# Improving Performances of a Cement Rotary Kiln: A Model Predictive Control Solution

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***Abstract*—In this work an advanced control system design aimed to the improvement of economic benefits and control performances of a cement rotary kiln located in an Italian cement plant is discussed. A Model Predictive Controller, together with other functional blocks designed to manage normal and critical situations, constitutes the core of the proposed strategy. Accurate identification procedures, aimed at obtaining accurate dynamical process models, have been performed. A suited cooperation of system modules and an ad hoc design of each of them allowed the meeting of control specifications, the increase of system reliability and the reduction of the standard deviation of critic process variables. In this way, the system can more safely operate closer to its operative bounds. The implementation of the proposed control system on a real plant has proven its soundness, leading to improvements in terms of energy efficiency, product quality and environmental impact, compared to the previous control system.**

***Index Terms*—cement rotary kiln, advanced process control, model predictive control, economic optimization, environmental emissions, process control**

## I. INTRODUCTION

In today's world, cement is the substratum for civil engineering and its applications. The world cement production has grown in a constant manner since the early '50s. In particular, in recent decades, there was an increasing need for innovations in the production chain, as well as an increased need for a high level of automation, also due to the complex chemical and physical processes involved [1].

In this context may be placed the process control optimization, which, by using advanced control strategies, has the task of finding a compromise between the economic goals and the productive ones. This idea has an enormous benefit: payback time is in the order of the weeks, or months, in opposition to the years required by a relevant replace of an old hardware unit [2]. This challenge has motivated the present work, which consists in the study, development and implementation of an advanced control system for the optimization of a rotary kiln process located in an Italian cement plant. For the formulation of the proposed system, Model Predictive Control (MPC) techniques have been adopted [3].

Model Predictive Control is an optimization-based closed loop control strategy, able to handle multi-input multi-output (MIMO) processes with constraints on the manipulated and controlled variables. Through the minimization of a cost function, it can also guarantee set-point tracking, while monitoring control efforts [4], [5].

The control system has been developed using a custom-made software: This choice was originally motivated by the need of not relaying on industrial and commercial products, in order to limit the economic burdens as well as to the need to customize the controller to specific needs of the system at issue.

In addition to the development of the Model Predictive Controller core module, the proposed control system has been equipped with other modules, at the scope to manage normal and critical situations. The system policy is based on the cooperation of these modules, which, together with an ad hoc module design, allowed the fulfillment of the required plant specifications.

The paper is organized as follows: in the Section II, after a brief introduction on the cement rotary kiln process, control specifications issues are defined. Section III describes the proposed advanced process control design. In Section IV, the control system results are discussed, through a comparison with the previous control structure performances. Finally, conclusions and future developments are reported in Section V.

## II. CEMENT ROTARY KILN CONTROL PROBLEM

### *A. A Briefly Description of the Process*

The cement is a hydraulic binder in the form of fine dust, inorganic and non-metallic. The fundamental component of the cement is the product of the baking of natural minerals, called clinker, which, combined with other components, gives rise to various types of cement. The clinker is made from lime, silica, alumina, iron and magnesium oxides, and other minor parts.

This work is focused on the clinker production phase of a dry process cement industry, a highly energy consuming process. The clinker process is the most important subpart of the cement production, in terms of potentially polluting emissions, quality and cost of the product. In Fig. 1, the clinker production process is schematically represented.

The raw meal, before the introduction in the rotary kiln, is preheated through a suspension pre-heater, while it is up in the air with exhaust gas of the combustion from the

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kiln. In the suspension pre-heater, composed by four cyclones stages, the heat transfer rate is increased, allowing the enhancement of the heat exchange efficiency. An induced draft (ID) fan pulls exhaust gas of the combustion from the kiln, which flows through the cyclones from the bottom upwards. Raw meal, finely milled, is mixed with the exhaust gas upstream.

