DEVELOPMENT AND APPLICATION OF AN APPROACH TO ASSESS THE GLOBAL THERMAL EFFICIENCY OF A THERMAL ELECTRIC POWER PLANT

Carlos Lueska, carlos@lueska.com.br
CHP Consultoria de Energia S/C, São Paulo, SP, Brazil

Miguel Mattar Neto, mmattar@ipen.br
Instituto de Pesquisas Energéticas e Nucleares, IPEN – CNEN/SP, São Paulo, SP, Brazil

Abstract. *First, it is presented and discussed a simplified approach to assess the global or net thermal efficiency of a thermal electric power plant using two fuels: blast furnace gas and wood tar. The performance tests results based on the proposed approach are, also, presented and discussed considering their related uncertainties. The codes ASME PTC 46 (Performance Test Code on Overall Plant Performance, 1996) and ASME PTC 19.1 (Test Uncertainty, Instrument and Apparatus, 1998) are the basis for the developed approach, for the performance tests, for the results assessment and for the uncertainties evaluation. Some conclusions and recommendations are addressed based on the presented results.*

Keywords*: thermal efficiency, uncertainty, performance test, thermal electric power plant*

1. INTRODUCTION

The determination of power plant thermal performance and electrical output is a common acceptance requirement. Performance tests results provide measures and evaluations of the overall thermal performance of a power plant and other subsystems at a specified cycle configuration, operating disposition, and/or fixed power level, and at a specific set of base reference conditions. So, performance test results can be used as defined by a contract to determine the fulfillment of contract guarantees. There are standards and codes like the ASME PTC 46 (1996) that can provide procedures to conduct the performance tests.

A working knowledge of power plant operations, thermodynamic analysis, test measurement methods, and the use, control and calibration of measuring and test equipment are necessary to the performance tests. The uncertainties assessment is mandatory to qualify the tests and to characterize their results. Once more, there are standards and codes like the ASME PTC 19.1 (1998) that can define acceptable methods used to provide meaningful estimates of measurement uncertainty and effects of individual uncertainties on test results.

This paper describes a methodology to assess the global thermal efficiency of a power plant fed by two different fuels, blast furnace gas and wood tar. The methodology was applied to the power plant performance tests to check if the global thermal efficiency satisfies an expected limit considering all tests uncertainties.

1.1. The thermal electric power plant under evaluation

The thermal electric power plant under evaluation has a configuration with a conventional Rankine regenerative cycle with a superheated steam boiler without re-heating followed by a condensation steam turbine with four bleeds for the boiler feedwater regenerative pre-heating. The net electric power generation capacity is 12,900 kW in the generator terminals which is compatible to the fuels availability (blast furnace gas and wood tar) and to the local conditions.

The main parts are:

- A multiple fuel boiler (blast furnace gas, wood tar, and natural gas in the absence of blast furnace gas)
- A condensation turbine with multiple stages.
- An electric generator with 15.2 MVA @ 13.8 kV.
- A steam condensator to the nominal pressure of 0.12 bar a.
- A cooling tower.
- Water treatment station.
- Sub-station and equipment to connect the power plant to steel mill where it is installed.

The steam boiler is water-tube type producing 60 t/h of steam @ pressure of 60 bar and temperature of 450 °C. It has a convection bundle (evaporator), a super-heater and four heat recovery equipment to efficiency increasing (economizator, air pre-heater, blast furnace gas pre-heater and condensate pre-heater).

The turbo-generator, with a nominal power of 12,900 kW, is composed by a steam turbine, a surface condensator, a gear, an electric generator, an exciter, and the respective control panels, controlled via PLCs (Programmable Logical Controllers) and a supervisory system (DCS).

The design reference conditions to the power plant are shown in Tab. 1.

Table 1: Thermal electric power plant design reference conditions

Sea level height	930 m
Atmospheric pressure	695 mmHg
Ambient Temperature	22^{o}C
Relative humidity	72.2%

The simplified sketch of the power plant is shown on Fig. 1.

The guaranteed global thermal efficiency to the power plant is 25.1 %, considering the design reference conditions and the fuels input on Lower Heating Value (LHV) basis.

2. POWER PLANT EFFICIENCY SIMPLIFIED ASSESSMENT METHODOLOGY

The efficiency simplified assessment is performed using the power plant installed instrumentation. The fuels properties characterization is obtained from universities and research centers laboratories.

