# Learning-based Predictive Control for Acid Flue Gas Abatement in Waste to Energy Plant*

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*Abstract*— **This work describes the application of a Model Predictive Control (MPC) strategy to the acid abatement process in a Waste to Energy (WtE) plant. By exploiting real closed-loop operational data, collected from an Italian WtE plant, black-box methods are applied to identify suitable prediction and simulation models for the development and validation of the learning-based MPC strategy. Simulation results under real operation conditions show an increment in cost-effectiveness of reagent usage in the abatement process, with potential savings of up to 24.5 tons/year. Furthermore, it also allows increasing the effectiveness in reference tracking and the compliance with stricter emission limits.**

## I. Introduction

Acid gas abatement in Waste to Energy (WtE) plants is a critical topic in managing and reducing pollutant emissions. The state of the art for acid flue gas treatment in WtE plants covers a wide range of issues, including the evaluation of different abatement technologies, the effectiveness of various chemical agents, and the modeling of the acid treatment process to enhance the tuning of conventional control schemes or to implement more advanced control structures. For example, the evaluation of single and double-stage acid flue gas treatment systems is described in [1]. The residues from neutralization processes using calcium-based sorbents are characterized in [2]. [3] and [4] evaluate the acid gas abatement during combustion by injection of the sorbent directly into the combustion chamber. The reactivity of sodium bicarbonate with $HCl$ and $SO_2$ acids at different temperatures is studied in [5]. The thermodynamic behavior of calcium and sodium based sorbents is analyzed in [6] and [7]. A conversion model for solid calcium hydroxide and sodium bicarbonate in the context of hydrochloric acid neutralization in a 2-stage acid abatement system is presented in [8]. All the previous works focus on the design of the abatement process and not on its real-time control.

Given an existing plant, some researchers have studied the modeling of the abatement dynamics and the optimal control of the process. The identification of a dynamic model for a 2-stage acid abatement system, aimed at improving the controller tuning, is presented in [9]. A linear Model Predictive Control (MPC) application for the first stage on a 2-stage acid abatement system is described in [10], manipulating the calcium hydroxide feed rate. The performance of the proposed controller is evaluated in simulation using a linear model as the plant dynamics.

In this work, we propose a completely data-driven approach to the design and validation of learning-based predictive control strategy [11], applied to hydrogen chloride ($HCl$) abatement in a WtE plant with a single-stage acid abatement system, using sodium bicarbonate ($NaHCO_3$). First, adequate prediction and simulation models are estimated from experimental data. Linear models are preferred for the prediction task to obtain a convex optimization problem in the MPC formulation. Instead, nonlinear models are preferred for the simulation task to achieve validation results as close as possible to the actual behavior of the plant. The results from the model identification procedure indicate that an auto-regressive (ARX) model offers a good trade-off for the prediction tasks, while a Hammerstein-Wiener model is required to reproduce the behavior of the plant in a large set of conditions. This setup is preferred due to its computational efficiency.

The usage of distinct models, a linear model within the MPC framework, and a nonlinear model for process simulation, enables a more robust evaluation of the feasibility and performance of linear MPC for the gas abatement problem.

## II. Hydrogen Chloride abatement process

The acid gas abatement system of the plant under study is shown in Fig. 1. The removal of hydrogen chloride is achieved by a single-stage dry sorbent injection. Sodium bicarbonate is injected into the quencher, upstream of the fabric filter. Most of the acid gas neutralization occurs within the dust cake that accumulates on the fabric filter, which contains fly ash, bicarbonate, and activated carbon for the removal of organic gases and mercury. Subsequently, the flue gases go through the Selective Catalytic Reduction (SCR) system that reduces nitrogen oxides, and finally, the flue gases are released into the atmosphere from the stack, achieving the reduction of pollutant components in compliance with emission standards.

The $HCl$ abatement process is described by the neutralization reaction process between acid and base reagents,

$$HCl + NaHCO_3 \Rightarrow NaCl + H_2O + CO_2 \qquad (1)$$

where $HCl$ is the acid and $NaHCO_3$ is the base that react to form a neutral compound in the form of $NaCl$ salt. Based on stoichiometry considerations, the ideal bicarbonate dosage corresponds to a one-to-one molar ratio with the acid

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present in the flue gas arriving at the quencher. However, the real process is affected by unknown inefficiencies and unmeasured disturbances that require a feedback regulation of the bicarbonate dosage, based on the measured output concentration at the stack.

