Advanced Process Control to Meet the Needs of the Metallurgical Industry

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Advanced process control and optimization systems are essential for the continued profitability of modern cement, mineral and metallurgical plants, due to the more stringent market requirements on costs, quality, environmental legislation and the increasingly competitive market situation. One of the methods of choice for performance improvement is an advanced process control and optimization system, based on artificial intelligence and model based control. These mathematical tools are complemented with process knowledge and project experience to generate a plant "autopilot", able to drive the installations at its best for long periods of time. This paper presents a general method for control and optimisation of industrial equipments like kilns, mills and furnaces. The basic idea is to use model predictive control as control synthesis technology and to represent the equipment or plant under consideration as a Mixed Logical Dynamic system, i.e., systems evolving according to continuous dynamics, discrete dynamics, and logical rules. In addition, the success of the implementation relies heavily on the usage of fuzzy control and neural networks. These technologies are used to provide robust process indicators or so called "soft sensors" to the model predictive controllers. These process dependent rules, which are designed or "trained" for each specific application, use all the available information to produce reliable signals of variables which are difficult or impossible to measure at high sampling rates. In particular, they detect faulty signals and adapt to the new situation automatically. The paper illustrates the method on the case of (cement, alumina, lime, titanium) kiln control and the scheduling of a synthetic rutile refinery.

Keywords:

Mixed Logical Dynamic system – Soft sensors – Metallurgical plants – Kiln control – Rutile refinery

Moderne Prozesssteuerung für die Hüttenindustrie

Systeme zur erfolgreichen Prozesskontrolle und -optimierung sind heute in modernen Zement-, Aufbereitungs- und metallurgischen Anlagen unerlässlich, um den stetig steigenden Anforderungen des Marktes bezüglich Kosten und Qualität, der Umweltgesetzgebung und dem Konkurrenzdruck im Markt begegnen zu können. Der Beitrag präsentiert eine allgemeine Methode zur Prozesskontrolle und -regelung, die mathematische Elemente mit praktischer Erfahrung kombiniert und daraus eine automatische Prozesssteuerung ableitet.

Schlüsselwörter:

MLD-System – Soft Sensors – Metallhütten – Ofenkontrolle – Rutilsynthese

Commande de processus avancée pour satisfaire aux exigences de l'industrie métallurgique

Control avanzada de procesos para satisfacer las necesidades de la industria metalúrgica

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1 Introduction

More stringent market requirements on costs, quality, environmental legislation and the increasingly competitive market situation puts energy intensive industry under pressure to leverage its asset management, increasing profitability. Furthermore, globalization influences the industry leading to the implied requirement for optimization of resources and production facilities. In this context, advanced process control and optimization systems is helping the modern cement, mining and metallurgical industry in its quest for higher profitability.

Industrial practice shows that the method of choice for design of robust advanced process control and optimization systems is to mix the best properties of "Artificial Intelligence" like Fuzzy Logic and Neural Network, with elements of the so called "Model Based Control" like Extended Kalman Filters and Model Predictive Control. These mathematical tools are complemented with process knowledge and project experience to generate plant "autopilots", able to drive the installations at its best for long periods of time. In the ideal case, these tools are brought together into one single real-time software environments that allows for fast control strategy development and make easy the design of the human-machine interfaces. See [1] for one of these industrial software systems.

The benefits from these systems are obtained due to the following mechanism (Figure 1):

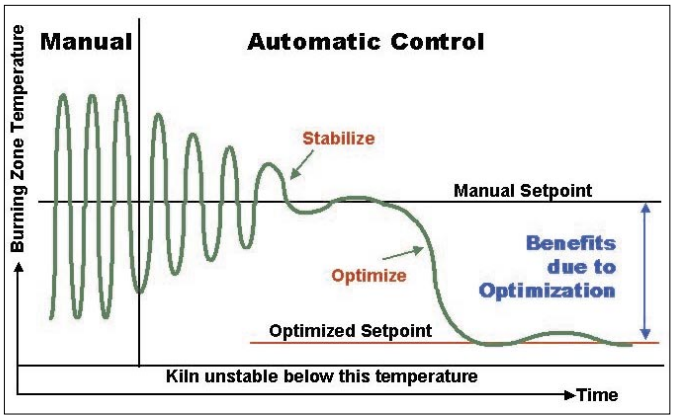

Fig. 1: Mechanism by which advanced process control produces benefits

- Enabled by the consistent application of the best control policies, a strong reduction in variance of the key process parameters is achieved.
- This allows driving the process targets closer to the limits,
- This means better economical performance and better asset utilization.

