Grant Agreement no.	**636834**
Project Acronym	**DISIRE**
Project full title	**Integrated Process Control Based on Distributed In-Situ Sensors into Raw Materials and Energy**
Dissemination level	PU
Version	v1-M18
Date of delivery	30/6/2016
Deliverable number	D2.3
Deliverable name	Performance assessment of data-driven MPC
AL / Task related	T2.3
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Keywords	Process Modelling, Process control, Streaming algorithms, Model predictive control, Stochastic control, Scenario-based analysis and control, Online identification
Abstract	The main objective of this document is to serve as a detailed whitepaper regarding the testing and verification procedures for DISIRE's data-driven proposition, including the definition of computable and/or measurable key performance indicators, create a taxonomy thereof, and assess the added value of the proposed control scheme using these indicators.
Note	First version to be submitted in M18. This report will be being updated and will be resubmitted in M28 and M32.

Acronym	*Meaning*
KPI	Key Performance Indicator
MPC	Model Predictive Control
NLPGCF	Naphtha LPG Cracking Furnace
SMPC	Stochastic Model Predictive Control
WBF	Walking Beam Furnace

Contents

Chapter 1

Definition of KPIs

1.1 About

In this document we provide a detailed description of the necessary procedure from the stage of proof-of-concept to the stage of application of the proposed control schemes in an industrial environment. The main focus is on the introduction, mathematical formulation and computation of key performance indicators for the industrial processes of DISIRE as well as a more general proposition for the process industry at large. The assessment framework is based on the principles we explain in Section 1.2 and then special attention is given to each one of the industrial applications of WP5, WP7 and WP8 separately where we present quantifiable results.

1.2 Assessment of performance

1.2.1 Critical points

The assessment of performance of industrial applications from the perspective of control has received little attention as such because it is usually studied in a per-case fashion. Only recently has the need for a more holistic definition of widely acceptable KPIs been identified. Here, with the help of the industrial partners of DISIRE, we have tried to identify the main types of performance assessmenent following a general-to-specific approach. Before we proceed to a further discussion of performance assessment, there should be first a distinction between two basic approaches to performance assessment: *in silico* and *in situ*. For every performance indicator we consider important that we propose a computationally feasible way to evaluate it before it is measured in an industrially relevant environment. We may, therefore, say that the very general term *performance assessment* refers to any of the following

1. Assessment of the **quality of measurements** and measuring devices, in comparison to other measuring devices, or with respect to the measuring noise as well as their reliability, life span and rate at which they produce outliers
2. **Data availability**, delay in the transport of data, reliability in transportation (e.g., packet loss) and storage. Availability of a data management system.
3. **Responsiveness of actuators**

4. Smoothness and **reliability of the overall operation** of the process via fault detection; assessment of how prone the process is to fault
5. Assessment of the **closed-loop performance** of the plant (will be discussed in further detail hereafter)
6. **Quality** of the final product
7. Impact on the **environment**, such as emission of pollutants and assessment of the short-, mid- and long-term possible effects to the environment
8. **Economic sustainability** of the process given its (installation and) operating cost, the additional technology/innovation cost and how it relates to the balanced benefit it brings about given the improvement of other KPIs, the price of the final product and the margin for reduction on the basis of the improvement of the process characteristics. On this topic, quite elucidating is a whitepaper of the Gartner/EBRC KPI initiatice and the KPI list of opsdog.com.
9. **Other** application-specific indicators which do not lie in any of the above categories

Indeed, notice that the question of assessing the performance of a plant is a multi-faceted problem and cannot be examined solely from the perspective of closed-loop control. It is easily understood that, for instance, the quality of the final product is in and of itself multi-parametric and depends on the configuration of the control system, the mode of operation, the quality of first materials, the quality of measurements and sensors and many another.

