

POLITECNICO DI MILANO

Facoltà di Ingegneria Industriale e dell'Informazione

Master of science in Energy Engineering



**ASSESSMENT OF THE SPECIFIC CONSUMPTION
OF A COAL-FIRED POWER PLANT BY SOLVING
MASS AND ENERGY BALANCES THROUGH
MONTE CARLO SIMULATION**

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Academic year 2017/2018

Acknowledgements

Alla fine di questo percorso sono tanti i momenti che mi tornano alla mente, e tutti mi fanno spuntare il sorriso sulle labbra. Non posso far altro che ringraziare di cuore tutte le persone che mi hanno accompagnato fin dal primo giorno in questa avventura.

Ringrazio il professor Viganò, che con pazienza e competenza mi ha guidato in questo lavoro di tesi.

Ringrazio tutti i miei compagni di corso: ognuno di loro mi ha insegnato qualcosa che mi ha reso una persona migliore.

Ringrazio le mie amiche e colleghe Fede, Ludo, Ale, Roby e Vale: donne ingegnere che col loro coraggio mi hanno fatto capire che nella vita tutto è possibile, basta volerlo.

Ringrazio la mia squadra, che dentro e fuori dal campo mi ha supportato con gioia e complicità e che ha sempre creduto in me.

Ringrazio zia Pasqualina, una seconda mamma, che ha fatto della lontananza solo un motivo per farmi sentire il suo affetto più forte.

Ringrazio Anna, più che una sorella una complice, che ha vissuto con me ogni secondo e che è stata sempre il mio esempio e il mio punto di riferimento.

Ringrazio i miei genitori, mia roccia e fonte di ispirazione: è solo grazie a loro se oggi sono qui e sono la persona che sono. Spero con questo traguardo di averli resi orgogliosi di me.

Giusy

Extended summary

Introduction

In the last decades, the environmental issues have become a priority, especially in the energy field. In this view the problem of existing power plants arises: their role in energy production is still very important and with the growing demand of the energy market it is likely to be so also in the near future. The main problem of these plants is their footprint on the environment. How to reconcile their presence with the pressing need to respect environment and health? New legislation at European level sets the guidelines to control the pollutant greenhouse gases emissions by fossil fuel plants.

As a result of this new regulations, many plants are required to enhance their monitoring and control system for pollutant emissions (named as Air Pollution Control-APC- system). This is the case of the "Federico II" coal power plant owned by ENEL in Brindisi. Over the years, its APC systems has been improved such as to become a model in Italy. Last of the changes introduced to monitor the chimney emissions is the installation of a new measuring instrument projected by Siemens, to respect the European normative 601/2012 of 21 June 2012. Based on this normative, the calculation of CO₂ emissions from most power plants must rely on the direct measurement of CO₂ emission at stack: it's no longer enough to calculate such emission from the information on the fuel composition. To fully exploit the new measuring instrument ENEL would like to utilize the additional information to improve the efficiency of the plant: this is the main objective of this thesis.

In particular, the specific consumption of the plant is the variable used to quantify the overall efficiency. It is the ratio between the energy consumption and the electric production. ENEL already calculate such efficiency based on a different method. In this thesis the approach based on the Monte Carlo simulation is considered. In fact, the measured variables can be seen as aleatory variables, that follow a statistical distribution characterized by a mean value and a standard deviation. Therefore the use of such variables needs a method that can manage them with the respective uncertainties. This work investigate the performances of the Monte Carlo approach and compares them against those achievable by the conventional application of uncertainties propagation law.

“Federico II” power plant

The "Federico II" thermal power plant in Cerano, Brindisi, is one of the most important in Europe and one of the largest, coming into operation in 1997. In the study of the “Federico

It's plant can be highlighted some critical points. The first one is related to the coal fed to the burners. The fuel is injected into the combustion chamber in suspension with air: the more fuel is needed, the more air is introduced. This technique does not allow to know the amount of fuel introduced. Moreover the fuel is taken from the storage dome which contains different quality of coal and the composition of coal is known only with significant uncertainty. These different types of coal are mixed together at the entrance of the burner, in undefined percentage.

Methodology

The purpose of this work is to calculate the specific consumption of the plant with the associated uncertainty. The system is described with a set of equations that takes in input only independent variables. The idea is to build a model of the plant that describes all its parts in a simple way and that utilizes information of both measurements at stack (such as volumetric flow rate and concentrations of different species) and data on the composition of fuel. Based on this information the model estimates the lower heating value of the fuel and, then, the specific consumption of the plant.

In order to do this, all the data are collected in the form of average value and standard deviation. Then a mass balance on the combustion chamber and a mass balance on the De-SO_x system are set up. The equations are then solved with the Monte Carlo method, that can be described in the following steps:

- The values of the independent variables are randomly extracted from the distributions (something on the order of 100,000 instances). These random data points simulate the values that would be seen over a long period for each input.
- For each data set solve the mathematical model (set of equations) to obtain the output variable starting from the statistical distribution of the input variables. The output variables are described as statistical distribution too. Therefore average value and uncertainty can be determined for them too.

The conventional approach which is considered to compare the performances of Monte Carlo method evaluates the mean value of the output based on the mean value of the input and estimates uncertainties of the output based on the propagation of uncertainties as defined in the ISO-GUIDE 98-3 [1].

Model description

Below are listed the mass balance equations of the problem. To obtain the value of LHV and specific consumption, the content of carbon and oxygen in the coal need to be calculated, as well as the total amount of coal introduced. The content of other elements is determined based on fuel composition data. Therefore, three balance equations are needed:

- balance for the element “sulfur”
- balance of the element “carbon”
- balance of the dry stoichiometric flue gas

Input variables

The following independent variables are utilized as input data for balance implementation. They are measured at the stack, along flue gas conduits and at the combustor inlet.

Some of the independent variables are:

Table 1 Independent variables in input

name	symbol	Unit of measure	distribution
oxygen volumetric content at stack on “as is” basis	$xO_{2stack,tq}$	-	Normal
carbon dioxide volumetric content at the stack on “as is” basis	$xCO_{2stack,ai}$	-	Normal
total flue gas flow rate at stack on “as is” basis	V_{fai}	Nm ³ /Δt	Normal
water vapor volumetric content at the stack	$xH_2O_{stack,ai}$	-	Normal
concentration of SO ₂ at stack	SO ₂ out	mg/Nm ³ dry 6%O ₂	Normal
fraction of fuel ash to fly ash	alpha	%	Uniform
excess CaCo ₃ in De-SO _x system	exc	%	Uniform
loss on ignition of fly ash	LOI	%	Normal
power output	Power	MW	Normal

Coal elemental composition

For each type of coal some samples are taken at the arrival of coal, therefore the elemental composition on “as is” basis, is determined in terms of Carbon, Hydrogen, Oxygen, Moisture, Nitrogen, Sulfur and Ash content. For every element content, the average value and standard deviation are calculated and assumed as parameters of a normal distribution.

These contents are not independent variables, in fact their sum must always equal 1: it's not possible to simply extract their value from their distributions, but each quantity must be related to the others. Therefore, carbon is taken as a reference quantity and all the other variables are expressed as a function of carbon. In this way, five variables to be randomly extracted are obtained.

table 2 list of the variables used to characterize the elemental composition of coal

name	symbol
Hydrogen	H/C
Sulfur	S/C
Nitrogen	N/C
Ash	ASH/C
Moisture	M

Hydrogen, Sulfur, Nitrogen and Ash content over carbon content are the independent variables, as well as the moisture content, while Carbon and Oxygen content are considered unknown, therefore calculated by solving the balance equations.

Output parameters

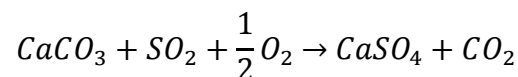
The procedure is finalized to obtain the total coal fed, its LHV and the specific consumption as statistical distribution through the Monte Carlo Method.

table 3 output parameters

name	symbol	u.m
Coal consumption	C_c	t/h
Lower heating value	LHV	kJ/kg
Combustion power	C.P.	kJ/h
Specific consumption	S.C.	kWh _{coal} /kWh _e

Balance on the element "sulfur"

In the De-SO_x reactor part of SO₂ is absorbed into alkaline droplets to form calcium sulphate mainly through reaction:



It can be seen that in the process of removing sulfur dioxide, carbon dioxide is generated according to the consumption of limestone.

From the measurement at chimney we obtain $[SO_x]_{out}$, volumetric outlet concentration on dry basis, at standard oxygen concentration. The value $[SO_x]_{in}$, referred to the standard oxygen concentration $[mg/Nm^3]$, is calculated starting from the sulfur content in the coal:

$$SO_{2in} \left[\frac{mg}{Nm^3} \right] = \frac{S}{C} * x_c * C_c * \frac{64}{32 * Vf} * 10^9 \left[\frac{tons}{g} \right]$$

The efficiency of the process is defined as:

$$eff_{de_{sox}} = \frac{SO_{2in} - SO_{2out}}{SO_{2in}}$$

The specific production of Carbon in the desulphurization reaction is:

$$[C_{desox}] = SO_{2in} * eff_{de-sox} * \frac{12}{64} * \frac{Ca}{S} \left[\frac{mg}{Nm^3} \right]$$

And multiplied by the volumetric flow rate:

$$C_{de-sox} \left[\frac{tons}{h} \right] = [C_{de-sox}] * Vf * 10^{-9} \left[\frac{mg}{tons} \right]$$

Balance for the element “carbon”

Figure 1 shows the schematic representation of system considered for the mass balances, with all the streams (in and out) that contain carbon. Four streams are highlighted:

C1 [t/h]: total carbon in the fed coal

C2[t/h]: total carbon contained in the fly ash

C3 [t/h]: total carbon introduced in the De-SO_x system

C4[t/h]: total carbon in the dry stoichiometric flue gas in the form of CO₂

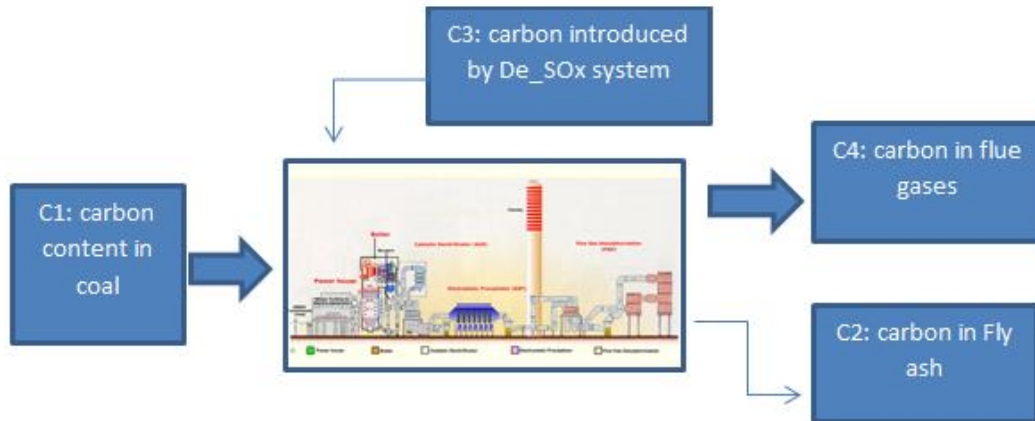


figure 1 scheme of the carbon balance in the plant

Input and output flows of carbon in the power plant

Carbon flow rate at the stack is calculated by means of the following equation:

$$C4[t/h] = Vf \left[xCO_{2stack} - xCO_{2air} \frac{xO_{2stack}}{xO_{2air}} \right] * \frac{Mc}{Vm} * 10^6 \left[\frac{g}{tons} \right]$$

The fuel ash is split in 10% into bottom ash and 90% into fly ash. The coefficient alpha sets these shares of fly ash. Then using the value of LOI the total carbon in the fly ash is determined. According to Burris&Al [10] being values of LOI higher than 4%, represents well the value of Carbon content.

$$\text{Fly}_{\text{ash}} = \left(\frac{\text{ash}}{c}\right) * x_c * \alpha$$

$$C_2 \left[\frac{\text{tons}}{h}\right] = \text{Fly}_{\text{ash}} \frac{\text{LOI}[\%]}{1 - \text{LOI}[\%]} * C_c$$

The last stream is the total carbon introduced in the De-SOx system, calculated in the previous paragraph by means of the sulfur balance.

$$C_3 \left[\frac{\text{tons}}{h}\right] = C_{de-sox}$$

The total carbon in the coal feed is the algebraic sum of all the carbon streams:

$$C_1 = C_4 - C_3 + C_2$$

Where C_1, C_2 and C_3 are function of x_c . Therefore, a linear equation is obtained, which allows calculating the value of x_c .

Balance for the dry stoichiometric flue gas

The coal oxygen content can be calculated using the following balance:

$$dsfg_{stack} - \Delta dsfg_{desox}$$

$$= (Mc - Mincomb) * dsfg_c + Mh * dsfg_h + Mo * dsfg_o + Ms * dsfg_s + Mn * dsfg_n$$

Where M_i are the mass of each species in tons/h. On the right hand side of the equation there is the dry stoichiometric flue gas flow rate at the outlet of the combustor (i.e. the difference between the flowrate measured at the stack and the delta introduced by the De-SOx system). The delta flue gas due to the De-SOx system is practically negligible and it has not been taken into account. The DSFG contributions of each species are:

table 4 dry stoichiometric flue gas volume contribution of different species

species	Reaction of combustion	DSFG [Nm ³ /kg]
C	$C + O_2 + 3.76N_2 \rightarrow CO_2 + 3.76N_2$	8.9075
H	$2H + 0.5(O_2 + 3.76N_2) \rightarrow H_2O + 3.76/2N_2$	20.977
N	$N + 0.5(O_2 + 3.76N_2) \rightarrow NO + 3.76/2N_2$	0.800
O	$2O \rightarrow O_2$	-2.643
S	$S + O_2 + 3.76N_2 \rightarrow SO_2 + 3.76N_2$	3.3365

LHV and specific consumption calculation

Once the amount of the carbon fed to the combustor is determined, the composition of coal is also known.

$$x_i = \frac{x_i}{x_c} * x_c \text{ [tons/h]}$$

Summing all the contributions the total dry flow rate of coal is calculated:

$$C_c = \sum_i x_i \left[\frac{\text{tons}}{\text{h}} \right]$$

To estimate the LHV of the burned coal different empirical correlations have been tested. The one that gives the best results is the Boie correlation

$$HHV = 84.13 * C + 378.13 * H - 26.57 * O + 25.04 * S$$

In the case of the coal considered to test the Monte Carlo simulation, the Boie's correlation predicts HHV with minimum error of 1.3 % and standard deviation of 126%.

LHV is calculated starting from the predicted LHV by correcting for the Moisture content. To consider the uncertainty in the prediction of HHV a random variable extracted from a normal distribution is used to alter Boie's estimate (this parameter is named k_LHV).

Finally we calculate the specific consumption as:

$$CS = \frac{\left(LHV \left[\frac{Kj}{kg} \right] * \frac{C_{al} \left[\frac{tons}{h} \right]}{1 - x_{h2o}} - \frac{C_{al} \left[\frac{tons}{h} \right]}{1 - x_{h2o}} * x_{h2o} * 2257.2 \left[\frac{Kj}{kg} \right] - C_{incomb} * 33778.6 \left[\frac{Kj}{kg} \right] \right) * \frac{10^3 \left[\frac{kg}{tons} \right]}{3600 \left[\frac{Kj}{KW} \right]}}{power[MW] * 10^3 \left[\frac{KW}{MW} \right]}$$

Results

The first quantity calculated in the system is the flowrate of coal burned and the associated composition. The graph in figure 2 shows the coal flow rate against the power output.

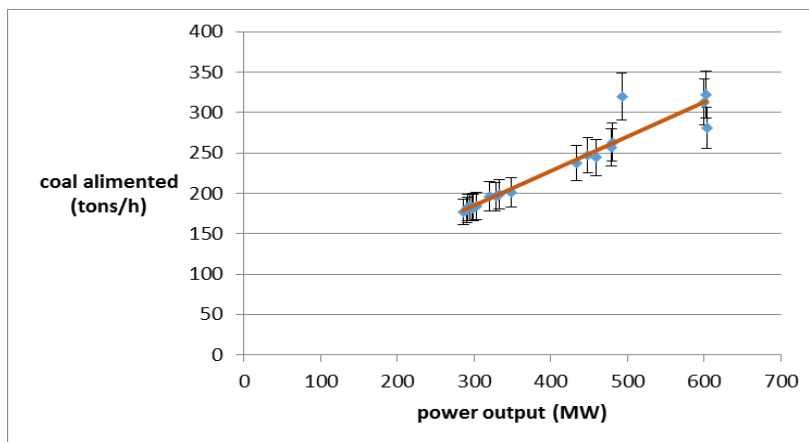


figure 2 coal consumption in function of the power output for each hour of operation with the associated error

A good correlation is highlighted with the only exception of one outlier. The origin of that outlier is not clear.

The description of the model highlights that the flowrate of carbon and oxygen to the burners are determined by means of balances, whereas are used to predict the values of H/C, N/C, S/C, ASH/C, which are assumed as independent variables. Anyway two redundant piece of information are available: the value of O/C from the coal analysis and the flowrate of carbon and oxygen calculated. The graph in figure 3 compares the distributions of O/C from coal analysis and that resulting from the model. It is possible to observe that the two curves (data from the coal analysis and calculated values) have different mean values and different dispersions, but they overlap in an area between 0,2 and 0,4 circa. This can be explained with the possible presence of systematic errors in some measurements at the stack. For example, a systematic error of +0.5 percentage points in the measurement of oxygen concentration at the stack could explain the found discrepancies. The redundancy of information could help us in correcting the possible systematic errors. In this work, reconciliation has not been carried on, because the literature does not report enough basic theory principles to match data reconciliation with the Monte Carlo method. Only a tentative of correction of the curve has been performed:

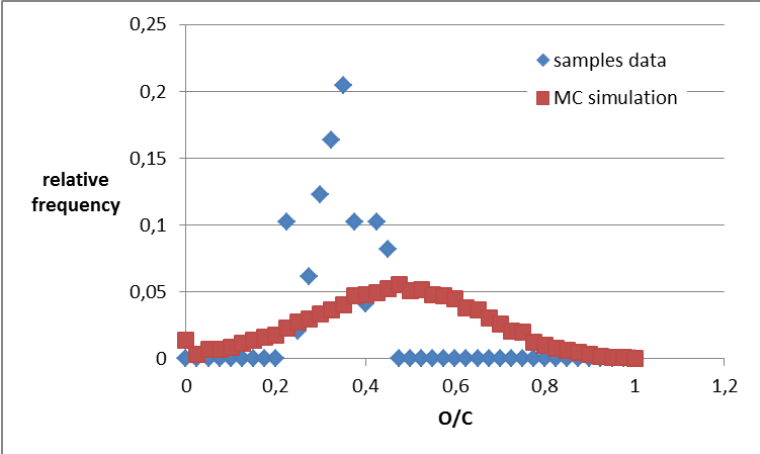


figure 3 distribution of the O/C in two different case: from the sampling and with Monte Carlo method

The average standard deviation is of the order of the 20% of the mean values circa the same of the LHV. Uncertainty on LHV is the main reason of this result.

The specific consumption depends on the composition of coal, its flow rate and LHV, as well as on the power output of the plant. The specific consumption is expressed as dimensionless variable (kWh_{coal}/kWh_{el}). The graph in figure 4 shows the distributions of

specific consumption for three different hours, when the power output of the plant was about 300, 460 and 600 MW respectively. As it can be see the higher is the power output, the lower is the mean value of the specific consumption. The mean value decreases because at higher power output corresponds higher efficiency.

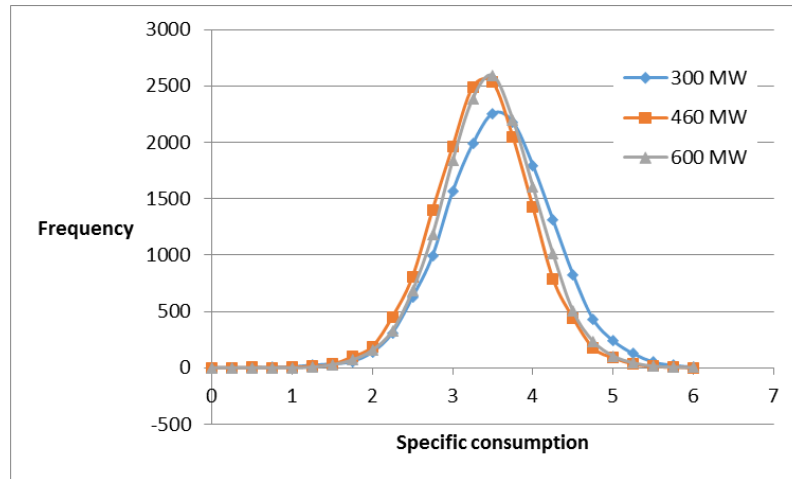


figure 4 distributions of specific consumption for three different hours of the test period, characterized by different power output

ENEL provided the specific consumption data calculated by themselves, with their method. The graph in figure 5 compares ENEL specific consumptions with the values given by the Monte Carlo method.

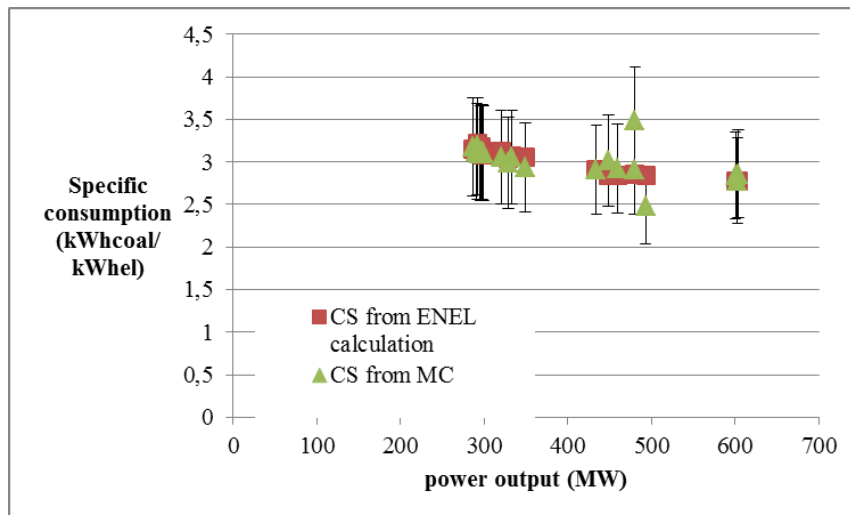


figure 5 SC trend with power output

We can notice some outliers, but in general the two result are aligned, with difference between 1% and 2%. To compare the results, the same material balance has been solved with the uncertainty propagation method, as shown in the graph in figure 6. The situation is

similar to the one predicted in figure 5. Concerning the standard deviation, instead, the uncertainty propagation gives lower values. This highlights the non-linear feature of the studied problem.

