Nonlinear Model Predictive Control of Municipal Solid Waste Combustion Plants

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Keywords : nonlinear model predictive control, municipal solid waste combustion

Abstract : Combustion of municipal solid waste (MSW; = household waste) is used to reduce its volume and to produce energy. It is performed in furnaces at large industrial plants for which the control problem is to maximize waste throughput and energy output while still fulfilling life time and environment related constraints. This inevitably leads to a constraint pushing control problem with the back-off to the dominating constraint being determined by the ability of the control system to suppress the (very) large variation in the controlled variables. This variation is a result of the heavily fluctuating waste composition.

Current MSW combustion (MSWC) controllers are of the multivariable PID type and are claimed not to be able to deliver an optimal disturbance rejection control and, thereby, economic operation performance. The reason for that is that such controllers are limited with respect to exploiting the interactions present in the MSWC process. A much better alternative in that respect is model predictive control (MPC) as this control strategy does fully exploit these interactions. MPC with a linear model, *linear* MPC, is then the seemingly most obvious form of MPC to consider first because of its computational advantages. However, LMPC is also claimed to not to be able to deliver an optimal MSWC disturbance rejection performance as the large size of the disturbances will enforce the manipulated variables to run over such a large operating range that a linear model is not sufficient to capture all control relevant dynamics.

Another alternative is *nonlinear* model predictive control (NMPC), which should be able to overcome both mentioned disadvantages and, thereby, to deliver a better MSWC disturbance rejection performance. Via simulations with an assumably realistic MSWC plant model and under assumably realistic disturbances, the main question addressed here is whether this is true. It is shown that NMPC indeed is inherently capable of suppressing MSWC plant disturbances much better than both a multivariable PID and LMPC based controller.

The results show that not only severe nonlinearity of the plant to be controlled is a motivation for applying NMPC but also the large size of the disturbances, even if the nonlinearity of the plant is not severe. The results also show that MPC, while being mostly used for setpoint tracking purposes, may also provide added value for disturbance rejection control problems.

Int. Workshop on Assessment and Future Directions of NMPC
Pavia, Italy, September 5-9, 2008

1 Introduction

Due to lack of space, combustion of municipal solid waste (MSW) forms a suitable alternative to dumping for many parts of the world, in particular highly densily populated ones, despite the associated (assumed) negative effects on the environment. Although the removal of waste is the main motivation for waste combustion, it also often represents a lucrative business as the waste combustor is paid for the amount of waste that is processed. Also, the energy that results from waste combustion is often used to produce heat and/or electricity that is sold to surrounding plants or communities.

The goal for MSW combustion (MSWC) controllers can be stated as to maximize waste throughput and (thereby) energy output while still fulfilling lifetime related and environmental objectives. This leads to a *constraint pushing* type of control behaviour where the aim is to operate as closely as possible to the dominating (environment or lifetime related) constraint while violating this constraint a minimal number of times. The *back-off*, i.e. average distance, to this constraint is determined by the capability of the combustion control system to suppress the variations that are present on the controlled variables. These variations are very large for MSWC plants due to the inevitable large variation in waste composition. Reducing the size of these variations reduces the back-off and, thereby, allows for the operation at an economically more profitable operating point. As the amount of waste that is processed per year is very large for a typical MSWC plant, each small gain in back-off leads to a large increase in profit for such plants.

Current MSW combustion control systems are of the multivariable PID type and are not thought to be able to deliver a good disturbance rejection and, thereby, economic operation performance. The main reason for that is thought to be the limited capability in exploiting the interactions present in the MSWC process. This has been the motivation to consider alternative multivariable MSWC control strategies that exploit these interactions much better. In particular, it has been the motivation to consider model predictive control (MPC) strategies due to the availability of a validated low order first-principles model of the MSWC process (see [1]). The most common implementation of MPC is in the form of *linear* MPC (LMPC), i.e. by using a linear model of the plant to be controlled. However, it is thought that also this type of controller is not capable of delivering a fully optimal control performance for MSWC plants. The reason for that is that the large size of the disturbances will enforce the manipulated variables to run over such a large operating range that a linear model is not sufficient to capture all control relevant dynamics. This has been the motivation to consider *nonlinear* MPC (NMPC), which uses a nonlinear model of the plant to be controlled. Helpful in this respect was that the literature on NMPC seemed to suggest that that this control strategy is computationally feasible for low order nonlinear models.