In particular, when it comes to evaluating the closed-loop performance of a process, the following critical points need to be taken into consideration:

1. The **tracking capability** the control system, that is, how well the controller meets the tracking requirements (if the control problem is a tracking problem)
2. The extent of **satisfaction of the prescribed constraints**, i.e., to what extent the process is operated within the desired bounds
3. The **economic performance** of the operation, i.e., how much energy needs to be consumed to properly operate the plant
4. The **smoothness of the control actions** — typically it is not desirable to operate the plant in a *bang-bang* manner, i.e., with abrupt changes in the manipulated variables as this may lead to the wear-out of the actuators
5. The **smoothness of the system's response** — a controlled system needs to be responsive (e.g., to changes in the set-points), yet abrupt changes need to be avoided
6. **Frequency characteristics** of the closed-loop system (when applicable)
7. **Technical sustainability** of the process, that is, under the current mode of operation is the process expected to run smoothly, or it may lead to wear-outs and faulty operation (this does not exclusively depend on the controller)

When at the stage of design, certain KPIs are associated with the feasibility of the proposed control (or other) algorithmic solutions.

1. **Technical feasibility**: when at the stage of controller design, technical feasibility is of great importance. What are the expected runtimes of the algorithms that are involved? Can they run on cheap hardware and, in particular, on the hardware that is mounted and used for that process? Can the algorithms run in finite-precision arithmetic if necessary?

How critical is that all numerical algorithms converge? What are the theoretical guarantees that the proposed closed-loop scheme will work adequately?

2. The **resilience** of the controlled system. What are the (extreme/adverse) scenarios that have been taken into account and how will the closed-loop system behave under extreme conditions?

In particular, regarding point 2, the designer is often tempted to assume that the process will behave in a similar way to the model or with some reasonable deviation from that. In practice this assumption may sometimes fail and *extreme events* may be encountered.

Finally, although not related to the controlled process directly, we should consider the reliability of the process models in regard to which we have the following quality indicators

1. The **predictive ability of the model** which has been defined and quantified in an extensive analysis in deliverable report D2.1 and
2. the **foresight** of the model, i.e., up to what time in the future it can be used to produce a reliable prediction. Looking back into D2.1., the predictive ability of a model is a function of a desired prediction horizon. Here, we ask up to what prediction horizon can the model give predictions with reasonable error.

The above list has been compiled taking into account many resources, both from inside DISIRE and outside of it. In particular, it is worth mentioning the sources we consulted

1. The industrial case studies of MEFOS, DCI and KGHM; the industrial partners of DISIRE and the experience of IMTL, LTU, DAPP and ODYS
2. The experience of various EU research projects such as Direction (reports D1.1, D1.3, D1.4, D1.6 and D1.7), http://effinet.eu (report D2.3), e-PRICE (report D1.2), ADVANCED (report D1.2)
3. Scientific literature resources [1–7], the book “Performance Evaluation and Benchmarking of Intelligent Systems” [8], the concepts of KPI-based fault diagnosis [9], and economic MPC [10] which is, effectively, a KPI-based control approach on which our analysis in report D2.1 was based.
4. A whitepaper by redlion on seven common industrial KPIs which we took into consideration for our mathematical abstraction in Section 1.2.3.

The assessment and verification approach of DISIRE will be carried out through modelling and simulation. It is therefore necessary that the proposed performance metrics be calculated/estimated in the corresponding modelling and simulation environment. As the current submission of this document is mid-term, some of the proposed performance indicators may be modified or updated. We plan to update this document at M21 (following an internal review), M28 and M32 (when will be the final submission). It is important to note that there is no single, unique or “best” way to mathematically define KPIs. It is purely a matter of design choice and it, after all, reflects the needs of every particular application.

1.2.2 Evaluation by simulations

The KPIs we present here are intented for both the application environment, where they measure the actual performance of the process, and for evaluation of the process in simulation. In the first case their values reflect an actual and measured performance, whereas in simulations a mere projection of the system performance is possible. Therefore, estimated KPIs by simulations are random numbers and the modelling uncertainty and other sources of noise need to be accounted for. This means that one-shot simulations may not be indicative for the performance a closed-loop scheme is likely to have. This can be remedied with two possible techinques: (i) the use of a very long simulation horizon so that “unlikely” or “extreme” events (drawn from the probability distributions of the uncertain parameters) may occur and influence the perfomance evaluation and/or (ii) by running many closed-loop simulations using different (random) realisations of the underlying uncertainty, that is, in a sense, perform Monte-Carlo simulations. Here we propose a combination of the two and from each such run a value is produced for every KPI. Overall, we estimate therefore probability distributions of the KPIs and not just values.