Only factors that have effective impact to the efficiency are taken in account. Factors that are not important to the efficiency are not evaluated.

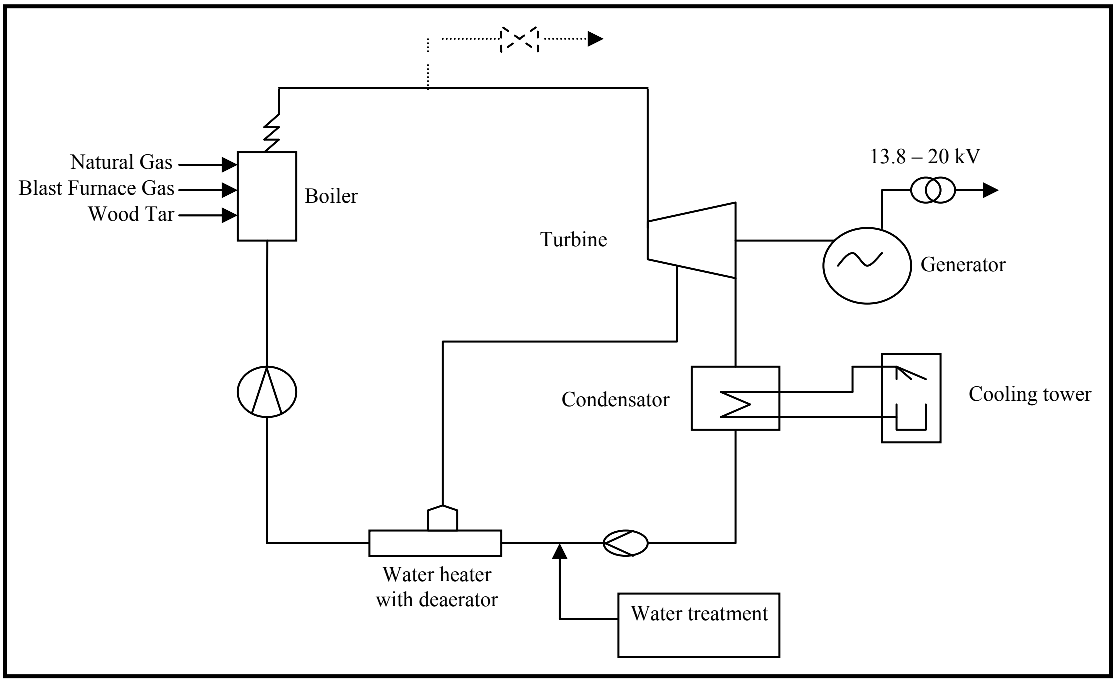

Figure 1. Thermal electric power plant simplified sketch

The power plant global or net thermal efficiency, on a fuels input on LHV basis, is evaluated by tests using the Direct Method of Measured Net Plant Power and Heat Input (ASME PTC 46, 1996), i. e., defining the tests limits and the measurements to be done.

During the tests it will be necessary to measure the input heat to the power plant from the fuels and from the combustion air to obtain the net electric generation and to determine the correction factors applicable to the adjustment of the electric generation and of the input heat to the design reference conditions.

The following measurements should be conducted:

- All input heat (plant thermal energy): primary input heat and thermal energy credits from the combustion air.
- Plant net electric energy output.

The fuels input heat to the power plant can be evaluated multiplying the measured fuels flows by the measured fuels average LHV during the tests. The combustion air heat credit is obtained multiplying the air combustion flow by its enthalpy at the average test temperature.

The only considered output is the net electric energy in the 20.5 kV bars measured in the energy gauge in the steel mill that is the energy user.

The corrected efficiency at the power plant design reference conditions is obtained dividing the Corrected Net Generated Electric Energy by the Corrected Input Heat, i. e.,

$$\eta = \frac{\left(P_{med} + \sum_{i=1}^{7} \Delta_i \right)}{\left(Q_{med} + \sum_{i=1}^{7} \omega_i \right)} \prod_{i=1}^{5} f_i \tag{1}$$

where, following the ASME PTC 46 (1996), η is the global thermal efficiency, P_{med}, is the measured net electric energy averaged on an hour basis during the test duration, Q_{med} is the average input heat to the boiler on an hour basis during the test duration. In the general case, five multiplicative factors (λ) and seven addictive factors (Δ) are considered to correct the net electric energy generation (P_{med}). Also, five multiplicative factors (γ) and seven addictive factors (ω) are considered to correct the average input heat to the boiler (Q_{med}). It is important to notice that in Eq. (1) the multiplicative factors f_i are equal (λ_i/γ_i).