However, so far, this motivation for applying NMPC has not been supported by experimental or synthetic data. The aim of this paper is to fill this gap. In other words, the main question addressed in this paper is whether NMPC based MSW combustion control systems are truly capable of delivering a largely better control performance than conventional and LMPC based such controllers. This question is answered here for a typical MSW combustion control *c.q.* disturbance rejection problem using simulations with an assumably realistic MSWC

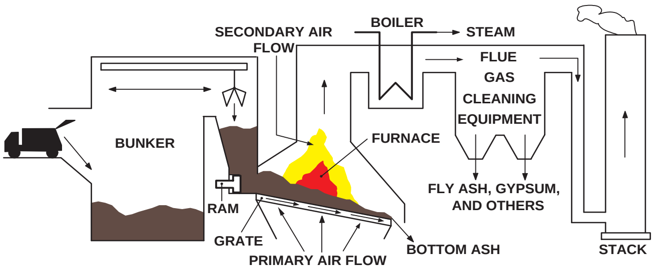

Figure 1: A typical MSWC plant.

plant model and under assumably realistic disturbances. Notably, these simulations are performed for the *state feedback* case, i.e. for the case that perfect information of the initial states and disturbances is available to the MPC controllers. This provides an answer to the question whether at least for this most ideal case the NMPC based controller is capable of outperforming the other two controllers. Only if this is the case, further research on NMPC based MSWC plant control can be motivated (taking into account model error, measurement noise and state estimation issues). As a side-effect, the results also answer the question whether LMPC based MSW combustion control is inherently capable of outperforming conventional such control.

The contents of this paper is as follows. First, in section 2, control of MSWC plants is discussed. This section also includes a definition of both the conventional, multivariable PID, MSWC controller and the MSWC control problem considered in the comparison of the controllers. Then, in section 3, the state feedback NMPC strategy considered in this comparison is outlined. The comparison itself is subsequently discussed in section 4. This section also discusses in more detail the setup of the corresponding simulations and the LMPC controller used in these simulations. The conclusions of the work presented here are collected in section 5.

2 Control of MSWC plants

Municipal solid waste is typically combusted at a plant as depicted in figure 1. After having been collected from households and transported to the MSWC plant, for example by truck, it is stored in a large bunker from which it is transported by cranes into a large chute. At the bottom of the chute the waste is pushed onto a moving grate by a ram. The waste is combusted while it is traveling on this grate using oxygen from air flows that are fed through holes in the grate (primary air flow) and furnace side walls (secondary air flow) to the solid waste layer and gas phase above it. The resulting flue gas enters a boiler delivering heat which is transformed into steam and, subsequently, into energy in the form of heat and/or electricity. The latter is typically sold to surrounding communities and/or industrial plants. Having passed the boiler, the flue gas is cleaned from residues that are not allowed to enter the surroundings.

Control of MSWC plants is performed by two independently operated control systems: (i) a control system for the furnace part, denoted as the *combustion*

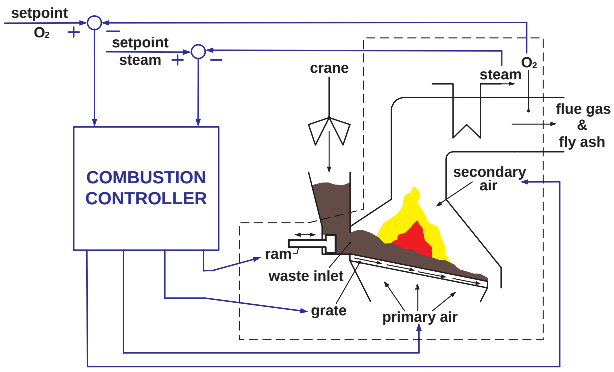

Figure 2: Combustion control at MSWC plants.

control system, and (ii) flue gas cleaning (air pollution, "post-combustion") control systems. The latter control systems, indeed, solely aim to minimze the amount of toxic flue gas components to below the limits required by law. The combustion control system controls the conditions in the furnace. Its aim can be stated as to maximize waste throughput and (thereby) energy output, while fulfilling lifetime related and environmental objectives. The reason for aiming to maximize waste throughput and energy output is that a waste combustor is paid for each amount of processed waste and produced energy. Consequently, the economically optimal operating point for an MSWC plant is a point that is as close to the dominating (environment or lifetime related) constraint as possible while violating this constraint a minimal number of times. The *back-off*, i.e. average distance, to this constraint is determined by the capability of the combustion control system to suppress the variations that are present on the controlled variables (CVs). These variations are very large for MSWC plants due to the inevitable large variations in the waste composition. In fact, minimization of these variations allows to operate closer to the dominating constraint and, thereby, to operate at an economically more profitable operating point. As the amount of waste that is processed per year is very large for a typical MSWC plant, each small gain in back-off leads to a large increase in profit over a year for such plants.

