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Neural Network-based modeling methodologies for energy transformation equipment in integrated steelworks processes

Stefano Dettori^{a*}, Ismael Matino^a, Valentina Colla^a, Valentine Weber^b, Sahar Salame^b

^a*Scuola Superiore Sant'Anna, Via Moruzzi 1, 56124. Pisa, Italy*

^b*ArcelorMittal Maizières Research SA, Voie Romaine, Maizières-lès-Metz, 57280, France*

Abstract

The paper proposes a methodology for modeling of energy transformation equipment which are commonly found in integrated steelworks, mainly focusing on steam production in the Basic Oxygen Furnace and auxiliary boilers, the electric power production in off-gas expansion turbines and some relevant steam and electricity consumers. The modeling approach is based on standard neural networks and Echo State Networks (ESN) for forecasting the variables of interest. All the models are intended as processes predictors to be used in a hierarchical control strategy based on multi-period and multi-objective optimization techniques and model predictive control. The overall target is the optimization of the re-use of off-gas produced in integrated steelworks by minimizing costs and maximizing revenues. Training and validation of models have been carried out by exploiting real historical data provided by steelmaking companies and have been successful tested.

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Nomenclature

BOFG	Basic Oxygen Furnace Gas	MPC	Model Predictive Control
BFG	Blast Furnace Gas	MOO	Multi-Objective Optimization
COG	Coke Oven Gas	NCV	Net Calorific Value
DSS	Decision Support System	NG	Natural Gas

* Corresponding author. Tel.: +39 050 882330.

E-mail address: stefano.dettori@santannapisa.it

ESN	Echo State Network	NMAE	Mean Absolute Error
FFNN	Feed-Forward Neural Network	NN	Neural Network
HP	High Pressure	NRMSE	Normalized Root Mean Square Error
LD	Linz and Donawitz	RH	Ruhrstahl-Heraeus
MP	Medium Pressure	STD	Standard Deviation

1. Introduction

The steel sector represents one the most energy-intensive industry and, therefore, relevant efforts are spent in order to improve energy efficiency and optimal exploitation in order to enforce competitiveness and environmental sustainability [1]. An efficient utilization of the energetic sources, such as byproduct gases and process heat, allows meeting energy demand of the process in a convenient way. In a context where the energy cost represents around 20-25% of the total production costs [2], the efficient use of byproducts gases can lead to considerable savings, through the production of heat, process steam and electricity. For these reasons, in the steelworks different systems distributes the off-gases (after a preliminary treatment) among the different internal utilities (production process and power generation facilities). Their availability is managed through a complex off-gas network. However, in some cases the off-gas production is not continuous but cyclic and heavily depends on the production scheduling. Discontinuity is also a characteristic of the electric and steam network within steelworks, but if in the first case the main issue is the minimization of purchase costs in the electricity market, in the case of the steam network different factors affect production and consumption, especially during the operation of some batch processes, such as the Ruhrstahl-Heraeus (RH) vacuum degasser.

A synchronized management of off-gas and steam networks is a crucial aspect in order to optimize plant operation, as it allows for example to reduce the off-gas flaring in torches, which is an obvious benefit in terms of environmental impact, to minimize the steam condensation, and to consider economical and energy-related issues. These complex objectives can be achieved through the combination of advanced control techniques, such as Model Predictive Control (MPC), and Multi-Objective Optimization (MOO) approaches, for instance Mixed Integer Linear Programming (MILP) or Genetic Algorithms (GA).

In literature, MOO techniques have been applied to off-gas management in the work described by Porzio et al [3] while, in another work, nonlinear MPC has been applied in order to optimize the operational costs of gas pipeline networks [4]. MILP allows optimizing the distribution of byproduct gases, such as described in several literature works [5-7]. In the paper of Wang [8] an optimization model considers both load and power generation scheduling. The cited works mainly focus only on some of the energy subsystems or on the long-term optimization of some of the sub-networks within the steelworks, by neglecting or simplifying the gasholder, off-gas and steam networks dynamics, which however provide useful information for a more effective optimization over short time horizons (e.g. a few hours).