For the power plant under evaluation, several corrective factors are not applicable. Only the corrective factors related to the power factor, to the continuous boiler bleed, the fuels LHV and to the fuels temperatures must be considered. So, the corrected electric energy P_{cor} is:

$$P_{cor} = (P_{med} + \Delta_2 + \Delta_3) \tag{2}$$

This is the net electric energy generated by the power plant at the 20.5 kV bars, without the plant auxiliary systems consumption. The power factor correction is $\Delta_2 = -16$ kW, and the continuous bleed correction is $\Delta_3 = (-)\ 0.75\%\ P_{med}$ (in kW).

The input thermal energy is:

$$Q_{cor} = Q_{med} + \omega_1 \tag{3}$$

where ω_1 is the boiler continuous bleed correction factor.

Once the input heat to the plant (control volume) is evaluated by the direct method, the correction factor related to the continuous bleed flow is calculated only for the electric energy generation. The measured heat from the flows and the fuels LHV plus the air combustion heat correspond to the input heat to the plant and $\omega_1 = 0$. Thus,

$$Q_{cor} = Q_{med} = LHV_{med\ (GAF)}\ x\ V_{med(GAF)} + LHV_{med\ (ALC)}\ x\ m_{med\ (ALC)} \tag{4}$$

where $LHV_{med\ (GAF)}$ is the average of the blast furnace gas LHV, $V_{med(GAF)}$ is the blast furnace gas average flow, $LHV_{med(ALC)}$ is the average of the wood tar LHV and $m_{med(ALC)}$ is the wood tar average mass flow.

3. UNCERTAINTIES ANALYSIS

3.1. Accuracy, Errors, and Uncertainty

It is no longer acceptable to present experimental results without describing the uncertainties involved. The true values of measured variables are seldom (if ever) known and experiments inherently have errors, e.g., due to instrumentation, data acquisition and reduction limitations, and facility and environmental effects. For these reasons, determination of truth requires estimates for experimental errors, which are referred to as uncertainties. Experimental uncertainty estimates are imperative for risk assessments in design both when using data directly or in calibrating and/or validating simulation methods.

Rigorous methodologies for experimental uncertainty assessment have been developed over the past 50 years. Standards and guidelines have been put forth by professional societies (ASME PTC 19.1, 1998) and international organizations (ISO, 1995). Recent efforts are focused on uniform application and reporting of experimental uncertainty assessment.

The accuracy of a measurement indicates the closeness of agreement between an experimentally determined value of a quantity and its true value. Error is the difference between the experimentally determined value and the true value. Accuracy increases as error approaches zero. In practice, the true values of measured quantities are rarely known. Thus, one must estimate error and that estimate is called an uncertainty, U. Usually, the estimate of an uncertainty, U_X, in a given measurement of a physical quantity, X, is made at a 95-percent confidence level. This means that the true value of the quantity is expected to be within the ± U interval about the mean 95 times out of 100.

As shown in Fig. 2a, the total error, δ, is composed of two components: bias error, β, and precision error, ε. An error is classified as precision error if it contributes to the scatter of the data; otherwise, it is bias error. The effects of such errors on multiple readings of a variable, X, are illustrated in Fig. 2b.

If we make N measurements of some variable, the bias error gives the difference between the mean (average) value of the readings, μ, and the true value of that variable. For a single instrument measuring some variable, the bias errors, β, are fixed, systematic, or constant errors (e.g., scale resolution). Being of fixed value, bias errors cannot be determined statistically. The uncertainty estimate for β is called the bias limit, B. A useful approach to estimating the magnitude of a bias error is to assume that the bias error for a given case is a single realization drawn from some statistical parent distribution of possible bias errors. The interval defined by $\pm B$ includes 95% of the possible bias errors that could be realized from the parent distribution.

The precision errors, ε, are random errors and will have different values for each measurement. When repeated measurements are made for fixed test conditions, precision errors are observed as the scatter of the data. Precision errors are due to limitations on repeatability of the measurement system and to facility and environmental effects. Precision errors are estimated using statistical analysis, i.e., are assumed proportional to the standard deviation of a sample of N measurements of a variable, X. The uncertainty estimate of ε is called the precision limit, P.