1.2.3 Mathematical formulation

As already discussed, there is not a single way to mathematically formalise the above indicators. Some KPIs have already been introduced in D2.1 for the processes of WP7 and WP8. Here, we follow a more generic approach to KPIs and make a few observations: (i) KPIs are evaluated having collected a sample of input/output data from the process. The length of this sample determines the type of the KPI and its scope. This was already discussed in D2.1 where we introduced what we call level-A and level-B KPIs; (ii) from this sample we need to extract a characteristic value, which is typically an index of a statistical distribution. Two very natural choices are the *average* and the *maximum/minimum* values of it, as well as some α-level average value at risk. There are, however, other sensible choices as well.

Reciting D2.1: “We will distinguish between *level-A* and *level-B* KPIs. Level A KPIs will be defined at a higher frequency resolution and will be used by the process operator to monitor the instantaneous performance of the process,” and “level-B KPIs will be used to assess the overall performance of the furnace throughout the course of the whole campaign.”

Hereafter we shall give examples of KPIs. In a stochastic framework, as discussed in Section 1.2.2 a number of K simulations is produced each one of which produces a KPI (a scalar). Them, the performance is evaluated using a *statistical estimator* $\hat{\rho}$ of a mapping ρ from the space of random variables to $\mathbb{R}$ — for instance if $\rho = \mathbb{E}$, then $\hat{\rho}_K$ can be the arithmetic mean because $\hat{\rho}_K \to \rho$ as $K \to \infty$.

First, we will provide some very generic formulas with which KPIs can be constructed from a set of measurements $\{s_i\}_{i=1,\ldots,K}$, with $s_i \in \mathbb{R}^s$. We associate with these measurements the sequence $\{\varsigma_i\}_{i=1,\ldots,K}$ with $\varsigma_i = \|s_i\|$, where $\|\cdot\|$ is a vector norm. A KPI is then a mapping $\mathrm{KPI} : \mathbb{R}^{s\times K} \to \mathbb{R}$. Here we will treat KPIs as costs, so lower values are always better. We identify the following generic types of indicators

1. The **average norm**, which is defined as

$$\|\{s_i\}_i\|_{av} = \frac{1}{K}\sum_{k=1}^{K}\|s_k\| \tag{1.1}$$

2. The **root mean square**, which is defined as

$$\mathrm{RMS}(\{s_i\}_i) = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\|s_k\|^2} = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\varsigma_k^2} \tag{1.2}$$

   Often the RMS value is used as RMSE (root mean square error) and ss the term suggests, that KPI is used to quantify *errors* such as tracking errors.
3. The **percentage of incidence** with respect to a condition A, that is

$$\sigma(\{s_i\}_i) = \frac{1}{H_s}\sum_{k=1}^{H_s}\nu(s_k \mid \mathrm{A}(s_k)), \tag{1.3}$$

   where $\nu(s_k \mid \mathrm{A}(s_k)) = 0$ if $\mathrm{A}(s_k)$ is false and $\nu(s_k \mid \mathrm{A}(s_k)) = 1$ otherwise.
4. The **average value at risk** of level α of the sequence $\{\varsigma_i\}_i$
5. Any of the above applied to a **distance-to-set** sequence, that is

$$\hat{s}_i = \mathrm{dist}(s_i \mid C) = \inf_{y\in C}\|y - s_i\|, \tag{1.4}$$

   and $\hat{s}_i \geq 0$; for example, we can as a KPI the average, or AV@R of these norms
6. The **maximum** of one of the above sequences, i.e., either $\{\varsigma_i\}_i$ or $\{\hat{s}_i\}_i$ (or the **minimum** when we intend to maximise the KPI).

