Process Integration in Energy and Carbon Intensive Industries through Exploitation of Optimization Techniques and Decision Support

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Process industries show an ever-increasing interest in reducing their environmental impact and energy consumption as well as maintaining an acceptable profit. This is particularly true for industries such as the steel one, which is among the highest energy consumers worldwide. Process modelling and optimization are techniques by which this problem can be effectively addressed, particularly if the overall system is optimised as a whole.

In this article we describe a model for a discrete dynamic optimization of the process gas network in an integrated steel plant. The main sub-plants are modelled in order to calculate mass and energy balances in different scenarios of operation. The scenarios are then exploited within a multi-objective optimization problem, where cost and CO_2 emissions are simultaneously minimised. The optimization is carried out by exploitation of evolutionary algorithms that enable a flexible problem formulation and to effectively generate a set of different trade-off solutions. Application of the model to an industrial case study results in an interesting potential for reduction of CO_2 emissions and costs.

The described optimisation model is embedded in a more general software tool to help the plant managers in their daily decision-making process.

1. Introduction

European manufacturing industries are nowadays challenged by several issues: among the main ones are the reduction of the environmental impact and the increase in the energy and resource efficiency, maintaining at the same time an acceptable profitability. A special attention has been given to the improvement of the energy efficiency: Atuonwu et al. (2011) in their article presented two optimization approaches for energy efficiency: sequential and simultaneous methods which reduce energy consumption by about 45 % and 55 %. Other research work presented by Smith et al. (2011) focused on a novel optimization methodology to minimize systematically overall cost by considering utility system failures, maintenance requirements and different operating strategies.

Steelmaking industries in EU-27 countries produced in 2012 about 118.6 Mt of steel from the Blast Furnace - Basic Oxygen Converter (BF-BOF) route and 50.8 Mt from the Electric Arc Furnace (EAF) route (World Steel Association, 2012). Considering that BF-BOF route consumes about 13 GJ to 14 GJ/t of iron produced (IEA, 2012) and EAF route uses 1.8 GJ/t of liquid steel produced (EC, 2012) the total energy consumption added up to more than 30 Mtoe. Therefore, the improvement and the increase of total processes energy and resource efficiency is not only important, but also strategic to maintain competitiveness in the international panorama.

Such a problem involves many complex aspects: the interconnection of the steelmaking production processes within a total system, causes any change in a sub-process to affect the total system. Process Integration (PI) methods can be beneficial in the reduction of total energy conversion in industrial

processes. Minimization of energy use has historically been the primary objective of process integration (Larsson and Dahl, 2003); techniques of process integration such as pinch analysis have been applied also for resource conservation (Sahu and Bandyopadhyay, 2011). PI methods have in the last years evolved towards the inclusion of advanced modelling and optimisation techniques such as flowsheeting modelling, artificial intelligence and evolutionary approaches in software tools for decision support.

The focus of this paper is on the application of such techniques to the problem of process gases management in the steel industry, which can bring to considerable savings in environmental and economical terms. The satisfaction of process energy demands through a correct exploitation of internal energy resources is in fact essential for the reduction of the external supply of energy such as for instance natural gas. This brings to an increase in the overall process energy efficiency and an economic saving, given the considerable purchasing cost of natural gas. Moreover, a correct management of the gases (e.g. in terms of storage management) can be beneficial for the abatement of CO_2 emissions.

The process gases management problem has been treated as an optimisation problem, in which two objectives are pursued: the minimization of total cost and of CO_2 emissions.

The article is organised as follows: Section 2 describes the overall software tool implementation. In section 3 an application to the process gas network is presented, and in section 4 conclusions are drawn.