This paper presents a general method for control and optimisation of industrial equipments like kilns, mills and furnaces. The basic idea is to use model predictive control as control synthesis technology and to represent the equipment or plant under consideration as a Mixed Logical Dynamic system, i.e., systems evolving according to continuous dynamics, discrete dynamics, and logical rules. In addition, the success of the implementation relies heavily on the usage of fuzzy control and neural networks. These technologies are used to provide robust process indicators or so called "soft sensors" to the model predictive controllers. These process dependent rules, which are designed or "trained" for each specific application, use all the available information to produce reliable signals of variables which are difficult or impossible to measure at high sampling rates. In particular, they detect faulty signals and adapt to the new situation automatically. The paper illustrates the method on the case of (cement, alumina, lime, titanium) kiln control and the scheduling of a synthetic rutile refinery.

The paper is organized as follows. Section 2 contains a brief introduction of the mathematical techniques needed and how they interact to produce an efficient design technology. Further, Section 3 and 4 present application examples in the cement and metals industry, respectively. Section 5 summarizes the results and indicates directions for further applications.

2 Control technology elements

Neuro-Fuzzy techniques and Model Predictive Control (MPC) are well known paradigms for control design, while Mixed Logical Dynamic systems represent a relatively new method created in the 90s. This chapter introduces the basic facts and indicates references for further reading. The chapter will also show how these elements are integrated to produce a systematic framework for control strategy and deployment.

2.1 Fuzzy Logic and neural networks

One of the main strengths of the control design technology being described in this paper is the integration of Artificial Intelligence tools for the development of the application. Indeed, on the one hand, fuzzy logic inference systems incorporate human knowledge to make and implement effective decisions during the process. On the second hand, neural networks are used to learn relationships between key process variables. Moreover, they adapt themselves to cope with changing process conditions. The integration of these complementary control techniques, coupled with extensive process experience and expertise, allows the engineering of powerful robust solutions, which provide substantial financial benefits to the factory for extended periods of time.

The applications presented in this paper use Neuro-Fuzzy ideas to construct so called "soft sensors". This technique is applied when it is impossible or difficult to physically measure a process variable that is important for the control and optimisation of the process. For instance, in mineral processing, an obvious example to be used in grinding is predicting particle size average as a function of the mill state and history. Another case would be the construction of free lime soft sensors for cement and lime kiln control. Yet another example is assessing the temperature distribution of a kiln or furnaces in a continuous manner.

Another important use of soft sensors is to provide a back-up for critical process measurement devices. In case of failure of critical process measurements, a soft sensor can provide the control strategy with a usable estimate of the missing measurement. This allows the control and optimising system to continue to work to its objectives while the failed device is repaired.

Finally, it is possible to develop numerous Neuro-Fuzzy applications to predict the same magnitude, but using different process variables as inputs. This allows for a situation where the different Neuro-Fuzzy predictions compete for the right to be used in the developed control and optimising strategy. This ensures that the best prediction is always used. This competition for the right to influence the control strategy is a powerful tool.

As the process conditions change, the Neuro-Fuzzy applications are able to adapt. This ability ensures that the prediction is relevant to the changing process conditions. By tightly integrating Neural Networks with Fuzzy Logic systems, the latter is able to "reason" on the prediction and to decide on the appropriateness of using the prediction. This ensures that only sensible changes are fed through to the process.

2.2 Model Predictive Control

Model Predictive Control (MPC) is based on the so called receding horizon philosophy, i.e., a sequence of future optimal control actions is chosen according to a prediction of the (short to medium term) evolution of the system during the interval $[t, t + T]$, where t is the current time and T is some application dependent prediction horizon length. The first term of the sequence is then applied to the

plant. When measurements (or new information) becomes available a new sequence, which replaces the previous one, is determined. Each sequence is computed by means of an optimisation procedure, which takes into account two objectives:

- optimise the performance and
- protect the system from constraint violations.

In mathematical notation, consider a plant of the form

$$x(t+1) = f(x(t), u(t)), x(0) = x_0,$$

where $x(t) \in X$ defines the system state and $u(t) \in U$ denotes the inputs to the system. Further, let us consider feedback control laws $u(t) = k\,(x(t))$.