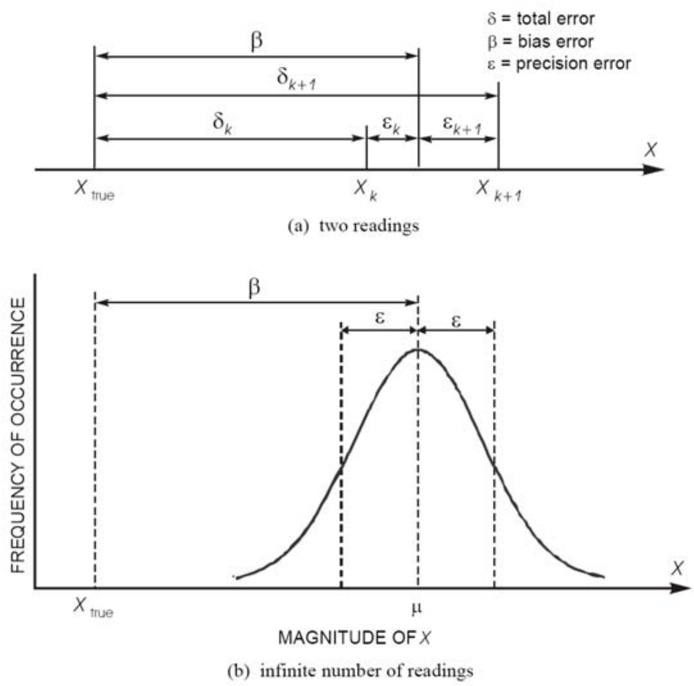

Figure 2: Errors in the measurement of a variable X

3.2. Measurement Systems, Data-Reduction Equations, and Error Sources

Measurement systems consist of the instrumentation, the procedures for data acquisition and reduction, and the operational environment, e.g., laboratory, large-scale specialized facility, and in situ. Measurements are made of individual variables, X_i, to obtain a result, r, which is calculated by combining the data for various individual variables through data reduction equations.

$$r = r(X_1, X_2, X_3, \ldots, X_J) \tag{5}$$

For example, to obtain the velocity V of some object, one might measure the time required (X_1) for the object to travel some distance (X_2) in the data reduction equation $V = X_2 / X_1$.

Each of the measurement systems used to measure the value of an individual variable, X_i, is influenced by various elemental error sources. The effects of these elemental errors are manifested as bias errors (estimated by B_i) and precision errors (estimated by P_i) in the measured values of the variable, X_i. These errors in the measured values then propagate through the data reduction equation, thereby generating the bias, B_r, and precision, P_r, errors in the experimental result, r.

3.3. Derivation of Uncertainty Propagation Equation

Bias and precision errors in the measurement of individual variables, X_i, propagate through the data reduction Eq. (5) resulting in bias and precision errors in the experimental result, r. One can see how a small error in one of the measured variables propagates into the result by examining Fig. 3. A small error, δ_{Xi}, in the measured value leads to a small error, *dr*, in the result that can be approximated using a Taylor series expansion of $r(X_i)$ about $r_{true}(X_i)$. The error in the result is given by the product of the error in the measured variable and the derivative of the result with respect to that variable dr/dX (i.e., slope of the data reduction equation). This derivative is referred to as a sensitivity coefficient. The larger the derivative/slope, the more sensitive the value of the result is to a small error in a measured variable.

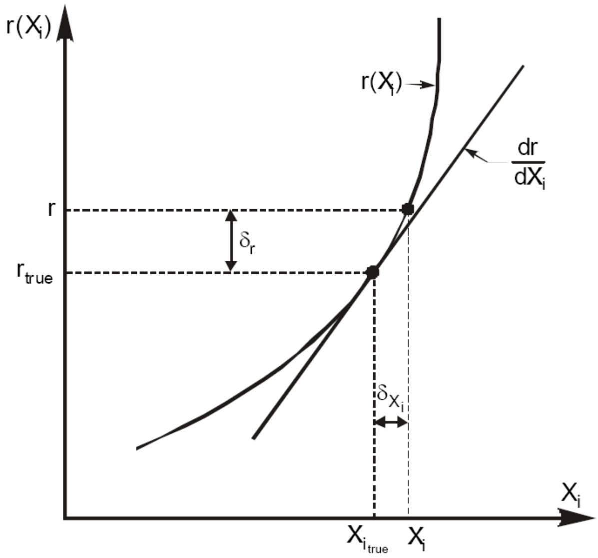

Figure 3: Schematic of error propagation from a measured variable into the result

In the following, an overview of the derivation of an equation describing the error propagation is given with particular attention to the assumptions and approximations made to obtain the final uncertainty equation.