2. Materials and Methods

2.1 Software framework

Within the framework of the ENCOP Project, an ongoing Research Fund for Coal and Steel project, a software tool has been realised based upon the structure of an integrated steel plant in Italy. Operational data of relevance for energy, material and carbon balancing have been collected and stored within a dedicated DB. Data have then been utilised within the software in different ways:

- For the monitoring of CO_2 emissions and generation of CO_2 reports;
- To forecast the CO_2 emissions trend based on historical patterns and on foreseen production programme;
- To give guidelines on the best periods for trading of the CO_2 allowances; and
- To validate process models, predict the plant behaviour in different scenarios of operation and optimize its overall performances.

Plant managers are allowed to interact with the different features of the tool through a user interface, and visualise the results in a customised form (e.g. the CO_2 emission reports can be produced both in graphical form on screen as well as in .pdf files). An overview of the tool structure is given in Figure 1. A comprehensive description of the various features of the software tool has been given in a recent work by Amato et al. (2013). In this paper the attention is focused on the most interesting feature from a process integration point of view, which is the exploitation of process models in order to simulate and optimise the overall plant based on different process configurations (which for practical reasons may not be tested directly on the real system).
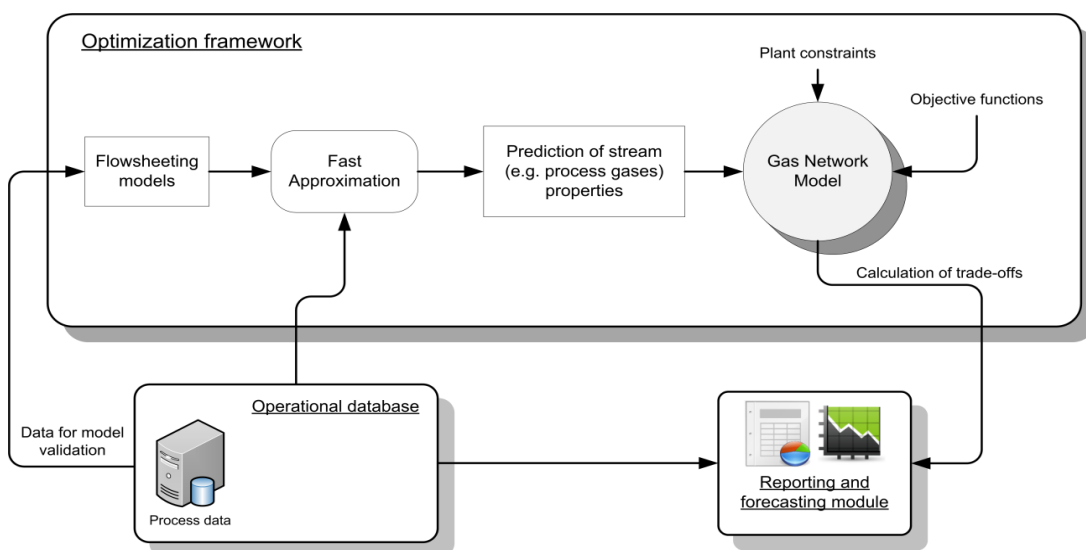

Figure 1: Overview of the architecture of the tool for Process Integration

2.2 Process models

The sub-plants which have a higher impact on the energy consumption and CO_2 emissions (BF, Coke ovens, steel plant) have been modelled through the Aspen Plus$^®$ software. Numerous examples of application of Aspen Plus$^®$ to the minerals and iron and steel industry are present in the literature: Schultmann et al. (2004) described a decision support system, KOSIMEUS, which exploits several steel sub-plant models realised with Aspen Plus$^®$, while Fröhling et al. (2010) utilise the software for the simulation of a Waelz kiln. A detailed description of the models is beyond the scope of this paper and can be found in (Porzio et al., 2013). In any case, modelling has been carried out starting from a definition of the different components included in the simulation. The physical properties database allows simulating the main physical processes and chemical reactions through the sequential exploitation of unit operations models linked in a process flowsheet and determining the outputs corresponding to a given set of inputs.