Model predictive control computes feedback control laws $k : X \mapsto U$ as follows.

- Given, $T > = 0$ a cost functional is selected

  $$J[\hat{x}(\cdot), \hat{u}(\cdot)] = \sum_{\tau=0}^{T-1} f_0(\hat{x}(\tau), \hat{u}(\tau))$$

- Then, at time t, with $x(t)$ denoting the current state of the plant, we choose

  $$k(x(t)) = u^*\,(0),$$

  where $u : [0 : T-1] \mapsto U$ is given by the function that minimizes the cost functional J and satisfies the dynamic constraints given by the plant model and the initial condition $x(t)$.

There is extensive literature on the properties of controllers obtained via this procedure. In particular, stability, robustness and measurement feedback control under these conditions are well covered issues, see [2, 3] for a survey.

MPC is often used for control and optimisation of industrial processes. For instance, in power generation these algorithms compute optimal setpoints for temperatures, pressures and fuel feed rates during the startups and shutdowns of large generating units [4]. Similarly, model predictive control is one of the building blocks of today's state-of-the-art process industry. See [5] for an example in the chemical industry.

Usually, the use of these techniques for real plants includes the development of (nonlinear) mathematical models describing the process, and the selection/design of a suitable cost functional, which takes into account the goals to achieve. For instance, the functional might penalize deviations from given desired operating points, or represent operating costs. The optimal inputs to the system are calculated via minimization of this functional, subjected to the constraints defined by the mathematical model. Clearly, to be successful the minimization algorithms must exploit the structure of the problem, as given by the model type and the optimisation functional characteristics.

2.3 Mixed Logical Dynamic Systems

A mathematical model in MLD formulation has the form

$$x(t+1) = Ax(t) + B_1u(t) + B_2\delta(t) + B_3z(t)$$

$$y(t) = Cx(t) + D_1u(t) + D_2\delta(t) + D_3z(t)$$

$$E_2\delta(t) + E_3z(t) \le E_1u(t) + E_4x(t) + E_5$$

where $x(t) \in \Re^n$ are the continuous and binary states, $u(t) \in \Re^m$ are the continuous and binary inputs, $y(t) \in \Re^p$ are the continuous and binary outputs, while the vectors $\delta(t)$, $z(t)$ represent auxiliary binary and continuous variables, respectively. The elements $A, B_1, B_2, B_3, C, D_1, D_2, D_3$, and E_1, E_2, E_3, E_4, E_5 are matrices of appropriate dimensions. Auxiliary constraints on the states, the inputs and the auxiliary variables are expressed via inequalities involving the matrices $E_i, i = 1\ldots5$. For a detailed description of such capabilities we defer the reader to [6].

Using mathematical models in the Mixed Logical Dynamic system formulation is natural for several reasons. Firstly, it includes continuous and boolean states and inputs. Secondly, it contains the description of all logical relationships of the process. Moreover, it allows the inclusion of piecewise linear relationships in the modelling with the sake of approximation of nonlinear relationships. Last but not least, there is a standardized way to treat model predictive control exploiting MLD models.

This approach to model generation increases dramatically the modelling possibilities. In particular, it allows for representation of processes as diverse as turning on/off parts of the plant, different types of start up and shutdown procedures, as well as the introduction of complex operating constraints like the switching between different operating conditions. Because of the presence of integer variables, the MPC scheme is formulated as a mixed integer linear or mixed integer quadratic program that can be solved efficiently using commercial solvers [7].

Although relatively new MLD technology has been used successfully in a number of industrial applications. The interested reader can find more details in [8] and [9].

2.4 Putting the pieces together

For control and optimisation of a given plant we propose a control scheme, which

- uses Neuro-Fuzzy techniques to filter and pre-process data and measurements creating reliable real time signals,