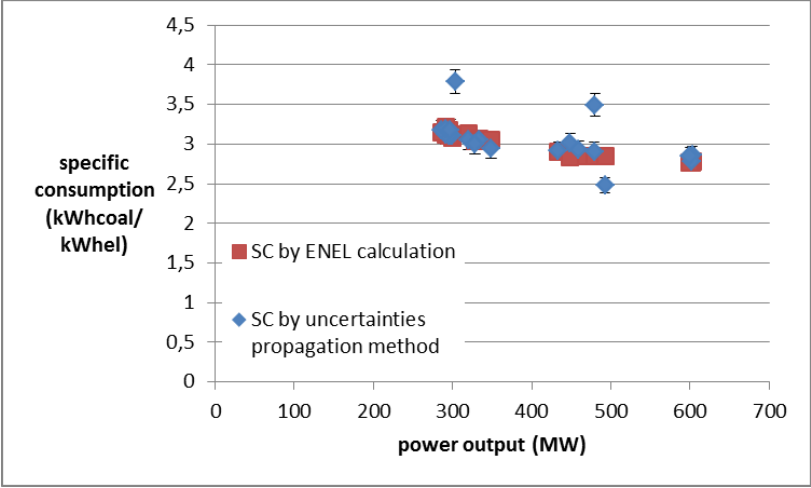


figure 6 specific consumption values and their standard deviation bars in comparison with the values of specific consumption calculated by ENEL

Conclusion

The developed method has been applied on a test period of one day of operation, on hourly basis. For the same test period ENEL provided the values of specific consumption calculated with the “Economy online” method. The mean values of the Monte Carlo method results are in substantial agreement with the specific consumption data calculated by ENEL, nevertheless the standard deviations associated with such mean values highlight uncertainty of the order of 20%. For the purpose of comparison, the uncertainty affecting the value of specific consumption, calculated by means of mass and energy balances, has been quantify also based on the law of uncertainty propagation. Surprisingly, this conventional method significantly underestimates the uncertainty on the results with respect to the Monte Carlo simulation. This relevant discrepancy may be due to the non-linear feature of the studied problem. The first measure for improving the accuracy of the specific consumption estimate is to enhance the evaluation of the combustion power (i.e. the product of coal LHV and coal flowrate). The simplest way to achieve such a result is to evaluate the combustion power based on a boiler energy balance. In this case, the role of the information regarding CO₂ concentration at the stack becomes absolutely minor, affecting also for a minimal extent the quantification of the stack loss at boiler outlet (through the heat capacity of flue gas).

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Abstract

The introduction of more severe legislation on the emission of power plants has forced many producers to adapt their APC (Air Pollution Control) systems. This mutation has interested in particular power plants powered with dirty fuels, such as coal. To monitor and check the effectiveness of pollutant abatement systems, many sensors are installed along the lines. All this equipment of course represents a significant cost, but also the opportunity to improve the performances thanks to a more accurate control. This is the case of the "Federico II" coal-fired power plant owned and operated by ENEL in Brindisi. One of the last improvements introduced is the installation of a laser-based CO₂ meter by Siemens to measure the CO₂ concentration in flue gas. It allows the direct calculation of CO₂ emissions, as required by the recent EU Monitoring & Reporting Regulation (MRR) (No. 601/2012, June 2012). The information coming from all the monitoring systems gives the possibility to set a number of material balances to quantify the coal consumption, its energy content (i.e. LHV= Lower Heating Value) and the specific consumption of the plant. The critical aspect of this approach is that all the calculated quantities are affected by significant uncertainties that can lead to anomalous results. In the past this problem was faced by ENEL with a proprietary method called "Economy On Line". The objective of this work is verify the potential of the approach based on mass and energy balances solved through Monte Carlo simulation. In this way variables are treated as statistical distributions from which values are extracted randomly, originating a huge number of combinations. The outcomes are the statistical distributions for the output variables, i.e. coal consumption, its LHV and the specific consumption. Results show that the method can work, giving mean values comparable with the result of the "Economy on line" method. However, the Monte Carlo method quantify the uncertainty of such results as rather significant, much greater than the estimates given by the method of uncertainty propagation. The integration of the Monte Carlo approach with a mechanism of data reconciliation, to exploit the available redundant information, is the main improvement envisaged as future development.

Key words

Monte Carlo simulation, coal, uncertainty, error propagation, lower heating value, specific consumption

Sommario

L'introduzione di una nuova e più severa legislazione sulle emissioni delle centrali elettriche ha costretto molti produttori ad adeguare i loro sistemi di abbattimento e misurazione degli inquinanti. Questa mutazione ha interessato in particolare le centrali elettriche alimentate con i combustibili più inquinanti, come il carbone. Per monitorare e verificare l'efficacia dei sistemi di riduzione delle emissioni, sono installati molti sensori lungo le linee: questi rappresentano un costo significativo, ma anche l'opportunità di aumentare le prestazioni grazie a un controllo più accurato. È il caso della centrale a carbone "Federico II" gestita da ENEL a Brindisi. Uno degli ultimi miglioramenti adottati è l'installazione di un nuovo strumento di misura di Siemens, introdotto per monitorare le emissioni di CO₂ al camino in modo diretto, come richiesto dalla normativa europea entrata in vigore (No. 601/2012, Giugno 2012). Le informazioni provenienti da tutti i sistemi di monitoraggio ci danno la possibilità di risolvere una serie di bilanci di massa e di calcolare la quantità effettiva di carbone introdotta, il suo contenuto energetico (cioè LHV = valore calorifico inferiore) e il consumo specifico dell'impianto. L'aspetto critico di questo approccio è che tutte le variabili calcolate sono influenzate da notevoli incertezze che possono portare a risultati anomali. In passato questo problema era affrontato da ENEL con l'uso del software proprietario "Economy on line". L'obiettivo di questo lavoro di tesi è di risolvere questo problema con un approccio alternativo: il metodo Monte Carlo, in cui le variabili misurate sono trattate come distribuzioni statistiche da cui i valori vengono estratti in modo casuale, originando un numero enorme di combinazioni. Ciò fornisce possibili distribuzioni statistiche per i risultati finali (carbone alimentato, rispettivo contenuto energetico e consumo specifico). I risultati mostrano che il metodo ha buoni riscontri confrontato con i risultati del metodo "Economy on line". Si vince però che il metodo stima tali grandezze con errori significativi, di gran lunga maggiori rispetto a quelli stimati dal metodo della propagazione degli errori. L'affiancamento del metodo Monte Carlo con un meccanismo riconciliazione dei dati per sfruttare le informazioni ridondanti disponibili potrebbe rappresentare un possibile lavoro futuro.

Parole chiave

Simulazione Monte Carlo, carbone, errore, propagazione dell'errore, potere calorifero inferiore, consumo specifico.

Introduction

In the last decades, attention to environmental issues have become a priority, especially in the energy field. Many big energy companies have chosen as politics to dismantle or not built any new fossil fuel plants, but to focus on energy from renewable sources.

In this view the problem of existing plants arises: their role in energy production is still very important and with the growing demand of the market it is likely to be so also in the near future. In particular this necessity is found in the Italian scenario. In fact, in Italy the distribution of energy sources is in proportion very different from that of other European countries (due to the absence of nuclear power plants and the high percentage of renewable sources). In our context coal power plants are a source of certainty for the energy market, both in terms of reliability (weak point of renewable sources) and in terms of geopolitical security (think about the risks related to the import of gas and other fossil fuels from countries with political instabilities). But the advantages of coal as fuel are not limited to these. Anyway the main problem of these plants is their environmental impact.

How to reconcile their important role with the pressing need to respect the environment and health? New legislation at European level sets the guidelines to control the pollution greenhouse gases emissions by fossil fuel plants.

As a result of this new regulation, many plants are required to enhance their monitoring and control system for pollutants emissions (Air Pollution Control system). This is the case of the "Federico II" coal power plant owned by ENEL in Brindisi. Over the years, the plant has improved its APC systems so as to become a model in Italy. Last of the changes introduced to monitor the chimney emissions and to increase their accuracy was the installation of a new measuring instrument projected by Siemens.

The investment is justified by the need to adapt to the new emission control systems, but at the same time the installation provides additional and more accurate data that are reflection of the operation of the plant itself.

The coal-fired plants presents some critical points typical of the fuel: in fact, the composition varies greatly and the method of introduction of fuel into the burners makes the uncertainty about the actual quantity of fuel used very high. Consequently, also the

calculation of the specific consumption of the plant, that is the ratio between the energy consumption and the electricity production, is characterized by a significant uncertainty. This calculation is very important because the specific consumption is the variable used to quantify the overall efficiency. ENEL already calculate such efficiency based on a different method, called “Economy on Line”. In this thesis an approach based on the Monte Carlo simulation is considered.

In fact, the measured variables can be seen as aleatory variables, therefore the use of such variables need a method that can manage them with the respective uncertainties.

The conventional approach which is considered to compare the performances of Monte Carlo method is the propagation of uncertainties. This method is regulated by the ISO-GUM International Guide - Guide to the expression of uncertainty in measurement [1]- which provides general indications for expressing measurement uncertainty in different contexts. The error propagation law is applied, which, starting from the uncertainties related to each independent variable, succeeds in returning the result of a function dependent on these variables, with an overall uncertainty that is the combination of the uncertainties of the input variables.

The Monte Carlo method is also used to reproduce and solve numerically a problem in which random variables are involved, and whose solution is too complex or impossible to solve in analytical way. Also in this case, all the input variables are available in the form of mean and variance and we have a series of equations describing the link between input and output variables. By extracting a random value from each input distribution, a value of the output variable can be calculated with the available equations. By repeating the process a large enough number of times, we obtain a series of values that form a statistical distribution. Both method are able to give to us the specific consumption of the plant, but with a different management of the associated uncertainty.

The present work is structured as follows. The first chapter introduces the main characteristics of the coal power plants, the critical points related to the fuel and the structure of the plants. The second chapter summarizes the basic principles of the current legislation on the methods to control emissions from energy plants. The third chapter illustrates the possible methods for estimating measurement uncertainty, the “Economy on Line” used by ENEL, the method of propagation of uncertainty and the Monte Carlo method. The fourth chapter explains in detail the balance equations that model the plant,

Introduction

and the sources of uncertainty that occur in the whole system, with particular reference to the “Federico II” power plant. In the fifth chapter the results of the calculation are shown. Finally, it concludes by listing the main critical points of the two methods, the problems still open on the subject, the possible solutions and the research in progress.

Chapter 1 Coal-fired Power Plants

In this Chapter are described the main aspects of energy generation from coal. In particular we want to underline the important role of coal as a source of energy, its main characteristics, its advantages and the environmental problem related to its use. Then we describe also the main characteristics and layout of a typical coal power plant.

Introduction

Energy share in the world

On a global scale, the generation of electricity and heat relies heavily on fossil fuels (coal, oil and gas), in fact these fuels are the main sources of global primary energy consumption with a share of about 81% in 2010. In the short to medium term, fossil fuels are expected to maintain their supremacy with a projected share of about 75% by 2035. The main problem related to the use of fossil fuel nowadays is the question of CO₂ emissions. This is better appreciated by considering the fact that about 84% of CO₂ emissions in 2010 were energy related and about 65% of all greenhouse gas (GHG) emissions in 2010 could be attributed to energy supply and consumption.

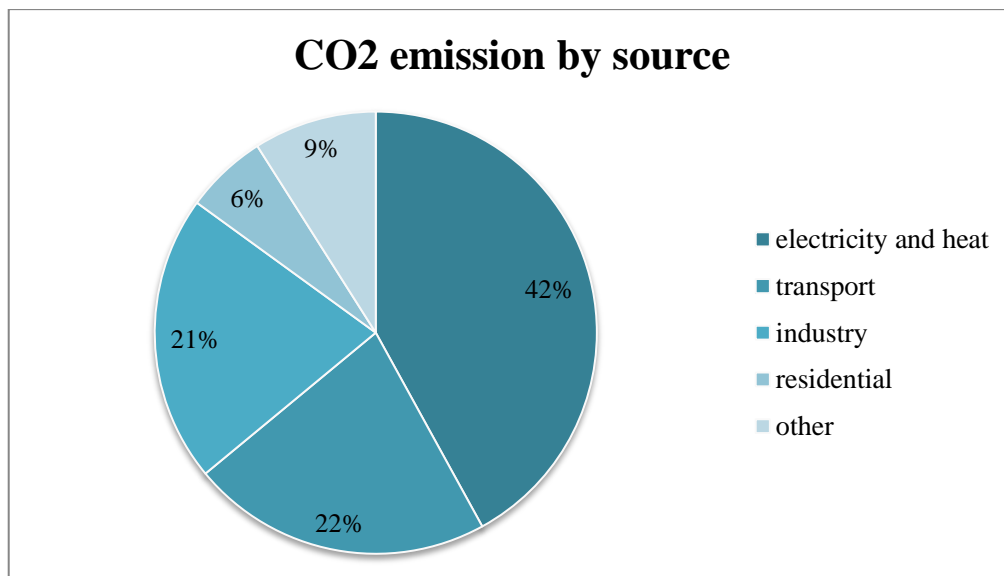


Figure 1.1 CO2 emissions by source

Coal-fired Power Plants

Electricity and heat generation remains the single largest source of CO₂ emissions with a very strong reliance on coal (the most carbon-intensive of fossil fuels) worldwide. For example, in 2009, 43% of CO₂ emissions from fuel combustion were produced from coal while oil and gas contributed 37% and 20%, respectively. In fact, IEA has projected that emissions from coal will grow to 14.4 GtCO₂ (i.e. approximately 41% of CO₂ emissions from all fossil fuels) by 2035. Thus, intensified use of coal (which is expected because of its fairly distribution at global level and its relatively low cost when compared to oil and gas) would substantially increase CO₂ emissions unless there is a very widespread deployment of Carbon Capture and Storage (CCS).

As we can see from the graph, coal is the most important source of electrical power in the world today. It is responsible for over 40% of world electricity production with an annual output of around 9700 TWh out of a global total of 23 816 TWh in 2014.

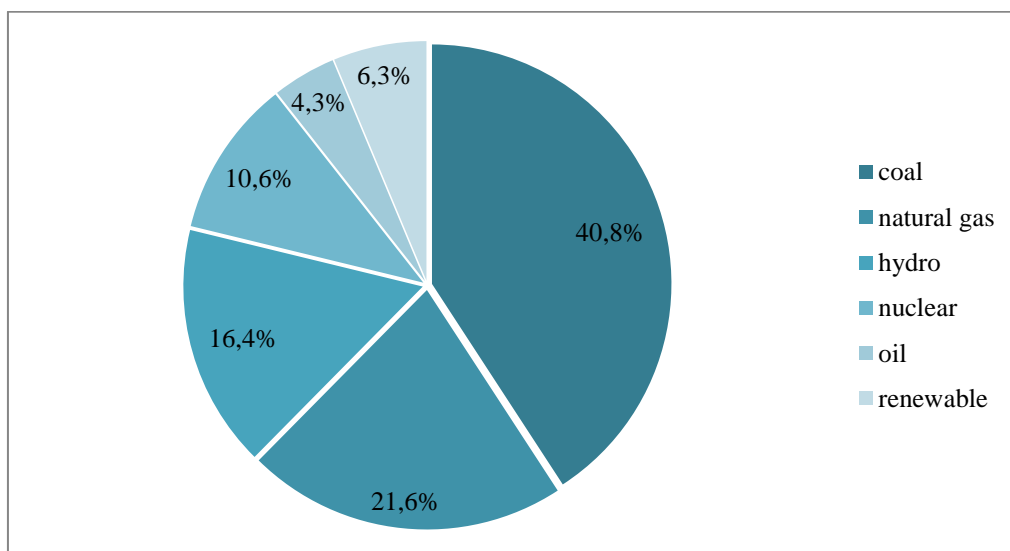


Figure 1.2 World electricity generation by source (23,816 TWh total) (IEA, 2016)

The world coal reserves are around one trillion tons, sufficient to last 200 years at current levels of production. Great part of world reserves (more than 60%) are concentrated in four nations: United States (25%), Russia (16%), China (11%), and Australia (9%).

Pro and cons of coal as a source of energy

The attractions of coal are many: it is so widespread, abundant, and where it is available it provides both a cost-effective and a secure source of electricity. In fact we can observe that

Coal-fired Power Plants

many of the major economies across the world, the United States and China for example, have built their economy on coal.

Also the cost of this fuel is an important factor in its dominance. Coal typically halves the cost respect to other fossil fuels in an energy content basis. Even if in recent years the price of fuels is more and more volatile, the cost is still low enough to make coal an attractive source of electricity. Then coal reserves are abundant and widely dispersed geographically. Importing countries will have the opportunity to choose their own suppliers, thus providing a variety of supply to make sure the reliability and quality of the product.

On the other hand, coal has a lower energy density than other fossil fuels and is more expensive to transport. In particular the transport with pipelines can't be used for coal, that is consequently more economic near to its source.

The major disadvantage of coal is its impact on the environment. Many coals contain significant amount of sulphur and trace elements including heavy metals such as mercury. So coal combustion can release apart from the typical NO_x, also SO₂ and trace element dangerous for humans and for the environment. On top of this, coal combustion generates more carbon dioxide (CO₂) for each unit of energy produced than any other fossil fuel.

In spite of its potential pollution effect, historically coal combustion has not be regulated, generating high levels of pollution in many parts of the world. Today the situation has changed and coal combustion is strictly controlled with advanced emission control system.

Italian situation

Italy is the only country in Europe that, although not using nuclear power, has an extremely low percentage of use of coal.

In fact, the share of Italian electricity production is unique in Europe: if the average generally sees a share of around 60-70% generated by a variable mix of coal and nuclear, in Italy the gas is predominant: in 2013 the electricity production comes 50% from natural gas, 8% from fuel oil, 12% from coal, 30% from renewables.

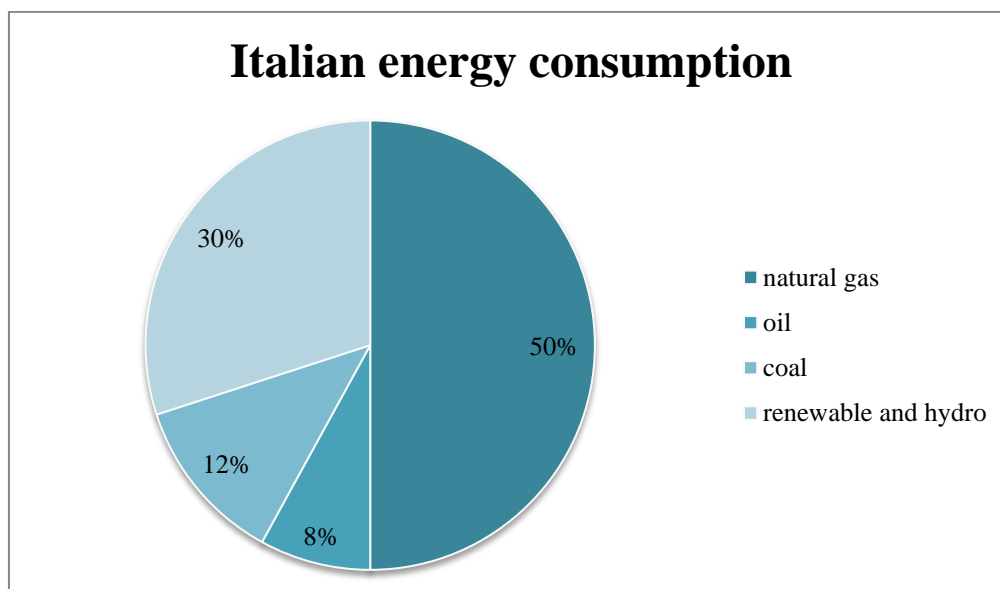


Figure 1.3 Italian electricity generation mix (source: IEA)

One of the problems is that in Italy coal suffers from the effects of a long misinformation: the Italian citizen is in fact not aware of the modern handling and combustion technologies available today in Italy, which make coal a source of electricity with numerous advantages. In fact, to ensure the security and competitiveness of energy supply, Europe expects to not produce more than 25-30% of its electricity from natural gas and maintain at least 45-50% of nuclear and coal in 2020.

The use of coal could help to diversify the mix of fuels used in Italy, where there is a strong imbalance towards methane and oil. It guarantees greater security in the procurement of primary energy sources: in fact the coal is extracted in over 100 countries in the world, has reserves estimated for 200 years and it can be transported in an environmentally safe way by sea. Indeed the United Nations Agency for Navigation has sanctioned the exclusion of the coal from the list of hazardous and harmful substances for sea transportation. Furthermore, the international coal market is less exposed to geopolitics disturbances and is completely independent from that of hydrocarbons. Thank to this, coal prices are stable.

Increasing the use of this energy source would allow one greater efficiency and a reduction in the cost of electricity which, in Italy, is one of the highest in Europe. Coal represents internationally a concrete alternative for electricity production: while in Italy it represents a modest share (11% against the average 34% of the EU), in countries careful to the environment like Denmark or Germany it is used to produce half of the national electricity.

Coal-fired Power Plants

The global trend manifested a relative increase in coal-fired thermal generation, given its greater cost-effectiveness and price stability compared to other sources, while in Italy this trend tends to be stable.

These consequences are particularly felt especially by industrial users: according to the Authority for Energy, Italian companies are constantly forced to face prices above the European average, with heavy repercussions on competitiveness especially in those sectors characterized by strong energy consumption.

Nowadays, Italy imports about 90% of its coal needs by sea, on an Italian fleet of about 60 vessels that guarantee a total load capacity of over 4.6 million tons. The origins are very diversified: the main importing countries are the USA, South Africa, Australia, Indonesia and Colombia, but also Canada, China, Russia and Venezuela.

The coal power plants currently operating in Italy are as follows:

- Fiumesanto Central (SS) owned by EP Production SpA, has two 320 MW coal sections.
- Friuli of Monfalcone Central, owned by A2A SpA made up of 4 sections, two of which coal-fired from 165 and 171 MW and two with 320 MW fuel oil.
- Torrevaldaliga Nord power plant owned by ENEL SpA, consists of 3 sections of 660 MW converted to coal. The plant has been operational since 2009.
- Brescia Central owned by A2A SpA, consists of 1 section of 70 MW coal fired.
- Brindisi South plant owned by ENEL SpA, consisting of 4 units each of 660 MW powered by coal.
- Sulcis power plant owned by ENEL SpA, consisting of one 340 MW coal-fired unit and an additional 240 MW unit.
- Fusina power plant owned by ENEL SpA, consisting of four units of 320 MW powered by coal and other two units of 160 MW.
- La Spezia power plant owned by ENEL SpA, consisting of one unit of 600 MW fed by coal (operating intermittently, closing).

Coal power plants

Nature of coal

The term coal embraces a wide range of materials. Within this range there are a number of distinct types of coal, each with different physical properties. These properties affect the suitability of the coal for power generation.

The hardest of coals is anthracite. This coal contains the highest percentage of carbon (up to 98%) and very little volatile matter or moisture. When burned it produces little ash and relatively low levels of pollution. Its energy density is generally higher than other coals at 23 MJ/kg to 33 MJ/kg. Anthracite is typically slow-burning and often difficult to fire in a power station boiler unless it is mixed with another fuel. While its energy content makes it attractive as a power plant fuel, the difficulty with firing it and its cost does not, so it has traditionally been used for heating rather than for industrial use.

While anthracite reserves are important, the most abundant of the coals are the bituminous coals. These coals contain significant amounts of volatile matter. When they are heated they form a sticky mass, from which their name is derived. Bituminous coals normally contain between 45% and 70% of carbon. Moisture content is between 5% and 10%. They burn easily, especially when ground or pulverized. This makes them ideal fuels for power stations. Some bituminous coals contain high levels of sulfur, which can be a handicap for power generation purposes.

A third category, called sub-bituminous coals or soft coals, are black or black-brown. These coals contain between 35% and 45% carbon and 15% to 30% water, even though they appear dry. They burn well, making them suitable as power plant fuels, and sulfur content is low. The last group of coals that are widely used in power stations are lignites.

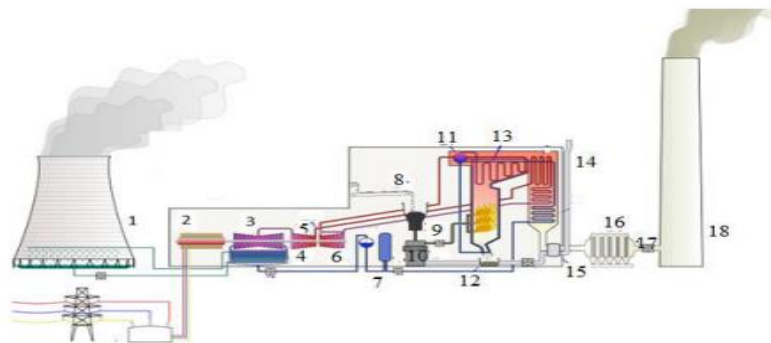
These are brown rather than black and have a carbon content of 20–35%. Moisture content is 30–50%. Lignites are formed from plants that are rich in resins and contain a significant amount of volatile material. The amount of water in lignites, and their consequent low carbon content, makes the fuel uneconomic to transport over any great distance. Lignite-fired power stations are usually found adjacent to the source of fuel.