Rather than presenting the derivation for a data reduction equation of many variables, the simpler case in which Eq. (5) is a function of only two variables is presented, hence

$$r = r\,(x,y) \tag{6}$$

The situation is shown in Fig. 4 for the kth set of measurements (x_k, y_k) that is used to determine r_k. Here, β_{xk} and ε_{xk} are the bias and precision errors, respectively, in the kth measurement of x, with a similar convention for the errors in y and r.

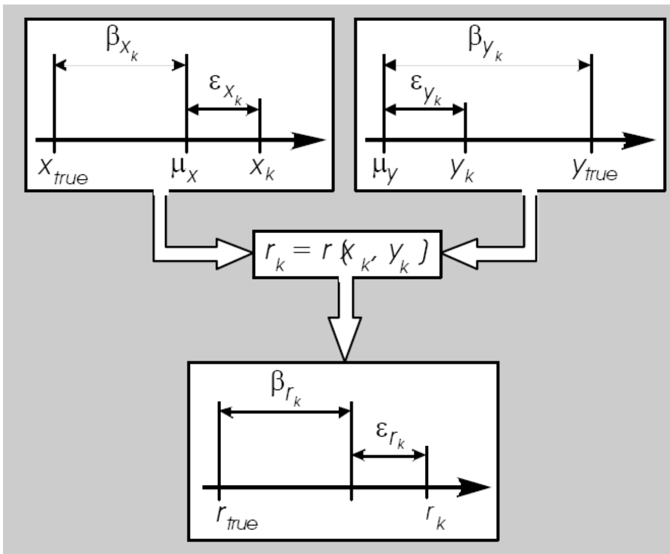

Figure 4: Propagation of bias and precision errors into a two variable result

Assume that the test instrumentation and/or apparatus are changed for each measurement so that different values of β_{xk} and ε_{xk} will occur for each measurement. Therefore, the bias and precision errors will be random variables relating the measured and true values

$$x_k = x_{true} + \beta_{xk} + \varepsilon_{xk} \tag{7}$$

$$y_k = y_{true} + \beta_{yk} + \varepsilon_{yk} \tag{8}$$

The error in r_k (the difference between r_{true} and r_k) in Eq. (6) can be approximated by a Taylor series expansion as

$$r_k - r_{true} = \frac{\partial r}{\partial x}(x_k - x_{true}) + \frac{\partial r}{\partial y}(y_k - y_{true}) + R_2 \tag{9}$$

Neglecting higher order terms (term R_2, etc.), substituting for $(x_k\text{-}x_{true})$ and $(y_k\text{-}y_{true})$ from Eqs.(7) and (8), and defining the sensitivity coefficients $\theta_x=\partial r/\partial x$ and $\theta_y=\partial r/\partial y$, the total error δ in the kth determination of the result r is defined from Eq.(9) as

$$\delta_{r_k} = r_k - r_{true} = \theta_x\left(\beta_{x_k} + \varepsilon_{x_k}\right) + \theta_y\left(\beta_{y_k} + \varepsilon_{y_k}\right) \tag{10}$$

Equation (6) shows that δ_{rk} is the product of the total errors in the measured variables (x,y) with their respective sensitivity coefficients.