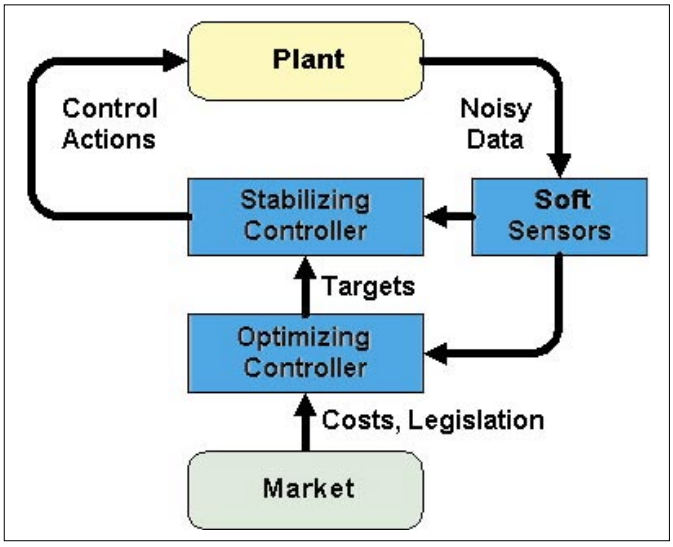

Fig. 2: Control structure

- uses Neuro-Fuzzy and/or standard MPC to stabilize the process on desired process targets and
- uses MLD and MPC ideas to generate optimal reference trajectories. This part of the algorithm is driven by optimization functionals related to economic performance [9].

The solution architecture looks as shown in Figure 2.

3 Example 1: cement kiln optimisation

ABB has developed a state-of-the art (cement) kiln control strategies that aim to stable and optimal kiln operation. Traditionally these control strategy were based on neural networks and fuzzy control. Its performance was and is very satisfactory in cement plants as it is revealed by its strong reference record. However, since there is a strong need for tools that offer optimal management of the alternative and traditional fuels involved in the kiln process, the system is being enhanced with an Alternative Fuels Optimisation Module based on the control design methodology depicted in Section 2.

The main idea is use the data gathered by the information management systems (equipment, process, market, laboratory) in order to calculate online the lowest cost fuel mix that satisfies the process and business constraints. The constraints to be satisfied are numerous. Probably the most important ones are

- Heat balance,
- Excess oxygen level,
- Clinker chemistry,
- Volatiles concentration (SO_3, Cl_2),
- Emission limits (SO_x, NO_x, CO_x, etc.),
- Maximum, minimum and speed of change constraints on actuators,
- Operative constraints on fuel consumption,
- Separate consideration of combustion process in precalciner and kiln,
- Contracts (with customers or suppliers) to be satisfied at any cost.

The basic element of this algorithm is a dedicated kiln model (Figure 3) in the MLD framework, which is used for Model Predictive Control as explained in Section 2.2 and 2.3. The mathematical model is able to estimate cooler, flame, burning zone, back end and preheater temperatures, kiln energy requirements, emission and volatiles levels, etc. The model parameters are tuned using a combination of neural networks and Kalman filtering techniques. Finally, we point out that the optimisation algorithms are able to cope with both hard and soft constraints, which enhances robustness and reliability of the optimisation process.

In the implementation of this algorithm the problem data is updated continuously. Then, at constant sampling times of about 15 minutes, computations are executed and new process targets and fuel setpoints are generated for implementation. Between sampling times, the "standard" Neuro-Fuzzy strategy guarantees process stability.

This advanced control application allows

- economically optimal reactions to changing conditions in fuel, waste, and raw meal quality,
- strict satisfaction of environmental, contractual and technical constraints.

A prototype implementation of this algorithm is being tested at a Swiss cement plant. We expect improved plant operating profits in the order of several thousands of dollars annually due to continuous optimal selection of operational parameters. See [10] for more details.

4 Example 2: optimal scheduling of a synthetic rutile refinery

Let us illustrate these issues on the example of a synthetic rutile refinery optimisation, where the coordination of batch and continuous processes is carried out to obtain the maximum profit and process stability.

Synthetic rutile (TiO_2) is produced using the Becher process. Briefly, the production process consists of two sections: the dry processing section (reduction and separation) and the wet processing section (aeration, cycloning, leaching and drying). The raw material for the process is $FeTiO_3$, the