The control strategy currently implemented in the studied plant is a conventional feedback plus feedforward control scheme, designed to regulate the concentration of $HCl$ in the flue gas at the stack. This is achieved by manipulating the bicarbonate feed rate based on measurements of the $HCl$ concentration in the flue gas at the stack and the $HCl$ concentration in the gas entering the quencher, generated during the waste combustion process. The controller is a multiple-input single-output (MISO) system, where the manipulated variable is the bicarbonate feed rate, the measured disturbance input is the HCl concentration in the flue gas entering the quencher, and the controlled output is the HCl concentration measured at the stack.

## III. Black-box modeling

The first step in the development of the control strategy is to obtain a dynamic model of the process. The data-driven modeling task is presented in this Section.

### A. Dataset

The dataset used in this study contains 52 days of 1-minute sampled data. It is formed by closed-loop data of different process variables measured by the Decentralized Control System (DCS) and Continuous Emission Monitoring System (CEMS) during normal operating conditions of the plant. It is subsequently divided into 15 days for model training, and the remaining dataset is used for extensive validation, evaluating both the accuracy of the identified models and the performance of the MPC strategy.

The main statistical properties of the variables used to describe the acid abatement process are reported in Table I. These are the acid concentration measured before entering the quencher ($HCl_{in}$), representing the disturbance input of the control system; the bicarbonate reagent feed rate used in the dry reaction process ($NaHCO_3$), used as manipulated variable in the dry reaction process; and the acid concentration measured in the flue gas at the stack ($HCl_{out}$), being the controlled process variable.

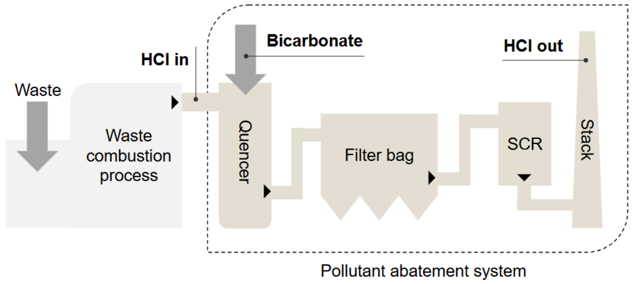


Fig. 1. WtE plant scheme showing the pathways of the flue gas generated from waste incineration through the pollutant abatement units.

In the system identification procedure adopted in this work, the model has 2 external inputs, which are the measured disturbance $HCl_{in}$ and the sodium bicarbonate feed rate $NaHCO_3$, while the model output is the acid output concentrations $HCl_{out}$. Meanwhile, the hyperparameters of each model class are tuned by a cross-validation process where the models are trained on different training sets and validated on the remaining datasets, to robustly identify combinations of hyperparameters that manage to achieve a good balance between model complexity and accuracy.

Additional process variables that could impact the acid abatement process, such as other acid concentrations (e.g. $HF$ and $SO_2$), pressure drop across the bag house, post combustion temperature, $O_2$ levels and flue gas flow rate, chosen by leveraging experts' knowledge about the acid abatement process, have been considered as additional inputs. However, their inclusion did not significantly improve accuracy and, in some cases, created over-fitting issues with poor generalization, while also adding complexity to the models.

TABLE I

Statistical description of the dataset

| | Max | Min | Mean | Median | Std |
|---|---|---|---|---|---|
| $HCl_{out}(mg/m^3)$ | 46.0 | 0.004 | 4.7 | 4.5 | 2.0 |
| $HCl_{in}(mg/m^3)$ | 3150 | 0.3 | 1211 | 1137 | 471 |
| $NaHCO_3(kg/h)$ | 2388 | 100 | 273 | 236 | 159 |

### B. Evaluation of model classes

Different black-box model classes [12] are evaluated to find suitable models to describe the process dynamics, both in prediction and simulation. Linear models, such as AutoRegressive with eXogenous input (ARX), AutoRegressive Moving Average with eXogenous input (ARMAX), and Output Error (OE) structures, are considered. Also, nonlinear models, such as Hammerstein-Wiener (HW) and Neural Network AutoRegressive with eXogenous input (NNARX) models, are evaluated.