The interest is to obtain a measure of the distribution of δ_{rk} for (some large number) N determinations of the result r. The variance of this "parent" distribution is defined by

$$\sigma_{\delta_r}^2 = \lim_{N\to\infty}\left[\frac{1}{N}\sum_{k=1}^{N}\left(\delta_{r_k}\right)^2\right] \tag{11}$$

Substituting Eq.(10) into Eq. (11), taking the limit as N approaches infinity, using definitions of variances similar to that in Eq. (11) for the β*'s*, ε*'s*, and their correlation, and assuming that there are no bias error/precision error correlations, results in the equation for $\sigma_{\delta r}$

$$\sigma_{\delta_r}^2 = \theta_x^2\sigma_{\beta_x}^2 + \theta_y^2\sigma_{\beta_y}^2 + 2\theta_x\theta_y\sigma_{\beta_x\beta_y} + \theta_x^2\sigma_{\varepsilon_x}^2 + \theta_y^2\sigma_{\varepsilon_x}^2 + 2\theta_x\theta_y\sigma_{\varepsilon_x\varepsilon_y} \tag{12}$$

Since in reality the various σ*'s* are not known exactly, estimates for them must be made. Defining u_c^2 as an estimate for the variance of the total error distribution, $\sigma_{\delta r}^2$, b_x^2, b_y^2, b_{xy} as estimates for the variances and covariance of the bias error distributions, and, S_x^2, S_y^2, S_{xy}, as estimates for the variances and covariances of the precision error distributions, results in the equation for u_c

$$u_c^2 = \theta_x^2 b_x^2 + \theta_y^2 b_y^2 + 2\theta_x\theta_y b_{xy} + \theta_x^2 S_x^2 + \theta_y^2 S_y^2 + 2\theta_x\theta_y S_{xy} \tag{13}$$

Notice that b_{xy} and S_{xy} are estimates of the correlated bias and precision errors, respectively, in x and y.

No assumptions have yet been made on types of error distributions. To obtain an uncertainty U_r at a specified confidence level (e.g., 95%), u_c must be multiplied by a coverage factor K

$$U_r = K\,u_c \tag{14}$$

Choosing K requires assumptions on types of error distributions. Assuming that the error distribution of the result, r, is normal so that we may replace the value of K for $C\%$ coverage (corresponding to the $C\%$ confidence level) with the t value from the Student t distribution. For sufficiently large number of measurements, $N \geq 10$, $t = 2$ for 95% confidence. With these final assumptions and generalizing Eq. (13) for the case in which the experimental result r is obtained from Eq.(5) provides the desired result

$$U_r^2 = \sum_{i=1}^{J}\theta_i^2 B_i^2 + 2\sum_{i=1}^{J-1}\sum_{k=i+1}^{J}\theta_i\theta_k B_{ik} + \sum_{i=1}^{J}\theta_i^2 P_i^2 + 2\sum_{i=1}^{J-1}\sum_{k=i+1}^{J}\theta_i\theta_k P_{ik} \tag{15}$$

where $B_i=tb_i$, $B_{ik}=t^2b_{ik}$, $P^i=tS_i$, $P_{ik}=t^2S_{ik}$ and t = 2 for $N \geq 10$. B_i and P_i are the bias limits in X_i; and B_{ik} and P_{ik} are the correlated bias and precision limits in X_i and X_k. S_i is the standard deviation for a sample of N readings of the variable X_i. The sensitivity coefficients are defined as

$$\theta_i = \partial r / \partial_{Xi} \tag{16}$$

The approach used in ASME PTC 19.1 (1998) follows, in close agreement, the derivation showed above.

3.4. The Case Study Uncertainty Propagation Equation

To perform the uncertainty analysis in the average values of the global thermal efficiency η related to the tests runs, it is necessary to obtain the data reduction equation according to the ASME PTC 19.1 (1998), in this case. Using Eqs. (1) to (4),

$$\eta = P_{cor} / Q_{cor} = ((1 - 0.0075)\ P_{med} - 16)/(LHV_{GAF}\ V_{GAF} + LHV_{ALC}\ m_{ALC} \tag{17}$$

Using ASME PTC 19.1 (1998) once more, the propagation equation is given by:

$$U_\eta = ((\theta_{Pmed}\ U_{Pmed})^2 + (\theta_{LHVGAF}\ U_{LHVGAF})^2 + (\theta_{VGAF}\ U_{VGAF})^2 + \\ + (\theta_{LHVALC}\ U_{LHVALC})^2 + (\theta_{mALC}\ U_{mALC})^2)^{1/2} \tag{18}$$

where

$$\begin{aligned} \theta_{Pmed} &= \partial\eta/\partial P_{med} \\ \theta_{LHVGAF} &= \partial\eta/\partial LHV_{GAF} \\ \theta_{VGAF} &= \partial\eta/\partial V_{GAF} \\ \theta_{LHVALC} &= \partial\eta/\partial LHV_{ALC} \\ \theta_{mALC} &= \partial\eta/\partial m_{ALC} \end{aligned} \tag{19}$$

and U_{Pmed}, U_{LHVGAF}, U_{VGAF}, U_{LHVALC}, and U_{mALC} are the uncertainties in the indicated variables, respectively.