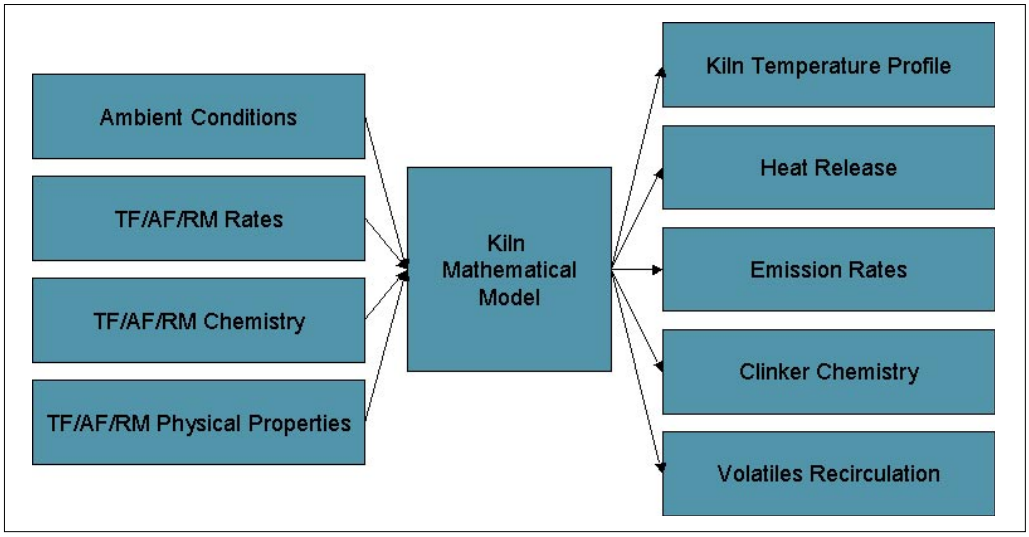

Fig. 3:
Kiln model input and outputs

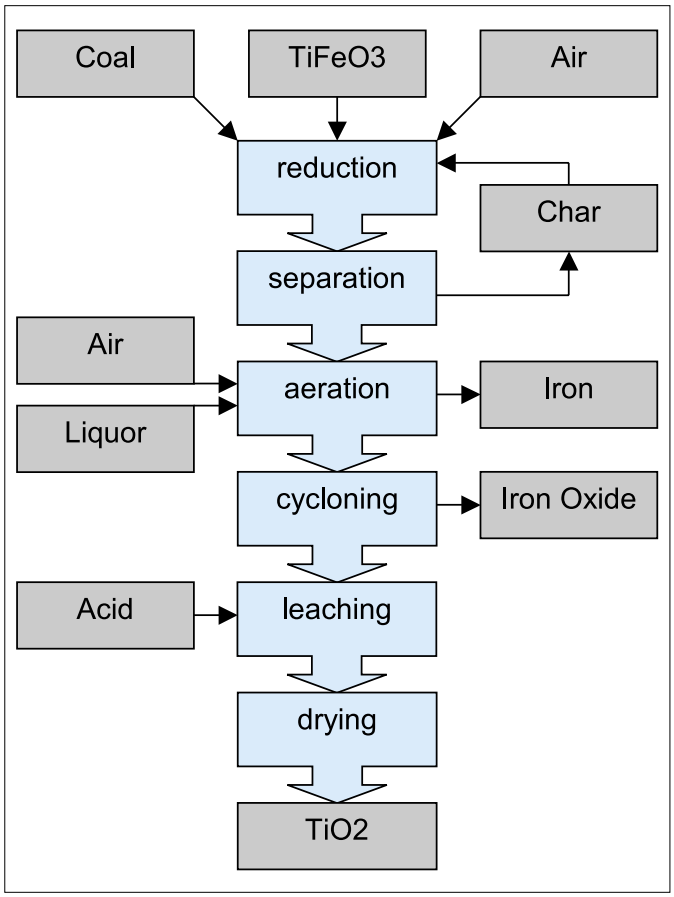

Fig. 4: Block diagram of synthetic rutile production process

final product is about 95 % TiO_2. A block diagram of the production process is shown in Figure 4.

In the dry (kiln) section the raw material is reacted with carbon monoxide to reduce the FeO in the mineral to iron metal, which can subsequently be removed. The main reaction can be written as:

$$CO + FeO{\cdot}TiO_2 \rightarrow CO_2 + Fe + TiO_2$$

This reaction is endothermic so that energy must be supplied throughout a kiln, which is essentially a counterflow heat exchanger.

The wet process objective is the separation of the rutile from the iron. It consists of the following steps:

- Aeration
  The goal is to eliminate metallic iron via a "rusting" process. The process is of batch type, which is carried out in an array of aerator vessels. Every batch lasts several hours and consumes relatively large amounts of electrical energy. If an aeration vessel cannot be discharged when ready, aeration and stirring must not stop.
- Cycloning
  Iron oxide particles are eliminated mechanically. This is a continuous process. However, the cyclone output can vary only between 80 and 100 % of the maximal rate.
- Leaching
  Other impurities are eliminated using sulphuric acid leaching. This is also a continuous process but one that is quite sensitive to product quality. Once stopped, restarting the process produces additional usage of raw materials (acid) and thus costs.
- Drying
  The acid is washed out and then the product is dried using the exhaust gasses from the kiln as main energy source.