Models with different structures and orders are estimated using the Prediction Error Method (PEM). The hyperparameters of each class are instead selected as a trade-off between model complexity, i.e., the total number of model parameters, and prediction accuracy, measured as the resulting Root Mean Squared Error (RMSE), evaluated for prediction and simulation. In particular, the NNARX model hyperparamaters tuning was divided into two steps, first, the choice of the autoregressive structure is decided. Subsequently, the network structure is chosen by testing both shallow and deep network structures. The identification results, in terms of Root Mean Square Error (RMSE) are reported in Table II, concerning both prediction, calculated for 1-step ahead prediction, and simulation performances.

### C. Prediction model

Within the scope of the predictive controller implementation, the ARX model is chosen as the preferred prediction model, considering its performance, in terms of RMSE,

TABLE II
SUMMARY OF IDENTIFICATION RESULTS FOR LINEAR AND NONLINEAR MODEL STRUCTURES

| | **Number of model parameters** | **RMSE** *Prediction* | **RMSE** *Simulation* |
|---|---|---|---|
| ARX | 9 | 0.34 | 2.58 |
| OE | 12 | 2.63 | 2.63 |
| ARMAX | 16 | 0.33 | 5.30 |
| HW | 15 | 1.41 | 1.41 |
| NNARX | 159 | 0.31 | 1.67 |

compared to other more complex models. The ARX model (2) represents the input-output relation as a single difference equation where the output at time $t$ is formed as a linear combination of past and possibly present values of the inputs, and past values of the output, plus an additive disturbance term, that is,

$$y(t) = \sum_{i=1}^{n_a} a_i y(t-i) + \sum_{m=1}^{M} \sum_{j=0}^{n_{bm}} b_{mj} u_m(t-n_{km}-j) + e(t), \quad (2)$$

where $M$ is the number of inputs, $n_a$ is the order of the output regressor, $n_{bm}$ is the order of the regressor for the $m^{th}$ input, $n_{km}$ is the delay of the $m^{th}$ input. The parameters of the ARX model are the coefficients $a_i$, for $i = [1, \dots, n_a]$ and $b_{mj}$, for $m = [1, \dots, M]$, $j = [0, \dots, n_{bm}]$, while the hyper-parameters of the model class are the lengths of the regressors $n_a$, $n_{bm}$ and the input delays $n_{km}$. The chosen prediction model is parametrized as $n_a = 3$, $n_b = [3, 3]$ and $n_k = [0, 0]$.

In compact form, the ARX model can be expressed as:

$$y(t) = \sum_{m=1}^{M} \frac{B_m(z)}{A(z)} z^{-n_{km}} u_m(t) + \frac{1}{A(z)} e(t) \quad (3)$$

with $A(z)$, $B_m(z)$, polynomials in the complex variable $z$, such that $y(t-1) = z^{-1} y(t)$.

### D. Simulation model

To evaluate the performance of the proposed control strategies, a simulation model is required, capable of reproducing the dynamics of the plant in a large set of conditions. A HW structure is selected as the simulation model, considering that the Input-Output nonlinearities implemented by the model allow for improving the simulation accuracy with respect to all the linear structures, and achieving results on par with more complex structures, such as the NNARX model.

The Hammerstein-Wiener (HW) model (4) extends the Output Error (OE) model class by including static nonlinearities to the input and output signals of the process,

$$\begin{aligned} w_m(t) &= l_m\left(u_m(t), \theta\right); \quad m = 1, \dots, M \\ x_m(t) &= \sum_{i=1}^{n_{fm}} f_{im} x_m(t-i) + \sum_{m=1}^{M} \sum_{j=0}^{n_{bm}} b_{mj} w_m(t-n_{km}-j) \\ y(t) &= h\left(\sum_{m=1}^{M} x_m(t), \theta\right) + e(t) \end{aligned} \quad (4)$$

where $l_m(\cdot, \theta)$ and $h(\cdot, \theta)$ are the input and output static nonlinearity functions, parametrized by $\theta$, and $w_m(t)$ is the transformed input signal arriving at the OE subsystem. In compact form, the HW model is expressed as:

$$y(t) = h\left(\sum_{m=1}^{M} \frac{B_m(z)}{F_m(z)} z^{-n_{km}} l_m(u_m(t), \theta), \theta\right) + e(t) \quad (5)$$

with $F_m(z)$, $B_m(z)$, polynomials in the complex variable $z$.