In particular, MPC strategies can obtain remarkable results when the models combine characteristics of simplicity and high prediction precision in describing non-linear behaviors [9] and mutual interactions between the various subsystems, especially when the constraints are of vital importance for issues related to the safety of plants operation. In the most industrial applications MPC typically exploits linear state space models for the prediction of future behavior of the controlled system, but a more detailed modeling of the processes involved can be obtained by means of artificial intelligence techniques, mainly based on Neural Networks (NN). Some interesting process models related to steelworks are described in works of Zhang et al., where the Blast Furnace (BF) off-gas production and consumption is modelled through an NN-based approach, which shows quite good performances [10]. Zhao et al. developed several models of BF gas (BFG) and Coke Oven Gas (COG) production and consumption, and their respective gasholder levels by means of Echo State Networks (ESN) [11-12]. Liu et al. propose an ESN-based approach for the prediction of steam production and consumption within steelworks, starting from historical data as inputs of the model, which are in fact autoregressive models [13].

For control purposes, suitable models must verify characteristics of local controllability (through control variables, such as scheduling or variables that can be calculated directly from it) and observability, which are necessary requirements for the system control.

In this context, the research project entitled "Optimization of the management of the process gas network within the integrated steelworks" (GASNET) aims at supporting the management of the off-gas network by considering environmental and economic objectives through the synchronization of off-gas, steam, and electricity networks, and through an intelligent and efficient consumption of external energy sources (e.g. natural gas). This work presents models developed within the GASNET project and related to energy transformation equipment, such as gas expansion turbines for electrical energy production, steam producers and consumers. The developed models take into account the influence of scheduling on the production of electric energy, steam and off-gas production and consumption.

The paper is organized as follows: Section 2 describes the strategy considered in GASNET project, Section 3 describes the modeling approach based on ESN for energy transformation equipment and steam production processes, section 4 presents the modeling methodologies and the achieved results, while Section 5 provides some concluding remarks.

2. GASNET strategy

A global view about plant operation, energy management and off-gas production, is needed in order to minimize production costs, improve the environmental impact and resources efficiency. Any kind of analysis must consider the correlations between the energy demands and the production of gas as well as the system dynamics. The optimization systems must be capable to predict the most relevant interactions among the processes, by complying with all the constraints (e.g. min/max pipelines flow rates, min/max mixing of the different fractions of gases, storage capacity of gasholders and steam accumulators, max boiler thermal power and steam production, etc.) and by ensuring stability. The final objective is to minimize the amount of flared off-gases, the natural gas consumption and the wasted steam. In this context, within GASNET project a Decision Support System (DSS) is being developed, whose purpose is to support the management of the off-gas and steam networks. This objective represents a significant step forward with respect to the significant results achieved within a previous project funded by the EU, the ENCOP project, whose DSS is described in [14].

The optimization system within the DSS, which is under development, is structured in two hierarchical levels, the power generation optimization and the Sub-networks level, which have different forecast horizons. The former has the task of optimizing, in the long-term, several objectives taking into account economic and environmental costs and decides the optimal subdivision of the use of the various energy resources, by exploiting information from energy market (i.e. electricity and NG prices). It determines, through MOO techniques, the amount of byproduct gases to be sent to the power plants, the NG to be consumed and the scheduling of the boilers which can satisfy the internal demand of steam. This layer provides to the lower level the target consumption of off-gases and NG and receives the constraints status related to the actual and future status of Gasholders, steam accumulators and main gas and steam network behaviors. The sub-networks level is subdivided in the BFG, BOFG, COG and steam networks, which are controlled by means of hybrid nonlinear MPC approach.

3. Modeling approach

In the steelworks, the main producers of steam are typically the BOF plants [15] and the electric power plants, but it is common to balance the steam demand through auxiliary steam generators that have fast start-up dynamics. In the BOF process, during the conversion of pig iron in steel, it is possible to recover the produced off-gas heat by means of different boilers, that allow producing steam with different levels of pressures, the High Pressure (HP) and Medium Pressure (MP). The MP steam is typically produced in the movable skirt of the Linz and Donawitz (LD) converter, while the HP steam is produced in the boilers downstream of the process. On the other hand, auxiliary boilers typically have different burners that allow producing steam through the exploitation of off-gas (e.g. BFG, BOFG, etc) and NG.