We used the technology outlined in the Section 2 of the paper for optimal control and scheduling of both the dry and the wet process steps. The goal is to reduce the operation costs and increase process stability by

- Optimizing the kiln operation,
- Deciding on the charge and discharge times of the aerator vessels,
- Regulation of the outflows between the continuous parts of the process (cycloning, leaching, drying).

The problem constraints are given by

- Kiln process constraints,
- Material availability in the different bins,
- Aeration (batch) process duration,
- Tanks or bins capacity,
- Outflow rate limits,
- Forecasted availability of the different process parts.

Both the process constraints and the cost function were modeled using the theoretical framework offered by the combination of Model Predictive Control and Mixed Logical Dynamical Systems (MPC+MLD), as depicted in Section 2.

The result is a decision support system that reacts immediately to process perturbations and reschedules the operations in an optimal way. For instance, if the drying section must stop for certain amount of time, the system computes automatically the command sequence that allows for the longest possible continuous operation of the leaching pads. In the same way, as the forecasted aeration batch duration changes, all process flows are adjusted so that the process remains as stable as possible and without costly interruptions.

The availability of reliable information in real time is crucial. This is achieved, for instance, by using soft sensors to predict the aeration time as a function of the properties of the material coming out of the kiln.

The estimated benefits of this solution are of the order of several hundreds of thousands of dollars per year.

5 Conclusions

Efficient and flexible software architectures together with more capable mathematical methods are putting the control engineers in the position to help customers to reach new levels of performance and environmental compliance: intelligent devices that communicate with each other interchanging mission critical information make available quality information, process data, market boundary conditions, maintenance plans and others in a consistent and correct form. This allows for coordination and optimisation of the

plant operations. Real time true optimisation is the result, which leads to

- Precise material balancing,
- Throughput as dictated by the market,
- Lower energy consumption,
- Better and more stable quality,
- Lower maintenance costs.

Advanced control methodology is key when it comes to reach these goals because it is the decision making element. There is a need for tools and platforms, where these "devices" can be implemented. In this context, the paper has shown a methodology for design and implementation of advanced control applications and illustrated it with two applications being implemented using the platform described in [1].

These ideas are also being applied in the metallurgical industry. For instance, systems for optimal control and scheduling of copper refineries are being tested with quite promising results.

Literature

[1] ABB Optimizer™ Expert Optimizer. Fact Sheet. www.abb.com/minerals

[2] Mayne, D.Q. et al. (2000): Constrained model predictive control: stability and optimality. – Automatica, **36**: 789-814.

[3] Camacho, E. & Bordons, C. (2000): Model Predictive Control. – Springer Verlag.

[4] Krueger, K., Rohde, M. & Franke, R. (2001): Optimal control for fast boiler startup based on nonlineal models and considering the thermal stress on thick walled components. Proc. of the IEEE Conference on Control Applications, Mexico City: p. 570-576.

[5] Scheley, M. et al. (2000) Nonlinear Model Predictive Control of a Styrene Polymerization Reactor. – In: Allgöwer, F. & Zheng, A. (Eds): Nonlinear Model Predictive Control, Part III: Applications of Nonlinear Predictive Control: p. 393-402; Birkhäuser.

[6] Bemporad, A. & Morari, M. (1999): Control of systems integrating logic, dynamics, and constraints. – Automatica, Special issue on hybrid systems, **35**: 407-427.

[7] Bixby, R.E. (2002): Solving real world linear programs: A decade and more of progress. – Operations Research, **50** (1).

[8] Gallestey, E. et al. (2002): Model Predictive Control and the optimization of power plant load while considering lifetime consumption. – IEEE Trans. on Power Systems, **17**, 1: 186-191.

[9] Gallestey, E. et al. (2003): Using Model Predictive Control and Hybrid Systems for optimal scheduling of industrial processes. – Automatisierungstechnik, **51**, 6: 285-295.

[10] Gallestey, E. et al. (2004): New levels of performance for the cement industry. – ABB Review 2004, 2: 13-19.

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