Tracking error KPIs along a simulation horizon H_s is given by the root-mean-square error, which essentially is a weighted 1-2-norm (sum of norms) of the total error, that is

$$\mathrm{KPI}_{\mathrm{tracking}} = \sqrt{\frac{1}{H_s}\sum_{k=1}^{H_s}\|\varepsilon_k\|^2}, \tag{1.5}$$

where ε_k is the tracking error at time k, that is

$$\varepsilon_k = z_k - z_k^{\mathrm{sp}}, \tag{1.6}$$

where z_k is the part of the system output that we need to steer to a set-point and z_k^{sp} is the set-point at time k.

Assume that the constraints $(x_k, u_k) \in \mathcal{C}$ need to be imposed. Then, the constraints satisfaction can be evaluated in various possible ways. First, counting the time instants when the constraint is not satisfied, that is

$$\mathrm{KPI}_{\mathrm{c/c}} = \frac{1}{H_s}\sum_{k=1}^{H_s}\nu(x_k, u_k \mid \mathcal{C}), \tag{1.7}$$

where

$$\nu(x_k, u_k \mid \mathcal{C}^c) = \begin{cases} 0, & \text{if } (x_k, u_k) \in \mathcal{C} \\ 1, & \text{if } (x_k, u_k) \notin \mathcal{C} \end{cases} \tag{1.8}$$

KPI (1.7) is useful when the extent of constraint violation is no more important than the violation it self, typically when it is very likely to lead to break downs and absolutely no constraint violations can be tolerated. $\mathrm{KPI}_{\mathrm{c/c}}$ gives the percentage of time instants when the constraints are violated, but would return a very high value if the constraints are consistently and continuously violated by an infinitesimally small amount and a very small return, if the constraints are rarely, but considerably violated.

When, we need to quantify the extent and intensity of constraints violation we may use an index such as the average or the AV@R or the maximum of the sequence

$$\{\mathrm{dist}((x_k, u_k) \mid \mathcal{C})\}_{k=1,\ldots,K}\,. \tag{1.9}$$

The smoothness of the operation of a process is estimated by the time-gradient of the actuation and response of the system. To the extent that all other KPIs are optimised or are kept within desired bounds, the smoothness of operation will determine the best mode of closed-loop operation. In certain cases, especially when the actuation is by valves or other moving mechanical parts, the minimisation of the corresponding KPI is vital for the longevity of the actuators. The gradient of $\{s_i\}_i$ will be denoted by $\{\nabla s_i\}_i$ where

$$\nabla s_i = s_i - s_{i-1}. \tag{1.10}$$

We may then derive various KPIs on the sequence $\{\nabla s_i\}_i$, or the sequence $\{\|\nabla s_i\|\}_i$.

The original seven KPIs proposed by redlion are the following: (i) *count* (good or bad) which is covered by the incidence class of KPIs presented in (1.3), (ii) the *reject ratio* KPI which is a quality KPI and is of the same general type as (i), (iii) the *production rate* which can be quantified as an average or AV@R of the measured production rate, or an average norm of a production vector can be computed (when multiple products are produced from the same process), (iv) *target KPIs* which are for KPIs similar to what set-points are for system outputs, i.e., they are desired values. In the case of KPIs, these are typically minimum or maximum desired values, (v) the *takt time* which is the amount of time for the completion of a task (e.g., the production of a product). In the process industry this is typically captured by the production rate, however, it is quite indicative of the speed of process and helps identify slow processes and bottlenecks, (vi) the *overall equipment effectiveness* is then used to quantify the utilisation of resources of the equipment. In our context this can be quantified by a distance-to-set from the system boundaries. Essentially, we ask the question: do we make the most out of the system and — in particular — the limits on its variables? and (vii) the *downtime* of the process which might be due to regular schedulled maintenance (which cannot be avoided with improved control techniques) or due to unexpected faults (which can be avoided by a controller which is "more gentle" with the actuators).