Layout of a typical coal power plant

Coal is the primary fuel in the generation of electricity in the world and in Europe, thanks to its characteristics of abundant availability, security of supply, competitiveness, and for its high security in handling, transport and use (it is neither flammable, neither explosive, nor pollutant for soil and water). The main technology behind the coal power plants is the Rankine cycle, a well-known technology that is able to provide a reliable and efficient production of electricity.

The energy path of a coal power plant starts from the steam generator area where are located the burners for set up the combustion of coal. The high temperature of the combustion gases causes the transformation of the water contained in the boiler tubes into steam. Steam, through large pipes, reaches the turbine, that with its rotation produce mechanical energy. The alternator that produces electricity is connected to the turbine, and converts the mechanical into electrical energy. The energy produced by the alternator is raised by voltage to 380 kV to be fed into the electricity grid.

The fumes, after the release of their heat to the steam generator, are sent to the chimney after passing through the denitrificators, the dust collectors and the desulfurizers for the abatement of nitrogen oxides, powders and sulfur dioxide, respectively. The steam, after having given up most of its energy to the turbine, it is conveyed to the condenser where it transfers its residual heat to sea water taken with suitable pumps. This vapor thus becomes water that is returned with pumps to the steam generator to repeat the cycle.



1	Colling tower	7	Deaerator	13	Superheater
2	Generator	8	Coal conveyor	14	Air Intake
3	Low pressure turbine	9	Coal hopper	15	Air preheater
4	Condenser	10	Pulverized fuel mill	16	Precipitator
5	Intermediate pressure turbine	11	Boiler drum	17	Induced draught fan
6	High pressure turbine	12	Ash hopper	18	Stack

Figure 1.4 general layout of a pulverized coal power plant

Boiler technology

In the study of our problem the main focus is on the boiler dynamics. In fact in this part of the power plant we have the main transformations of coal, that are responsible both for the heat released to the cycle and for the composition of the flue gas.

The boiler in a coal-fired power plant converts chemical energy contained within the coal into heat energy that is captured and carried away in hot, high-pressure steam. A PC plant burns coal that has first been ground to a fine powder using large grinding mills. A typical plant will have several of these, each feeding a single burners. These burners are where the coal, mixed with air, is injected into the boiler where it ignites in a high-temperature fireball inside the furnace, consuming the fuel and releasing chemical energy as heat. Several burners are used to create a stable fireball in the middle of the furnace where combustion takes place. The temperature within the fireball may reach 1500–1700°C in the hottest part of the flame. While efficiency is the most important factor driving boiler design, flexibility has also been recognized as vital in recent years. Coal-fired power plants have traditionally operated as base-load power stations operating essentially at full output all the time. This is no longer the situation everywhere. In some regions coal-fired power stations are being used to support the generation of renewable electricity. This means they have to be able to operate both efficiently and effectively at part load as well as full load, and to be able to change output load as required by the grid. One technique being used to achieve this is sliding-pressure operation under which the steam pressure is allowed to fall as output falls but steam temperature is maintained. With sliding-load operation it is possible to maintain relatively high efficiency at part load, even though this may involve falling below the critical point of water.

The boiler heat comes from the combustion of pulverized coal with air, in the furnace. In the furnace, the flue gas evaporates the feedwater in the wall tubes, and then it passes to the convection zone, where the flue gas contacts with the superheaters, the reheater and the economizer heat surfaces. An important variable is the coal's LHV (Lower Heating Value), that measures its specific combustion energy. In the furnace, pre-heated hot air and burners are used to burn the pulverized coal. The air is classified as primary or secondary air. The primary air is 20-30% of the total air, and is used to dry and pneumatically transport the coal to the burners, while the remaining air (secondary air) is directly mixed in the burners

with the coal/primary air mixture. To burn pulverized coal the type of furnace used is a chamber fired furnace and the type of burners are chosen according to the conditions. The following picture illustrates the influence of the excess air in the combustion process.

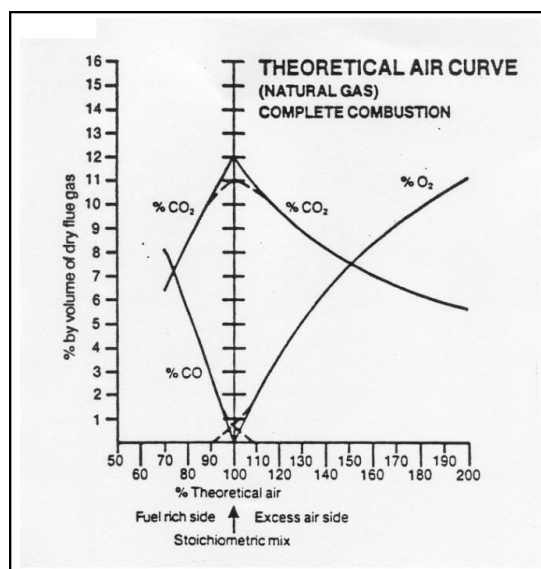


Figure 1.5 Combustion gas concentrations at percent of the theoretical combustion air

To a low quantity of air (below 100%) the combustion is not complete and that is why the CO level is high, while when the theoretical air approximates 100%, the efficiency increases and the CO is converted rapidly to CO₂. However, the best level involves an excess of 15-20%, because the CO reaches ppm level, which means an optimal efficiency. In this range, the CO₂ level decreases due to dilution in the excess air. For excess levels from 25 to 45%, the NO_x formation increases, and for higher levels the temperature decreases and the NO_x formation decreases. In order to have a complete burn, the furnace must fulfill the following conditions:

- The flame temperature must be enough to ignite the coal and air.
- The coal and the air must be thoroughly mixed.
- The needed residence time of the coal must be meet.
- The correct air fuel ratio must be achieved.
- The equipment must have means to hold and discharge the ash, discontinuously.
- The control system must be capable to regulate the coal feed flow.

The gross of the ash is removed in the bottom grate of the furnace and since it is too hot, it's common to quench it with water. The dust that remains in the flue gas after the dust collector is fly ash, and is removed in the dust collector. The unburnt carbon exits in the

bottom ash, and may be from 80 to 98%, depending on the residence time of the coal in the furnace.

Emission control for coal-fired power plants

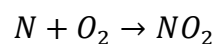
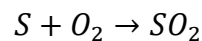
The combustion of coal is the dirtiest of the large-scale methods of generating electricity, primarily because of the range of pollutants that are found within the fuel.

The burning of coal is responsible for serious pollution environmental problem which only in recent years has been managed to contain within acceptable limits, using refined technologies, technologies not applied by all, due to the high costs. In the South of the world, in fact many plant still operate with traditional technology, without any pollution control device.

In other country where environmental issues are more strictly regulated, coal is used in a clean way, as shown by numerous plants operating in Italy and abroad. Technologies commercially available (Clean Coal Technologies) allows to limit emissions at the same levels as those produced by plants powered by petrol. Finally, a further observation concerns the use of by-products of a thermoelectric plant, quantitatively very important if the fuel is coal. Ashes, which are considered non-hazardous special waste, are used for the production of cement or as a material inert in road paving.

As said, the main reason of the pollution effect of a power plant is the nature of the fuel. One of the chemicals that are dangerous for the health is sulfur. Often it is present in coal with a percentage of more than 3% and it may reach as much as 10%. When the coal is burned this sulfur is converted into sulfur dioxide and carried off by the flue gases.

There is a small amount of organic nitrogen within coal too. During combustion this is converted into nitrogen oxides of various sorts. However, the main source of these gaseous nitrogen compounds is the nitrogen in air that can become oxidized at the high temperatures encountered within coal furnaces. The main reactions that takes place during combustion are the following:



Coal-fired Power Plants

Coal usually contains a significant amount of mineral impurity too. A large part of this fuses to create solid lumps, which are left behind in the combustion chamber as slag. However, some are reduced to tiny solid particles that get carried away with the flue gas. The particles may contain heavy metals, such as cadmium and mercury, that, if allowed to escape, will be released into the environment. Some coals, particularly the bituminous varieties, contain large amounts of volatile organic compounds and these, or fragments of them generated by their incomplete combustion, can also be released. Incomplete combustion of the carbon in coal may also lead to significant levels of carbon monoxide within the flue gases.

In the following figure there is a typical example of a configuration of flue gas treatment line.

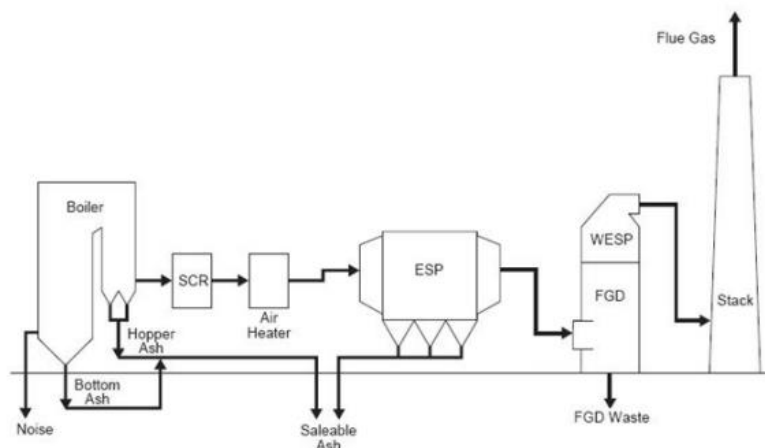


Figure 1.6 Typical flue gas treatment line

Environmental regulations require that as far as possible pollutants materials are removed from coal-fired power plant flue gases before the latter are released into the atmosphere. To avoid all the problems related to dirty emission, the flue gas coming from the boiler is treated before being sent to the capture plant (with CCS) or to the stack (without CCS). In the power plant, the ash, the NO_x and the SO₂ flue gas content are all removed to a concentration below the limit. Ash is mainly coal's non-combustible matter and is partially removed in the bottom of the furnace (bottom ash). The ash leaving the furnace in the flue gas is named fly ash.

Coal-fired Power Plants

Other trace elements such as heavy metals may require their own removal plants but often these can be tackled alongside one of the other pollutants, making an additional chemical treatment process unnecessary.

Table 1.1 air quality standard

Pollutant	Concentration	Averaging period	Permitted exceedances each year
Fine particles (PM2.5)	25 µg/m ³	1 year	n/a
Sulphur dioxide (SO₂)	350 µg/m ³	1 hour	24
	125 µg/m ³	24 hours	3
Nitrogen dioxide (NO₂)	200 µg/m ³	1 hour	18
	40 µg/m ³	1 year	n/a
PM10	50 µg/m ³	24 hours	35
	40 µg/m ³	1 year	n/a
Lead (Pb)	0.5 µg/m ³	1 year	n/a
Carbon monoxide (CO)	10 mg/m ³	Maximum daily 8 hour mean	n/a

Table 1.1 contains concentrations of various power plant airborne pollutants that are considered permissible in the EU good air quality to be maintained. Internationally, standards are tending to converge as the effects of even low levels of pollution on human health become more widely recognized.

The PM10 particulate matter standard is for dust particles greater than 10 µm in diameter; this is generally the standard of importance when considering dust from coal-fired power plants. There are other standards including PM2.5 for particles up to 2.5 µm in diameter.

A power plant represents a concentrated source of pollutants, but these are released in hot gases from a tall stack so that they should rise high into the atmosphere and become diluted before humans or other life-forms come into contact with them. However, the behaviour of the pollutants once they enter the atmosphere is not always predictable. The behaviour of the plume of exhaust gases from a power plant stack will depend on atmospheric

Coal-fired Power Plants

conditions, so sometimes the pollutants will fall close around the plant and at other times they may be carried across continents. In the following table are described the value of emission limit from coal fired plants of different species.

Table 1.2 emission limit for a coal fired power plant per day

species	Emission limit
Sulfur dioxide emissions for plants built after 2003	200 mg/m ³
Sulfur dioxide emission limits after 2016	150 mg/m ³
Nitrogen oxide emissions for plants built after 2003	200 mg/m ³
Nitrogen oxide emission limits after 2016	150 mg/m ³
Dust emission limits after 2016	20 mg/m ³

For sulfur dioxide the limit for plants built after 2003 is 200 mg/m³, falling to 150 mg/m³ after 2016. Permitted emission levels for nitrogen oxide are the same. Dust emissions are to be below 20 mg/m³ after 2016 and there is a proposed emission limit for mercury of 30 mg/m³. As said before, these EU limits are probably some of the strictest to be found, but as with air-quality standards, the regulations are becoming stricter everywhere.

There is one other important combustion product of coal combustion not included in the preceding tables or discussion: carbon dioxide. This is the reaction product when carbon is burned in air. The flue gases from the boiler of a typical advanced coal-fired power plant may contain up to 14% carbon dioxide depending on the specific plant conditions.

The release of carbon dioxide from the combustion of fossil fuels in power plants and elsewhere into the atmosphere is widely regarded as the main cause for a steady but accelerating rise in average global temperatures over the past 150 years. This is seen as potentially damaging for the global environment. The capture and removal of carbon dioxide from fossil fuel power plant flue gases is not yet mandatory anywhere, but measures to try and control its emissions are being introduced in some parts of the world, particularly the EU. At the same time, methods for capturing the gas are being developed and there is a growing consensus that these will need to be deployed on a commercial scale

after 2020 if global warming is to be limited. If this becomes necessary, then coal-fired power plants will be in the front-line since they are the greatest emitters.

Sulfur dioxide removal

An important impurity to be removed from the flue gas is the SO_2 . There are no combustion strategies that can be used to control the generation of sulfur dioxide in coal power plants. If sulfur is present in coal it will be converted into sulfur dioxide during combustion.

The main sulfur compound to be eliminated are:

- Sulfur dioxide: the chemical compound with the formula SO_2 . It is a toxic gas with a pungent, irritating smell that is re-leased by volcanoes and in various industrial processes.
- Sulfur trioxide: the chemical compound with the formula SO_3 . In the gaseous form, this species is a significant pollutant, being the primary agent in acid rain. It is prepared on massive scales as a precursor to sulfuric acid.
- Sulfuric acid: a highly corrosive strong mineral acid with the molecular formula H_2SO_4 . It is a pungent-ethereal, colorless to slightly yellow viscous liquid which is soluble in water at all concentrations.

The only recourse is to capture the sulfur, either before the coal is burned using a coal-cleaning process, or after combustion using some chemical reagent inside the power plant (sulfur scrubbers).

This can be done either by wet flue gas desulfurization (WFGD) or by dry flue gas desulfurization (DFGD), being the first one the main technology (around 85% of installed capacity). There are many chemicals that are potentially capable of capturing sulfur dioxide from the flue gases of a power station but the cheapest to use are lime and limestone. Both are calcium compounds that will react with sulfur dioxide to produce calcium sulfate. If the latter can be made in a pure-enough form it can be sold into the building industry for use in wall boards.

The main reaction that takes place in the reactor is:



Wet scrubbing technology is technically complex. It has been likened to a chemical plant operating within a power station. For this reason it requires skilled staff to operate. Nevertheless, it provides a proven method for removing high levels of the sulfur from a coal-fired power plant's flue-gas stream.

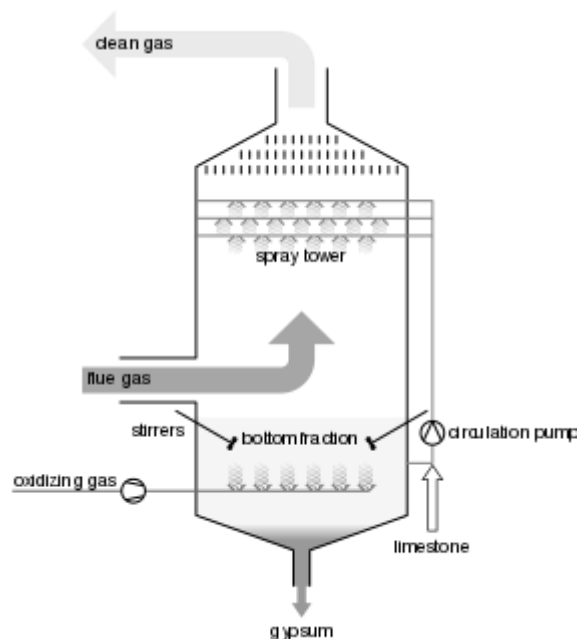


Figure 1.7 scheme of a DE-SO_x system

As we can see in the schematic representation of the reactor, the limestone is atomized in fine particles and injected as liquid, in fact the technique is also called wet scrubbing. The flue gases pass across the tall reactor and go through the slurry to let the reaction take place. The sulfur dioxide is captured and goes to the bottom of the reaction with the unreacted lime and gypsum.

This kind of system can capture up to 97% of the sulfur within the flue gas.

Nitrogen oxide capture

Also the nitrogen oxide present in the flue gases can be removed by injecting a chemical in the reactor that converts nitrogen oxide into nitrogen and water. The main chemicals used are ammonia gas or urea.

If the reaction takes place at a temperature between 870°C and 1200°C the reaction is spontaneous and we call the removing technique Selective Non Catalytic reduction (SNCR). Instead if the temperature is lower we need to add a catalytic agent, so we call the

technique Selective Catalytic Reduction (SCR). SNCR will remove between 35% and 60% of the nitrogen oxide from the flue-gas stream. However, if care is not taken it can lead to contamination of fly ash with ammonia and to ammonia slip- the release of excess ammonia into the atmosphere. Nevertheless, it has been utilized at power plants in several parts of the world. More widely used than SNCR is SCR. SCR units are commonly found on gas turbine power stations but may also be fitted to a coal-fired power plant where low nitrogen oxide combustion strategies do not reduce the emissions levels to below the regulatory limits.

The main reactions that takes place in the reactor are:

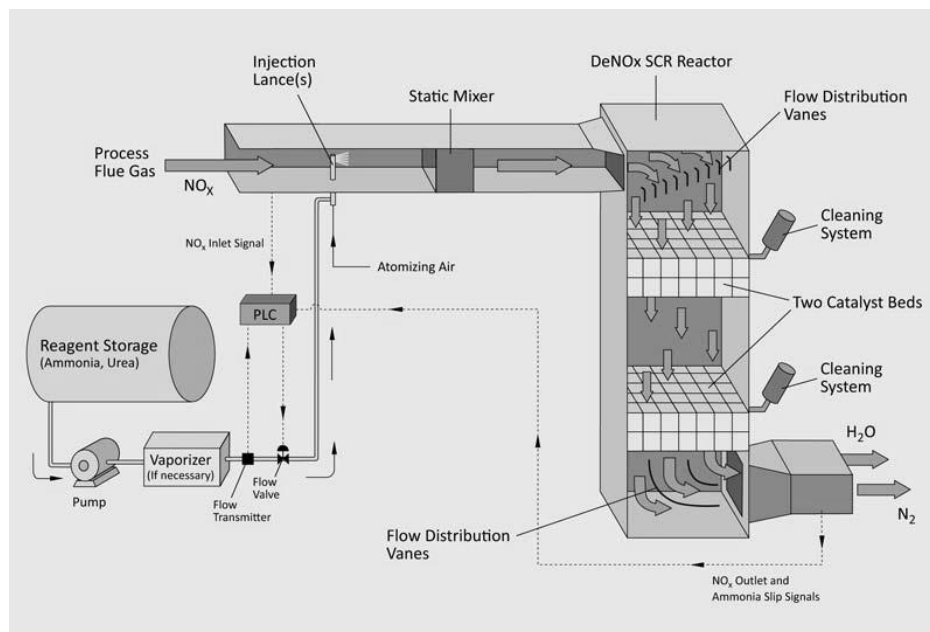
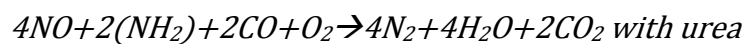
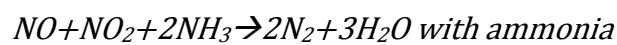


Figure 1.8 scheme of a denitrification system

Particle control devices

The flue gas is introduced to some form of particulate control systems soon after the boiler. Typically, the particulate fraction is separated with electrostatic precipitators (ESP) or fabric filters. Mechanical collectors, such as cyclones, may be used after small boilers, where the emission limit required is more lenient. Cyclones are used also as a part of

circulation fluidised bed combustion. The ESPs can be classified into two types according to the flue gas temperature:

- the cold-side ESP operates with a flue gas temperature below 150 °C;
- the hot-side ESP operates at higher temperatures of up to about 350 °C.

The collection efficiency depends on a range of parameters such as area of the electrostatic fields, the number of fields, size of the flue gas particles, ash receptivity, flue gas temperature, and moisture content. The overall collection efficiency can be over 99.9 %. The efficiency is lowest for the 0.05–1.0 µm particle-size range, and a fraction of fly ash will therefore penetrate the ESP. The fly ash collected on the electrostatic fields of the ESP is shaken off to the hoppers. The hoppers are exhausted via channels and combined to the silo. This collected portion of fly ash can be called pulverised fly ash (PFA). Fabric filter systems have similar overall particulate removal efficiency to ESPs (greater than 99 %) in combustion systems, but are superior at controlling fine particulate matter and less sensitive to particulate loading and fly ash characteristics. The fabric filters can be cleaned by a reverse air system, in which the gases are reversed through isolated cleaning compartments in a predetermined cycle, with the reverse air directed to those compartments still on line. A shake/deflate system may also be employed (bag shaking and reverse air). Pulse-jet cleaning can be used on the systems in which the flue gas is directed from the outside of the fabric through to the inside. Cleaning is carried out using short bursts of compressed air directed into the mouth of each bag.

Thesis objective

From the analysis of typical coal power plant layout, it's clear how these plants are complex and how many equipment are installed along the lines to control the pollution release into environment. All these control strategies are regulated by EU normative, so they are mandatory for the plant management.

Many plants have adapted their pollutants abatement and measurement systems in order to respect the stringent level of emission permissible by law and avoid economic penalties. This is the case of the "Federico II" coal power plant owned by ENEL in Brindisi. Over the years, the plant has improved its systems of abatement and control of emissions so as to become a model in Italy. These improvement concern not only the equipment installed, but also a series of instrument to measure and control the good operation of the plant.

The investment is justified by the need to adapt to new emission control systems, but at the same time it provides additional and more accurate data that are reflection of the operation of the plant itself. These data can be utilized to improve the quality of calculation in the mass balances done along the line and estimate in a more accurate way the performances of the plant. In particular, accurate monitoring of specific consumption and performance degradation diagnostics are key elements for improving profit margins for a power plant.

The coal-fired plants presents some critical points typical of the fuel that prevent the accuracy of the calculation. The first concerns the composition of coal: it varies greatly and the method of introduction of fuel into the burners makes the uncertainty about the actual quantity of fuel used very high. Consequently, also the calculation of the specific consumption of the plant is characterized by a great uncertainty. Then, the quantification of the Lower Heating Value (LHV) is affected by a high level of uncertainty respect to other kinds of fuels.

The thesis objectives are mainly two. The first is to build a model of the power plant that can describe the main reactions and transformations of the fuel through the various equipment along the line and that can connect the input data of coal with the output data of flue gases. The attention in the model proposed is focus in the following points:

- Implementation of carbon balance
- Implementation of balance on the De-SO_x system

- Analysis of the impact of estimation of LHV calculating applying empirical equation

The output of our calculation is the real quantity of coal introduced with its composition and the specific consumption of the plant.

The second step of this thesis work is to find a method that can solve the balance equations, taking into account that the input variables that the instrument provides us are aleatory variables, therefore the methodology has to manage such quantities with the respective errors. In particular, two methods have been used: the method of propagation of error and the Monte Carlo method. Both methods are able to give to us the specific consumption of the plant, but with a different management of the associated error.

To check the validity of the model and the resolution method adopted we need a preliminary step: the analysis of the operating data of Federico II power plant. This is important to try to have coherent data, both in terms of temporal intervals both in terms of elemental composition.

Chapter 2 Current legislation on CO₂ emission

This Chapter concentrates mainly on legislation associated with CO₂ emissions of power plants. The Chapter gives an overview of the Emission Trading System (EMS) and issues related to that. Especially, the most important changes in the monitoring and reporting requirements that came into force with the new EU Monitoring and Reporting Regulation (MRR), compared to the 2007 Monitoring and Reporting Guidelines (MRG) that were in force during the second trading period are presented. Compared to the MRG, the MRR emphasizes the quality of the measuring systems and their correct use in the practical determination of activity data. Then an overview on the main CO₂ measurement technique is carried out.