## IV. DATA-DRIVEN MODEL-BASED MPC

The Model Predictive Control scheme is well-suited for multi-objective control problems subject to constraints. In this case, balancing the reagent consumption while tracking the reference output concentration value and satisfying the regulation limits on the acid concentration values. The MPC strategy is defined as an iterative optimization problem, integrated with the prediction model.

### A. Optimization problem

A Finite Horizon Optimal Control Problem (FHOCP) is formulated as a convex optimization problem with a quadratic cost function and linear constraints, which considers not only the system evolution, physical limits of actuators, and reference tracking, but also compliance with the regulations. The system evolution is described by the identified ARX model, and the optimization problem is solved for a specified prediction horizon $N$, which, in the context of acid abatement, is set to 30 minutes to introduce the stringent constraints based on half-hour average output acid gas concentration values within the control problem.

The cost function is formulated based on the main objectives of the control task, specifically in the acid abatement control problem the objectives that have been considered are the reference tracking error, weighted by $Q_y$, which penalizes any deviation from the specified reference output concentration values; and the bicarbonate feed rate, weighted by $R$, which penalizes any over and under or over dosage, compared to the ideal feed rate calculated through the stoichiometric balance for the $HCl$ mass flow arriving from the combustion process. Finally, a weighted sum of slack variables is added to handle soft constraints. Summarizing, the cost function is

$$\begin{aligned} J_{min} = &\sum_{i=0}^{N} (y(i) - y_{ref})' Q_y (y(i) - y_{ref}) + \\ &+ \sum_{i=0}^{N-1} (u(i) - u_{stoich})' R (u(i) - u_{stoich}) + \sum_{i=1}^{2} \rho \epsilon_i \end{aligned} \quad (6)$$

Where $y$ is the acid output concentration measured at the stack, $d$ is the input acid concentrations entering the acid abatement system, $u$ is the bicarbonate feed rate, and $\epsilon$ are slack variables to implement soft constraints.

The optimization problem is subject to a set of linear constraints (7) that impose all the technical and operational conditions of the plant. First, a constant behavior is set for the disturbance input $d(i)$ along the horizon, using the current measurement of input acid concentration. Then, constraints to limit the control action $u(i)$ between the lower and upper mass rate values are considered. This ensures that the MPC works inside feasible control signal values. Next, a terminal constraint on the output $y(N)$ is defined to ensure asymptotic stability.

Emission limits are then introduced through the implementation of upper limits on the average output concentration during the horizon, as both hard and soft constraints. The bounds are chosen based on the regulations reported in the Integrated Environmental Authorization (IEA) document of the WtE plant. There are critical limits that cannot be surpassed and are set as as hard constraints. There are also less stringent limits, at lower concentrations, that can be surpassed during critical situations with high concentrations measured at the stack, but must still be respected during most of the plant operation time. Finally, constraints to enforce the system dynamics of the identified ARX prediction model are imposed. Additionally, the positivity of slack variables used to implement the soft constraints is also imposed.

The set of constraints reads as follows,

$$\begin{cases} d(i) = HCl_{in}(t), i \in [0, N]_{\mathbb{Z}} \\ u_{min} \leq u(i) \leq u_{max}, i \in [0, N]_{\mathbb{Z}} \\ y_{ref} - \epsilon_1 \leq y(N) \leq y_{ref} + \epsilon_1 \\ \frac{1}{N} \sum_{i=0}^{N-1} y(i) \leq HCl_{out,30min-hard-limit} \\ \frac{1}{N} \sum_{i=0}^{N-1} y(i) \leq HCl_{out,30min-soft-limit} + \epsilon_2 \\ y(i+1) = ARX(y(i), d(i), u(i)), i \in [0, N]_{\mathbb{Z}} \\ \epsilon_i \geq 0, i \in \{1, 2\} \end{cases} \tag{7}$$

The control action is computed following the Receding Horizon (RH) principle, where the optimization problem is solved, based on past and current process measurements, at each time instant, providing the optimal control sequence for the interval $[t, t+N-1]$. Then, only the first element of the control sequence $u(t)$ is applied to the system. The procedure is repeated at time $t+1$, generating a time-invariant feedback control law.

