2002–2006	0.523	0.628	8.962609	7.881
2007–2011	0.787	0.845	12.99184	11.004

regression model. This is because the coefficient of determination R^2, is higher 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 [29] 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.

5. Discussion

The graphs of the input and output shown in Figs. 2 and 3 are stochastic, confirming the fact that in a production system the input and output are stochastic in nature as earlier clarified in the introductory section. The power generation system considered in this research is a single-input-single-output-system (SISO). Hence, the transfer function modelling was done on the assumption that the system is single-input-single-output-system (SISO). Accordingly, considering Fig. 1 and Eq. (1), the forcing function is q_g, the gas consumed by the turbine. The forcing function is actually what drives the turbine and generates electricity in the process.

Coefficient of performance is being used restrictively in thermodynamics for evaluating the efficiency of refrigerating systems and heat pumps. However, under portability concepts, this term has been ported to systems engineering particularly time series modelling using transfer function. In its simplest form involving parsimony of parameters, transfer function represents a coefficient relating output Y_t to input X_t as in Eq. (46). In this regard ω_0 is the coefficient of performance. Practically, Eq. (46) implies that given some autonomous value μ_y for every unit increase in x_t, the output Y_t changes by ω_0 which is the coefficient of performance.

In the case problem, the transfer function model for Ughelli gas turbine power station is: $\widehat{Y}_t = \mu_y + 0.002073617x_t$ which is valid for the period 2002–2006 and $\widehat{Y}_t = \mu_y + 0.002343345x_t$ that applies for the period 2007–2011.

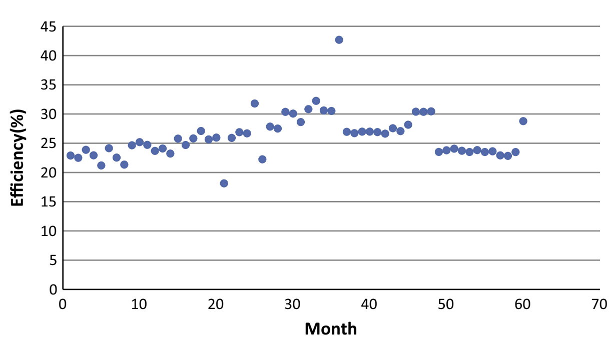

Figure 9 Monthly efficiency measurements in the period 2002–2006.

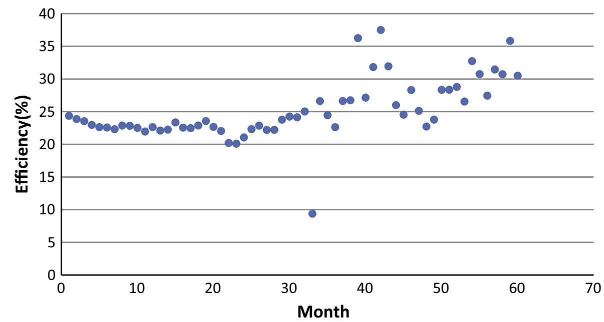

Figure 10 Monthly efficiency measurements in the period 2007–2011.

Table 7 Efficiency Vs coefficient of performance for the two periods.

Period	Average efficiency (%)	COP
2002–2006	26.13	0.002073617
2007–2011	25.16	0.002343345

In this situation, the coefficients of x_t denoted by ω_0 refers to the transfer function parameter that measures the level of efficiency of gas conversion to power by the turbine system. This parameter ω_0 we earlier referred to as the coefficient of performance (COP).

The results suggest that response Y_t has an average autonomous power output μ_y from where power output varies with gas supply at the rates of 0.002073617 and 0.002343345 for the two periods respectively. In other words, a unit input of gas will change the power output by 0.002073617 MW in the years 2002–2006 and by 0.002343345 in the years 2007–2011.

Continuing the discussion on the implications of COP, it is important to note that the average efficiency over a given period say period 1 could be higher than in another period say period 2 and yet the COP in the first period could be lower than in the second period.