4. PERFORMANCE TESTS RESULTS

To do the power plant variables measurements under test conditions it is necessary first to load the steam turbine up to the open admission valves conditions during at least one hour to the stabilization of the plant equipment (stabilization period). After that, one runs the test itself. During the stabilization and the test, the measurements are taken to assess the global thermal efficiency, the correction factors and the uncertainties.

Initially, during two hours the stabilization measurements were taken. Then, the run test I were performed and measured (N = 50 to 120 readings in different instruments).

In the run test I, it was noticed an electric energy generation increase due to an incident of a failure of a regenerator. This occurrence would indicate that the ideal number of power plant regenerators was smaller than the designed (i. e., three and not four feedwater pre-heaters). Thus, it was decided to do an extra run test II during two hours under the modified configuration (N = 50 to 120 readings in different instruments).

The obtained average values for the considered variables to the global thermal efficiency assessment and their random uncertainties (standard deviations) are shown in Tab. 2.

Table 2: Considered variables average values and their random uncertainties

	Run Test I	**Run Test II**
P_{med} (J/s)	11,650,000 ± 357,000	11,864,000 ± 455,000
LHV_{GAF} (J/Nm^3)	4,403,672 ± 113,022	4,399,486 ± 71,162
V_{GAF} (Nm^3/s)	9.26 ± 0.21	9.19 ± 0.22
LHV_{ALC} (J/kg)	19,954,662 ± 75,348	19,954,662 ± 75,348
m_{ALC} (kg/s)	0.143 ± 0.00389	0.142 ± 0.00361

Thus, substituting the values of Tab. 2 in the Eqs.(2) and (4), the average values of P_{cor} and Q_{cor} in the run tests are obtained and shown in Tab. 3.

Table 3: Average values of P_{cor} and Q_{cor}

	Run Test I	Run Test II
P_{cor} (kW)	11,563	11,775
Q_{cor} (kW)	43,631	43,265

The average net thermal efficiencies shown in Tab. 4 are obtained from Eq. (16) and the values from Tab. 3.

Table 4: Average net thermal efficiencies

	Run Test I	Run Test II
$\eta = P_{cor} / Q_{cor}$	0.265 (26.5%)	0.272 (27.2%)

In this assessment, the bias uncertainties related to the variables P_{med}, LHV_{GAF}, V_{GAF}, LHV_{ALC}, and m_{ALC} are shown in Tab. 5.

Table 5: Variables bias uncertainties

U_{Pmed}	0.2236%
U_{LHVGAF}	0.7141%
U_{VGAF}	3.0017%
U_{LHVALC}	1.0000%
U_{mALC}	0.1414%

Therefore, in the run tests I and II, the variable bias uncertainties at their average values are shown in Tab. 6.

Table 6: Variable bias uncertainties at their average values

Bias Uncertainties	Run Test I	Run Test II
U_{Pmed} (J/s)	26,049	26,528
U_{LHVGAF} (J/N m$^{3)}$	31,447	31,417
U_{VGAF} (Nm^3/s)	0.278	0.276
U_{LHVALC} (J/kg)	199,547	199,547
U_{mALC} (kg/s)	0.000202	0.000201

The bias and the random uncertainties are combined by SRSS (square root of the sum of the squares), based on ASME PTC 19.1 (1998). Using the bias uncertainties from Tab. 6 and the random uncertainties from Tab. 2, the obtained combination is shown in Tab. 7.

Table 7: Variables bias and the random uncertainties combination

Combined Uncertainties	Run Test I	Run Test II
U_{Pmed} (J/s)	357,949	455,000
U_{LHVGAF} (J/N m$^{3)}$	117,315	71,162
U_{VGAF} (Nm^3/s)	0.35	0.22
U_{LHVALC} (J/kg)	213,299	75,348
U_{mALC} (kg/s)	0.00390	0.00361

The variables sensitivity coefficients θ_i are obtained by derivation of the reduction data Eq. (17) and are shown in Tab. 8.