A further efficient way to recover energy from off-gas production is to use the gases into expansion turbines, which allow energy production through an electric generator. For instance, the produced BFG can be expanded, by obtaining electric power and also allowing the outlet gas pressure to be controlled before being sent to relative gas network.

In this paper a methodology is proposed for the modeling of energy transformation equipment, production and consumption of steam, by exploiting a black-box approach based on a combination of static back propagation NNs and a novel recurrent NN named Echo State Network (ESN) [16-17].

The developed models are the BOF Steam production in the HP Boilers and Movable Skirt, Auxiliary Boilers, the steam and electricity consumption on RH Vacuum degasser, and the BFG expansion turbine.

With regards to auxiliary boilers, the main behavior to model is the thermal power required for the production of a steam mass flow demand. The thermal power is computed as follows:

$$W_{\text{thermal}} = \sum_{i=1}^{N_s} \dot{m}_i \cdot NCV_i \quad (1)$$

where i is the i -th gas type, NCV_i is its Net Calorific Value, and \dot{m}_i is the gas flow used during the combustion.

4. Model Architectures

In order to model the total steam production in the BOF process, two different models have been developed, the Movable Skirt model and the LD Boiler model, by exploiting the features of ESNs, in order to obtain a quantitative prediction of the total steam production related to the scheduling of the process itself. The two models allow forecasting the steam production for the next two hours, starting from input related to the scheduling (converter on-off), the movable skirt position, the volume flow of the BOFG, the blown oxygen volume flow and the current value of the steam production, which takes into account the past behavior of the steam production process. These are the most correlated parameters with respect to the related targets and have been selected through both a preliminary correlation analysis and discussion with the technical personnel of the company. The selected sample time is 1 minute.

According to the model objectives, for the auxiliary boilers, it is sufficient to model the nonlinear behavior of the combustion efficiency. A fast and efficient way to model this relationship is the use of simple NNs, in particular the Feedforward NNs (FFNNs).

The goal of the BF Expansion Turbine Model is the prediction every 15 minutes of the electrical energy produced by the BFG expansion turbine. Typical dynamic responses of an expansion turbine combined with an electric generator are in function of the size, and in the order of seconds. In this case, with a sample time of 15 minutes, the dynamic behavior can be neglected. For the case study, the dynamic behavior of the electric power generation through the expansion turbine will be considered as instantaneous. In order to predict the future horizons of the electric power, the forecasted values of BFG flow are needed. These values are computed through BFG flow models. According to this objective, it is sufficient to model the nonlinear function of the turbine efficiency through a FFNN-based approach.

The steam and electricity forecasted consumption on RH vacuum degasser have been modeled starting from the RH scheduling (on-off) and the current steam and electricity consumption. The ESN approach is suitable for this purpose. The sample time of the model is 1 minute.

5. Data selection strategy and training algorithms

In order to train the models, a dataset of real historical data has been used and splitted into training and validation dataset respectively of 70% and 30%. 6 months of data are sufficient for the training procedure and the validation. Additional 6 months of data have been used as test dataset for the developed models.

For the model training and simulation, the development environment is based on Matlab. In particular, for ESNs, within the GASNET project, a toolbox for the training and simulation has been developed. The training procedures exploit Pseudoinverse calculation method for the training of the weights of the model [18]. The main ESN hyperparameter (number of neurons, spectral radius, connectivity, input-output scaling) have been heuristically tuned in function of the results obtained on validation dataset.

For the models based on FFNN, the offline training procedure exploits standard back-propagation algorithm, in particular the Levenberg–Marquardt [19], which minimizes the overall mean square error. The number of neurons has been heuristically tuned in order to minimize the error on the validation set.