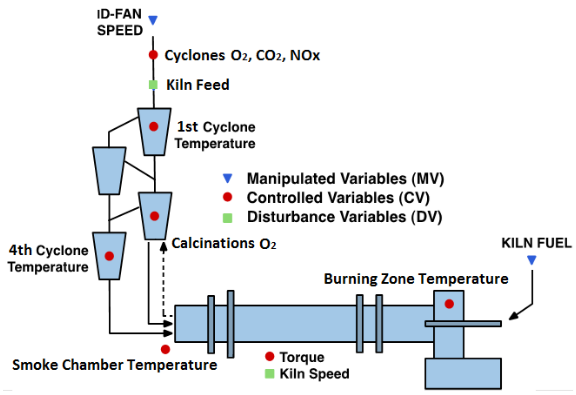


Figure 1. Schematic representation of the cement kiln unit.

A rotary kiln is a steel cylinder that rotates around its axis. The kiln is horizontally sloped of about 2.5%-4.5%, allowing processed mixture to move along it. The kiln fuel is introduced through a burner placed at the end of the kiln. Raw meal, after its entry in the furnace, is subjected to calcination, solid phase reactions and clinkering [1], [2], [6].

### B. *Control Specifications*

The introduction of an Advanced Process Control (APC) system in a clinker production unit of a cement plant must lead to productivity and efficiency increase, while assuring the desired quality of byproducts; in addition, pollution impact should be kept within given limits and fuel consumption should be minimized. For the attainment of such objectives, an APC has to assure proper chemical and physical reactions, complying with environmental, thermo-dynamical and mechanical constraints [7], [8].

In a cement rotary kiln, the main thermo-dynamical constraints concern cyclones, smoke chamber and burning zone temperatures, together with oxygen concentration, while environmental ones refer to carbon dioxide and nitrogen oxides levels. Finally, mechanical constraints involve kiln torque. Furthermore, “quality constraints” are related to free lime analysis, performed on clinker samples, collected at the end of the cement rotary kiln [1], [2].

After the definition of the just mentioned project specifications, performed in cooperation with plant managers, an accurate study of the chemical and physical phenomena involved in the considered cement rotary kiln has been conducted. In addition, with the support of plant operators and engineers’ interviews, a preliminary plant inspection has been accomplished in order to investigate about plant sensors/analyzers equipment, local control loops and typical operations in the normal process driving. From this study, the fundamental process variables to be kept under control were identified: upstream (cyclones) and calcination area oxygen concentrations analysis, carbon dioxide and nitrogen oxides levels analysis, together with the temperatures at the top (first cyclone) and at the bottom (fourth cyclone) of the pre-heater tower. Finally, smoke chamber temperature, kiln torque and burning zone temperature have been chosen as furnace variables. An important feature of the available set of analyzers lies in the presence of oxygen concentration analysis at the calcination area: this analyzer guarantees a greater feedback from the combustion area, compared to the classical cyclones oxygen analyzer, which is positioned upstream; in fact, given its upstream location, this analyzer, may cause delayed responses and inaccuracies on the combustion control. In case of bad measurements of oxygen concentration of the calcination area, the redundancy of the oxygen analyzers is exploited temporarily controlling the kiln using measurements from the cyclones oxygen data analyzer. As control inputs ID fan speed and fuel charge rate have been selected. In the plant configuration, fuel charge rate is regulated through a PID controller, while ID fan speed acts directly on a valve. Common industrial terminology adopts the expressions Manipulated Variable (MV) and Controlled Variable (CV) to indicate input and output variables, respectively. Furthermore, two measurable input Disturbance Variables (DVs) have been considered, i.e. input variables that are not under direct control of the proposed APC system: meal flow rate has been set as DV because of the management choice of keeping this variable under the direct control of operators. Kiln speed, that influences rings clogging, has been set as a second DV. In the plant configuration, meal flow rate is regulated through a PID controller, while kiln speed acts directly on a valve. In Table I-Table III MVs, CVs and DVs are summarized. In Fig. 1, sensors and actuators positions are depicted.