1.2.4 Performance evaluation in the context of SMPC

The evaluation of performance in the context of SMPC naturally produces certain KPIs by looking at the SMPC problem which was introduced in Chapter 3 of D2.1 which is written as

$$V^\star(p, \hat{\mathbf{w}}_k, k) = \min_{\pi} \mathbb{E} V(\pi, p, k), \tag{1.11}$$

where V is the total cost function along a prediction horizon N given by

$$V(\pi, p, k) = \sum_{j=0}^{N-1} \ell(x_{k+j|k}, u_{k+j|k}, k+j), \tag{1.12}$$

subject to the system constraints, i.e., the system dynamical equations which are equality constraints, the system constraints on states and inputs which are inequality constraints and, possibly, input-disturbance couplings. The function ℓ naturally merges together various system objectives such as economic (reduction of actuation energy, e.g., fuel), tracking accuracy, cost terms on state or input derivatives to lead to a smooth operation, soft constraints and more. A weight factor is assigned to each such sub-cost to produce the single cost function ℓ which best reflects the operation objectives. This choice induces a KPI which can be

$$\mathrm{KPI}_{\mathrm{smpc}} = \hat{\rho}_K(\{\ell(x_k, u_k, k)\}_{k=1,\ldots,K}), \tag{1.13}$$

where $\hat{\rho}_K$ is a statistical estimator as discussed in Section 1.2.3, for example

$$\mathrm{KPI}_{\mathrm{smpc,av}} = \frac{1}{K} \sum_{k=1}^{K} \ell(x_k, u_k, k), \tag{1.14}$$

or

$$\mathrm{KPI}_{\mathrm{smpc,AV@R}_\alpha} = \inf_{t \in \mathbb{R}} \left\{ t + \frac{1}{\alpha N} \sum_{k=1}^{K} [\ell(x_k, u_k, k) - t]_+ \right\}, \tag{1.15}$$

which is an estimator of the average value at risk with confidence level α and can be computed by a linear programming solver.

Another metric is related to the evaluation of the complexity of the SMPC problem. SMPC problems can be rather complex, especially as the number of scenarios can give rise to problems with millions of variables. We ask whether the chosen complexity is reasonable? Essentially, the question we address is how many scenarios should we take into account so as to have a reliable representation of the uncertainty's PDF that is suitable for closed-loop simulations. Maggioni and Pflug provide a rigorous answer to this question in [11]; in brief, as more scenarios are introduced into the problem or, in general, as the *filtration* becomes finer, say $\mathfrak{F} \subseteq \mathfrak{F}'$, the respective value functions increase:

$$V^\star(p, \hat{\mathbf{w}}_k, k; \mathfrak{F}) \leq V^\star(p, \hat{\mathbf{w}}_k, k; \mathfrak{F}'), \tag{1.16}$$

and the required computational time increases accordingly. This property is known as *informa-*

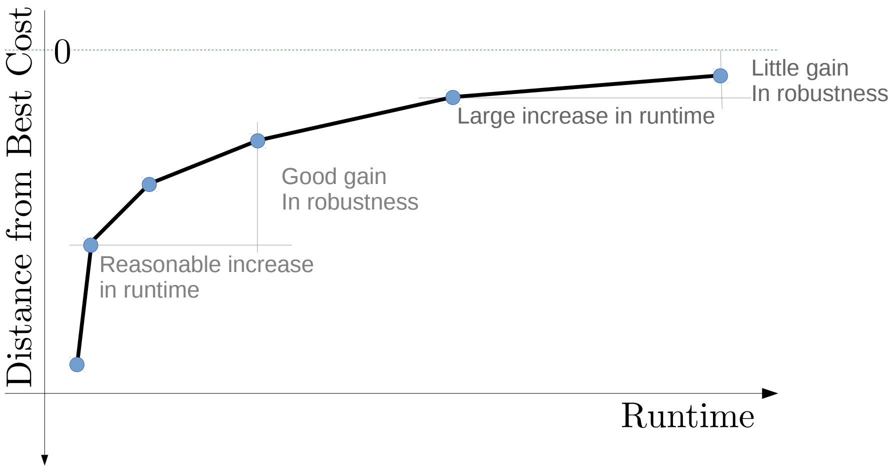

Figure 1.1: Total cost $V^\star(p, \hat{\mathbf{w}}_k, k; \mathfrak{F})$ vs runtime for various (increasing) number of constraints.

tion monotonicity.