Table 8: Variables sensitivity coefficients

θ_{Pmed}	=	$\partial\eta/\partial P_{med}$	=	$0.9925 / (LHV_{GAF}\, V_{GAF} + LHV_{ALC}\, m_{ALC})$
θ_{LHVGAF}	=	$\partial\eta/\partial LHV_{GAF}$	=	$(-1)\, V_{GAF}\, 0.9925\, P_{med} / (LHV_{GAF}\, V_{GAF} + LHV_{ALC}\, m_{ALC})^2$
θ_{VGAF}	=	$\partial\eta/\partial V_{GAF}$	=	$(-1)\, LHV_{GAF}\, 0.9925\, P_{med} / (LHV_{GAF}\, V_{GAF} + LHV_{ALC}\, m_{ALC})^2$
θ_{LHVALC}	=	$\partial\eta/\partial LHV_{ALC}$	=	$(-1)\, m_{ALC}\, 0.9925\, P_{med} / (LHV_{GAF}\, V_{GAF} + LHV_{ALC}\, m_{ALC})^2$
θ_{mALC}	=	$\partial\eta/\partial m_{ALC}$	=	$(-1)\, LHV_{ALC}\, 0.9925\, P_{med} / (LHV_{GAF}\, V_{GAF} + LHV_{ALC}\, m_{ALC})^2$

Copyright © 2007 by ABCM

The sensitivity coefficients θ_i at the variables average values are obtained from Tab. 8 and Tab. 2 data and shown in Tab. 9.

Table 9: Sensitivity coefficients at the variables average values

	Run Test I	**Run Test II**
θ_{Pmed} **(s/J)**	2.27473E-08	2.29401E-08
θ_{LHVGAF} **(Nm^3/J)**	-5.62428E-08	-5.78105E-08
θ_{VGAF} **(s/Nm^3)**	-0.026746732	-0.027675369
θ_{LHVALC} **(kg/J)**	-8.68544E-10	-8.93264E-10
θ_{mALC} **(s/kg)**	-0.121199309	-0.125526627

Using the propagation Eq. (18), the combined uncertainties values from Tab. 7 and the sensitivity coefficients from Tab. 9, the resultant uncertainties in the net thermal efficiency are shown in Tab. 10.

Table 10: Net thermal efficiency resultant uncertainties

	Run Test I	**Run Test II**
U_η	± 0.0140 (± 1.40%)	± 0.0150 (± 1.50%)

Therefore, using the results from Tab. 4 and Tab. 10, the net thermal efficiencies are shown in Tab. 11.

Table 11: Performance tests net thermal efficiencies

	Run Test I	**Run Test II**
$\eta \pm U_\eta$	26.5 ± 1.4 %	27.2 ± 1.5 %

5. COMMENTS AND CONCLUSIONS

It was used a methodology to assess the global thermal efficiency of a power plant fed by two different fuels, blast furnace gas and wood tar, based on the Direct Method of Measured Net Plant Power and Heat Input, according to the ASME PTC 46 (1996).

The methodology was applied to power plant performance tests and uncertainty analyses of the obtained results were performed according to the ASME PTC 19.1 (1998).

The obtained results for the net thermal efficiencies in the run tests I and II satisfy the expected limit of 25.1% for the power plant net global thermal efficiency under the specified conditions (11,446 kW, in the 20.5 kV bars, for the fuels flows and respective fuels LHVs).

It is important to check prior the performance tests if the plant installed instrumentation has the uncertainties defined for all used sensors and data acquisition systems.

The tests indicated that the blocking of one feedwater pre-heater would give a small advantage over the non blocking condition considering the obtained net thermal efficiency results.

The paper showed that is possible and relatively easy to conduct performance tests in small thermal electric power plants to assess their net thermal efficiencies using simplified approaches based on ASME PTC 46 (1996) and ASME PTC 19.1 (1998) and their industrial instrumentation.

5. REFERENCES

ASME, 1996, Performance Test Code on Overall Plant Performance, The American Society of Mechanical Engineers, New York, NY, USA, (ASME PTC 46, 1996).

ASME, 1998, Test Uncertainty, Instrument and Apparatus, The American Society of Mechanical Engineers, New York, NY, USA, (ASME PTC 19.1, 1998).

ISO, 1993, Guide to the Expression of Uncertainty in Measurement, International Organization for Standardization, Geneva, Switzerland.

6. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.