Closed loop tests have been performed in order to achieve accurate dynamical models that relate the process variables to the controller outputs. A black box approach for the identification procedure has been adopted obtaining first order plus dead time (FOPDT) and second order plus dead time (SOPDT) models [9], [10].

TABLE I. MANIPULATED VARIABLES (MVS)

| TAG | Variable Name / Acronym | [Units] |
|---|---|---|
| K01IDF_S | ID Fan Speed – ***Fan Speed*** | *[%]* |
| K02F_CR | Coal - ***Kiln Fuel*** | *[Kg/h]* |

TABLE II. CONTROLLED VARIABLES (CVS)

| Sensor / Analyzer | TAG | Variable Name / Acronym | [Units] |
|---|---|---|---|
| Analyzer | A01UO2_P | Cyclones Oxygen - $O_{2Cy}$ | [%] |
| Analyzer | A01DO2_P | Calcination Oxygen - $O_{2Ca}$ | [%] |
| Analyzer | A02CO2_P | Carbon Dioxide- $CO_2$ | [%] |
| Analyzer | A03NOX_C | Nitrogen Oxides - $NO_x$ | *[ppm]* |
| Sensor | C01C_T | 1st Cyclone Temp - $T_{1Cy}$ | [℃] |
| Sensor | C04C_T | 4th Cyclone Temp - $T_{4Cy}$ | [℃] |
| Sensor | K05SC_T | Smoke Chamber Temp - $T_{Sc}$ | [℃] |
| Sensor | K06_T | Kiln Torque - $M_t$ | [%] |
| Sensor | K07BZ_T | Burning Zone Temp - $T_{Bz}$ | [℃] |

TABLE III. DISTURBANCE VARIABLES (DVS)

| TAG | Variable Name / Acronym | [Units] |
|---|---|---|
| K03M_CR | Meal Flow Rate - ***Meal*** | *[t/h]* |
| K04R_S | Rotation Kiln Speed - ***Kiln Speed*** | *[rpm]* |

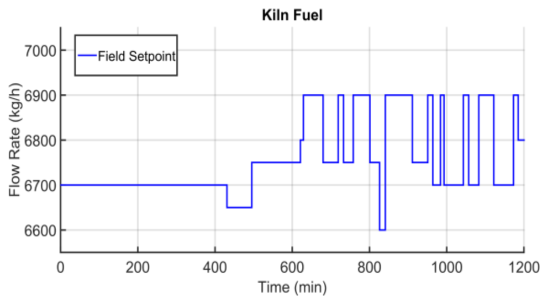


Figure 2. Kiln fuel during step test phase.

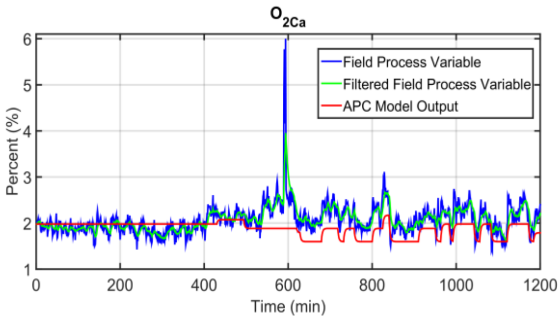


Figure 3. Calcination Oxygen during Kiln fuel step test phase.

The measurements sample time adopted in the identification phase has been one minute; consistently, also APC system cycle time has been set at one minute.

In Fig. 2, fuel charge rate signal during the step test phase is shown; in Table IV, an exemplification of the moves executed on fuel charge rate is given that reports on variations and time elapsed between two consecutive moves. Fig. 3 shows one of the controlled variables, i.e. the calcination oxygen ($O_{2Ca}$), during the step test phase concerning the manipulation of the fuel charge rate. The exploited measurements for identification are the process variables filtered by a first order exponential filter (green line), with a time constant of six minutes. Red line shows the APC prediction obtained from the FOPDT model resulting from the identification phase, and used in the control formulation.