The models are intended to calculate mass and energy balances of the different plants, with a particular focus on the calculation of process gases properties. The effects of variations in different operating conditions can be estimated, in order to analyse of the plant performances and to construct different scenarios. The attention on the process gases is of particular importance: their energy content and impact on the CO_2 emissions of the plant is considerable. The models are interlinked and an external optimisation is launched in order to calculate best trade-offs from an economical and environmental point of view.

However, problems arise in optimising the system of flowsheeting models: in fact, the approach adopted by many widely adopted methods - such as, for instance, genetic algorithms (GAs) and more in general all evolutionary algorithms – consists in testing different configurations of the model by changing its parameters, collecting and evaluating their performances and to suitably combine the tested candidate configurations in order to create, according to their evaluations, a new set of model parameters until an optimal solution is obtained.

The test of thousand of different model configurations can be required by such a process. A simple example is given in which GAs are used for the optimization of a process simulated through Aspen (simulation performed in 5 min): if 100 generations of the Gas optimization process are used in order to find, exploiting a population of 50 individuals, an optimal configuration of the model, the optimization process would require 20 d of continuous computation, which is unacceptable in any industrial context.

In order to make the developed models usable within an optimization context, a technique based on clusterization and subsequent interpolation of clustered information has been employed for the creation of a fast approximation of the Aspen Plus models (Vannucci et al., 2011). The proposed technique has been applied to several plants, including a blast furnace and a pilot gasification reactor (Vannucci et al., 2012).

The computational time of approximated models is extremely low if compared to that required by the original Aspen version and makes their integration into the optimization framework feasible.

The original Aspen models are used in order to produce a wide set of data samples including all the input and output variables of the model; these data are then used during the training of the approximated model which can be summarized in two main phases: firstly input space is subdivided into a set of R regions by means of a Self Organizing Map, a particular kind of unsupervised neural network which preserves, after the clustering, the topology and distribution of original data; secondly a representative output is assigned to each region, taking into account all samples associated to that region in the original data set.

The obtained data structure is subsequently used for model simulation by means of suitable interpolation operations which exploit the created clusters, the relative distance between them and the output values assigned to each cluster. This operation is extremely fast, in line with the requirements of the optimisation.

The described approach has been tested on the approximation of several industrial plants obtaining very satisfactory results in terms of reliability, measured as the discrepancy between the outputs of original and approximated models (which has been found <10 % in all the tests).

2.3 Models Optimisation

The concurrent optimisation of costs and CO_2 emissions is carried out by means of the Strength Pareto Evolutionary Algorithm 2 (SPEA2) (Zitzler et al., 2002). It is a particular Evolutionary Algorithm (EA) model suitable for multi-objective optimisation that exploits the concept of Pareto dominance in order to build a set of Pareto-optimal solutions (*Pareto-set*) (Coello Coello et al., 2007).

As any other evolutionary algorithm, it is an iterative and stochastic process in which an initial population of candidate solutions (called *individuals* or *chromosomes*) is made evolve by means of *genetic operators* such as *crossover* and *mutation*. In the problem object of this paper, each chromosome codifies a possible solution to the gas network optimization problem in the form of an array of real values that identify, for each splitter in the network, how its inbound gas flow is split towards its different outbound pipes.

At each iteration (*generation*) the newly generated population is then evaluated in order to calculate costs and CO_2 emissions. The non-dominated solutions are stored in an external archive whose aims are to maintain the best solutions and to lead the algorithm towards the optimum Pareto-front.

The main reason leading to the choice of EAs is that they allow a very flexible problem formulation: in fact, no constraints subsist on the type of underlying model used to evaluate the fitness of each candidate solution, so that even software simulators can be employed.

In order to obtain the best performances and to maintain the computation time within the required time limits, the gas network model, as well as the SPEA2 algorithm, has been implemented in C++ as a generic and modular library by means of which it is possible to represent different network configurations. It is composed by sub-plants, gas-holders, torches, power plants, gas mixers and gas splitters modules that are connected by pipes. Each module is characterized by a transfer function which connects the inbound and outbound gas properties. Moreover, the evaluation of the two fitness functions is performed in parallel by means of a multi-threading approach in order to exploit the power of the new multiple cores CPUs.