6. Results

In order to evaluate the accuracy of the developed models, the percent Normalized Mean Absolute Error (NMAE) and the percent Normalized Root Mean Square Error (NRMSE) have been computed. The test results, computed on the test dataset, are shown in Table 1. For confidentiality constraints, all the variables and results have been normalized with respect to their ranges. Figure 1 shows some examples of results on the prediction on the test dataset, in particular for the models related to the production of electricity of the BFG expansion turbine and the production of steam in the BOF MP boilers. The obtained results are very promising: the models predict the variables of interest with a precision that is considered good for process control applications and can be effectively used within an MPC or MOO approach. The obtained models can be further refined with a more rigorous optimization of the hyperparameters, which would allow to obtain a higher precision. In addition, the chosen architectures of the models for process modeling allow an online tuning of the parameters, with the possibility of refining the models to the current state of the processes and plants.

Table 1: Test results of developed models.

Model	Section	Output var.	Description	NRMSE	NMAE
LD BOF Steam Production	HP Boilers	\dot{m}_{HP}	Steam mass flow production in HP boilers	4.2 – 6.5	1.9 – 3.1
	MP Boilers (Movable Skirt)	\dot{m}_{MP}	Steam mass flow production in MP boilers	6.0	2.9
Auxiliary Boilers	-	$W_{thermal}$	Thermal Power	3.6	2.0
RH vacuum degasser	Steam Consumption	\dot{m}_{RH}	Steam consumption in RH process	6.1 – 7.3	2.3 – 3.8
	Electricity consumption	W_{RH}	Electric power consumption in RH process	5.2 – 5.6	4.1 – 4.4
Expansion Turbine	-	W_{ET}	Electric power production in the BF Expansion turbine	0.4	0.3

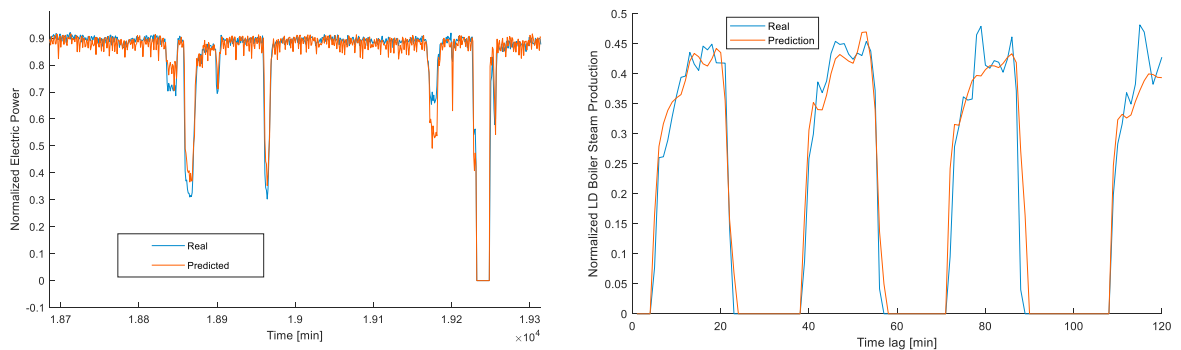


Fig. 1: Example of prediction of Electric power produced in the BFG expansion turbine (a) and Steam Production on the BOF boilers (b).

7. Conclusions

A neural network-based methodology for the modeling of energy transformation equipment, steam consumption and production processes within integrated steelworks is presented. The developed models will be useful as forecaster for the model predictive control approach and the multi period and multi objective optimization in phase of development within the GASNET project, which will optimize the production and distribution of energy

resources (such as by-products gas and steam) within the integrated steelworks, with the additional objective of minimizing the flaring of overproduced gas in torches, with strong benefits in terms of environmental impact and reduction of costs related to waste of energy resources. Two different NN-based approaches, FFNNs and ESNs, have been exploited in order to model in an effective way the complex interaction between the scheduling of the processes, the controllable variables and the output variable of interest. The results obtained demonstrate the feasibility of the methodology used.