This is illustrated in Figure 1.1: finer filtrations incur an increased computational cost, but also offers an improvement in the total cost, i.e., every instance of the SMPC problem will produce a sequence of control functions which will lead to lower expected cost. The desired balance between optimality and performance needs then to be decided by the designer and taking into account the available sampling time and the computational capabilities that are available.

Chapter 2

Case Study: Walking Beam furnace

2.1 Quality of data

The data collected from the WBF are of rather high quality with no missing values and a high sampling rate ($1s$) which allows us to perform filtering and obtain very accurate measurements. There are so far no calibration data, so we cannot know whether there are biases in the measurements. From the data we have received, we cannot deduce anything about the downtime/uptime of the process.

2.2 Closed-loop performance

2.2.1 Economic performance

The economic operation of the furnace will be evaluated by the consumption of fuel for the combustion at the three zones.

KPI	*note*	*value*
$\mathrm{KPI}^1_{f,av}$	Average fuel consumption at Z1	12.037 $\mathrm{kg/h}$
$\mathrm{KPI}^2_{f,av}$	Average fuel consumption at Z2	9.2570 $\mathrm{kg/h}$
$\mathrm{KPI}^3_{f,av}$	Average fuel consumption at Z3	53.391 $\mathrm{kg/h}$
$\mathrm{KPI}^1_{fr,av}$	Average fuel rate at Z1	32.256 kg/h
$\mathrm{KPI}^1_{fr,av}$	Average fuel rate at Z2	24.266 kg/h
$\mathrm{KPI}^1_{fr,av}$	Average fuel rate at Z3	27.155 kg/h

Table 2.1: KPIs for the economic operation of the furnace.

2.2.2 Tracking capability

The current control system seems to obtain in general good tracking, but, it can be seen, there are certain time instants where the tracking error too high (about $\pm 50°\mathrm{C}$).

KPI	*note*	*value*
$\mathrm{KPI}_{\mathrm{tr}}$	tracking RMSE	9.70 $^\circ\mathrm{C}$
$\mathrm{KPI}^{1}_{\mathrm{tr,max}}$	Maximum tracking error, Z1	31.2 $^\circ\mathrm{C}$
$\mathrm{KPI}^{2}_{\mathrm{tr,max}}$	Maximum tracking error, Z2	44.5 $^\circ\mathrm{C}$
$\mathrm{KPI}^{3}_{\mathrm{tr,max}}$	Maximum tracking error, Z3	51.6 $^\circ\mathrm{C}$
$\mathrm{nKPI}_{\mathrm{tr}}$	tracking RMSE considering only nonzero errors	15.3 $^\circ\mathrm{C}$
$\mathrm{nKPI}_{\mathrm{a}}$	Average norm of tracking error – only nonzero errors	11.1 $^\circ\mathrm{C}$
$\mathrm{nKPI}_{\mathrm{q,95\%}}$	Quantile-95% of tracking error – only nonzero errors	34.6 $^\circ\mathrm{C}$
$\mathrm{nKPI}_{\mathrm{q,97.5\%}}$	Quantile-97.5% of tracking error – only nonzero errors	41.5 $^\circ\mathrm{C}$
Active control	Time during which the controller was active	30.16 h
Total time	Total duration of the campaign	310.48 h

Table 2.2: KPIs determined from $H_s = 111773$ filtered data points.

2.2.3 Smoothness of operation

The smoothness of the operation of the furnace is quantified using the time-gradient of the control actions and the responsiveness of the temperatures at its three zones. We will investigate whether we can obtain a better tracking result at an improved smoothness, or at least a not too higher smoothness. Currently, we do not have an indication about whether there should be an upper bound on the gradient of the actuation.