Regulation

In the last few years, the introduction of new regulations and norms has impacted the CO₂ measurement. European Commission set new regulations for third Emission Trading System period (2013-2020), that increase requirements for risk assessment, uncertainty estimation and continuous accuracy surveillance for CO₂ monitoring system. In particular we refer to the EU Monitoring & Reporting Regulation (MRR) (No. 601/2012, June 2012) about the monitoring of emissions of stationary installations.

The norm asks for monitoring and reporting of greenhouse gas emissions in accordance with five principles: completeness, consistency, comparability, transparency and accuracy. Then with each measurement we have to guarantee integrity of methodology and continuous improvement. To reach this objective it's important to measure the CO₂ with the more accurate technique on the market, and to ensure the accuracy of the instruments.

The third ETS period (2013-2020) involves several modifications and updates compared to previous ones. Regulation has been developed to enhance the harmonization of approaches at European level after the one already achieved through the implementation by Member States of the MGR 2007. Furthermore, it takes into consideration several better practices found in the Member States.

EU ETS system for monitoring and reporting provides a building block system of monitoring methodologies. Each parameter needed for the determination of emissions can be determined by different data quality levels. These data quality levels are called “tiers”. Table 2.1 presents definitions of the tiers on maximum permissible uncertainty for the method. It can be seen that there are uneven acceptable uncertainty levels for different CO₂ monitoring methods within the tiers. The tiers with lower numbers represent methods with lower requirements and less accurate than higher tiers.

Table 2.1 Definitions of tiers on maximum permissible uncertainty, with different measurement method (MRRGD4, 2012)

Tier number	Power plant category	Annual emission [tCO₂]	Standard method [%]	Measurement method [%]	Energy balance method [%]
1	A1	<25000	±7.5	±10.0	±7.5
2	A2	25000-50000	±5.0	±7.5	±7.5
3	B	50000-500000	±2.5	±5.0	±5.0
4	C	>500000	±1.5	±2.5	±2.5

Basic principles

The basic principles at the base of the new European legislation are now explained in order to understand the logic underneath the normative.

Completeness (Article 5): the completeness of the emission sources and the source flows is the central element of the EU monitoring principles ETS. In order to guarantee the completeness of the monitored emissions, the manager should take into account the following considerations:

- all combustion activities of a plant must be included in the EU ETS, if the threshold of any of the other activities is exceeded;

- Article 20 requires that both emissions produced during normal operations, both during extraordinary events including start-up, shutdown and emergency situations have to be included

Consistency and comparability (Article 6, paragraph 1): time series of data must be consistent over the years. Arbitrary changes of the monitoring methods are prohibited. This is why the monitoring plan must be approved by the competent authority. Because the same monitoring approaches are defined for all plants, data created are also comparable between plants. This does not imply a requirement for the production of time series of data, but assumes that the manager, the verifier or the competent authority can use these series as a means of performing consistency checks.

Transparency (Article 6): all collection and compilation activities and calculation of data must be carried out in a transparent manner. This means that the entire data flow must be documented in transparent manner and all relevant information must be stored and stored safely. In particular, the verifier the competent authority must be authorized to access these information. The requirement of transparency is in the interest of the manager himself, he favors the transfer of responsibility between existing and new staff, reduces the probability of errors and omissions, reduces the risk of returning excess , or insufficient shares.

Accuracy (Article 7): managers must ensure that the data is accurate, that is, they are not systematically and consciously inaccurate. Due diligence is required to the managers, with efforts to be made to achieve the highest possible level of accuracy. "The highest possible level" can be interpreted as the case in which is technically feasible and "without having to bear costs disproportionately high".

Integrity of the methodology (article 8): this principle is the fundamental element to any MRV system. The M & R explicitly cites it along with other elements necessary for good monitoring:

- the method of monitoring and data management must allow the verifier to reach "reasonable guarantees" about the communication of emissions;
- the data must not be tainted by relevant inaccuracies and must be impartial;
- the data must provide a reliable and balanced report of the emissions of a plant;
- in the search for greater accuracy, managers can evaluate the benefit, taking into account the higher costs. They will aim to "get the maximum accuracy possible,

except when this is technically the case not achievable or involves disproportionately high costs ".

Monitoring approaches

Like the MRG 2007, the M & R allows the manager to choose the monitoring methodologies from a system of constitutive elements based on different monitoring approaches. However, the M & R greatly exceeds the MRG in flexibility, since currently all types of combinations are allowed approaches, provided that the manager demonstrates that they will not take place neither double accounting, nor data gaps in relation to emissions.

The methodological choice requires the approval of the competent authority that, as a rule, is implicitly granted as a party of the approval of the monitoring plan.

The following methods are available:

1. Calculation-based approaches:

- standard methodology (in which it is distinguished between the emissions of combustion and process emissions)
- mass balance

2. Measure-based approaches

3. Non-level-based methodology ("alternative approach")

4. Combinations of approaches

Standard methodology

The principle of this method is the calculation of emissions through data relating to the activity (for example, the quantity of fuel or consumed input material), multiplied by a factor of emission (and other factors). These additional factors are the oxidation factor for emissions of combustion, and the conversion factor for process emissions. Both are used to correct the value of emissions in the case of incomplete chemical reactions.

As part of this methodology, CO₂ emissions are calculated with the following formula:

$$Em = AD * EF * OF$$

where :

- E_m are the combustion emissions [t CO₂]
- AD indicates the data related to the activity [TJ, t or Nm³]
- EF is the emission factor [t CO₂/ TJ, t CO₂/ t or t CO₂/ Nm³]
- OF is the oxidation factor [dimensionless]

Factors with units in tons are usually used for solids and liquids, Nm³ are typically used for gaseous fuels. Fuel activity data (including the case where fuels are used as material entering the process) must be expressed as net calorific value:

$$AD = FQ * NCV$$

Where:

- FQ is the amount of fuel [t or Nm³]
- NCV indicates the net calorific value [TJ / t or TJ / Nm³]

Activity data may refer to an incoming material (e.g. limestone or soda), or to the output one resulting from the process, for example the clinker (cement) or quicklime. In both cases, activity data is used with positive values, considering the direct correlation with the emission value.

Mass balance

The standard approach finds direct application in cases where a fuel or a material is directly related to emissions.

However, in cases such as full-cycle steel mills or industrial sites chemical, it is often difficult to directly link emissions to individual incoming materials, since the products (and the waste) contain significant amounts of carbon. Therefore, it is not sufficient to account for the amount of carbon not emitted by an oxidation factor or a conversion factor. On the contrary, we consider a complete balance of incoming and in carbon exit from the plant, or a defined part of it. The following formula is applicable to the mass balance:

$$Em_{mb} = \sum_i (f * AD_i * CC_i)$$

where :

- Em_{mb} are emissions from all source streams included in the budget of mass [t CO₂]
- f is the factor for the conversion of the molar mass of carbon into CO₂. The value of f is 3 664 t CO₂/ t C

- i is the index for the material or fuel considered
- AD_i indicates the data relating to the activity (i.e. the mass in tons) of the material or of the fuel considered. Incoming materials or fuels are considered with positive values; the outgoing materials or fuels have negative activity data. The mass flows to and from the stocks must be adequate taken into account, in order to provide correct results for the calendar year
- CC_i indicates the carbon content of the component under consideration, always dimensionless and positive

Measurement based methodology

Flue gas measurements in the stack provide an attractive online method for CO₂ monitoring. In contrast to the first and second trading periods, the measurement-based method is now recognised as equivalent to calculation-based methods for the determination of CO₂ emission sources. There, the CO₂ emissions are measured from chimney by means of CO₂ concentration and flue gas flow measurements in addition to required auxiliary measurements. This method utilizes sensors that primarily exist in power plants, but the accuracy and therefore calibration requirement might be further increased. Direct measurement is well suited for processes with changing fuels and mixed fuels, if all the used fuels are included in ETS. Compared to the MRG, the regulations for measurement based methodologies have been significantly updated. In contrast to the calculation based methods, the greenhouse gases are themselves the object of the measurement in the measurement based methods. This may be difficult in installations with many emission sources. On the other hand, the strength of the measurement based methodologies is the independence of the number of different fuels and materials applied e.g. where many different waste types are combusted. Also stoichiometric relationships are irrelevant when using the measurement based method. Often a part of the used fuels are bio-based which are not included in the ETS. In practise, this complicates the use of direct measurement.

For quality assurance purposes, installation operators must establish a procedure that ensures the calibration, adjustment and checking of measuring equipment at regular intervals. All the measurements shall be carried out based on international standards:

- EN 14181 Stationary source emissions – Quality assurance of automated measuring systems

- EN 15259 Air quality – Measurement of stationary source emissions – Requirements for measurement sections and sites and for the measurement objective, plan and report.
- EN ISO 14956 Air quality - Evaluation of the suitability of a measurement procedure by comparison with a required measurement uncertainty

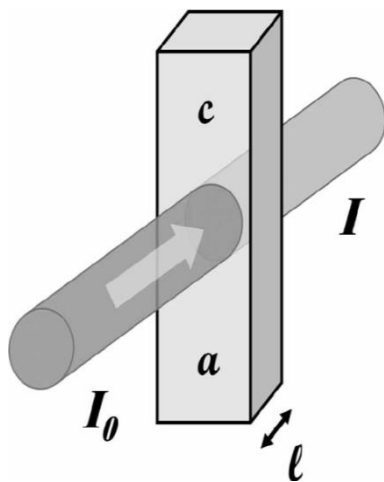
CO₂ measurement technique

The measurement systems used for measuring the properties of flue gas are known as continuous emission monitoring systems (CEMS) and are equipped with an analyser that has been approved by authorities. CEMS are usually provided with functions for measuring the concentration, temperature, pressure and flow rate of regulated substances. Therefore, CEMS are significant in environmental supervision and pollutant control in thermal power plants. Real-time information on the composition of combustion gases is important for improving efficiency and reducing emissions. It provides the operators of power plant with real time information about current emission levels and this way enables a proactive reaction on potential problems on time. Also the 15 storage of history values enables long term reporting and trending of emission parameters and this way helps to follow up environmental performance and continuous improvement.

There is a wide spectrum of different sampling and analytical techniques used for combustion control and combustion emissions monitoring.

One approach to monitor gas composition is to collect a sample gas, which can then be analysed either by spectroscopic techniques or by room temperature gas sensors. However, there are many sources of errors related to the extraction and preconditioning of the sample gas. In particular, when the main fuel is coal, it must be taken care to remove sulphuric acid mist and dust, which cause pipe blockages and contamination, from the flue gas. These kinds of measurements are usually also time-consuming. Due to low concentrations the gas has to be extracted for a long time before an amount sufficient for reliable measurement is obtained. The gas composition could change during cooling to room temperature, so analysis of the gas at high temperatures is preferred.

Another solution is Optical spectroscopic: this techniques is based on the property of chemical molecules to absorb a certain amount of energy, if emitted at a proper wavelength.



In particular, following the Lambert-Beer law, we know the relationship between absorbance and concentration of an absorbing species.

$$A = \log_{10} \frac{I_0}{I_1}$$
$$C = \frac{A}{\alpha l}$$

Figure 2.1 Lambert-Beer law representation

C is the concentration of the absorbing species

A is absorbance

I_0 is the intensity of the incident light

I_1 is the intensity after passing through the volume

T is the transmission

A is absorbance

α is the absorption coefficient (depending on the wavelength and the species)

CO₂ gas is a strong absorber in the infrared and near infrared spectrum.

Based on this Lambert-Beer principle, there are two ways to measure the concentration in the flue gas:

- Extractive : a sampling system is used to collect a sample and to bring it into a measurement chamber remoted, where infrared spectroscopy principle is applied.
- In Situ : the sample stays in its environment

In the case of large power plants with very large and high stacks, the in situ principle would offer a better solution. Optical spectroscopic techniques based on infrared radiation or laser spectroscopy can work well without preconditioning of the gas. They therefore have the potential to be used in in-situ measurements with fast response and are ideally suited for industrial applications provided they can measure with sufficient sensitivity. Optical measurements do not require contact with the high temperature gas, but do require line-of-sight measurement. Absorption or scattering in the optical path can affect the received signal. Placement of a sensor directly in the high temperature gas would avoid

such interferences, so sensors for in-situ monitoring of combustion gas components at the high temperatures of combustion processes have been developed.

Example case: “Federico II” power plant solution for monitoring of emissions

In the ENEL plant there are a series of instrument to measure all the pollutants and the functional information at chimney. Each instrument has a different measuring principles that reduce as much as possible the error of evaluation.

In the following table are listed all the species measured and the related instrument:

Table 2.2 Measuring instrument at chimney

species	constructor	model	Measuring principles
O ₂	Siemens	Oximat6	Para magnetism
NO _x	Siemens	Ultramat6	NDIR
CO	Siemens	Ultramat6	NDIR
SO ₂	Siemens	Ultramat6	NDIR
ASH	Sick malhak	Ultramat6	Scattering light
H ₂ O	Siemens	LDS6	NDIR
NH ₃	Siemens	LDS6	NDIR
Pressure	Siemens	sitrans	piezoelectric membrane
Temperature	nd	PT100	nd

In our balances mainly the measures of three devices are used:

- LDS 6 Analyser System to evaluate the spectroscopy in situ
- Flowsic 100 to evaluate the flow rate
- Ultramat 6 to analyse the gas based on an extractive system

LDS 6 Analyser System

LDS 6 is a diode laser gas analyser with a measuring principle based on the specific light absorption of different gas components. LDS 6 is suitable for fast and non-contact measurement of gas concentrations or temperatures in process or flue gases. One or two signals from up to three measuring points are processed simultaneously by the central analyser unit. The in-situ cross-duct sensors at each measuring point can be separated up to 700 m from the central unit by using fiber-optic cables. The sensors are designed for operation under harsh environmental conditions and contain a minimum of electrical components.

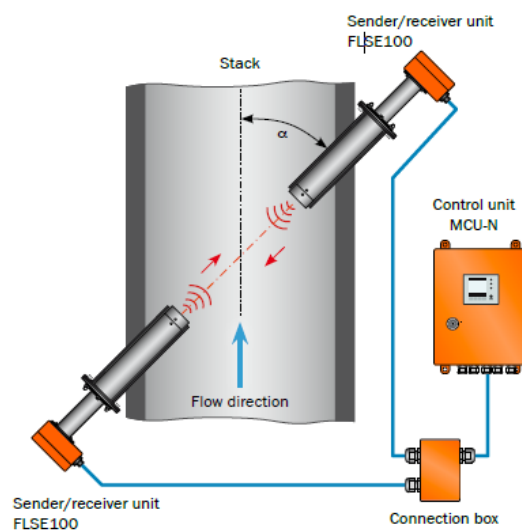


Figure 2.2 LDS 6

The in-situ gas analyser LDS 6 is characterized by a high availability and unique analytical selectivity, and is optimally suitable for numerous applications. LDS 6 enables the measurement of one or two gas components or - if desired - the gas temperature directly in the process:

- With high dust load
- In hot, humid, corrosive, explosive, or toxic gases
- In applications showing strong varying gas compositions
- Under harsh environmental conditions at the measuring point
- Highly selective, i.e. mostly without cross-sensitivities

In our study case plant LDS 6 is utilized to measure the concentration of different species. In the following table are listed the main species with the relative accuracy.

Table 2.3 Accuracy of LDS6

species	accuracy
O ₂	2%
CO ₂	2%
H ₂ O	5%

Flowsic 100

Flowsic 100 is a flow measuring device for continuous emission monitoring. The Flowsic100 standard version contains two FLSE100 sender/receiver units, a MCU control unit and a connection box. The MCU is used for input and output of signals and for calculation of volume flow to reference conditions standardization.

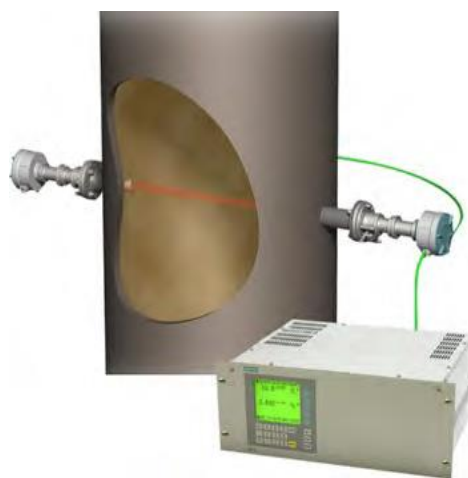


Figure 2.3 FLOWSIC 100

The measuring principle is the Ultrasonic transit time measurement, that is able to evaluate gas velocity, volume flow (actual condition), volume flow (standard condition), gas temperature, speed of sound.

In particular in our case, the interest is on the evaluation of the volume flow at actual condition.

We know the following specifics of the chimney:

Angle of inclination	45°
Length	10.41 m
Diameter	6.8 m
Area	36.3 m ²

The instrument is able to evaluate gas velocity in the range 0-40 m/s with an accuracy of ± 0.1 m/s. From the velocity we can calculate the volume flow rate at standard condition with the formula:

$$V_{standard} \left[\frac{m^3}{h} \right] = v \left[\frac{m}{s} \right] * area [m^2] * 3600 \left[\frac{s}{h} \right] * \frac{273}{273 + T} * \frac{p}{1013.25}$$

ENEL provide us a set of data of the flow rate at standard condition and the flow rate “as is” basis. Knowing also the section of the chimney we are able for each measure to identify the coefficient of amplification of the error, starting from the accuracy of the Flowsic100.

Ultramat 6

The Ultramat 6 single-channel or dual-channel gas analyser operates according to the NDIR two-beam alternating light principle and measure gases highly selectively whose absorption bands lie in the infrared wavelength range from 2 to 9 μ m, such as CO, CO₂, O, SO₂, NH₃, H₂O as well as CH₄ and other hydrocarbons.

Single-channel analysers measure up to 2 gas components, dual-channel analysers up to 4 gas components simultaneously.



Figure 2.4 Ultramat 6

Chapter 3 Alternative methodologies

In this Chapter the different possible approaches to solve the problem are described. First we comment on the method used by ENEL for the calculation of the specific consumption and its limits. Then we explain the basic principle and the steps of the two method that we implement in our work : the Monte Carlo method and the error propagation method.

Introduction

The aim of this work of thesis is to estimate the specific consumption of the plant, using the additional information that comes from the new instruments installed at the chimney.

The set of equipment at the stack gives us a lot of information, such as the volumetric flow rate, the concentration of oxygen, sulfur and carbon dioxide at the outlet. This values are related to the concentration of the different species in the coal introduced in the burner. So we have a set of redundant information.

As said before, the real quantity and composition of coal introduced is very variable and difficult to calculate, but it's a fundamental information to calculate calorific value and specific consumption of the plant. With this set of redundant information, we want to estimate this unknown and reducing the error related to the SC calculation.

The model of the plant is described with a set of equation that takes in input only independent variables, all with a certain distribution that depend on the methodology of measurement.

The problem that we are solving looking for the value of the specific consumption of a power plant starting from measured independent variables present a series of critical points. First, to find the value of our objective function we need to find a way to manage the error associated with the input variables. How does uncertainties propagate? How we can minimize their impact on the total error?

Then, looking at the kind of data that ENEL provide us, we have a set of redundant information. In fact we have both data of the input coal and input chemicals in the different steps of the line, but also data of the output concentration of CO₂, pollutants as SO₂ and NO_x and water. Of course the input and the output variables are correlated: for example the quantity of carbon burned is the main responsible for the concentration of CO₂ at stack.

Knowing the equation that correlate input and output, how we can reconcile them? How we can find systematic error in our set of independent variables? Is it possible a reconciliation when we adopt Monte Carlo method?

In literature these kind of problems have been faced by many authors in different field of scientific application, not only in the energy production scenario.

One of the guideline when we deal with uncertainties is ISO GUM [1] that provides the basic framework for evaluating uncertainties in measurement. The ISO GUM approach is summed up in this chapter. In our methodology the standard help us to face with the propagation of the error.

Respect to the error propagation method, Monte Carlo Simulation is a computational and probabilistic method that can be used to propagate the uncertainty coming from inputs to the model output. It is a less complex method relative to the analytical methods, but it requires much more computing resources. The main aspects and characteristics of the method are explain by Morgan and Henrion [2],Gentle [3], Glasserman, [4], Ayyub and Klir [5]. About the Monte Carlo method and the propagation of the errors the main references used in this work is Coleman and Steele [6], that explain a method in which simulated raw data for the input variables are obtained by adding random errors to the true values. A random error is obtained by multiplying a Gauss-normal random number to the prescribed uncertainty. In the MC simulation, this random generation of variables is repeated in a large number of times (N). The calculated uncertainty can be obtained by taking the sample standard deviation of the simulated data.

The issues of reconcile redundant sets of data has been explored many authors. On-line performance monitoring, efficiency analysis and condition monitoring are widely used methods for efficiency and reliability enhancement of power plants. Jiang et al. [7] developed a method for integrated sensor and equipment performance monitoring in power plants, which can detect and identify both sensor biases and equipment faults in the system. Blanco et al. [8] modelled a new process for multivariate detection of quasi steady states in power plants, and diagnosis outcomes could be applied to early warning systems. Guo, Lui &Li [9] investigate a data reconciliation model for the overall thermal system of a steam turbine. These are only some example of the great number of articles and publications on the reconciliation problem: the approach mostly used is the minimization method solved with iterative procedure. These techniques are able to check if the system variables are

affected by systematic errors but their drawback is that to obtain an overall minimum error often they change the value of all the independent input variables, even if they didn't present any systematic error.

In literature the Monte Carlo approach is not applied to performance monitoring of coal power plant, and the hypothesis at the base of the application is that the input sets of variables are not effected by systematic error. So we can't find any theoretical base to apply a reconciliation algorithm in the Monte Carlo approach.

In this work our focus is on two statistical method that can give in output the result as a statistical distribution, that are:

- Error propagation
- Monte Carlo method

This two are proposed as alternative to the ENEL calculation method, that we'll describe in the following paragraph.

Economy On Line

Accurate monitoring of specific consumption and performance degradation diagnostics are key elements for improving profit margins for a power plant. With the introduction of the software Economy on Line (EoL), ENEL has the objective to utilize a homogeneous tool for in-line calculation of Specific Consumption for all plants in the ENEL GEM coal area, to optimize the exercise of the UP with orientation to best practice and optimize maintenance operations by analysing the performance degradation of the main elements of the plant.

The software is able to calculate and present the individual causes of deviation of the specific consumption according to indirect method, calculate specific consumption using the budget method (ASME PTC 6 standards), calculate effective specific consumption curves by combining the two methods. Then it can present the current operating point and process automatic reporting.

The system is applied in eight power plants and twenty-one productive sections. In particular, in coal power plants of Brindisi, Fusina, La Spezia, Sulcis, Bastardo, Porto Marghera, Genova, Torre Valdaliga.

The Economy On Line system is based on the information infrastructure of the 3SE system, for the acquisition of the quantities contributing to the calculation. The elementary values of the contributors are acquired from the real-time database of the PI systems installed at the plants, with a base sampling of 30 seconds.

The use of individual contributors within the calculation is preceded by some pre-processing steps:

- data filtering / pre-processing: each value that contributes to the calculation, acquired from the process system of the plant, is subjected to a numerical filtering. This filtering is carried out in order to eliminate the effects deriving from possible spurious acquisitions and the oscillatory variations of some contributing quantities attributable to the characteristics of the main water-steam cycle. Furthermore, the plant quantities used are subjected to the possible conversion of units of measure, in order to achieve the homogeneity of the parameters that contribute to the various plants.
- data validation and replacement: For each value contributing to the calculation is configured a trust range that can be based on:
 - a. Lower and upper fixed thresholds
 - b. Variable thresholds calculated as a function of an acceptable range around a reference curve

If the thresholds (fixed or variable) configured for the individual contributing quantities are exceeded, the application would only use the valid values to determine the average value of the data, discarding any unreliable measures.