3. Case study presentation

3.1 System description

The described models have been applied to an industrial system in order to optimise the management of its process gas network. Within the considered system, every unit (sub-plant) is considered as either a producer or a consumer of process gas (and therefore energy). Fuel gas is produced by plants such as the blast furnace (BF), the coke ovens and the steel plant converter. Gas is consumed either by the sub-plant themselves (e.g. BF cowpers, coke ovens) or by external users such as gas-fired power plants (3 of which are present in the considered case). Excess gas or peak energy demands are managed by exploitation of a buffer capacity represented by 3 gasholders (one per each process gas). The transfer of gas to external consumers brings a saving in the total cost as well as an advantage in terms of the direct CO_2 emissions of the steel plant (which arise when a gas is consumed locally inside the plant boundaries for energy demand satisfaction or an excess of gas is sent to a torch). The amount of gas which is transferred to the power plants also influences their performance in terms of specific consumption and electric power production; in case there is a deficit in the supply of process gas, in fact, an addition has to be made by purchasing natural gas from external supplier at a higher cost.

A time horizon of one hour has been considered to realise the case study, divided into 4 discrete intervals of 15 minutes, which usually correspond to the average gas sampling period in the involved plant. The problem can therefore be assimilated to a discrete multi-period optimisation problem.

Plant constraints have to be satisfied by the network optimisation model, mainly regarding bounds on the heating values of the mix of different process gases, minimum and maximum gasholders capacity as well as flowrates through the pipelines. Energy demand also has to be satisfied at every time step.

3.2 Results and Discussion

The proposed optimisation model has been utilised to formulate different scenarios, in order to estimate the impacts on costs and CO_2 emissions of different plant operating conditions. As an example, a comparison has been carried out between two optimised scenarios:

- In the first one, both production and demand correspond to the values registered during the plant operations in the considered time period (P100-D100);
- In the second one, a 20 % reduction in the BF and BOF gas production has been assumed. A 10 % reduction in the energy demand of the BF cowpers has also been assumed, taking into account a deterioration of the plant performances when the production is less than 100 %. The production and demand of coke ovens gas has been assumed to be equal to 100 % (P80-D90).

Simulations have also been carried out in order to estimate the impact of a 20 % reduction in the production and a demand equal to 100 % of the nominal. However, the optimisation procedure was in such an instance unable to get feasible solutions and therefore the results of such a procedure are not presented here.

In Figure 2 the results relative to the two objective functions in the two scenarios are shown. A 20 % lower production results in an average decrease of the profit by 13 %, and of CO_2 emissions by 13.8 % on average. The reduction in CO_2 emissions is a direct consequence of the lower gas production. The reduction in the profit is less straightforward to calculate since the cost function is composed both by the value of gas sold to power plants, the cost of natural gas purchasing as well as the value of the CO_2 allowances on the market (assumed to be 7 €/t).