KPI	*note*	*value*
$\mathrm{KPI}^{1}_{\nabla\mathrm{oil}}$	Mean absolute oil rate gradient, Z1	46.1 $\mathrm{kg/h^2}$
$\mathrm{KPI}^{2}_{\nabla\mathrm{oil}}$	Mean absolute oil rate gradient, Z2	46.4 $\mathrm{kg/h^2}$
$\mathrm{KPI}^{3}_{\nabla\mathrm{oil}}$	Mean absolute oil rate gradient, Z3	47.9 $\mathrm{kg/h^2}$
$\mathrm{KPI}_{\nabla\mathrm{oil}}$	Mean absolute oil rate gradient	321.61 $\mathrm{kg/h^2}$

Table 2.3: KPIs for the smoothness of control actions and the responsiveness of the furnace taking into account the 31.2 hours of operation when there was fuel flow higher than $10kg/h$ in zones 1 and 3 and higher than $3kg/h$ in zone 2.

2.2.4 Process quality characteristics

The quality of the process, that is the quality of the combustion is assessed by the excess of Oxygen in each zone. As discussed in D2.1, the availability of Oxygen determines the efficiency of the combustion and it is generally desired to have full combustion under adequate excess of Oxygen. Notice that here, unlike other KPIs reported above, the KPIs reported here need to be maximised.

The quality of combustion, from the data which we have gathered, is judged to be adequate and it is rare that the furnace runs out of Oxygen at any of its zones. This is illustrate in Figure 2.1, but it can also be seen in Table 2.4. Indeed, in a mere 0.0329% of time does the concentration of Oxygen drop under the value of 1.5% and it is even more rare (0.0024%, 0.01% and 0.0017% for the three zones respectively) for the excess of Oxygen to drop under the critical value of 1% when the combustion is inadequate.

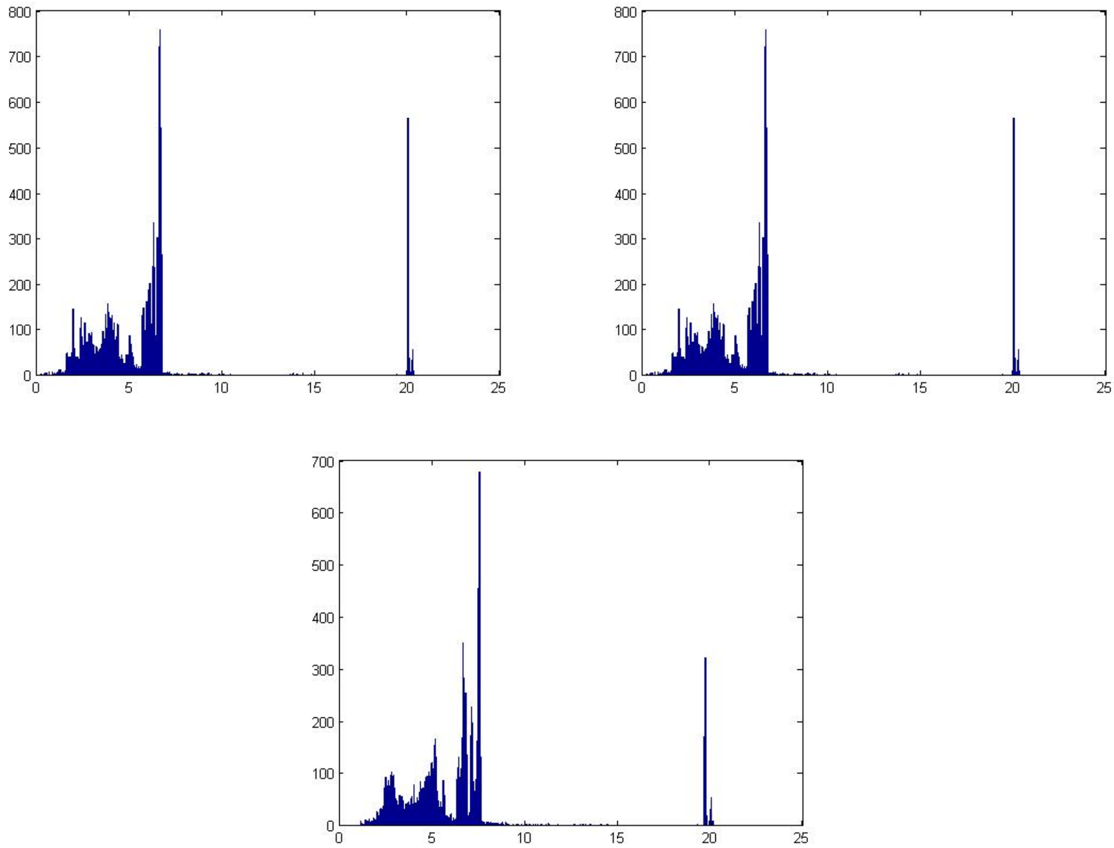

Figure 2.1: Histogram of the excess of Oxygen for the zones of the WBF. Notice that most of the time, the Oxygen concentration is retained above the critical value of 1.5%. The “outliers” at around 20% occur when there is no combustion.