The application calculates the curves of the specific net consumption on a daily basis according to the load, using the historical data calculated by the application itself and present in archive.

The specific consumption curves are used by the application in order to provide the operator an indication of the average performance obtained by the production section in the last operating period (15-30 days), and to highlight the current performance level (point of operation) compared to what has been obtained in the last period.

The Specific Consumption curves are obtained by subdividing the total load range of the production unit into 20 bands and determining, on a statistical basis extended to the last 15-30 days of operation, a pair (Power output, specific consumption) for each load band.

The SC curve is then calculated by quadratic interpolation of the individual points identified.

The application calculates the SC curves related to:

- CS (net) curve from the financial statements: It is calculated using the net specific consumption values evaluated with the budget method (ASME standards) sampled per minute. The curve is indicative of the actual performance obtained from the production section in the last operating period.
- CS curve (net) Optimum Recalculated: It is calculated using the specific net consumption values obtained by the difference between the value of SC from the financial statements (ASME standards) and the total deviation due to internal causes. The curve represents the optimal value of SC obtainable, depending on the load, in relation to the average environmental conditions of the last operating period.
- CS Curve (net) Recalculated Reference: It is calculated using the net specific consumption values obtained by the difference between the value of CS from the Budget (ASME standards) and the total deviation due to both internal causes and external causes. The curve represents a value of C.S. net, depending on the load, brought back to the reference conditions.

SC samples used for the construction of the curves are subjected to a filtering action aimed at eliminating unreliable values. A first filtering is carried out by eliminating the samples excessively different from the SC curve of reference. The remaining samples are subjected to further filtering based on the standard deviation from the average value of each band.

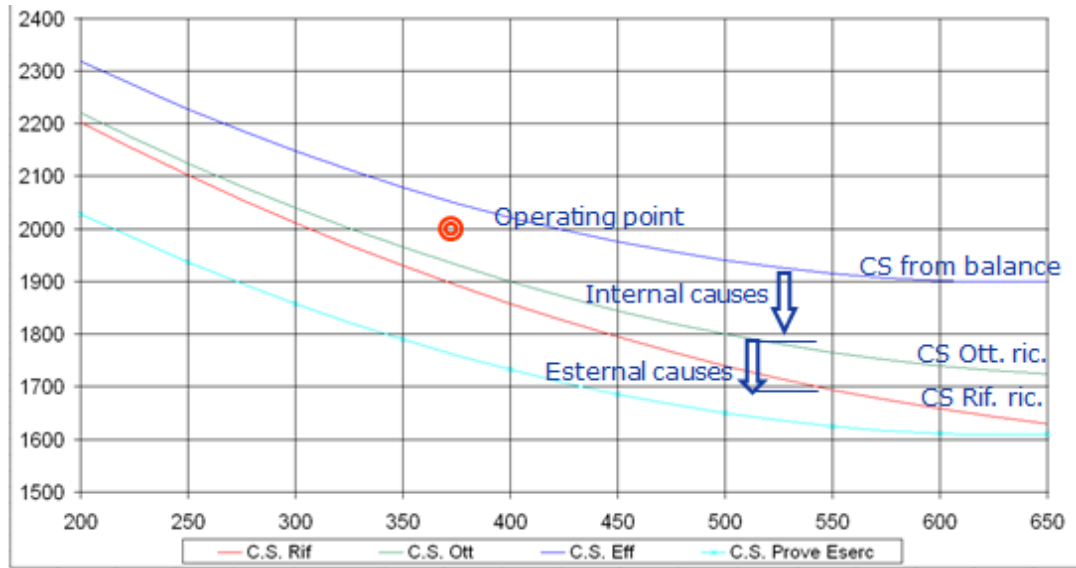


Figure 3.1 different curves of SC

There is also a diagnostic page in Economy On Line, set up with the aim of providing operators with a tool that facilitates the diagnosis of any calculation anomalies and of the main contributing measures. In the "Economy On Line Diagnostic Messages" box, any anomaly conditions that may cause degraded operation of the calculation module are highlighted.

The internal calculation operated by the software are not clear. We know that it does not require a fuel flow measurement, and the hinge measurement is the feed water flow rate. The main inlet variables are the flow rate at stack and the power output on the economizer: these values are utilized to find the concentration of CO₂ at stack and setting up material and energy balances to calculate the specific consumption.

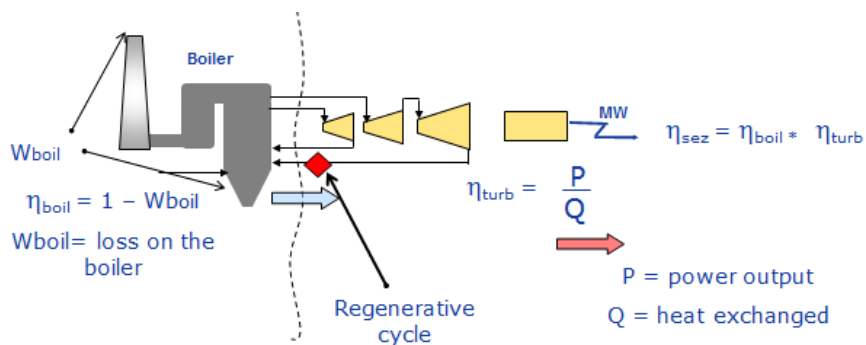


Figure 3.2 main element for the calculation of EoL

The plant manager is looking for an alternative approach to calculate the specific consumption, using the information at stack.

Propagation of uncertainties

The first of methods proposed is prescribed by the ISO-GUM, Guide to the expression of uncertainty in measurement - published jointly by CIPM (Comitè International de Poids et Mesures), ISO (International Standard Organization), IEC (International Electrotechnical Commission), IFCC (International Federation of Clinical Chemistry), IUPAC (International Union of Pure and Applied Chemistry, IUPAP (International Union of Pure and Applied Physics) and OIML (Organization Internationale de Métrologie Legale) with the aim of providing uniform criteria at the level world with which to measure measurement uncertainty.

The first concept at the base of this approach is the “true value” of a measurement. The term “true value” represent the value that the measurand would assume if the measurement was not affected by any errors. The presence of systematic or random errors in measurement prevents finding the true value of the measurand. One of the fundamental postulates of measurement theory establishes that true value of an experimentally accessible quantity, is itself unknown, either because it can't be defined in a rigorous way, either because it is not completely accessible from the instrumentation. It follows that, a given measure would turn out to be simply an approximation of the true value moving away from this of a certain amount that was defined as “error”.

The international guide “Guide to the expression of uncertainty in measurement” provides information on the determination of the measurement uncertainty in concrete cases, and contains the basic guidelines for the analysis and processing of experimental data. The final purpose of these guidelines is to try to get an estimate of the consistency of the uncertainty at least realistic, to be declared each time measurements are made in different fields: industrial, commercial, health, environmental, etc.

The GUM classifies the uncertainties in categories A and B according to the method used to estimate them. Precisely, they are of category A those estimated by means of statistical analysis of series of observations and the uncertainty is determined by the same experiment

or measurement that is being performed. Uncertainties of category B are assessed by different means, for example, through:

- previous measurement data;
- technical specifications declared by the manufacturer;
- data provided in calibration certificates or others;
- uncertainties assigned to reference values taken from manuals.

In the evaluation of measurement uncertainty, it is assumed that systematic errors (bias, polarizations) present in the measure have been corrected.

This classification is valid for the measures carried out in a direct way. In the model of the plant made in this work, the measurand Y (output) is linked by a functional relation f to N variables X_1, X_2, \dots, X_N (inputs). For this reason, to estimate the final value of the output and the associated error, we apply the law of propagation of uncertainty.

The uncertainty of the measurand Y can be determined with this relations only if:

- the function f is linear;
- sensitivity coefficients (df/dx_i) can be calculated (i.e. f continuous and derivable);
- the uncertainties $u(x_i)$ with $i = 1 \dots N$ are known.

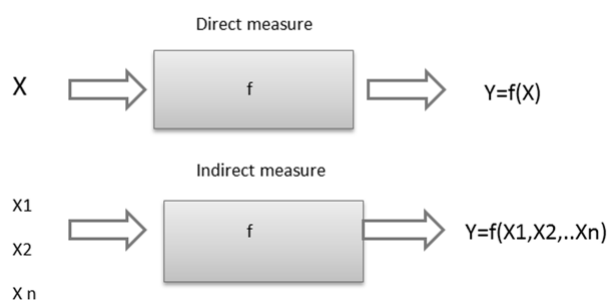


Figure 3.3 scheme of the kinds of measurements

The steps to be followed for evaluating and expressing the uncertainty of the result of a measurement may be summarized as follows:

- 1) Express mathematically the relationship between the measurand Y and the input quantities X_i on which Y depends:

$$Y = f(X_1, X_2, \dots, X_N)$$

The function f should contain every quantity, including all corrections and correction factors, that can contribute to the result of the measurement.

In our case the function f is the function that takes in input all the measured variables and gives in output the value of the specific consumption.

- 2) Determine x_i , the estimated value of input quantity X_i , either on the basis of the statistical analysis of series of observations or by other means. In our problem we have thirteen independent variables that take part in the formula: they are determined on the basis of statistical analysis, so we have an average value and a standard deviation for each of them.
- 3) Evaluate the standard uncertainty $u(x_i)$ of each input estimate x_i .
The entity of the error depends on the sensibility of the instrument.
- 4) Calculate the result of the measurement, that is, the estimate y of the measurand Y , from the functional relationship f using for the input quantities X_i the estimates x_i obtained in step 2.
- 5) Determine the combined standard uncertainty $u_c(y)$ of the measurement result y from the standard uncertainties and covariances associated with the input estimates.

$$u_c(y) = \sqrt{\left[\frac{\partial Y}{\partial X_1} u(x_1) \right]^2 + \left[\frac{\partial Y}{\partial X_2} u(x_2) \right]^2 + \dots + \left[\frac{\partial Y}{\partial X_n} u(x_n) \right]^2}$$

We calculate the value of the partial derivative of each variables with a numerical method and we apply the formula to calculate the total error.

The contribution of each variables to the total error changes on the base of its impact on the total result. The error of variables with an higher impact should be reduced to have a more precise result.

Monte Carlo Method

Basic concept

The reason to use a numerical method to determine the uncertainty is mainly due to the fact that the application of the GUM or other analytical methods may not be reasonably possible in some contingent practical situations (e.g. measures obtained by digital processing), unless simplifications are introduced in models, which may however lead to incorrect results.

In such situations, numerical simulation can be the path to follow for achieve the goal that we set ourselves. Address a problem through one numerical simulation means treating the real problem by reproducing it in a controllable context. The simulation techniques are conception completely different from the analytical methods. Simulation techniques numbers are obligatory when the scenario in which the experimenter acts can't be described completely and perfectly by exact mathematical rules but only through probabilistic constructs. This happens for example when not all the variables that contribute to the experiment, in this case to the measurement process, can be kept under control, as they are subject to random fluctuations.

The advantages a simulation method can offer with respect to an analytical method are the following:

- simulation makes it possible to analyse complex systems for which the implementation of analytical methods would require considerable efforts and / or simplifications that are not always acceptable;
- through the simulations it is possible to study the effects of modifications on the structure of the system, altering the model and observing the effects;
- detailed observation of the simulated system can lead to one better understanding of the system itself and suggest improvements to this that otherwise could not emerge;
- the simulations allow you to experiment with new situations of which there is little knowledge and addressing them by providing information on "what can happen", and the effects of these changes can be tested before being implemented for the system itself.

On the other hand, the simulation methods have the disadvantage of providing an estimated but not exact result and may require major implementation efforts and high computational

costs. In any case, the use of simulations rather than of analytical methods can still be advantageous, especially when the model has a structure too complex to allow the use of the exact analytical method or when it requires stringent and hardly feasible assumptions.

Among the most used and known numerical simulations there is the Monte Carlo simulation (MCS). Monte Carlo method is a numerical method based on probabilistic procedures, used in statistics for the resolution of many problems, which present analytical hitch difficult to overcome or problem that involve also random variables. It takes its name from the casino of Monte Carlo, the symbol of gambling par excellence.

Monte Carlo is a term covering mathematical methods which rely on game of chance, probability theory and use of repeated random sampling to compute their results. The general approach of Monte Carlo to solving a problem is to create an experiment with a random element. This experiment is then performed repeatedly and an estimated result to our problem is obtained.

From its definition, it is clear, that Monte Carlo in fact doesn't give us exact results, such as a "real" mathematical analysis might do. The fact that this method is built around random sampling and games of chance means that the answers obtained are statistical and subject to the laws of chance. This property of Monte Carlo methods has been a source of doubts about its usefulness. The major strength of Monte Carlo anyway is in its simplicity. Once a random variable is found, the sampling and evaluation are very straightforward. Another major advantage of Monte Carlo is that these methods lend themselves to a wide range of problems— anything from calculating an integral to nuclear physics computations and complicated higher-dimensional integration of functions. In fact, for many complex problems, Monte Carlo is often the only feasible solution.

The Monte Carlo (MC) method, is based on the fact that a direct analytical solution of the problem can be too expensive or even impossible. The problem is then solved numerically, producing a sufficiently high N number of possible combinations of the values that input variables can assume and calculating their output on the basis of the model equations. To construct each of the N combinations is randomly extracted a value for each input variable, in accordance with the specified probability distribution and respecting the correlations between variables. Repeating this process N times (with N quite

"large" to allow statistically reliable results) we will obtain N independent values of the output variables, which represent a sample of the possible values assumed by the output, sample that can be analysed with statistical techniques to estimate the descriptive parameters, reproduce histograms of frequencies, and obtain numerically trends in output distribution functions.

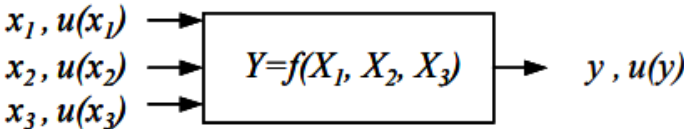


Figure 3.4 input and output of Monte Carlo method

The MCS method can be used regardless of the nature of the model: linear, weakly non-linear or strongly non-linear. The method does not need to make assumptions about the magnitude of the uncertainties entering or on the distribution of output (conditions for the central limit theorem).

The main disadvantages of the method are due to the fact that the number generators are not purely random (pseudo-random). This means for example that the distribution of a generated sequence by randomly extracting numbers from a uniform pdf (of the generator), it will not be perfectly uniform. The quality of the generation in any case improves as the number of generations increases and the number of simulations can be chosen according to the quality to be obtained. This however, in the case of very complex models, it may require a very high time of processing. Another problem is related to non-repeatability of the experiment, the sequence of random numbers generated, in fact, just for the randomness of the generator, it should be non-repeatable. In practical cases however, using the same seed that starts the generation, the generated sequence is the same and this allows you to obtain repeatability of results and test the procedure.

In our problem, we have the case of independent input variables with only one output quantity Y. Known the pdfs relating to each input quantity pdf (xi) for i = 1, . . . , N, we want to determine the pdf (y) of the measurand Y.

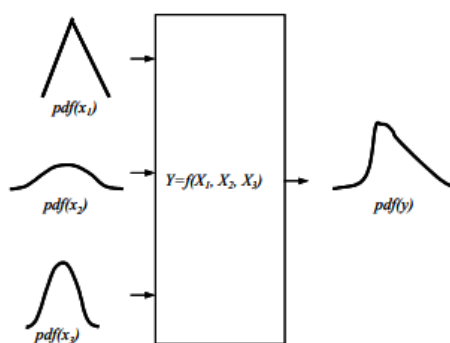


Figure 3.5 pdf role in a Monte Carlo simulation

Specific problems of Monte Carlo simulation

The model

The goodness of the Monte Carlo simulation depends primarily on the assumptions underlying the model and the consequent equations that express the mathematical relations between the input and the output variables. Then you have to choose the degree of detail with which the model of the problem is constructed. It's important to specify the variables that the decision maker can control (parameters) and identify those that depend on uncontrollable external events (input variables). Moreover it's important to identify and determine the functions that best describe the trends over time of the variables, highlight the correlations between the variables that can be significant for the purposes of the analysis, etc. All this is necessary to obtain a sufficiently simple model to be understandable and make it usable in practice. Anyway, the simplifications can give too much vision reduction of the problem under examination or underestimation of important aspects, which can lead to incorrect conclusions about the results of the simulations. In conclusion we can say that the construction of the model is a critical phase and largely influences the effectiveness of the model itself and the validity of the results simulations for decision-making purposes.

Assignment of probabilities to input variables

Another obvious difficulty encountered in the Monte Carlo simulation is the assignment of the probabilistic descriptions to the random events that determine the values of the input

variables; that is in practice to determine for these variables an appropriate estimate of their statistical distributions.

For some types of events or factors, historical series of values derived from experience are available. In this case, one possibility is to use statistical techniques to perform a "best fit" of the time series of the data to the trends of predefined distribution functions. Another possibility is to use non-parametric techniques such as the resampling method. The basic idea of this technique is the following: the values are extracted randomly (with re-entry) directly from the original data series. An undoubted advantage of this method is that it allows to capture all the complexes correlations between the variables but without having to identify the statistical distribution function in advance to which the data best fit. A limitation of this system is that its validity depends on how much the data of the past can be representative of future events.

When historical data are not available, it is possible to rely on a subjective judgment, i.e. one subjective evaluation of the probability. To estimate subjective probabilities, the decision maker fixes the possible values that the variable in object can take, associated with the relative cumulative probability, thus obtaining a discrete random variation.

Then we have to specify that Monte Carlo simulation represents a valid instrument to describe mass and energy balances if the input independent variables are not affected by systematic measurement errors. In this case the resolution lead to big error in the final result. To solve this kind of problem systematic errors have to be detect previously, with alternative methodologies, and corrected before entering the Monte Carlo process.

Correlations between input variables

A very important aspect to keep in mind when building a model is the possible correlation between the input variables. Although it is often assumed for convenience that all variables are among them independent, this is a hypothesis that very often is unrealistic. The problem of correlation requires specific treatments, not always easy (except for introducing simplifications that could however invalidate the significance of the results themselves).

Number of iterations required

As we said, also the output variable is a random variable; with the Monte Carlo method however, it's not obtained an analytical formulation, but a sample of values whose

frequency allows to obtain an approximate indication of the probability distribution of this variable. It follows that it is not even possible to accurately calculate the statistical indicators of interest (for example average and standard deviation).

Anyway, it is known that by increasing the number of simulations we obtain a larger sample and therefore greater precision and accuracy (in practice it is an application of the well-known theorem of central limit). In practice, as the number of iterations increases, there is a convergence of the output towards the values that would be analytically "exact". Evidently, higher N, the more the results of the output can be considered "precise". In principle, therefore, it is enough to increase the number of simulations to obtain an exact value. With the current computing powers we can safely say that setting a very high N is no longer a problem. It is also possible to determine the degree of reliability and accuracy of the related output to the value of N chosen; this allows to fix the minimum N value in order to have a certain degree of precision.

Scheme of the Monte Carlo simulation

Depending on the number of factors involved, simulations can be very complex. But at a basic level, all Monte Carlo simulations have four simple steps:

1) Identify the Transfer Equation

To do a Monte Carlo simulation, you need a quantitative model of the business activity, plan, or process you wish to explore. The mathematical expression of your process is called the "transfer equation." This may be a known engineering or business formula, or it may be based on a model created from a designed experiment (DOE) or regression analysis.

2) Define the Input Parameters

For each factor in your transfer equation, determine how its data are distributed. Some inputs may follow the normal distribution, while others follow a triangular or uniform distribution. You then need to determine distribution parameters for each input. For instance, you would need to specify the mean and standard deviation for inputs that follow a normal distribution.

3) Create Random Data

To do valid simulation, you must create a very large, random data set for each input—something on the order of 100,000 instances. These random data points simulate the values that would be seen over a long period for each input.

4) Simulate and Analyse Process Output

With the simulated data in place, you can use your transfer equation to calculate simulated outcomes. Running a large enough quantity of simulated input data through your model (usually, in a MC simulation N is taken as 10^6 to 10^8) will give you a reliable indication of what the process will output over time, given the anticipated variation in the inputs.

Chapter 4 Model implementation

In this Chapter the layout of our study case plant is described, highlighting the main parts and the critical points. Then the equations utilized in the balances are described and the theoretical bases and hypothesis behind them are pointed out. All the steps of the calculations to obtain the specific consumption are shown.

Federico II thermal power plant , case study

The "Federico II" thermal power plant in Cerano (Brindisi) is one of the most important in Europe and one of the largest, coming into operation in 1997.



Figure 4.1 Federico II power plant

Layout

The operation cycle of the plant begins with the arrival of coal, in the homonymous park for open-air storage, from Costa Morena. Here coal, especially in the summer period, must be continually "moved" to prevent self-combustion. From the point of storage, the coal is brought via a conveyor belt into the boiler, after being reduced to powder by the mills. This pulverized coal is then fed into a combustion system where it is mixed with air and ignited under controlled conditions, releasing chemical energy as heat. This heat is captured by water within tubes in the boiler and the heat converts the water into steam. The combustion system and boiler must be closely integrated for highest efficiency and will normally be considered a single unit in modern plants. Once combustion is complete most of the ash residue falls to the bottom of the combustion chamber and is removed as slag. However,

some ash forms into fine particles that are carried away with the hot combustion gases. These particles must be removed at a later stage.

The heat produced is thus used to bring water to the steam state in the boiler tubes. This is then overheated and then brought to a considerable pressure to then reach the turbines. The turbines present are four and coaxial and respectively for high, medium, and low pressure (two of the latter type). These are connected to an alternator at a voltage of 20 kV. The transformers, finally, allow to raise this voltage to 380 kV to be fed into the transport network. The steam path continues after passing the turbines, it has now lost a large part of its energy and is conveyed into the condenser that has the task to completely cool the steam and bring it back to the liquid state so that it can be reused in a new cycle.

For cooling, the sea water taken from the pumps is used and it is then poured into a calm basin that has the function of not discharging it in a completely direct way, because it has become at the same time warmer, at sea avoiding an imbalance in the marine ecosystem.

Fumes produced during combustion in the boiler are instead directed to the chimney after passing through the denitrifiers (which reduce the percentage of nitrogen and its oxides), the electrofilters (which retain the ashes) and the desulfurizer (which decreases the percentage of dioxide sulfur). Sulfur dioxide is reacted with limestone thus forming gypsum and together with the sludge and ash produced, they are sold in Italy and abroad as bases for concrete and for building materials.

In the ENEL Brindisi power plant many control devices are placed on the chimney. Some of them are:

- LDS 6 Analyser System to evaluate the spectroscopy in situ
- Flowsic 100 to evaluate the flow rate
- Ultramat 6 to analyse the gas based on an extractive system

The working principles and the structure of these instruments has been described in Chapter 2.