## V. MPC SIMULATION RESULTS

The MPC scheme described in the previous section is implemented in a Python environment, where the "cvxpy" [13] library is used for the formulation of the optimization problem, and "osqp" [14] is used as the solver to handle the quadratic programming problem and obtain the optimized solution.

The simulation and prediction models were identified offline using the training dataset as explained in Section III, while the remaining part of the dataset is used for the evaluation of the control strategy. The validation of the MPC is performed on two weeks of experimental plant data. The computation time for simulating the closed-loop system for the two weeks is 5 minutes.

The simulation architecture is shown in Fig. 2. It is composed of the simulation model (HW model) and the MPC implementation, which takes as input the process variables, including the disturbance input ($HCl_{in}(t)$), the controlled output ($HCl_{out}$) and past control actions ($NaHCO_3(t-1)$), to solve the optimization problem.

The parameters of the MPC strategy are set as follows. The reference output concentration is $y_{ref} = 5$, considering that the daily average limit is set to 5 $mg/m^3$. The weighting factors in the cost function are $Q_y = 4$, $R = 0.01$, $\rho = 0.1$. The bounds on the output concentration are $HCl_{out,30min-hard-limit} = 30$, $HCl_{out,30min-soft-limit} = 10$, and the limits on the input feed rate are $u_{min} = 100, u_{max} = 1000$.

The control scheme simulation is carried out using two weeks of validation data not used to train the models involved in the simulation. The performance results are shown in Table III, where the Mean Integral of Absolute Error (8) and Mean Integral of Squared Error (9) have been considered as performance indicators to compare the the MPC structure and the conventional control structure used in the real plant,

$$MIAE = \sum_{i=1}^{H} \frac{1}{H} |y_{ref}(i) - y(i)| \tag{8}$$

$$MISE = \sum_{i=1}^{H} \frac{1}{H} (y_{ref}(i) - y(i))^2 \tag{9}$$

where $y_{ref}$ indicates the reference value, $y$ represents the observed output values, and $H$ is the total simulation steps involved in the MPC validation.

Both control schemes resulted in an average output acid gas concentration of around 4.5 $mg/m^3$. However, the MPC managed to make a more cost-effective usage of the reagent

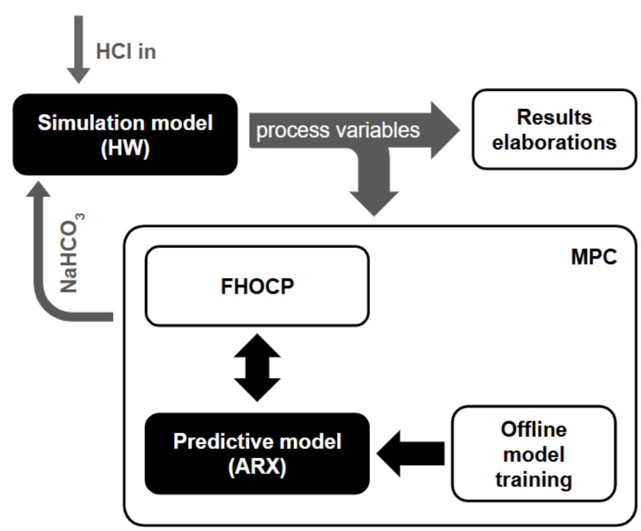


Fig. 2. Scheme representing the simulation structure. The MPC block is composed of the prediction model, obtained through offline system identification, and the optimization problem (FHOCP). The MPC interacts with the simulation model by retrieving process variable information and computing the optimal bicarbonate feed rate to apply for control purposes.

and also improved the tracking error as indicated by the MIAE, where there is a reduction of $57\%$. Similarly, the MISE reduction of $79\%$ suggests that the MPC manages more appropriately any strong deviation of the output from the reference, caused by critical events, such as rapidly rising input acid concentrations generated during waste combustion and low residual reagent accumulated on the fabric filter.