In Fig. 4, the calcination oxygen model mismatch calculated as the difference between the filtered field $O_{2Ca}$ measurements and its predicted trends is shown as blue line; green line represents the filtered model mismatch (the same filter used in the identification phase has been adopted). This filtered model mismatch has been used in the APC formulation.

In the considered cement plant, laboratory analyses on clinker samples, collected at the end of the cement rotary kiln, are carried out every four hours. Free lime values ranging from 0.4% to 1% are considered acceptable. Outside this range, critical situations such as over-burning or cooling may occur. In the actual first release of the realized APC system, this analysis has been exploited to modify suitably fuel charge rate constraints, as will be shown below.

TABLE IV. EXAMPLES OF FUEL CHARGE RATE MOVES DURING STEP TEST PHASE

| Move Number | Move Magnitude [Kg/h] | Wait [min] |
|---|---|---|
| 1 | -50 | 64 |
| 2 | +100 | 126 |
| 3 | +50 | 8 |
| 4 | +100 | 51 |
| 5 | -150 | 39 |
| 6 | +150 | 14 |
| 7 | -150 | 25 |
| 8 | +150 | 43 |
| 9 | -150 | 25 |
| 10 | -150 | 15 |

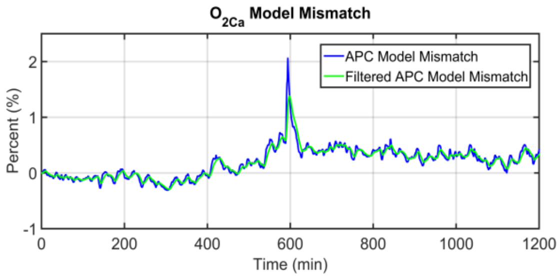


Figure 4. Calcination oxygen model mismatch.

## III. ADVANCED PROCESS CONTROL DESIGN

The basic architecture of the proposed APC system (for a generic control instant $k$) is shown in Fig. 5. Model Predictive Control (MPC) techniques have been adopted for controlling the rotary kiln process. MPC is an advanced control strategy, particularly suited for industrial control applications, characterized by multi-input multi-output processes with constraints on the MVs and the CVs. Through an on line optimization, set-point tracking is performed based on CVs and MVs trends predictions, while monitoring control efforts [11], [12]. The Model Predictive Control uses a mathematical model of the process in order to predict the dynamic behavior of the system variables [13]. Basic MPC consists of a Dynamic Optimizer (DO block in Fig. 5) which, through the “receding horizon idea”, computes the future control moves [3], [4], and [5]. The basic MPC-DO module computes the optimal future control moves by the minimization of a quadratic cost function, subject to linear inequality constraints. The cost function and the constraints adopted are reported in [3]. An important remark is the introduction of a slack variable for each CV, useful for infeasibility handling: it eventually allows some CVs constraint to be relaxed. The insertion of this variables vector in the DO cost function is suitably weighted by a matrix $\rho$, while its inclusion in DO linear inequality constraints takes place through weighting parameters named “Equal Concern for Relaxation” (ECR) [14]. The design choice of assigning “independent” CVs slack variables on the Dynamic Optimizer is useful to avoid “induced” relaxations that could not be prevented by a sole weighting of ECR values: “induced” relaxations can affect controller and process performances and possibly its safety causing, for example, unnecessary prolonged constraints violation or a less prompt response of the system. ECR parameters, in cooperation with $\rho$ matrix, allow assigning a priority ranking in constraints relaxation. For example, keeping both oxygen variables within their operative range has higher priority than the satisfaction of nitrogen oxides constraints while nitrogen oxides operative limits satisfaction is more stringent than the observance of temperature constraints.

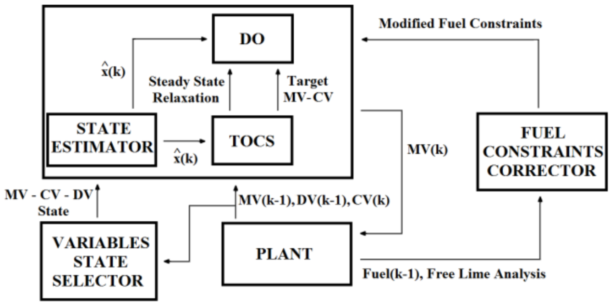


Figure 5. APC system basic architecture.