KPI	*note*	*value*
$\mathrm{KPI}^1_{O_2,cl}$	Incidence of low oxygen ($< 1.5\%$), Z1	0.0045%
$\mathrm{KPI}^2_{O_2,cl}$	Incidence of low oxygen ($< 1.5\%$), Z2	0.0220%
$\mathrm{KPI}^3_{O_2,cl}$	Incidence of low oxygen ($< 1.5\%$), Z3	0.0329%
$\mathrm{KPI}^1_{O_2,\min}$	Minimum oxygen, Z1	0.095%
$\mathrm{KPI}^2_{O_2,\min}$	Minimum oxygen, Z2	0.008%
$\mathrm{KPI}^3_{O_2,\min}$	Minimum oxygen, Z3	0.010%
$\mathrm{KPI}^1_{O_2,av}$	Average Oxygen, Z1	13.92%
$\mathrm{KPI}^2_{O_2,av}$	Average Oxygen, Z2	13.44%
$\mathrm{KPI}^3_{O_2,av}$	Average Oxygen, Z3	12.03%
$\mathrm{KPI}^1_{\mathrm{suff},av}$	Average duration of suffocation period ($< 1.0\%$), Z1	$5.57min$
$\mathrm{KPI}^2_{\mathrm{suff},av}$	Average duration of suffocation period ($< 1.0\%$), Z2	$10.17min$
$\mathrm{KPI}^3_{\mathrm{suff},av}$	Average duration of suffocation period ($< 1.0\%$), Z3	$10.0h$
$\mathrm{KPI}^1_{\mathrm{suff},\max}$	Max. duration of suffocation period ($< 1.0\%$), Z1	$11.2min$
$\mathrm{KPI}^2_{\mathrm{suff},\max}$	Max. duration of suffocation period ($< 1.0\%$), Z2	$42.0min$
$\mathrm{KPI}^3_{\mathrm{suff},\max}$	Max. duration of suffocation period ($< 1.0\%$), Z3	$13.7min$

Table 2.4: KPIs for the smoothness of control actions and the responsiveness of the furnace taking into account the 31.2 hours of operation when there was fuel flow higher than $10kg/h$ in zones 1 and 3 and higher than $3kg/h$ in zone 2.

Chapter 3

Conclusions and planned work

During this first phase of the project ($\leq$M18) we have introduced a complete mathematical framework with which we may assess the performance of a controlled system in simulation taking into account the modelling uncertainty. The uncertainty of the system models has been reported in D2.1, while here we focus on the assessment of the controlled plant in closed-loop with the proposed stochastic MPC controllers.

The next steps are to use the proposed framework to compute all the KPI values (along with an estimation of their uncertainty as discussed) for the proposed controllers and assess the expected performance and benefit of implementing the proposed technology. Those KPI values will be compared with the currently implemented “baseline” solutions. This will clearly assist in a cost-benefit analysis.

The contribution of all partners to the making of this report is analysed in Table 3.1.

Partner	*Contribution*
IMTL	IMTL performed a literature review regarding KPIs currently in use in industrial applications and proposed a taxonomy of KPIs in Chapter 1.
LTU	LTU assisted IMTL in the mathematical formulation of the KPIs reported in this report.
MEFOS	MEFOS proposed KPIs related to the economics of the walking beam furnace.
G-Stat	G-Stat proposed indicators of computational feasibility.
ODYS	ODYS reviewed this report.

Table 3.1: Contributions of DISIRE partners to report D2.3 (up to month 18).

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