TABLE III
CONTROL RESULTS FO TWO WEEKS OF SIMULATION DATA

| | **MIAE** $(mg/m^3)$ | **MISE** $(mg/m^3)^2$ | **Mean** $NaHCO_3$ $(kg/h)$ |
|---|---|---|---|
| Plant data | 1.4 | 3.4 | 250 |
| MPC | 0.6 | 0.7 | 247 |

A comparison of the manipulated variable (bicarbonate feed rate) between the plant data and the signal generated by the MPC is given in Fig. 3. It shows a significant reduction of events with high dosage peaks when using the MPC approach, and a diminished signal variance. These results suggest that the MPC scheme can help to minimize the mechanical strain on the bicarbonate feeder's actuators by reducing the operation within high dynamic ranges. Additionally, the activation of auxiliary feeders, which are daisy-chained to the primary feeder, can be minimized by avoiding the saturation of the primary actuator.

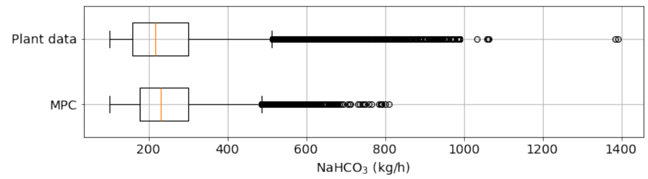


Fig. 3. Box plot comparison of bicarbonate mass rate between observed data with conventional control scheme (Plant data) and MPC results. The MPC results show a reduction in the severity of peak reagent demand and also a reduction in the variance.

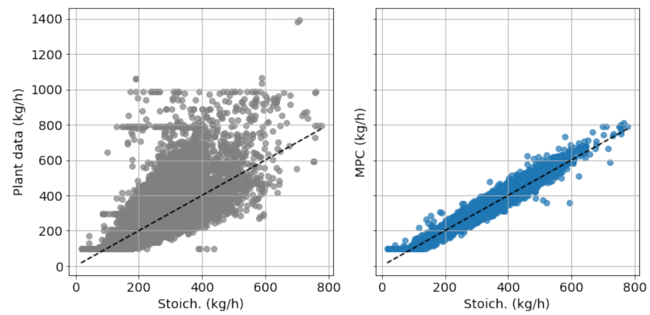


Fig. 4. Scatter plot comparison between the ideal feed rate based on stoichiometry on the x-axis and the feed rate produced by the control strategies on the y-axis, for the measured plant data (left) and MPC simulation (right).

Fig. 4 shows a scatter plot between the ideal stoichiometric bicarbonate feed rate and the feed rate imposed by the control laws. The conventional controller (left) shows strong cases of over-dosage (scatter points above the bisector) and under-dosage (below the bisector), while the MPC strategy (right) manages to improve this behavior. It optimally regulates the bicarbonate feed rate by reducing the deviation from the ideal level, thereby preventing over-dosage and under-dosage situations during the acid abatement process. Moreover, in the available measurements, the conventional scheme leads to critical situations as shown in Fig. 5. This is particularly evident after some time under favorable conditions, such as low acid concentrations in the arriving gas and low output concentration levels. Under these conditions, the conventional controller often overcompensates its feedforward term, resulting in an under-dosage of bicarbonate, which leads to a reduction of the residual reagent accumulated in the dust cake. Consequently, any sudden increase in the input acid concentration can not be adequately neutralized, leading to elevated output gas acid concentrations. In response, the controller produces an overdose of bicarbonate in an attempt to restore the output concentrations to nominal levels, producing a waste of reagent. This critical behavior is significantly mitigated by the MPC approach, which utilizes the prediction model to evaluate the optimal bicarbonate demand. The corresponding optimization problem considers the projected evolution of the abatement process and incorporates a penalty term to discourage unnecessary or aggressive bicarbonate demands. This formulation prevents spikes in reagent usage and reduces the risk of excessive under-dosage events.