Consider Figs. 9 and 10 which show the variations of efficiency over the two periods. Table 7 shows the average efficiency over the periods and their corresponding coefficients of performance. If coefficient of performance is used as the metric, a unit input of gas will change the power output by 0.002073617 MW in the years 2002–2006 and by 0.002343345 in the years 2007–2011 as stated earlier. Similarly, if efficiency is used as the metric, a unit input power supplied to the gas burned by the turbine will change the power output by 0.2613 MW in the years 2002–2006 and by 0.2516 MW in the years 2007–2011.

Ordinarily, using the efficiency as the metric, the system managers would assume that the period 2002–2006 was better than in the period 2007–2011 whereas the reverse is the case.

The primary reason for performance assessment/evaluation is to improve performance. Hence, better metric for performance appraisal would improve system performance. To achieve higher COP therefore, the managers require an appraisal/adjustment in one or all of manpower, machine, money, method and material as the case may be.

In general, therefore, the major advantages of this method include but not limited to:

(a) Greater accuracy in efficiency measurement over a given period.
(b) Statistically robust efficiency measurements.
(c) Better plant fault diagnosis and superior aid to predictive and preventive maintenance.

On the face value, the process of coefficient of performance (COP) determination looks computationally demanding. However, with adequate software developed for this purpose, COP determination can be made simple and as input and output data are updated, new COP values can be obtained which can serve as operations and maintenance managers guide to action. This is another important advantage of this method over others.

The lower operational efficiency obtained in the years 2002–2006 was because the aged Delta I and Delta II turbines, which were replaced in 2002 and 2005 respectively, were still operational in this period. But in the period between 2007 and 2011, the old turbines were no longer operational as they had been replaced in the previous years; hence, the operations efficiency was higher.

The current metering system at Ughelli Power Plant provides only for monthly records of gas consumption. But there is a need for daily recording of gas consumption for more accurate and effective performance evaluation of the power generators. Daily gas consumption data would enable yearly performance appraisal of the power station using transfer function modelling.

Performance evaluation is very important in electrical power systems [30,31]. This is the second practical application of our theoretical proposal [1]. In view of the foregoing facts, it is obvious that transfer function could determine operations and maintenance effectiveness. Also, transfer function can actually notify operators when a facility is due for maintenance or replacement. Traditionally, maintenance operations are usually carried out after a specified time interval even if the equipment or processor is performing optimally, or when the equipment or processor is not performing. Transfer function approach to performance evaluation and maintenance will eliminate this problem. In other words, the problems of scheduling a particular time period for maintenance when the transfer function/coefficient of performance is still good or not scheduling when the transfer function/coefficient of performance is not good are eliminated.

It is noteworthy that to obtain increased value of ω_0 requires improved maintenance and operational skills of the engineers and technicians managing and operating the power plant. From our findings official corruption, inadequate funding and apparent neglect by the successive Nigerian governments had impacted negatively on the operations of Ughelli Power Station, although the ongoing restructuring in the Nigerian power sector is expected to bring about significant improvements.

6. Conclusion

Effective maintenance and efficient performance of power generation facilities are highly desirable [32–34]. Electricity power supply acts as an engine that drives an economy. Sufficient power supply is very vital for industrial development and economic growth of any nation. The authorities in Nigeria as part of their effort to reform the power sector in the country set benchmark for performance evaluation of power generation, transmission and distribution facilities. Chief Executive Officers of Power companies that failed to meet the minimum benchmark requirements were sacked by the government [35]. We have successfully developed in this paper a very sound and statistically robust method of evaluating the performance of gas power plants. It is suggested that the authorities in Nigeria and elsewhere adopt this research for performance evaluation of power generation facilities by determining the critical value of coefficient of performance (ω_0) for each gas power plant below which the plant is assumed to have underperformed. Based on the fact that the power plant has underperformed, we suggest a ω_0 value which must be above 0.002073617, the highest value we obtained from our analysis as the tentative benchmark for ω_0. An appropriate benchmark should be determined based on the analysis of performance data obtained from very highly efficient power generation stations.

Finally, if the recommendations of this research are implemented by setting an excellent benchmark and making sure power generation stations stick to it. There will be resultant improvement in the operations of the power stations, with attendant improvement in power generation in Nigeria and elsewhere. This will have a very positive effect on the state of Nigeria's economy which has been declining over the years. The same applies to other countries that are in similar situation as Nigeria.

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