In the proposed control system, the only economic variable is the fuel charge rate that, together with ID fan speed, must guarantee a "zone control" for all CVs: no trajectory tracking is performed for any of the controlled variables, limiting the DO controller action to the satisfaction of the given CVs boundary constraints. The calculation of DO fuel charge rate steady state target is executed by a Target Optimization and Constraint Softening (TOCS) module (see Fig. 5): this module, searching for CVs and MVs optimal steady state targets, attempts to fulfill DO steady state constraints [5], [15].

A linear cost function subject to linear constraints is adopted within the TOCS module. The cost function is, for a generic control instant $k$:

$$\begin{aligned} V_{ss}(k) = {c_{MV}}^T \cdot \Delta MV_{ss} + {c_{CV}}^T \cdot \Delta CV_{ss} + \\ + {\rho_{ss\_min}}^T \cdot \varepsilon_{ss\_min} + {\rho_{ss\_max}}^T \cdot \varepsilon_{ss\_max} \end{aligned} \tag{1}$$

where $\Delta MV_{ss}$ and $\Delta CV_{ss}$ are the optimal steady state moves to be computed, $\varepsilon_{ss\_min}$ and $\varepsilon_{ss\_max}$ are the slack variables for the possible CVs constraints relaxation, $\rho_{ss\_min}$ and $\rho_{ss\_max}$ are suitable weighting vectors and $c_{MV}$ and $c_{CV}$ are the economic cost weights of the MVs and of the CVs, respectively. According to DO module, among economic cost weights, only $c_{MV}$ related to fuel charge rate is non zero (positive value in the minimization problem).

The linear constraints are:

$$\begin{array}{rl} \text{i.} & lb_{du\_ss} \le \Delta MV_{ss} \le ub_{du\_ss} \\ \text{ii.} & lb_{u\_ss} \le MV_{ss} \le ub_{u\_ss} \\ \text{iii.} & MV_{ss} = MV(k-1) + \Delta MV_{ss} \\ \text{iv.} & \Delta CV_{ss} = G \cdot \Delta MV_{ss} \\ \text{v.} & CV_{ss} = \widehat{CV}\left(k + H_p \middle| k\right)\big|_{\Delta\mathcal{U}(k)=0} + \Delta CV_{ss} \\ \text{vi.} & lb_{y\_ss} - ECR_{lb\_ss} \,.\, \varepsilon_{ss\_min} \le CV_{ss} \le \\ & ub_{y\_ss} + ECR_{ub\_ss} \,.\, \varepsilon_{ss\_max} \\ \text{vii.} & \varepsilon_{ss\_min} \ge 0;\ \varepsilon_{ss\_max} \ge 0 \end{array} \tag{2}$$

where $MV_{ss}$ and $CV_{ss}$ are the optimal steady state values for the MVs and CVs, i.e. the end terms of DO MVs and CVs reference trajectories: they are obtained applying the optimal steady state moves $\Delta MV_{ss}$ and $\Delta CV_{ss}$ to $MV(k-1)$ and $\widehat{CV}\left(k + H_p \middle| k\right)\big|_{\Delta\mathcal{U}(k)=0}$, i.e. to the "free predictions" of MVs and CVs at the end of the prediction horizon $H_p$. $\widehat{CV}\left(k + H_p \middle| k\right)\big|_{\Delta\mathcal{U}(k)=0}$ takes into account disturbance variables information, in a feedforward sense. $G$ is the input-output gain matrix. For each variable $v$, $lb_v(i)$ and $ub_v(i)$ vectors are the lower and upper bounds and $ECR_{lb\_ss}$ and $ECR_{ub\_ss}$ matrices assign, in cooperation with $\rho_{ss\_min}$ and $\rho_{ss\_max}$ vectors, a priority ranking in CVs steady state constraints relaxation, according to DO module.