Half-hour average values of output acid gas concentration are also evaluated, due to their relevance in regulatory compliance. According to the Best Available Techniques Reference (BREF) document for waste incineration [15], typical half-hour $HCl$ output concentration associated with the use of sodium bicarbonate in the dry flue gas cleaning range between 6 and 30 $mg/m^3$. In Fig. 6, the minimum value of 6 $mg/m^3$ is used as a benchmark to assess the two control schemes' performances. The observed data indicate that this threshold is exceeded in 25 instances under the existing control strategy, whereas the MPC scheme reduces these exceedances to 8 occurrences, indicating that the MPC controller can improve the compliance of half-hour emission limits.

## VI. CONCLUSION

In this work, we have proposed a Learning-based Predictive Controller, which uses data-driven methods to build dynamic models for regulating hydrogen chloride in a waste-to-energy plant. It demonstrates the potential of optimal control strategies for enhancing the reagent management in WtE plants. Integrating a prediction model in the control strategy enables more cost-effective regulation of the bicarbonate feed rates while maintaining the output concentrations within the regulatory limits. Unlike conventional feedforward plus feedback control schemes, which exhibit aggressive overcompensation, the MPC approach provides a smoother and more effective operation. Although the average output concentration under MPC was kept close to that of the existing control system to enable a fair comparison, the MPC strategy achieved not only a reduction in reagent consumption but also tracked the reference value more efficiently.

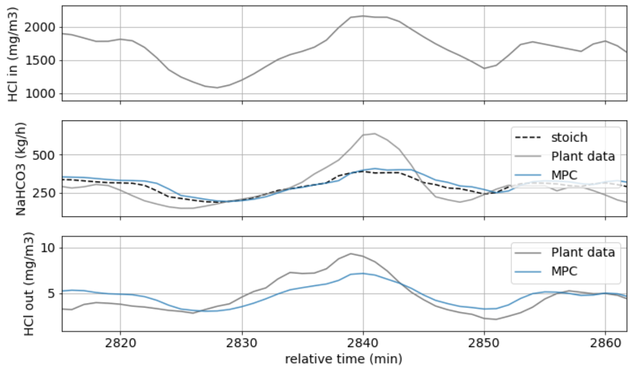


Fig. 5. Overcompensation behavior of the standard controller in the real plant compared to the MPC. The conventional controller tends to reduce excessively the bicarbonate feed rate ($NaHCO_3$) during favourable conditions. This leads to suboptimal performance when managing rising acid concentrations ($HCl$ in) generated during waste combustion. The delayed response causes a rapid increase in acid output concentrations ($HCl$ out), which results in an aggressive controller response leading to reagent overdosage.

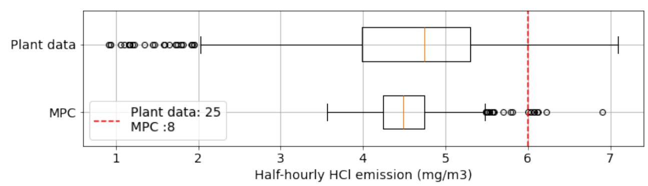


Fig. 6. Box plot comparison of half-hour average values of acid gas concentration between observed data with the conventional control scheme (Plant data) and the MPC results. In red it is shown the minimum output concentration level achievable with the usage of sodium bicarbonate as reported in the BREF document (6 mg/m3).

The fully data-driven approach employed to derive and validate the MPC scheme in simulation, specifically through the differentiation of the prediction and simulation models, enables a robust assessment of the feasibility of the MPC strategy before its implementation in the real plant. This methodology not only enables the safe tuning of the controller and early identification of potential criticalities associated with the MPC approach, but it also allows the assessment of the potential benefits in terms of performance and operational efficiency.

Furthermore, the proposed method can be extended to the control of other process variables within the WtE plant by following the same high-level methodology described for the acid abatement case. This involves identifying suitable process models, determining relevant regulatory and technical limits, and formulating the optimization problem, properly defining the control objectives and constraints.

Despite these advantages, using closed-loop data for the models' derivation introduces certain limitations, as the data tends to be close to the reference output concentration. To address this, limited open-loop testing could gather valuable data to enhance model accuracy and robustness, thereby extending the applicability of the MPC scheme to lower output concentrations, as regulatory requirements are becoming more stringent.

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