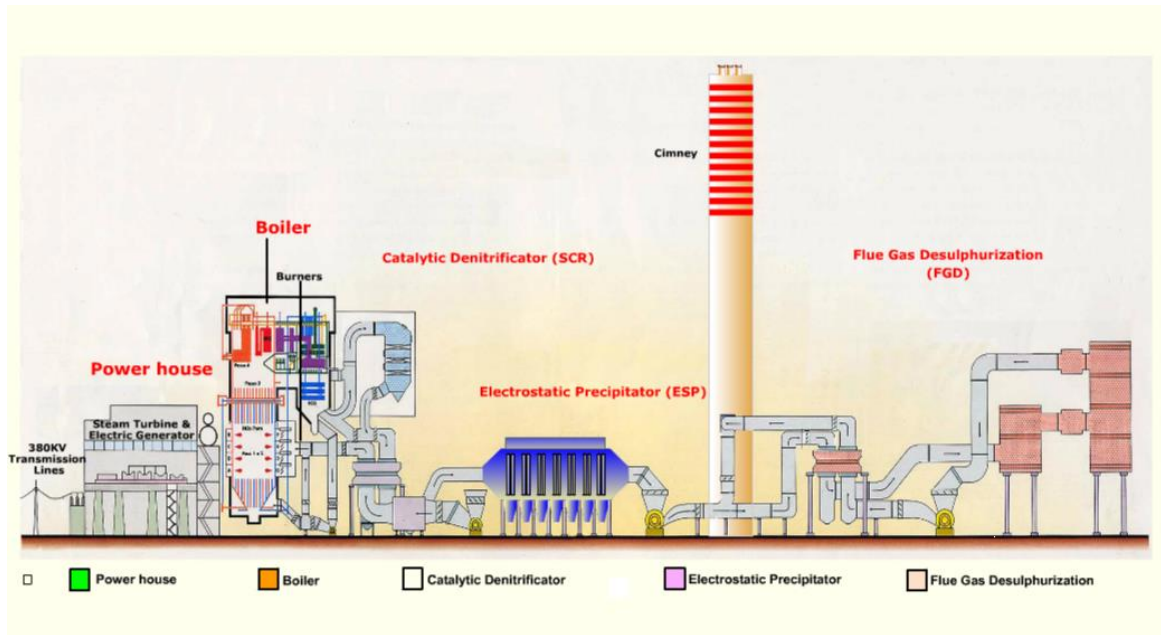


Figure 4.2 scheme of the “Federico II” coal-fired plant

Moreover, the Cerano plant is home to the pilot plant for carbon dioxide capture, which has been operational since June 2010. The CO₂ is sent in liquid form to the methane extraction areas where it will be put in place to avoid creating different balances. of pressures in the subsoil. This project is making the classification of clean plants climb to "Federico II", which was considered by the WWF to be one of the worst in 2007. A plant that applies all these processes, including carbon dioxide capture, may be called a zero-emission plant, although in fact, traces of all will still be released.

Efficiency is the key to modern coal-burning technology. The higher the ratio of electrical energy output to chemical energy input of the coal combustion process, the cheaper each unit of electricity produced will be. For modern plants without carbon dioxide capture, higher efficiency also means lower emissions per unit of electricity produced. Of the chemical energy contained with the coal, around 15% is lost to the energy conversion system. The remainder is utilized to heat steam so that the hot steam contains around 85% of the original chemical energy. Converting the hot steam into electricity relies on the Carnot thermodynamic cycle. Conversion efficiency depends on the temperature and pressure of the steam (more accurately the temperature and pressure drop that is achieved between steam turbine inlet and outlet), so the development of coal-fired power plant technology is directed at producing steam at the highest temperature and pressure possible.

Model implementation

From an energy viewpoint, therefore, the two most important components of a coal-fired power station are the boiler, which produces high-temperature, high-pressure steam, and the steam turbine, which must then convert the energy carried by that steam into electrical energy. The average efficiency of coal-fired plants operating across the globe is around 28% and that of the U.S. coal fleet is around 33%.

Fuel introduced

In the “Federico II” power plant mainly bituminous coal is fed. Coal is imported from different area of the world, so the composition can vary from one charge to another. Table 4.1 summarizes for the six type of coal the composition and the related uncertainty and the number of samples on with statistical data has been calculated.

Table 4.1 characteristic of different types of coal introduced in the plant [the elemental composition is expressed in %wet basis]

	South-African		Russian		American		Indonesian		Colombian	
Number of samples	48		27		17		54		50	
	Aver age	σ	Aver age	σ	Aver age	σ	Aver age	σ	Aver age	σ
C	65,37	2,27	65,76	0,84	69,61	1,27	63,59	2,39	62,28	3,32
H	4,18	0,28	5,46	0,16	5,21	0,23	6,04	0,30	5,48	0,34
N	1,63	0,19	1,83	0,09	1,22	0,08	1,20	0,22	1,25	0,13
O	13,88	2,24	17,18	1,68	11,78	0,86	24,01	2,33	20,26	3,07
S	0,45	0,07	0,27	0,04	0,77	0,05	0,61	0,16	0,56	0,06
ASH	14,52	0,92	9,47	2,06	11,40	0,89	4,46	0,79	10,16	1,76
MOISTURE	7,29	0,94	10,09	1,39	8,29	0,90	13,69	1,18	12,42	0,93

It can be noticed that the main differences between the coals fed are the content of oxygen, moisture and ash.

In the plant the coal is mainly stored in silos before be injected in the furnace: this means that it's not sure of what type of coal is burned in a determined period, because the kind of

coal can be mixed in the silos with a share that varies in an uncontrollable way. This is an additional cause of uncertainty in the calculation of the specific consumption of the plant.

Critical points

In the study of the “Federico II” plant some critical points can be highlighted. The first one is related to the coal introduced at the inlet of the furnace. The fuel is injected in the combustion chamber using a fan: the more fuel is needed, the more air is introduced. This technique introduced in the study variables and unknowns related the real quantity and composition of the coal introduced.

Another variable is represented by the use of different type of coal, of different origin and with different percentage of moisture. These species of coal are mix together before the entrance in the burner, in undefined percentage. So the exact composition and quantity of fuel is unknown.

Due to the new normative introduced in Europe (European normative 601/2012 of 21 June 2012), the installation new control devices at the chimney has become mandatory. These instruments are used to measure directly the emission at the stack, in order to have an accurate control of the respect of the limit: it's no longer enough to calculated the emission on the base of the characteristic of fuel. This represents an important cost for the plant, however the investment can be also seen as an opportunity to optimize the process and try to reduce the uncertainties related to the critical point previously explained.

To fully exploit the new measuring instrument, ENEL would like to utilize the additional information to improve the efficiency of the plant: this is the main objective of this thesis.

In particular, the specific consumption of the plant is the variable used to quantify the overall efficiency. It is the ratio between the energy consumption and the electric production.

In this chapter the model of the plant is described. The origin of all the input variables with the respective uncertainty is explained. Then the hypothesis and the basic concepts below the drawing up of mass balance equations are illustrated.

Mass balance

The main objective of this work is to identify the correct amount of coal burned starting from the values of concentration and flowrate of different species at chimney. The idea is to build a model of the plant that describes all its parts in a simple way and that utilizes

Model implementation

information of both measurement at stack and measurement of the composition of fuel. The model starts from these information and it is able to calculate the effective lower heating value of the fuel and the specific consumption of the plant.

In the scheme we can see the control volume for our balances, in which the main inlet and outlet streams are highlighted.

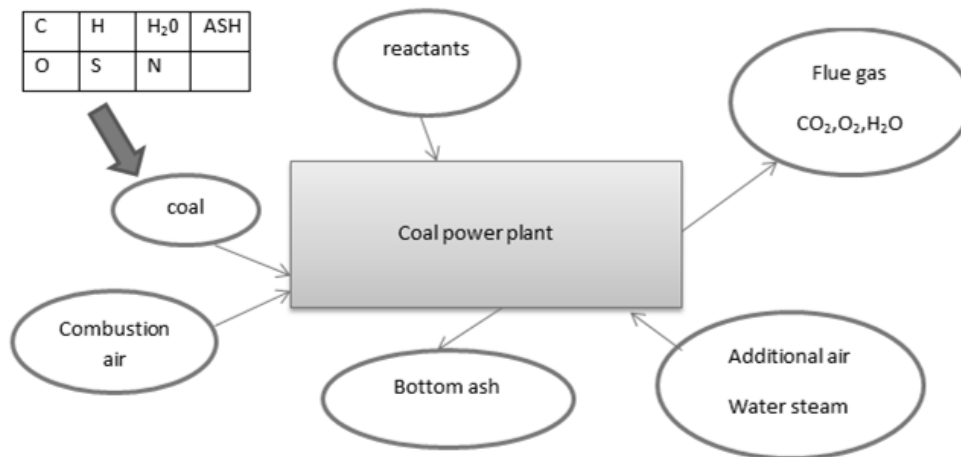


Figure 4.3 Control volume of the model, with the main inlet and outlet streams

In order to do this, all the data are collected in the form of average value and standard deviation. Then a mass balance on the combustion chamber and a mass balance on the DeSO_x system are set up. In this model the presence of alternative fuel such as methane or fuel oil is not considered. The only source of primary energy is the coal combustion. This situation is the most common for the plant, but also the main source of uncertainties, in fact the contribution of other fuels is more controllable and it doesn't represent particular issues for the management of the plant.

Below are described the mass balance equation of the problem. To obtain the value of LHV and specific consumption we need to calculate the carbon and the oxygen in the coal and the total amount of coal consumption. So we need three balance equations:

- balance on the element "sulfur"
- balance of the element "carbon"
- balance of the dry stoichiometric flue gas

Input variables

Within the control volume are present very different fluxes both for chemical nature and for method of measurement. They can be distinguished as:

- Known entity mass fluxes; it is possible measure them precisely or their assigned value is sufficiently reliable.
- Fluxes that only can be estimated, because can be measured only with low precision or are unknown.

The following measurements are utilized as input data for balance implementation. They are measured at stack, along flue gas conduits and at the combustor inlet.

Table 4.2 Independent variables of the model

name	symbol	Unit of measure	distribution	σ
oxygen volumetric content at stack on “as is” basis	$xO_{2stack,ai}$	-	Normal	0.1*
carbon dioxide volumetric content at the stack on “as is” basis	$xCO_{2stack,ai}$	-	Normal	0.5**
total flue gas flow rate at stack on “as is” basis	V_{fai}	Nm ³ /h	Normal	4800***
water vapor volumetric content at the stack	$xH_2O_{stack,ai}$	-	Normal	0.3*
concentration of SO ₂ at stack	SO_{2out}	mg/Nm ³ dry 6%O ₂	Normal	4.75*
fraction of fuel ash to fly ash	$alpha$	%	Uniform on the range 0.85-0.95	0.02
excess CaCo ₃ in De-SO _x system	exc	%	Uniform	0.005
Loss on ignition of fly ash	LOI	%	Normal	0.05
Power output	$Power$	MW	Normal	negligible

*standard deviations determined by means of the test of variability (QAL2)

Model implementation

** fixed value of standard deviation. The instrument is not certified QAL1 yet. We make an hypothesis for this value waiting for the analysis.

*** calculated value, see Chapter 3

Table 4.3 Constant values

name	symbol	Unit of measure
Average volumetric content of oxygen in the dry air	xO_{2air}	-
Average volumetric content of carbon dioxide in the dry air	xCO_{2air}	-
Molar volume	V_m	Nm ³ /mol
Molar mass of carbon	M_c	g/mol
Molar mass of sulfur	M_s	g/mol
Molar mass of nitrogen	M_n	g/mol
Molar mass of hydrogen	M_h	g/mol
Molar mass of oxygen	M_o	g/mol

Coal elemental composition

For each type of coal a number of samples taken at the arrival of coal is available, so it's possible to calculate the elemental composition in "as is" basis. In particular, the percentage of Carbon, Hydrogen, Oxygen, Moisture, Nitrogen, Sulfur and Ash are calculated. For every element average and standard deviation are obtained, with the hypothesis of normal distribution.

Table 4.4 summarize the number of data available for the five types of coal that mainly are used in the Federico II coal fired power plant.

Table 4.4 Number of samples received for each coal category

Type of coal	Number of samples
Russian	27
South African	48
Colombian	50
Indonesian	54
American	17

Each sample refer to the weighted average of a lot of 10 000 tons of coal.

Coal composition content are not independent variables: their sum is must always equal 1: therefore, and it's not possible to simply extract them from the statistical distribution. So, we take carbon as a reference quantity and we express all the other variables as a function of carbon. In this way, we obtain five variables to be randomly extracted. Table 4.5 summarize the main symbol used to represent them in the equations.

Table 4.5 Symbols used for the extracted coal composition variables

name	symbol
Hydrogen	H/C
Nitrogen	N/C
Sulfur	S/C
Ash	ASH/C
Moisture	M

In this way Hydrogen, Sulfur, Nitrogen and Ash content over Carbon content are independent variables, while Carbon and Oxygen content are consider unknown. These terms are calculate starting from the stack composition.

Model implementation

Table 4.6 value of normalized elemental composition in function of carbon content with the relative standard deviation

	South-African		Russian		American		Indonesian		Colombian	
	average	σ	average	σ	average	σ	average	σ	average	σ
H/C	0,064	0,005	0,083	0,003	0,075	0,004	0,095	0,006	0,088	0,007
N/C	0,025	0,003	0,028	0,001	0,018	0,001	0,019	0,003	0,020	0,002
S/C	0,007	0,001	0,004	0,001	0,011	0,001	0,010	0,002	0,009	0,001
ASH/C	0,222	0,016	0,144	0,031	0,164	0,013	0,070	0,013	0,163	0,030

In our case, data at stack refer to a period of the 2018. To have coherent data we choose to run the equations with the kind of coal utilized in that period, the Colombian coal. Anyway, having data of all the other coal alimented we make statistical analysis also on the other typology and we test the equation for the HHV for all the possible coal fed.

Data at the stack

From the measurement at the stack we have data of the percentage of carbon dioxide and oxygen, moisture and SO₂ in the flue gas and the volumetric flow rate. The data available are the data measured the 10th of July 2018, with a time interval of one minute. In particular:

- For the flow rate we have data of measurements on “as is” basis (m³/h) and at normalized condition. The method to calculate the standard deviation is reported in Chapter 3
- O₂ and the moisture content are on volumetric basis (v/v%). Standard deviations determined by means of the test of variability (QAL2)
- CO₂ is calculated on volumetric basis. We fixed value of standard deviation, because the instrument is not certified QAL1 yet. We make an hypothesis for this value waiting for the analysis
- The SO₂ content is measured in mass, with a reference condition of 6% of oxygen

Model implementation

We consider constant the percentage of oxygen and carbon dioxide in the air.

To have coherent data and to avoid inertia effect we calculate for each hour the medium value, in order to have a data for each hour of the day.

The value of SO₂ is measured on dry basis after the gas cooler by the NDIR analyser.

Fly ash data

About the data of the ash, we have a set of data of the LOI (loss on ignition), from which we can extract average and standard deviation. We has 147 sampling in different month of the year 2017. The value of LOI refer to the percentage of unburned species in the fly ash. The instrument online is used only to make the sampling, while the analysis is performed in laboratory.

Then we know that the total ash of the coal is distributed in 10% bottom ash and 90% fly ash. A uniform statistical distribution could be assumed in the range 0.85-0.95 for the ash fraction which ends in the fly ash.

Additional data

We have also information about the excess of lime in the De-SO_x, that we consider uniform distributed.

The net power output is measured in MW. We have all the data of the 10th July 2018, with a time interval of 30 seconds. Also here, to have coherent data we make the average value for each hour of operation.

Output parameters

The procedure is finalized to obtain the total coal fed, the LHV and the specific consumption as distribution of value through the Monte Carlo Method.

Table 4.7 output parameters

name	symbol	u.m
Coal consumption	C _c	t/h
Lower heating value	LHV	kJ/kg
Combustion power	C.P.	kJ/h
Specific consumption	S.C.	kWh _{coal} /kWh _{el}

Normalization of results to standard conditions

Concentration measurements expressed as mass per unit volume, e.g. mg/m³, are affected by temperature, pressure, moisture, and oxygen concentration. Concentrations expressed as volume per unit volume, e.g. ppm, are unaffected by temperature and pressure, but affected by moisture and oxygen. Mass emissions results, e.g. kg/h, are unaffected by temperature, pressure, oxygen and moisture levels.

The concentration of water vapour and oxygen affects the measured concentration of a substance by adding to the volume of measured gas. This is particularly relevant for processes involving combustion, where oxygen will be consumed and water vapour produced during the combustion process. The oxygen level can cause significant changes in measured concentrations. Many emission permits therefore require the concentration results to be expressed at a standard oxygen reference level. It is important that an oxygen reference level is set that is appropriate for the process. It should be based on the typical oxygen level of the process when it is running at normal conditions and the fuel type used. Different oxygen reference values are used for different fuels, e.g. 3 % for gas or liquid fuels, 6 % for solid fuels and 11 % for most incineration processes. (European Commission, 2010) Emissions of flue gases are often expressed on a dry gas basis, so that variation in the moisture of flue gas does not affect the assessment of the emissions.

Reference conditions are specified for temperature and pressure, and may also be set for moisture and oxygen content. Concentration measurements are usually reported at Normal Temperature and Pressure (NTP). Notion of NTP may vary between countries but e.g. in Europe it stands for 273 Kelvin (K) and 101.3 kilopascals (kPa).

We can calculate the variables in dry basis, at oxygen concentration of 0%:

$$x_{O2_{stack,dry}} = x_{O2_{stack,ai}} * \frac{1}{1 - x_{h2o_{stack}}}$$

$$Vf = Vf_{ai} * \frac{20.95 - x_{O2_{stack,dry}}}{20.95} * (1 - x_{h2o_{stack}})$$

$$x_{co2_{stack}} = x_{co2_{stack,ai}} * \frac{20.95}{20.95 - x_{O2_{stack,dry}}} * \frac{1}{1 - x_{h2o_{stack}}}$$

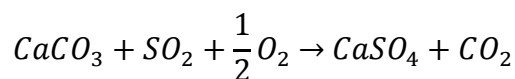
Balance for the element “sulfur”

An important impurity to be removed from the flue gas is the SO₂. There are many chemicals that are potentially capable of capturing sulfur dioxide from the flue gases of a power station but the cheapest to use are lime and limestone. Both are calcium compounds that will react with sulfur dioxide to produce calcium sulfate. If the latter can be made in a pure-enough form it can be sold into the building industry for use in wall boards. In the “Federico II” power plant WFGD (wet flue gas desulfurization) with limestone is used.

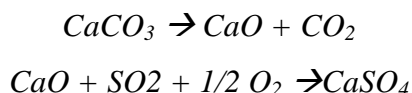
One of the simplest methods of capturing sulfur dioxide is to inject one of these sorbent materials into the flue-gas stream as it exists the furnace. Reaction then takes place in the hot gas stream and the resultant particles of calcium sulfate, and of excess sorbent, are captured in a filter downstream of the injection point.

Depending on the point of injection of the sorbent, this method of sulfur removal can capture between 30% and 90% of the sulfur in the flue-gas stream.

In the reactor, part of SO₂ is absorbed into the alkaline droplets to form calcium sulphate mainly with reaction:



Using gypsum - limestone flue gas desulphurization main reaction is as follows:



It can be seen that in the process of removing sulfur dioxide greenhouse gas carbon dioxide was generated, and the amount of CO₂ is related to the amount of limestone.

We consider all sulphur is converted in SO₂ during combustion, being this compound the most representative of the outlet concentration.

The S/Ca ratio can be calculated as:

$$S/Ca \text{ (molar ratio)} = \frac{[W_i - W_o(1 - LOI)]/80}{W_o * CaCO_3\% / 100}$$

where:

W_i: Sample weight during sulfation reaction at time t_i (CaSO₄+CO₂)

W_o: Initial sample weight (CaCO₃)

Model implementation

LOI: Loss on ignition,

80: Molecular weight of S+O3

100: Molecular weight of CaCO3.

Generally the ratio Ca/S lies in the range 1.02-1.1. In our system we have an average value of Ca/S of 1.03.

From the measurement in the chimney we have obtained [SOx]out, the volumetric outlet concentration dry basis, standard oxygen concentration.

[SOx]in, referred to the standard oxygen concentration [mg/Nm3], is calculated starting from the concentration of the coal:

$$SO2in \left[\frac{mg}{Nm^3} \right] = \frac{S}{C} * x_c * C_c * \frac{64}{32 * Vf} * 10^9 \left[\frac{tons}{g} \right]$$

The efficiency of the process can be calculated as:

$$eff_{desox} = \frac{SO2in - SO2out}{SO2in}$$

The specific production of Carbon in the desulphurization reaction is:

$$[C_{de-sox}] = SO2in * eff_{desox} * \frac{12}{64} * \left(\frac{S}{Ca} \right) \left[\frac{mg}{Nm^3} \right]$$

And multiplied by the volumetric flow rate:

$$C_{de-sox} \left[\frac{tons}{h} \right] = [C_{de-sox}] * Vf * 10^{-9} \left[\frac{mg}{tons} \right]$$

Balance for the element “carbon”

This is the schematic representation of our system, with all the streams (in and out) that contain carbon.

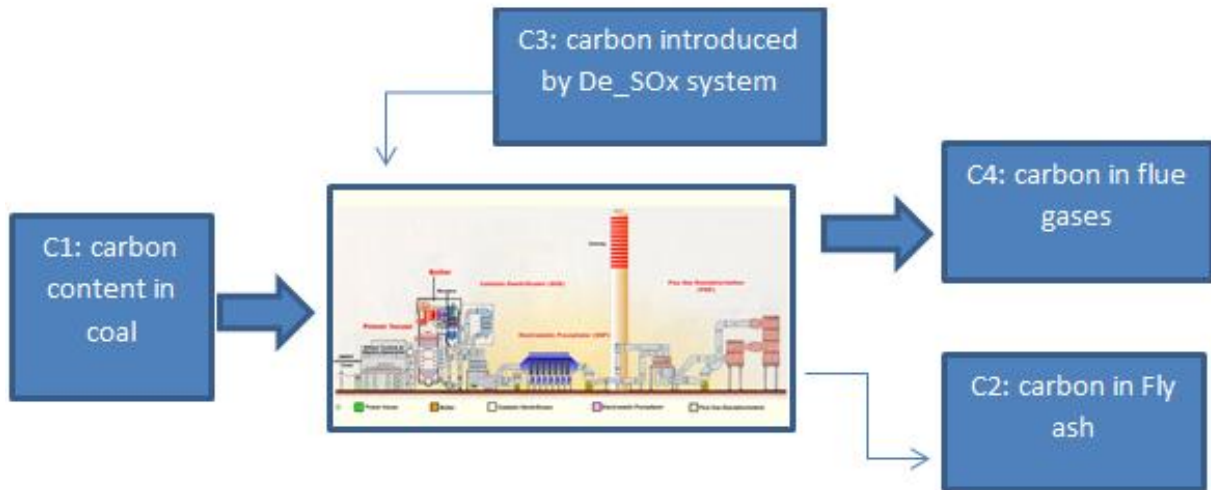


Figure 4.4 input and output flows of carbon in the power plant

We have four streams:

C1 [t/h]: total carbon in the inlet coal

C2[t/h]: total carbon contained in the fly ash

C3 [t/h]: total carbon introduced in the De-SOx system

C4[t/h]: total carbon in dry stoichiometric flue gas in the form of CO₂

To proceed with the calculations, for each independent variable was collected a random value calculated with a mean equal to the measured value and a relative standard deviation calculated from the data available. Then the derivate parameters quantities at stack were calculated.

Carbon at the outlet is calculated from the data at the stack:

$$C4 \left[\frac{\text{tons}}{\text{h}} \right] = V_{f, \text{ dry}} \left[x_{CO2_{stack}} - x_{CO2_{air}} \frac{x_{O2_{stack}}}{x_{O2_{air}}} \right] * \frac{\frac{Mc}{Vm}}{10^6 \left[\frac{g}{tons} \right]}$$

The fuel ash is split in 10% into bottom ash and 90% into fly ash. Coefficient alpha determines the shares of fly ash.

Then using the value of LOI we can calculate the total carbon in the fly ash. According to Burris&al [10] being the value of LOI higher than 4%, it is very close to the value of carbon.

$$\text{Fly}_{\text{ash}} = \left(\frac{\text{ash}}{c}\right) * x_c * \text{alpha}$$
$$C_2 \left[\frac{\text{ton}}{h}\right] = \text{Fly}_{\text{ash}} \frac{\text{LOI}[\%]}{1 - \text{LOI}[\%]} * C_c$$

The last stream is the total carbon introduced in the De-SOx system calculate in the previous paragraph.

$$C_3 \left[\frac{\text{tons}}{h}\right] = C_{de-sox}$$

The total carbon at the inlet is the sum of all the streams:

$$C_1 = C_4 - C_3 + C_2$$

Where C_1, C_2 and C_3 are function of x_c . We obtain a linear equation from with we can calculate the value of x_c .

Balance for the dry stoichiometric flue gas

The percentage of oxygen can be calculated using the following balance:

$$\begin{aligned} dsfg_{stack} - \Delta dsfg_{desox} \\ = (Mc - Mincomb) * dsfg_c + Mh * dsfg_h + Mo * dsfg_o + Ms * dsfg_s \\ + Mn * dsfg_n \end{aligned}$$

Where M_i are the mass of each species in tons/h.

