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# Fourier transform method for sensitivity analysis in coal fired power plant

Cirilo S. Bresolin [a], Joao C. Diniz da Costa [b], Victor Rudolph [b], Paulo Smith Schneider [a,*]

[a] Department of Mechanical Engineering, Universidade Federal do Rio Grande do Sul, Porto Alegre 90050-170, RS, Brazil
[b] Division of Chemical Engineering, The University of Queensland, Brisbane, Qld 4072, Australia

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**Abstract**

This work proposes a Fourier transform method to determine the sensitivities associated with a real coal power plant using a Rankine cycle. Power demand determines the plant revenue and is supposed to be the most important parameter to be accurately measured, and this hypothesis is at the center of this study. The results confirm that under full design load, variables such as steam pressure, temperature and mass flow rate are closely dependent on power demand, though overall thermal efficiency is more sensitive to boiler efficiency. Partial load simulation shows that the overall thermal efficiency remains strongly dependent on the boiler parameters, but other operational variables such as steam temperature at the turbine outlet changes its sensitivity according to the load. The results from the Fourier transform method are in good agreement with those determined by classical differential and Monte Carlo methods. However, the Fourier transform method requires only a single run, providing major savings in computational time as compared to the Monte Carlo method, a major advantage for analysis of power systems whether operating under full or partial load.


*Keywords:* Sensitivity analysis; Coal fired power plant; Uncertainty analysis; Differential method; Monte Carlo method; Fourier transform method

## 1. Introduction

Open energy markets allow energy to be sold in short intervals, ranging from 5 min segments upwards. In the case of integrated electricity grids, unexpected outages of a major power train at a power station can cause supply shocks and large spikes in spot prices. In a tight competitive energy market, power generation plants must have a capability to predict demand with high accuracy and cope with small discrepancies while minimizing standby provisions but still retain enough supply flexibility to manage (or take advantage of) unanticipated infrastructure failures. These issues are outside the control of the plant and have a high level of uncertainty.

The profitability of the plant relies on the difference between the revenue generated, i.e., the power that is exported, and the costs of production, i.e., the efficiency of the plant. To evaluate plant efficiency and, consequently, gain insight on how best to control costs, measurement of the plant operation is required. All of these measurements have some degree of uncertainly, related to instrument accuracy, calibration, maintenance and so on, and they also affect the outcome with different degrees of sensitivity. It is, consequently, important for plant management to understand and know which measurements are most critical and how accurate they need to be, since this will influence maintenance and upgrading decisions and resource allocations.

The techniques for both uncertainty and sensitivity analysis are quite similar, and their difference lies principally in the interpretation of results. The main objective is to calculate the uncertainties of the results due to the uncertainties of the inputs, which leads to the reliability of the system. Sensitivity analysis helps to resolve how variation in the input data affects the output of a system. Both uncertainties

* Corresponding author. Tel.: +55 51 3308 3931; fax: +55 51 3308 3355.
*E-mail address:* pss@mecanica.ufrgs.br (P.S. Schneider).

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**Nomenclature**

| | |
|---|---|
| $A$ | amplitude |
| $c$ | coefficients of Fourier transform |
| DM | differential method |
| $g(t)$ | Fourier transform |
| $\bar{g}$ | sample spectrum mean |
| $h$ | specific enthalpy (kJ/kg) |
| HP | high pressure turbine group |
| HHP | high pressure preheater |
| $I$ | data importance index |
| IP | intermediate pressure turbine group |
| $K$ | number of points $K$ needed to run method |
| $k$ | sample length, isentropic coefficient, integer number |
| LP | low pressure turbine group |
| LPP | low pressure preheater |
| $\dot{m}$ | mass flow rate (kg/s) |
| MCM | Monte Carlo method |
| $n$ | sample length |
| $p$ | confidence |
| $P$ | pressure (kPa), energy |
| $p'$, $p''$ | confidence interval upper and lower limits |
| $S$ | sensitivity index |
| $s$ | specific entropy (kJ/kg K) |
| $S^2$ | sample variance |
| $T$ | temperature (°C or K) |
| $t$ | time (s) |
| $u$ | data bias |
| $u^2$ | data variance |
| $v$ | specific volume (m$^3$/kg) |
| $V_Y$ | global variance |
| $V_{Y\mid X}$ | local variance of $Y$ given by the individual variance of $x$ |
| $\dot{W}$ | power output (kWe) |
| $X, \bar{x}$ | input data, input data mean value |
| $Y, \bar{Y}$ | output data, output data mean value |

*Greek symbols*

| | |
|---|---|
| $\eta$ | efficiency |
| $\sigma$ | critical pressure factor (dimensionless) |
| $\sigma^2$ | population variance |
| $\chi^2$ | chi square distribution coefficient |
| $\omega$ | frequency (rad/s) |
| $\varepsilon_0$ | isentropic ratio (dimensionless) |
| $\rho$ | density (kg/m$^3$) |

*Subscripts*

| | |
|---|---|
| D | design conditions |
| E | electric |
| $i$, $j$ | individual data, input or inlet |
| o | output or outlet, initial condition |
| P | pump |
| s | sampling |
| ss | isentropic expansion |
| t | turbine |

of measurements and variation in input data may be seen as biases of mean values, and therefore, the same techniques can be employed for different purposes. Deviations in sensitivity analysis can be taken as arbitrated rates of mean values, for example 1% of every mean value of data input. In this paper, we focus on sensitivity analysis as applied to routine operation but note that the same kinds of techniques can be applied to uncertainty analysis applied to demand variation.

There are a variety of methods that have been developed to examine the issues of process sensitivity and uncertainty. Lomas and Epperl [1] suggested that the differential method is preferable for individual parameters, but the Monte Carlo Method may be better for global sensitivity identification. Hamby [2] compared fourteen sensitivity analysis techniques when applied to a common model (of dispersion of radiation pollution in the atmosphere) and concluded that most provide very similar outcomes. Macdonald and Stracham [3] also reviewed the application of these methods to predict uncertainties of thermal models, including possible sources of uncertainty in simulated models.

Taking an output $Y$ from a set of equations $Y = f(x_1, \ldots, x_n)$, where $x_1, \ldots, x_n$ are the input data with known probability distributions, the probability distribution of $Y$ can be found by sensitivity methods. The deviation of a given input datum will be propagated into the solution of the equation set. Indices relating probability distributions of input and output data provide useful connections, and two classical methods are reviewed in this paper.

The differential method (DM) with a global covariance $u_Y^2$ is calculated after the product of each first order partial derivative of $Y$ with respect to its $x_i$ parameters by the corresponding deviation $u_i$ [1,4]

$$u_Y^2 = \sum_{i=1}^{n} \left(\frac{\partial Y}{\partial x_i}\right)^2 u_i^2. \tag{1}$$

Two indices were proposed by Hamby [2]. A dimensionless number called the importance index $I_i$ of a given data $i$ relates to sensitivity as follows:

$$I_i = \left(\frac{\partial Y}{\partial x_i}\right) \cdot \frac{\bar{x}_i}{\bar{\bar{Y}}}. \tag{2}$$

This index indicates a rate or proportion between deviations, and it takes into account the relative rate of variation of the input data rather than its absolute deviation. A sensitivity index $S_i$, is given by

$$S_i = \left(\frac{\partial Y}{\partial x_i}\right)^2 \cdot \frac{u_i^2}{u_Y^2}, \tag{3}$$