TOCS formulation provides a single slack variable for each output variable constraint; in this way, an accurate management of the constraint relaxations can be performed. As additional feature, a suitable pre relaxation of the operational constraints is forwarded by TOCS to the DO module in addition to steady state targets. This feature guarantees consistency between steady state targets and constraints. In situations where the desired plant configuration is not feasible with respect to steady state models as derived from identification phase, a non zero pre relaxation related to one or more CVs is imposed by TOCS.

In order to guarantee consistency between DO and TOCS modules, the prediction horizon $H_p$ has been set to 120 minutes, thus allowing steady state reaching for all CVs. Moreover, steady state step max constraints (see point i in (2)) on MVs steady state moves have been set coherently with the control horizon (10 moves [16]) set in the DO formulation.

The feedback strategy adopted in the proposed APC system takes into consideration the model mismatch (eventually filtered) [17] calculated as explained in the previous section. The state estimator module (see Fig. 5) computes the state evolution in accordance with state space models derived from identification phase, allowing the model mismatch treatment in the DO and TOCS modules.

In the APC system, two other key modules are proposed in addition to the DO, TOCS and state estimator just described: a variables state selector and a fuel constraints corrector (see Fig. 5). At every APC cycle, plant operators can modify the problem formulation acting on a variable on/off state selector thus determining which MVs, CVs or DVs must be considered in DO and TOCS problems solution. In addition to the operators variable selection, based on process driving requirements, situations like bad data detection (e.g. sensors spikes) and local loops deficits (e.g. deviation of the process variable from the set point of its control loop) are handled. The fuel constraints selector plays an important role on the quality specification: as stated in the previous section, in the considered cement plant, every four hours a new clinker free lime laboratory analysis is available. This information has been exploited in order to avoid overburning or cooling, that are critical conditions for clinker quality. Heuristic rules to be used for fuel charge rate constraints adjustments have been designed which are reported in Table V. When a new free lime value is available, new charge rate constraints adjustments are eventually considered as suggested from the lookup table (Table V). The actual application of these constraints variations takes into account the actual fuel charge rate value. Two possible situations may arise:

- Fuel Charge Rate inside the Operating Constraints: In this case the constraint to update is directly updated according to the variation as resulting from the lookup table.

TABLE V. HEURISTIC RULES FOR FUEL CHARGE RATE CONSTRAINTS ADJUSTMENT

| Lower Bound Change [Kg/h] | Free Lime Analysis [%] | Upper Bound Change [Kg/h] |
|---|---|---|
| -100 | 0.1 | 0 |
| -100 | 0.2 | 0 |
| -50 | 0.3 | 0 |
| 0 | 0.4 | 0 |
| 0 | 0.5 | 0 |
| 0 | 0.6 | 0 |
| 0 | 0.7 | 0 |
| 0 | 0.8 | 0 |
| 0 | 0.9 | 0 |
| 0 | 1 | 0 |
| 0 | 1.1 | +50 |
| 0 | 1.2 | +100 |
| 0 | 1.3 | +150 |
| 0 | 1.4 | +200 |
| 0 | 1.5 | +250 |

- Fuel Charge Rate outside the Operating Constraints: In this case, the constraint to update is firstly aligned to the actual fuel charge rate value, and then updated according to the variation as resulting from the lookup table.

Consequently to the lower or upper bound fuel charge rate variation, some CVs constraints may need to be adjusted: TOCS module, when the new constraints setup becomes available, eventually pre relaxes some of the CVs constraints, thus allowing to have a "well posed" DO steady state configuration. In this way, consistency between steady state constraints and optimal targets is assured. If from TOCS computation pre relaxations are required, plant operators are informed by a visual and acoustic alarm indicating the necessary CVs constraints changes. Therefore, operators can modify the interested operative bounds so to restore a correct constraints configuration.