On the right of the equal is calculated the dry stoichiometric flue gas at the outlet of the combustor, which is equal to the difference between the one measured at the stack and delta introduced by the De-SOx system. It must satisfy the constraint of equality with the stoichiometric flue gas produced by the combustion of all the species present in the fuel.

Model implementation

The delta flue gas due to the De-SO_x system is practically negligible and it has not been taken into account.

The DSFG contribution of each species is:

Table 4.8 DSFG contribution of different species

species	Reaction of combustion	DSFG [Nm ³ /kg]
C	$C + O_2 + 3.76N_2 \rightarrow CO_2 + 3.76N_2$	8.9075
H	$2H + 0.5(O_2 + 3.76N_2) \rightarrow H_2O + 3.76/2N_2$	20.977
N	$N + 0.5(O_2 + 3.76N_2) \rightarrow NO + 3.76/2N_2$	0.800
O	$2O \rightarrow O_2$	-2.643
S	$S + O_2 + 3.76N_2 \rightarrow SO_2 + 3.76N_2$	3.3365

LHV calculation

With these information the composition of the inlet carbon is calculated:

$$x_i = \frac{x_i}{x_C} * x_C \text{ [tons/h]}$$

And summing all the contributions we can obtain the total coal introduced at the burner, dry (we don't consider the tons of water to obtain the composition dry basis that is needed in the calculation of the LHV):

$$C_c = \sum_i x_i \left[\frac{\text{tons}}{\text{h}} \right]$$

Having data of the different carbon in inlet, we have the possibility to estimate the LHV starting from the composition of the coal.

Heating value quantify the energy content of the fuel, two definitions are generally provided:

- Higher heating value (HHV): represent the heat of combustion when water vapor produced is totally condensed
- Lower heating value (LHV): represent the combustion heat when water produced remains in steam phase

Difference between the two heating values consists in the water enthalpy of evaporation. In the calculation of the specific consumption heating value refers to LHV, measured in

Model implementation

[kJ/kg], because coal plants often do not condensate the steam in flue gases. Higher heating value is converted in lower heating value through the relation:

$$LHV = HHV - \Delta H_{ev_{H_2O}} * m_{H_2O}$$
$$\Delta H_{ev_{H_2O}} = -2440 \left[\frac{kJ}{kg} \right]$$
$$m_{H_2O} = x_{H_2O} + \left(\frac{x_{H_2O}}{M_{H_2O}} - \frac{x_{Cl}}{M_{Cl}} \right) * \frac{M_{H_2O}}{2}$$

The thermal energy released during combustion process can be directly measured using a heating bomb or, if this instrument is not available or the procedure is too expensive, it can be calculated using empirical equation. There is large number of empirical equations in literature, most of them suitable to calculate energy content of coals. Here are reported the most used ones, which calculate the higher heating value of dry and ash free material in [Kcal/kg]. also the formula previously used by the plant is reported, in order to make a comparison. The result of these formulas are then compared with the value of HHV calculated with the standard methodology on the samples, that we have in the database. All the composition are expressed in dry bases.

Correlation by Eni

$$HHV = 8081 * C + 34467 * \left(H - \frac{O}{8} \right) + 2250 * S$$

Dulong's equation

$$HHV = 80.93 * C + 342.82 * \left(H - \frac{O}{8} \right) + 22.53 * S$$

Strache's equation

$$HHV = 81.48 * C + 342.68 * H - 36.65 * O + 25.04 * S$$

Boie's equation

$$HHV = 84.13 * C + 378.13 * H - 26.57 * O + 25.04 * S$$

The empirical equations proposed to calculate the substance heating value were applied on collected data, to define which of them result more accurate for waste materials. Using this procedure we can estimate for each kind of coal the distribution of the relative error. The following table compare the percentage errors related to the mean value, standard

Model implementation

deviation and maximum minimum values of the higher heating values (HHV) measured with the calorimetric bomb compared with values calculated through empirical equations.

Table 4.9 Errors of HHV correlations

Error (kcal/kg)						
correlation		Mean value	Standard deviation	%	Maximum value	Minimum value
Russian	ENEL	923	205	22%	1236	602
	Dulong	1456	162	11%	1657	1171
	Strache	110	105	95%	341	-3
	Boie	41	96	232%	231	-82
South-african	ENEL	663	242	36%	894	-217
	Dulong	1056	220	21%	1305	296
	Strache	162	342	211%	594	-768
	Boie	69	305	442%	453	-708
Colombian	ENEL	1152	257	22%	1499	607
	Dulong	1751	234	13%	2049	1208
	Strache	386	398	103%	952	-476
	Boie	281	355	126%	794	-476
Indonesian	ENEL	1352	188	14%	1717	898
	Dulong	2003	164	8%	2336	1641
	Strache	513	824	161%	6025	-96
	Boie	396	834	211%	6063	-164
American	ENEL	921	107	12%	1111	748
	Dulong	1386	82	6%	1572	1269
	Strache	-82	81	-98%	95	-205
	Boie	-110	75	-69%	63	-213

Table 4.10 average value of the error of different HHV correlation

Error (kcal/kg)					
correlation	Mean value	Standard deviation	%	Maximum value	Minimum value
ENEL	1002	200	21%	1291	528
Dulong	1530	173	12%	1784	1117
Strache	217	350	95%	1602	-310
Boie	136	333	189%	1521	-328

From the comparison we can say that the equation that better fits our data is Boie's equation. The values refer to the Colombian coal, the one utilized in our simulation, but the same analysis is been performed on all the five kind of coal fed in the plant. Boie's equation result to be the best for all the typology, with different errors.

We calculate the mean HHV with the correlation and then we add the associated error. We report the distribution of the error for Boie's equation: we will extract the deviation from the mean value in this distribution.

The correlation takes in input the dry composition of the fuel.

$$HHV = HHV_{mean} \pm error_{HHV}$$

Then, to calculate the lower heating value we apply the relation previously reported.

Specific consumption calculation

Finally we can calculate the specific consumption as:

$$CS = \frac{\left(LHV \left[\frac{Kj}{Kg} \right] * \frac{(C_{al} \left[\frac{tons}{h} \right])}{1 - x_{h2o}} - \frac{(C_{al} \left[\frac{tons}{h} \right])}{1 - x_{h2o}} * x_{h2o} * 2257.2 \left[\frac{Kj}{kg} \right] - C_{incomb} * 33778.6 \left[\frac{Kj}{kg} \right] \right) * \frac{10^3 \left[\frac{kg}{tons} \right]}{3600 \left[\frac{Kj}{KW} \right]}}{power[MW] * 10^3 \left[\frac{KW}{MW} \right]}$$

Mainly we have three contribution:

- the energy produced by the burning of the coal
- the energy subtracted by the presence of water in coal
- the energy lost for the incomplete combustion of coal

Chapter 5 Results

In this Chapter the main results of the procedure are explained. The resolution of the mass balance allows determining the composition of the coal burned, as well as evaluating the LHV and the specific consumption. The database of fuel properties contains data related to five types of coal: Russian, South African, Colombian, Indonesian, American. The method has been tested on operating data related to a determined period of the year 2018. In this period the main fuel burned is a type of Colombian coal, therefore the characteristics of the burned fuel are those determined for Colombian coal.

Monte Carlo method results

The Monte Carlo method with respect to the method of uncertainties propagation, brings along to some advantages:

- It is able to calculate the output variables as distributions of values
- It provides the distributions of all the calculated variables, not only of the objective function
- we can verify what are the real distributions of the outputs, instead of just assuming they are normal.

In the following graph in figure 5.1, it is shown how the average output value of the simulation differ from the expected result. We can notice that the solution converge when the number of iteration grows.

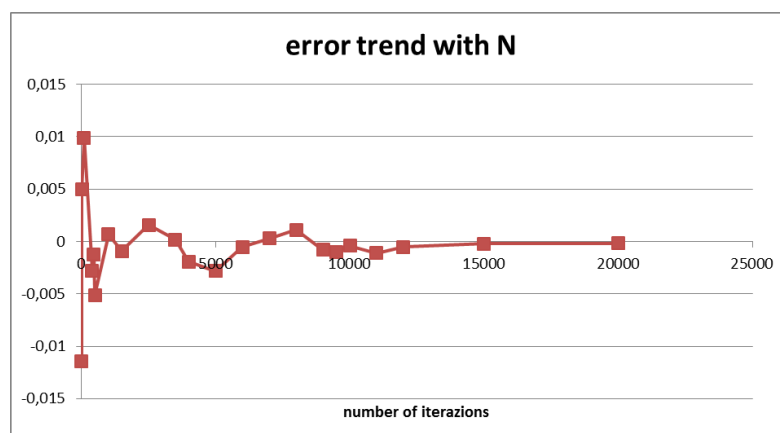


Figure 5.1 error trend with N

Results

The number of iterations N that have been chosen for our problem is $N=15000$. This is a reasonable number of iterations that leads to convergence.

Coal consumption

The first variables calculated are the real flow rate of coal burned and its composition.

In the graph in figure 5.2 hourly average flow rate coal burned during the day of the test can be seen. It is possible to observe that the coal consumption is near 200 tons/h during the afternoon and the night, while it's higher in the morning.

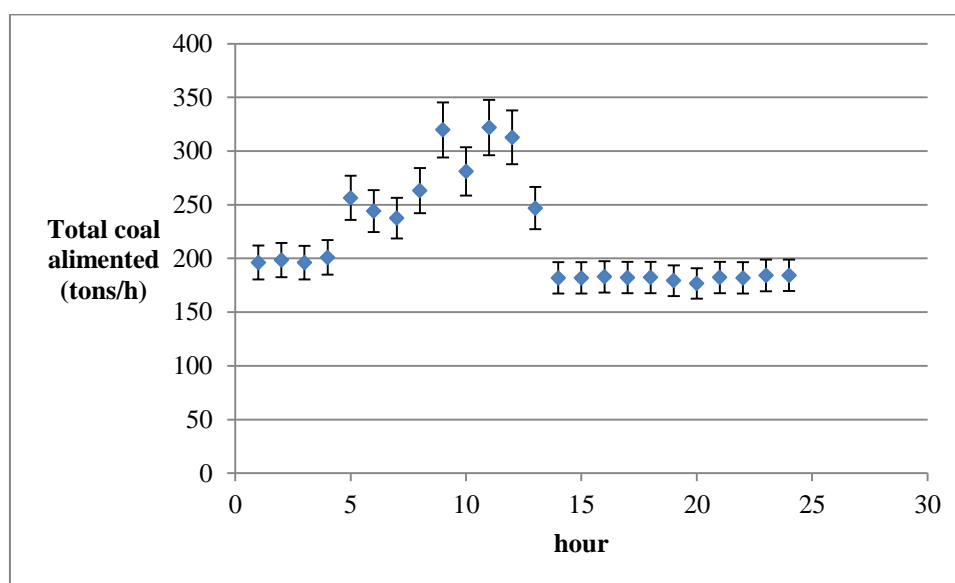


Figure 5.2 hourly averages of coal consumption during the day of the test and associated standard deviation

From the graph in figure 5.3 it is possible to observe that this behaviour is in accordance with the power output of the plant: in pick hours the power output is higher and the flow rate of coal burned too. While, when the power output is near 300 MW, the flow rate of coal is pretty stable too.

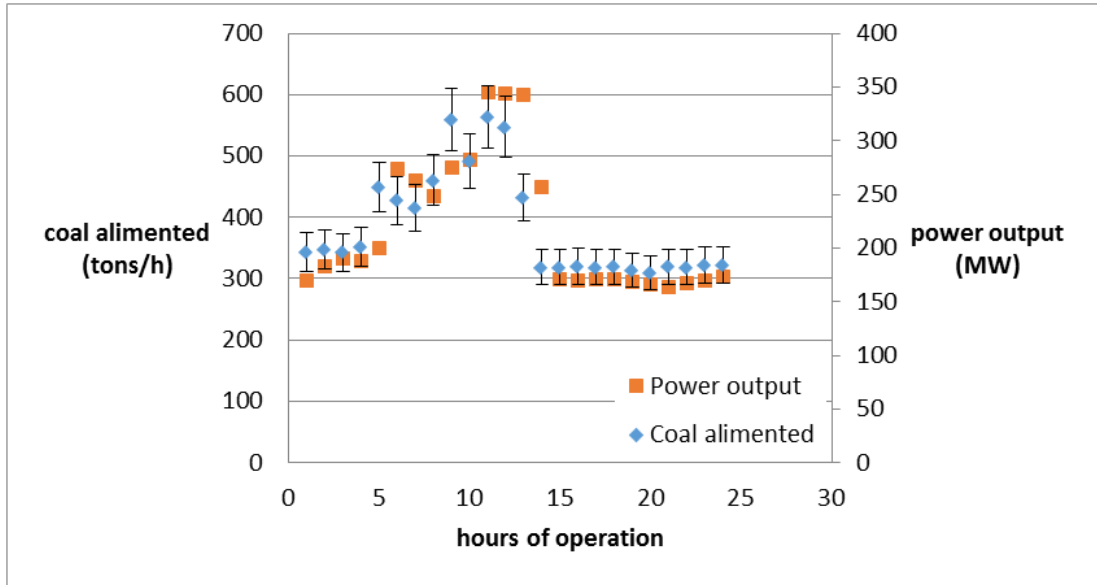


Figure 5.3 comparison between coal flow rate and power output during the operation hours

Time lapse of one hour is detected between the two series. It was not possible to determine the origin of this time lapse, but it's likely to be due to different time basis of different measurement unit (i.e. one set on solar time, other on daily saving time). By correcting the time lapse it's possible to plot coal flow rate against power output (figure 5.4). A good correlation is highlighted with the only exception of one outlier. The origin of that outlier is not clear.

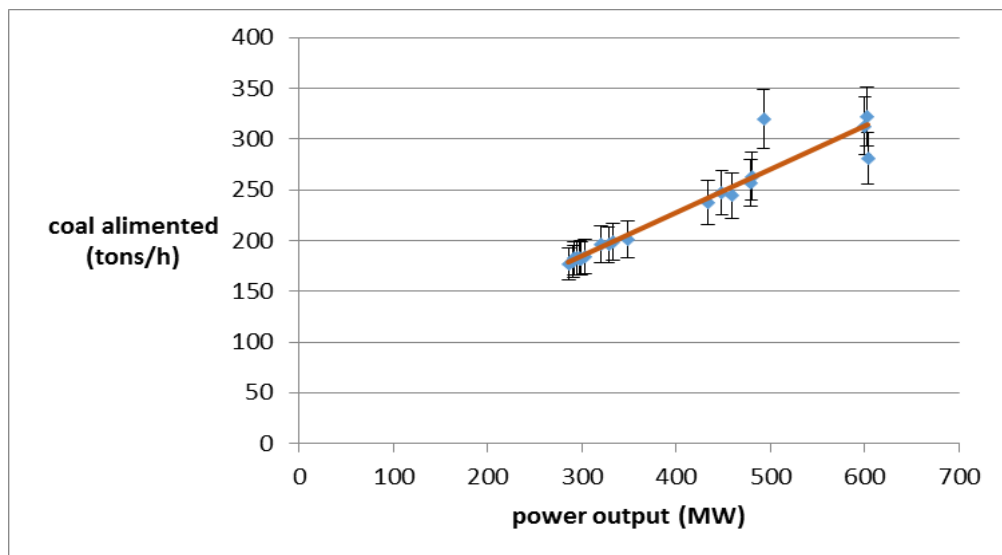


Figure 5.4 coal flow rate against power output

Coal composition

The description of the model, highlights that the flowrate of carbon and oxygen to the burners are determined by means of balances, whereas are used to predict the values of H/C, N/C, S/C, ASH/C, which are assumed as independent variables.

Anyway two redundant piece of information are available: the value of O/C from the coal analysis and the flowrate of carbon and oxygen calculated. The graph in figure 5.5 compares the distributions of O/C from coal analysis and that resulting from the model.

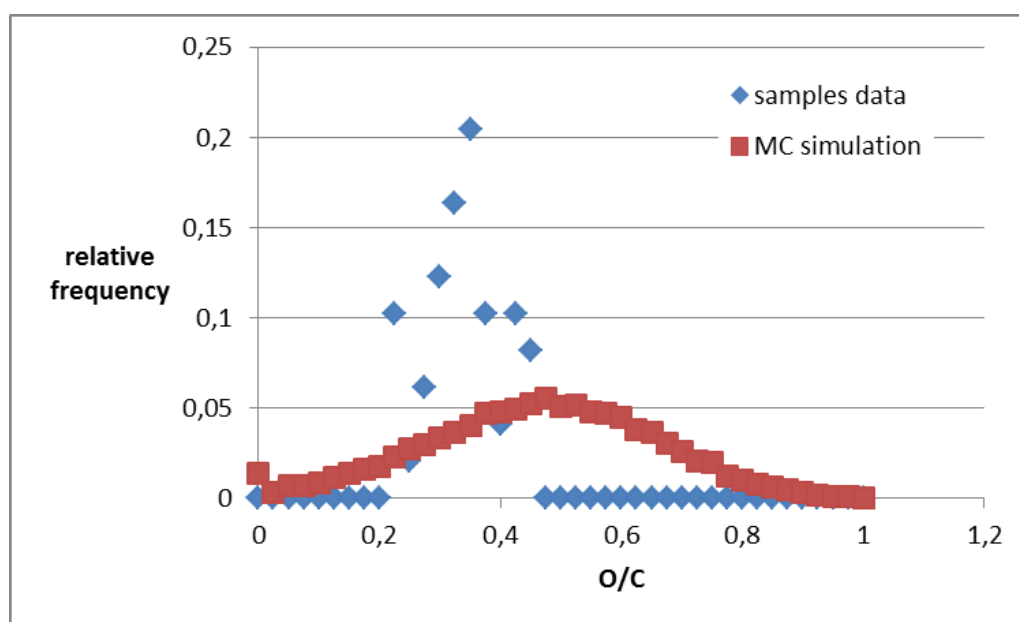


Figure 5.5 mass ratio O/C distribution from coal analysis and that resulting from the model

It is possible to observe that the two curves (data from the coal analysis and calculated values) have different mean values and different dispersions, but they overlap in an area between 0,2 and 0,4 circa. This could mean that measured variables are affected by systematic errors, in particular concentration of oxygen at the stack (%v/v) can be overestimated by the instrumentation. The redundancy of information could help us in correcting the possible systematic errors. In this work, reconciliation has not been carried on, because the literature does not report enough basic theory principles to match data reconciliation with the Monte Carlo method.

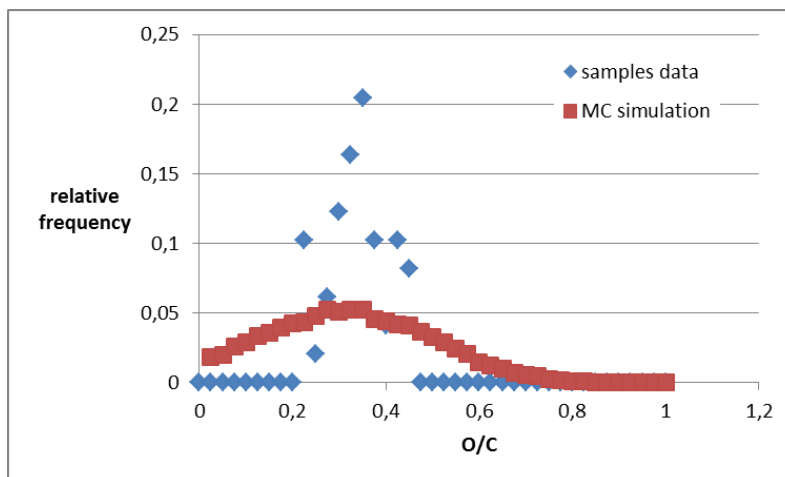


Figure 5.6 mass ratio O/C distribution with value of O₂ stack corrected

To appreciate the effect of data reconciliation on the output of Monte Carlo simulation a tentative correction of the oxygen concentration measured at the stack of the plant is been introduced. By reducing such variable of -0.5 percentage point the graph in figure 5.6 has been obtained. As it can be noticed the mean value of the two distribution is almost the same, whereas no modification has been introduced for what concern dispersion.

Lower heating value

The LHV in the model is predicted with the Boie’s equation, which result to be the correlation that best fits the data of the different coal types. Anyway the uncertainties associated with this correlation is very significant, and affect the variability of results for a large extent. The graph in figure 5.7 shows the mean LHV value on hourly basis predicted by correlation, with the associated uncertainty.

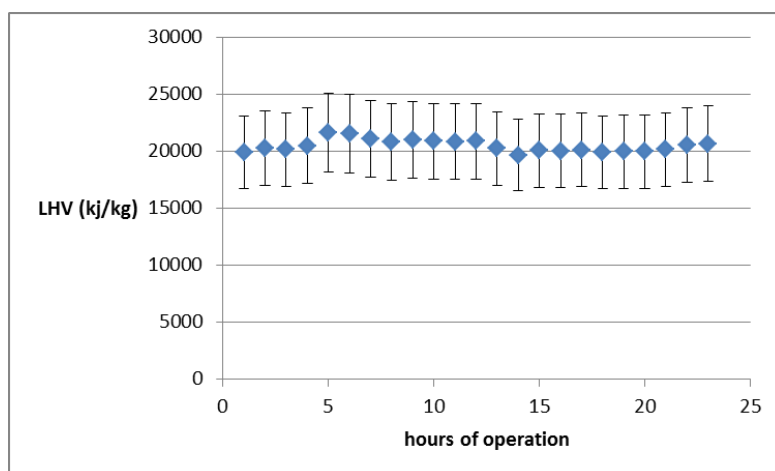


Figure 5.7 LHV in the hour of operation

Results

The mean LHV resulting from the simulation is almost constant in a range comparable with LHV typical of the type of coal of the test period. This is due to the uncertainty introduced by Boie’s correlation only for a minor extent, the main influence can be attributed to the uncertainties in the coal composition. To improve the accuracy of estimation rather than rely on an empirical correlation, the energy balance of the boiler could be required. With this approach the maximum uncertainty expected for the LHV is on the order of 2% [19].

Combustion power

Combustion power is calculated as the product between the LHV and coal flow rate. The combustion power is a key value in the estimation of the specific consumption.

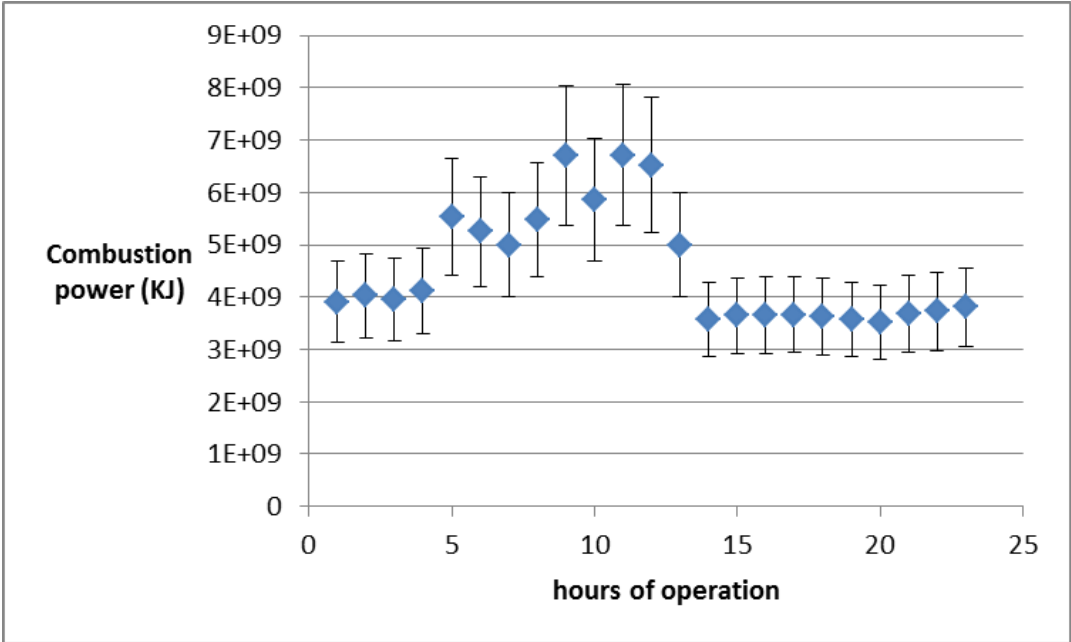


Figure 5.8 Combustion power during the hours of operation

The average standard deviation is of the order of the 20% of the mean values, circa the same of the LHV. Uncertainty on LHV is the main reason of this result.