The effect on the external power plants has also been estimated. The three plants have different cycle configurations, but all of them allow for co-firing of natural gas and process gas. According to different availability of process gases, the power plants can operate with different mix of gases according to the
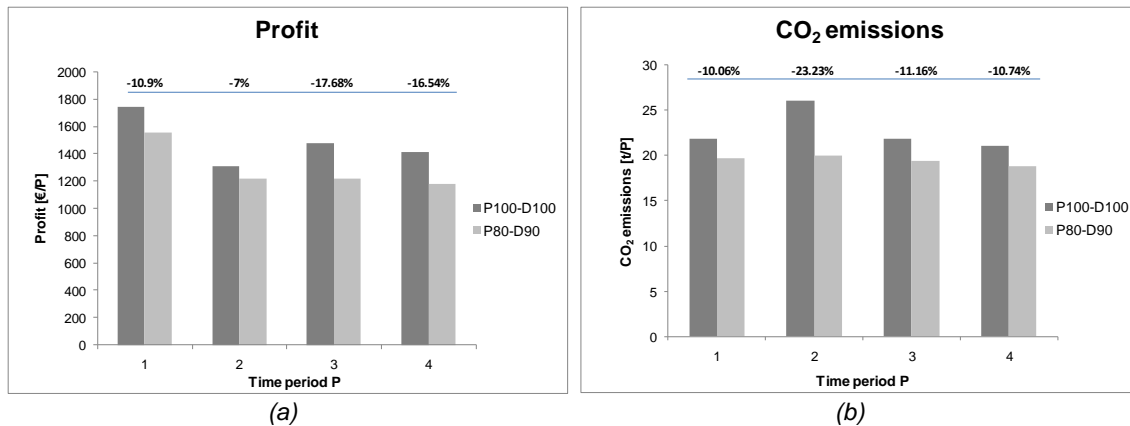
Figure 2: Values of the two objective functions in the different scenarios. The relative difference between the two scenarios is shown for each time period both for profit (a) and CO_2 emissions (b)

required electric power output. However, for the purposes of this study it has been assumed that the electric power production is constant and equal to the nominal value of each power plant in the considered time frame. An addition of natural gas sufficient to provide the turbines and boilers of the required thermal energy to feed the gas and steam turbines is therefore taken into account.

In the P80-D90 scenario, the three power plants (PP1, PP2 and PP3) are supplied by 49.1 %, 7.43 % and 66.66 % less gas than in the P100-D100 scenario. In Table 1 the amount of gas that is sent to the power plants in the two optimised scenarios is shown, taking into account the energy content of the gas mix (expressed in GJ). The amount of process gas provided to PP2 by the steel plant does not decrease as much as the other two because the price of gas purchasing is much more convenient.

In this study, the power plants have been considered outside the boundaries of the system and therefore the objective functions do not take into account of the potential benefits or drawbacks which are now simply a consequence of the steel plant operations. Nevertheless, there is a direct correlation between process gas sold to power plants and savings of natural gas in the plants themselves. The inclusion of the power plants within the system boundaries and the impact of different system configurations on the electric power generation efficiency during different load demands will be object of future studies.

Table 1: Distribution patterns of process and natural gas to external power plants. The values reported are the results of the two optimised scenarios

Scenario	Period	Process gases sent to power plants [GJ]			Natural gas consumption at power plants [GJ]		
		PP1	PP2	PP3	PP1	PP2	PP3
P100-D100	1	56.76	147.64	52.39	147.21	200.68	75.01
	2	3.06	143.04	51.30	200.91	205.28	76.11
	3	15.79	149.90	50.38	188.18	198.42	77.03
	4	16.56	140.61	47.09	187.41	207.71	80.31
	Total	92.17	581.18	201.16	723.71	812.09	308.46
P80-D90	1	29.72	149.79	17.45	174.25	198.53	109.95
	2	12.96	127.83	17.14	191.01	220.49	110.27
	3	2.93	131.90	16.80	201.04	216.42	110.60
	4	1.30	128.51	15.69	202.67	219.81	111.71
	Total	46.91	538.02	67.07	768.97	855.25	442.54

4. Conclusions

The present paper describes the main features of a software tool for decision making support in energy and carbon intensive industries. In its prototypal form, the tool has been exploited within the context of an integrated iron and steel industry. In particular, the optimisation framework of the process gas network has been illustrated, which is the most interesting application of the tool from a process integration point of view. Operational process data are collected and stored within a dedicated database, and utilised within

the tool to generate reports and forecasts based on the production planning of the enterprise.Process models have been realised to simulate the plant behaviour in different operating conditions, with a special focus on the gas composition. Models have been approximated in order to be efficiently included within a multi-objective optimisation framework, aimed at the calculation of gas management practice which allow convenient trade-offs between cost and CO_2 emissions. Results show that the tool can be useful in the elaboration of different scenarios also taking into account external power plant operations.

Acknowledgements

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