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References

- [1] Uribe-Soto, Wilmar, et al. "A review of thermochemical processes and technologies to use steelworks off-gases." *Renewable and Sustainable Energy Reviews* 74 (2017): 809-823.
- [2] Rizwan Janjua. "Energy use in the steel industry." [Http://Www.iea.org/](http://www.iea.org/), International Energy Agency (IEA), 23 Oct. 2014, www.iea.org/media/workshops/2017/ieaglobalironsteeltechnologyroadmap/171120ISTRMSession2Cullen_NEW_and_APPROVED.pdf.
- [3] Porzio, Giacomo Filippo, et al. "Comparison of multi-objective optimization techniques applied to off-gas management within an integrated steelwork." *Applied Energy* 136 (2014): 1085-1097.
- [4] Gopalakrishnan, Ajit, and Lorenz T. Biegler. "Economic nonlinear model predictive control for periodic optimal operation of gas pipeline networks." *Computers & Chemical Engineering* 52 (2013): 90-99.
- [5] Kong, Haining, et al. "An MILP model for optimization of byproduct gases in the integrated iron and steel plant." *Applied Energy* 87.7 (2010): 2156-2163.
- [6] Zeng, Yujiao, et al. "A novel multi-period mixed-integer linear optimization model for optimal distribution of byproduct gases, steam and power in an iron and steel plant." *Energy* 143 (2018): 881-899.
- [7] de Oliveira Junior, Valter B., João G. Coelho Pena, and José L. Félix Salles. "An improved plant-wide multiperiod optimization model of a byproduct gas supply system in the iron and steel-making process." *Applied energy* 164 (2016): 462-474.
- [8] Wang, Zhaojie, et al. "An integrated optimization model for generation and batch production load scheduling in energy intensive enterprise." *Power and Energy Society General Meeting, 2012 IEEE*. IEEE, 2012.
- [9] Henson, Michael A. "Nonlinear model predictive control: current status and future directions." *Computers & Chemical Engineering* 23.2 (1998): 187-202.
- [10] Zhang, Qi, et al. "Supply and demand forecasting of blast furnace gas based on artificial neural network in iron and steel works." *Advanced Materials Research*. Vol. 443. Trans Tech Publications, 2012.
- [11] Zhao, Jun, et al. "A two-stage online prediction method for a blast furnace gas system and its application." *IEEE Transactions on Control Systems Technology* 19.3 (2011): 507-520.
- [12] Zhao, Jun, et al. "Hybrid neural prediction and optimized adjustment for coke oven gas system in steel industry." *IEEE transactions on neural networks and learning systems* 23.3 (2012): 439-450.
- [13] Liu, Ying, et al. "Data-driven based model for flow prediction of steam system in steel industry." *Information sciences* 193 (2012): 104-114.
- [14] Porzio, Giacomo Filippo, et al. "Reducing the energy consumption and CO₂ emissions of energy intensive industries through decision support systems—an example of application to the steel industry." *Applied energy* 112 (2013): 818-833.
- [15] Chen, Lingen, et al. "Thermodynamic optimization opportunities for the recovery and utilization of residual energy and heat in China's iron and steel industry: A case study." *Applied Thermal Engineering* 86 (2015): 151-160.
- [16] Jaeger, Herbert. "The "echo state" approach to analysing and training recurrent neural networks—with an erratum note." Bonn, Germany: German National Research Center for Information Technology GMD Technical Report 148.34 (2001): 13.
- [17] Lukoševičius, Mantas, and Herbert Jaeger. "Reservoir computing approaches to recurrent neural network training." *Computer Science Review* 3.3 (2009): 127-149.
- [18] Jaeger, Herbert. Tutorial on training recurrent neural networks, covering BPPT, RTRL, EKF and the "echo state network" approach. Vol. 5. Bonn: GMD-Forschungszentrum Informationstechnik, 2002.
- [19] M. T. Hagan and M. B. Menhaj. Training feedforward networks with the Marquardt algorithm, *IEEE Transactions on Neural Networks*, vol. 5, no. 6; 1994, p. 989-993.