Specific consumption

The specific consumption depends on the composition of coal, its flow rate and LHV, as well as on the power output of the plant. The specific consumption is expressed as dimensionless variable ($\text{kWh}_{\text{coal}}/\text{kWh}_{\text{el}}$). The graph in figure 5.9 shows the distributions of specific consumption for three different hours, when the power output of the plant was about 300, 460 and 600 MW respectively. As it can be seen the higher is the power output, the lower is the mean value of the specific consumption. The mean value decreases because at higher power output corresponds higher efficiency. The dispersion of the result in the three cases are comparable.

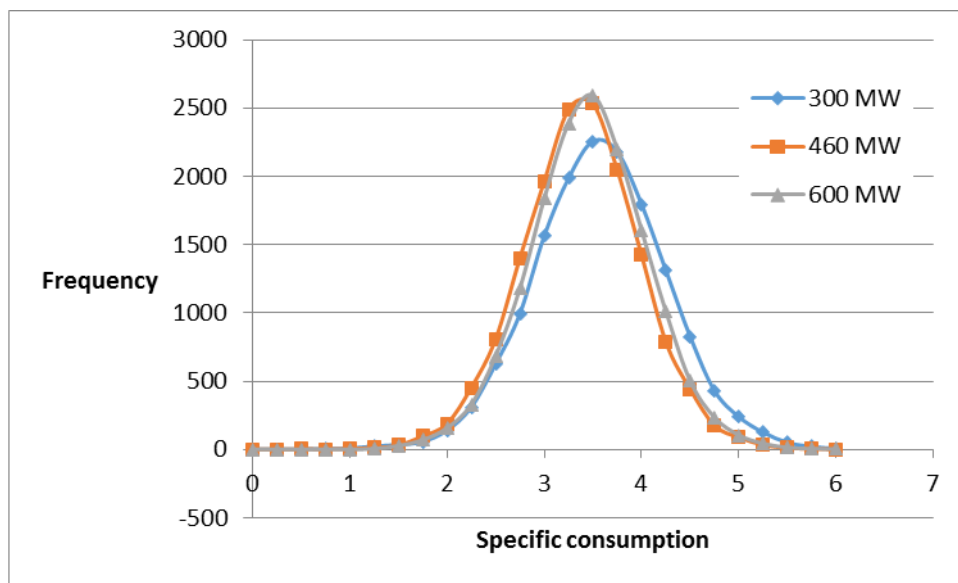


Figure 5.9 distributions of specific consumption for three different hours of the test period, characterized by different power output

ENEL provided the specific consumption data calculated by themselves, with their method. The graph in figure 5.10 compares ENEL specific consumptions with the values given by the Monte Carlo method.

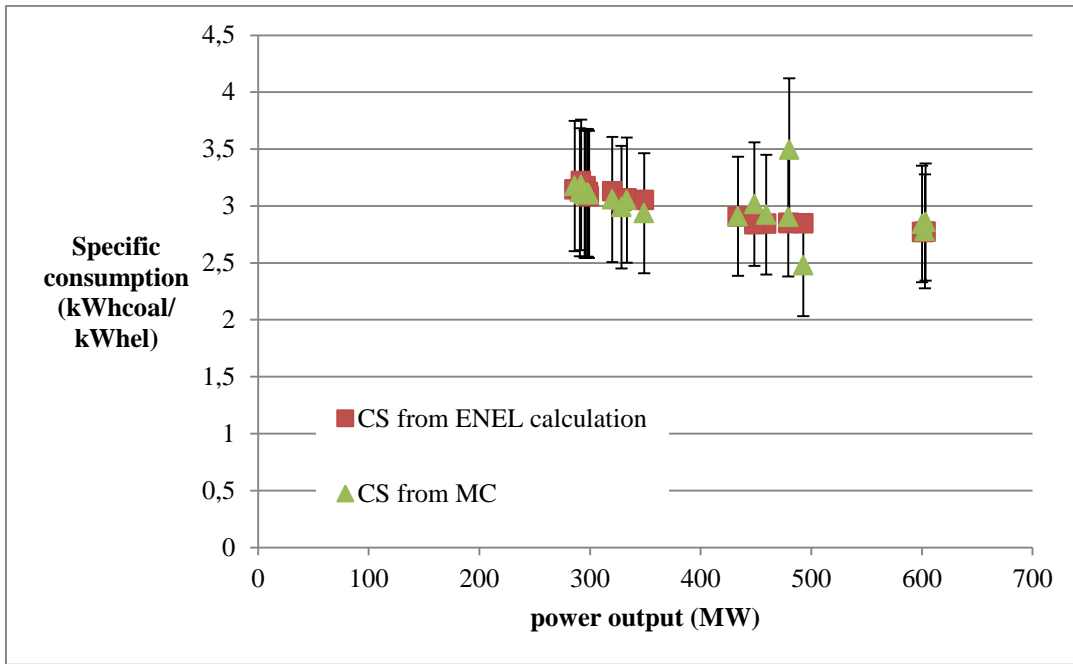


Figure 5.10 SC trend with power output for the ENEL data and the Monte Carlo results

We can notice some outliers, but in general the two result are aligned, with difference between 1% and 2%. The uncertainty associated with the result is between 15% and 20%. The differences between ENEL data and the monte Carlo mean vale can be better seen in the graph in figure 5.11.

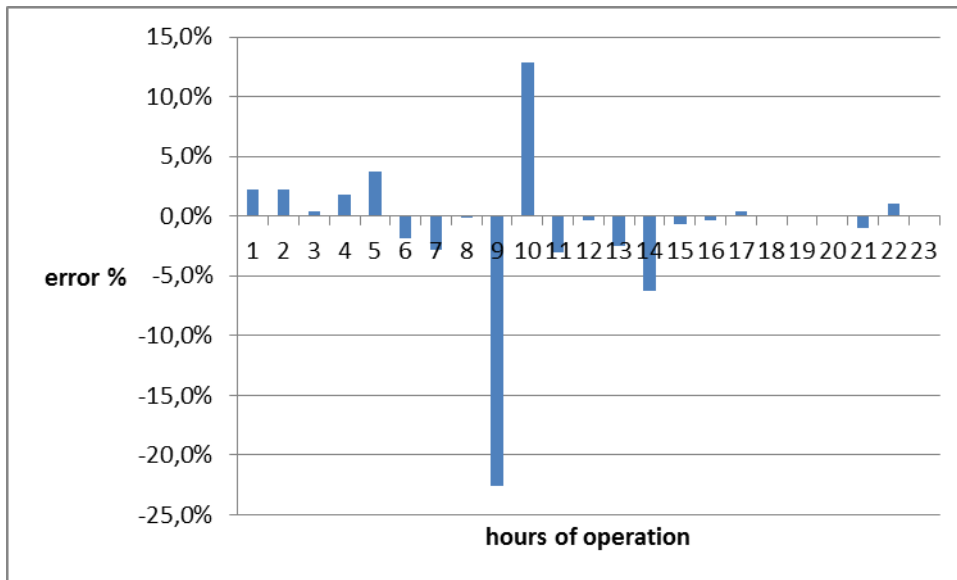


Figure 5.11 error between calculated SC and ENEL SC

Input variables analysis

For the sake of completeness, the following graph reports for each hour of test period the trends of the main input variables.

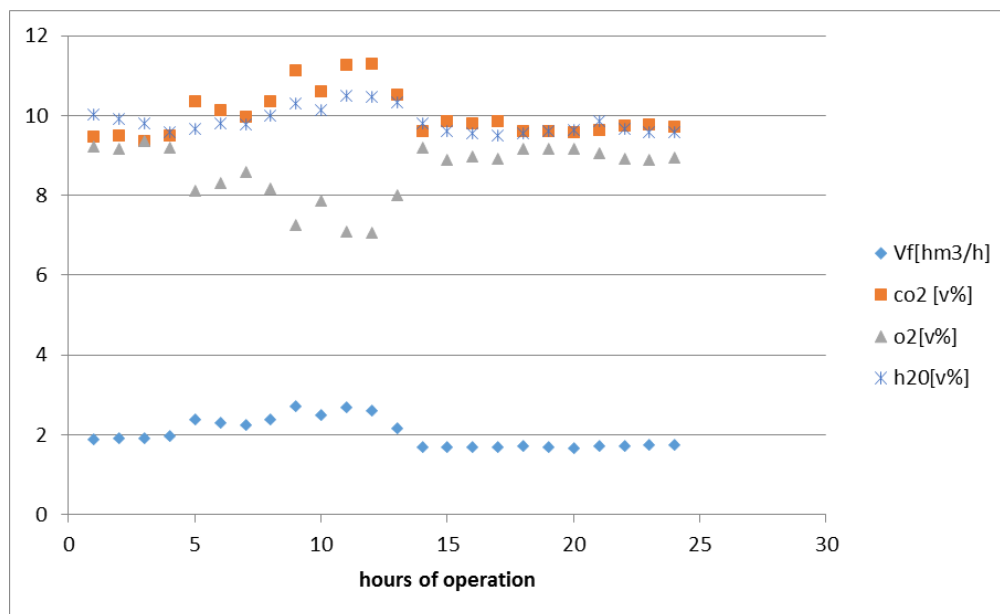


Figure 5.12 trends of the variables measure at stack during the test period

It is possible to observe that when the flowrate of flue gas is higher the concentration of O_2 is lower, and therefore the concentration of CO_2 and H_2O are also higher. These trends are justified by the higher efficiency of the boiler at higher load (i.e. with higher flowrate of flue gas), when the combustion is carried out with reduced excess air. The concentration of SO_2 at stack doesn't follow any trend, because it is mainly influenced by the dynamics of the De- SO_x system and its control algorithm.

Results based on the law of propagation of uncertainty

With the uncertainty propagation method, the focus is only the calculation of the specific consumption. The mean value of the sought variable is calculated starting from the mean values of all the input variables, whereas the associated uncertainties is determined through the formula of uncertainty propagation.

Table 5.1 summarized the specific consumption values calculated with this method and the associated uncertainties for each hour of the test period.

Table 5.1 specific consumption values calculated with uncertainty propagation method

hour	SC (KWhcoal/KWhel)	Error (KWhcoal/KWhel)	Error (%)
1	3,26	0,03	1%
2	3,19	0,03	1%
3	3,18	0,15	5%
4	3,12	0,14	4%
5	3,06	0,11	4%
6	3,03	0,12	4%
7	3,05	0,12	4%
8	3,03	0,11	4%
9	3,63	0,12	3%
10	2,58	0,09	3%
11	2,97	0,15	5%
12	2,78	0,14	5%
13	2,84	0,12	4%
14	3,02	0,14	5%
15	3,10	0,13	4%
16	3,12	0,14	4%
17	3,11	0,12	4%
18	3,11	0,12	4%
19	3,10	0,11	4%
20	3,12	0,09	3%
21	3,33	0,1	3%
22	3,32	0,13	4%
23	3,32	0,11	3%
24	3,32	0,05	2%

It is possible to notice that the mean values are aligned with those produced by the Monte Carlo method. Concerning the standard deviation, instead, the uncertainty propagation gives lower values. This highlights the non-linear feature of the studied problem and, therefore, the underestimation of the uncertainties produced by the conventional method of uncertainty propagation.

Results

The graph in figure 5.13 reports the results of the uncertainties propagation methods, in terms of specific consumption values and their standard deviation bars in comparison with the values of specific consumption calculated by ENEL. The situation is similar to the one predicted in figure 5.10.

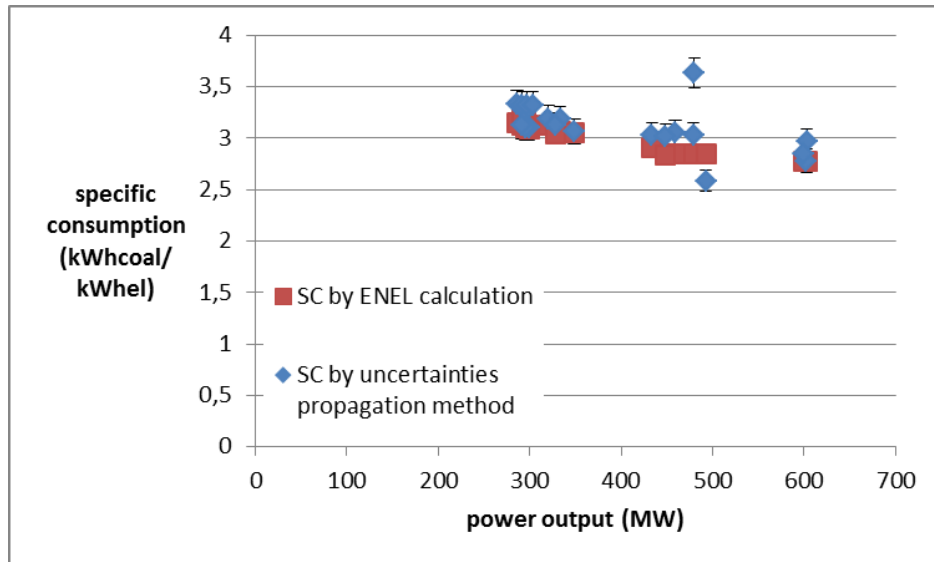


Figure 5.13 comparison between the SC values and their uncertainties determined through the uncertainty propagation method and the data from ENEL(including the plant power output)

The uncertainty on each independent variable gives a different contribution to the total uncertainty of the result. This is shown in the graph in figure 5.14, where the squares of such contributions to the square of the specific consumption uncertainties are reported.

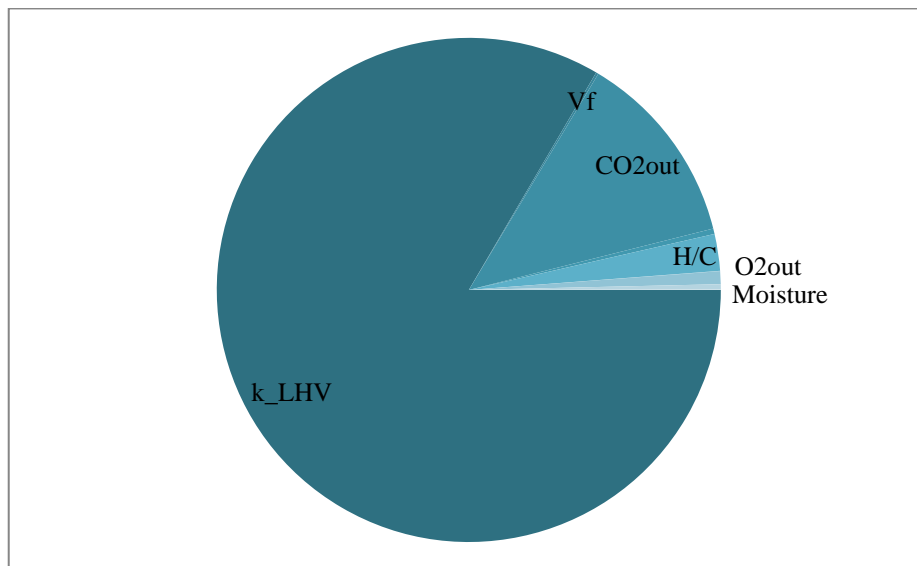


Figure 5.14 contribution to the square of the specific consumption uncertainties from the different input (independent) variables.

Results

The main source of uncertainty is the estimate of coal LHV. The second contribution is due to the uncertainty on the carbon dioxide concentration measure at stack.

To check how the uncertainty associated with LHV estimation influence the dispersion of the result also in the Monte Carlo method, the distribution of the specific consumption in two cases are compared: the base case, whit the uncertainty calculated from the data available and the second case, obtained using half of the uncertainty on LHV estimation.

The evidence that the main source of uncertainty is the LHV uncertainty is confirmed by the results of the Monte Carlo simulation: in the graph in figure 5.15 the standard deviation of the CS in the second case is circa half of the one in the base case.

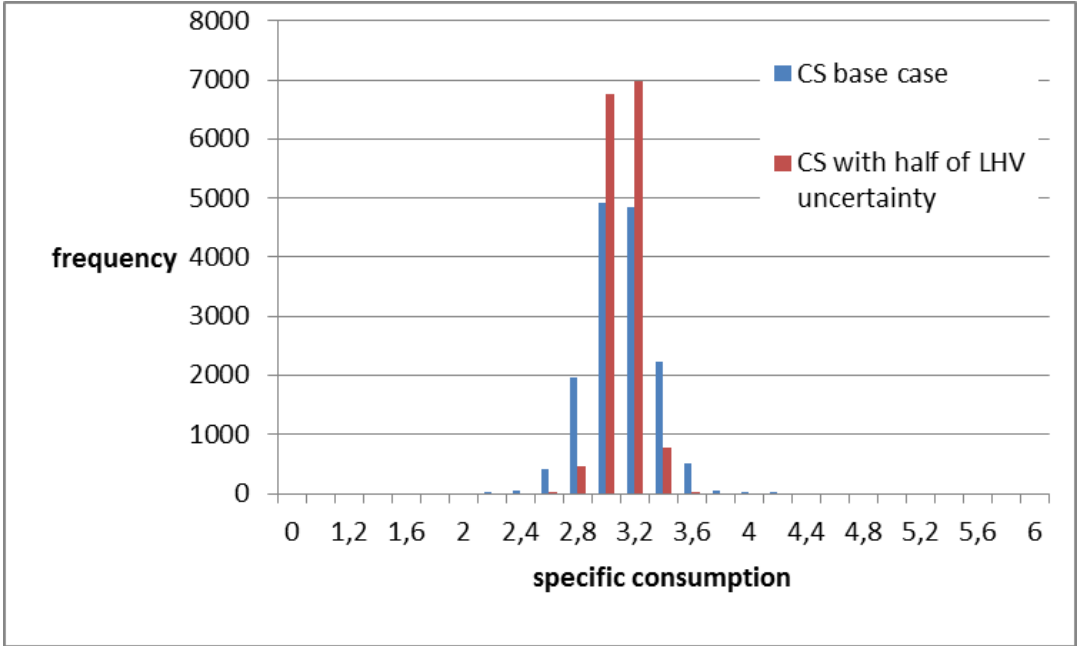


Figure 5.15 comparison between SC distribution in two differnt case: with the total LHV uncertainty and with half of its value

Chapter 6 Conclusion

This work has considered the study case of the coal-fired plant “Federico II” in Brindisi owned and operated by ENEL. The main goal was to investigate the potential of improving the plant performances by optimizing its control thanks to a new instrument installed at chimney: a laser-based meter of CO₂ concentration produced by Siemens.

ENEL uses the variable “specific consumption” as efficiency index of the plant. They calculate it by means of a proprietary method called “Economy online”, which does not require to know the concentration of CO₂ at the stack. In this work, the specific consumption has been calculated by solving mass and energy balances, which rely on the concentration of CO₂ at the stack, though Monte Carlo simulation. This approach was chosen in order to reliably quantify the uncertainty that affects the calculation result.

The inputs of the developed method are all independent variables, some of them measured at the stack (flue gas flowrate and species concentrations) whereas others are characteristics of the burned coal. Each of the former has been represented by means of a normal statistical distribution centered on the measured value and featuring a standard deviation coherent with the measurement uncertainty. For the latter, the parameters of the corresponding normal statistical distributions have been determined based on the data referred to a number of sample analyses. A few input variables are assumptions, for which reasonable mean values and ranges of variation have been defined and, then, used in terms of uniform statistical distributions.

Data on the LHV of the different types of burned coal have been used to test different empirical equations that correlate calorific value to composition: the correlation giving the best results on all types of coal has resulted to be the Boie’s equation, which has been adopted for all the subsequent evaluations.

The model solved with the Monte Carlo approach is composed of three balances:

- the carbon elemental balance from the burners to the stack;
- the sulfur-carbon elemental balance in the De-SO_x system;
- the overall balance of the “dry stoichiometric flue gas” from the burners to the stack.

The developed method has been applied on a test period of one day of operation, on hourly basis. For the same test period ENEL provided the values of specific consumption calculated with the “Economy online” method. The mean values of the Monte Carlo method results are in substantial agreement with the specific consumption data calculated by ENEL, nevertheless the standard deviations associated with such mean values highlight uncertainty of the order of 15%.

Among the various inputs, only a pair of redundant species of information are present: the oxygen content of the burned coal from the samples analysis, and the flowrate of flue gas at stack. Techniques to manage redundant information with Monte Carlo simulation have been sought in the literature, but no significant method was found. The lack of appropriate techniques to cope with this problem has been confirmed also by some experts in Statistics. Therefore, the use of the measured data at the stack of the plant has been preferred, and the data on coal oxygen content have been used just to check the coherence of the Monte Carlo results. This check evidenced some discrepancies, which can be explained with the possible presence of systematic errors in some measurements at the stack. For example, a systematic error of +0.5 percentage points in the measurement of oxygen concentration at the stack could explain the found discrepancies. In the scientific literature several data reconciliation methods are available to exploit data redundancy for reducing results uncertainty, but no one is based on Monte Carlo simulation. This is an area of investigation that deserves more efforts in future works.

For the purpose of comparison, the uncertainty affecting the value of specific consumption, calculated by means of mass and energy balances, has been quantify also based on the law of uncertainty propagation. Surprisingly, this conventional method significantly underestimates the uncertainty on the results with respect to the Monte Carlo simulation. This relevant discrepancy may be due to the non-linear feature of the studied problem. However, the conventional method highlights that the main contribution to the specific consumption uncertainty is given by the uncertainty in estimating the LHV based on coal composition. This evidence is confirmed also by the results of the Monte Carlo simulation, which have been obtained halving the uncertainty on LHV estimation.

Therefore, the first measure for improving the accuracy of the specific consumption estimate is to enhance the evaluation of the combustion power (i.e. the product of coal LHV and coal flowrate). The simplest way to achieve such a result is to evaluate the

Conclusion

combustion power based on a boiler energy balance. In this case, the role of the information regarding CO₂ concentration at the stack becomes absolutely minor, affecting also for a minimal extent the quantification of the stack loss at boiler outlet (through the heat capacity of flue gas).

List of symbols

$x_{O_{2stack,ai}}$	-, oxygen volumetric content at stack on “as is” basis
$x_{CO_{2stack,ai}}$	-, carbon dioxide volumetric content at the stack on “as is” basis
V_{fai}	Nm ³ /h, total flue gas flow rate at stack on “as is” basis
$x_{H_2O_{stack,ai}}$	-, water vapor volumetric content at the stack
$De-SO_x$	Desulfurization
SO_{2in}	mg/Nm ³ , Concentration of SO ₂ at De-SO _x system inlet
SO_{2out}	mg/Nm ³ , Concentration of SO ₂ at stack
alpha	-, Fraction of fuel ash to fly ash
exc	-, excess CaCO ₃ in De-SO _x system
LOI	-, Loss on ignition of fly ash
V_m	0.022414 Nm ³ /mol, Molar volume
C_c	Tons/h, Coal consumption
C.P.	kJ/h, Combustion power
S.C.	-, Specific consumption
$x_{O_{2stack,dry}}$	-, oxygen volumetric content at stack on dry basis
$x_{CO_{2stack}}$	-, CO ₂ volumetric content at stack on dry basis
V_f	Nm ³ /h, total flue gas flow rate at stack on dry basis, 0% oxygen content
S/Ca	-, Molar ration between sulfur and limestone in De.SO _x system reaction
σ	Standard deviation

List of acronyms

LHV	kJ/kg, Lower heating value
HHV	kJ/kg, higher heating value
MC	Monte Carlo
APC	Air pollution control
SCR	Selective catalytic reduction
SNCR	Selective non catalytic reduction
EoL	Economy on line
ASME	American society of mechanical engineers

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