## IV. ADVANCED PROCESS CONTROL RESULTS

The proposed APC has been installed on an Italian cement plant replacing a previous manual conduction of standard PID loops; it has been implemented on a SCADA system [18] that manages the rotary kiln. Fig. 6 shows the probability density function (PDF) of three critic kiln process variables before and after the APC activation: The specific consumption, the $O_{2Ca}$ and the $NO_x$. The performances of the APC system are compared to that of the previous standard PID controller. The results depicted in Fig. 6 refer to a period of approximately three weeks before and four weeks after the APC activation, respectively. APC main contribution is the reduction of the standard deviation of the most critic process variables, such as $NO_x$ and $O_{2Ca}$. Consequently, the system can more safely approach its operative constraints. This has contributed to the achievement of energy efficiency and to the reduction of the specific kiln consumption, while monitoring quality specifications. Fig. 7 shows examples of free lime analysis before and after APC activation, with similar plant boundary conditions.

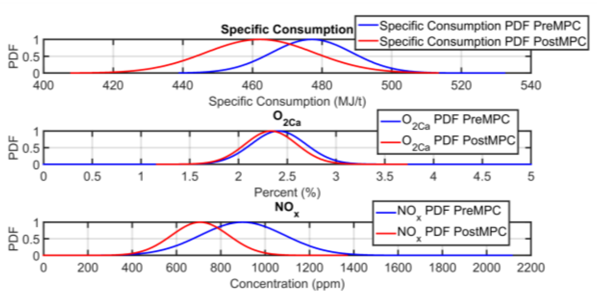


Figure 6. Specific consumption, calcination oxygen and nitrogen Oxides Probability Density Function Pre and Post MPC.

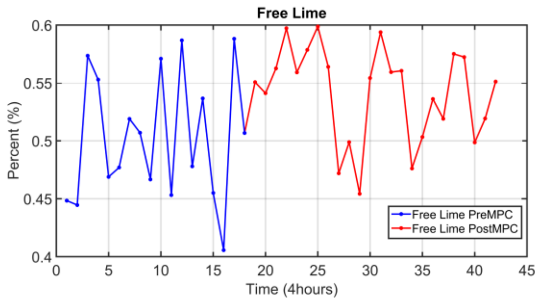


Figure 7. Free lime analysis Pre and Post MPC.

Additional advantage gained with the implementation of the APC system is the reduction of the environmental impact in term of chemical emissions, i.e. of average nitrogen oxides and oxygen concentrations.

The overall results obtained after approximately a year since APC first start up, can be summarized as in the following:

- 4.5% average reduction of $O_{2Ca}$ concentration with a standard deviation reduction of about 6%;
- 20% average reduction of $NO_x$ concentration with a standard deviation reduction of about 32%;
- 2% average reduction of the specific consumption;
- 7% average increase of the free lime;
- 86% controller uptime.

For the computation of the average specific consumption, coal heating power and meal free lime has been taken into account. Finally, with regards to the computation of the controller uptime, this does not include APC shut down situations like cyclones cleaning and raw mill stop.

## V. CONCLUSIONS

An APC system has been implemented on a rotary kiln placed in an Italian cement plant, in order to improve performances and efficiency, reduce energy consumption and costs thus gaining addition Government benefits. After initial phases of plant inspection and pre tests, followed by identification procedures, aimed at obtaining accurate dynamical process models, a tailored design step has been performed. At the basis of the proposed architecture lies the adoption of an MPC strategy for attaining an optimal compromise while searching between conflicting specifications, i.e. maximization of the productivity, minimization of fuel consumption and monitoring of the pollution impact and of the product quality. For the fulfillment of these objectives, MPC module cooperates with other two fundamental blocks, useful, for example, to detect abnormal situations or to exploit quality measurements, respectively.

The system is actually in use in an Italian cement plant providing benefits to both customers and environment. Possible future developments may concern the design of a free lime estimator (“soft sensor”), in order to conduct the system closer to the free lime upper bound, guaranteeing further improvements on the conduction of the plant and on energy saving requirements.

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