A typical combustion control system for MSWC plants is depicted in figure 2. The CVs here are (i) the steam production ϕ_{st} and (ii) the O_2 concentration in the flue gas. The manipulated variables (MVs) are (i) the setpoint for the ram frequency u_{ram}, which determines the waste flow to the furnace, (ii) the setpoint for the grate frequency u_{sog}, which determines the residence time of the waste on the grate, (iii) the primary air flow ϕ_{prim} and (iv) the secondary air flow ϕ_{sec}. Typically, an upper limit is imposed on ϕ_{st} out of lifetime considerations. Also, a lower limit is imposed on O_2 (by law) to ensure that sufficient O_2 is available for combustion and, thereby, to prevent the formation of undesired elements (CO). The aim of the combustion controller is to maximize u_{ram} and ϕ_{st} while violating these limits a minimum number of times. This implies that the optimal operating point is as close as possible to one of the two limits, whichever dominates, while violating it as few times as required. Violation occurs due to the waste composition variation induced disturbances on the CVs. Obviously, the combustion controller that reduces the corresponding fluctuations in ϕ_{st} and O_2 to a minimum is the one that allows to operate the MSWC plant at its economic optimum.

The control problem considered in this paper is that of minimizing as much as possible the fluctuations in ϕ_{st} and the O_2 by optimally manipulating u_{ram}, u_{sog}, ϕ_{prim} and ϕ_{sec}. The constraints on ϕ_{st} and O_2 are, notably, not explicitly taken into account here: the handling of these constraints (which is considered one of the main motivations for applying MPC) by the controllers considered in this paper is not discussed here.

One of the controllers that is used in this paper for tackling the considered control problem is of the conventional, multivariable PID type. This controller, which for reasons of space is not discussed here in detail, has been designed on the basis of a detailed analysis of the MSWC plant dynamics as encountered in estimated black-box models and first-principles models (see [1, 2]). This controller is thought to sufficiently well represent the performance of commercially available conventional MSWC plant controllers (in fact, to even perform better).

3 A state feedback MSWC NMPC strategy

3.1 Model

The state feedback MSWC plant NMPC strategy proposed and employed here uses an extended version of one of the two low order ($n \approx$ 3-4) first-principles models presented in [1]. One of these two models has been adapted to and validated against real-life data, though in an indirect manner using closed-loop system identification techniques to remove the validation problems due to the large disturbances present on the data. See [1] and [2] for the applied validation techniques and corresponding results. The validated model was found to be in good agreement with the real MSWC plant dynamics, providing confidence in the hypothesis that the main dynamics of an MSWC plant can be captured in a low order first-principles model. For reasons of space, these dynamics, as encountered in the mentioned MSWC plant models, are not discussed here. For that, see [1].

3.2 Implementation

The state feedback MSWC plant NMPC strategy proposed and employed in the simulations here follows the standard receding-horizon control approach of repeatedly, i.e. at each sample time, solving a finite-horizon open-loop optimal control problem for newly provided initial state and disturbance values. The first of the resulting MVs are then implemented at the next sample time on the plant to be controlled, after which the optimal control problem is solved again for newly obtained initial state and disturbance values. In addition, as is common in (N)MPC applications, the disturbances in the optimal control problem are held constant over the whole prediction horizon.

The optimal control problem is solved using a sequential approach where the integration of the model equations and the computation of constraint and objective function values are solved in an inner loop to provide the objective function and constraint values and their gradients to the nonlinear programming problem (NLP) solver in the outer loop. For the computation of the gradients, sensitivity equations are used. Also, the MVs are parametrized as piecewise constants. The NLP is solved by means of a sequential quadratic programming (SQP) method derived from [3].

No stability constraints are employed. Instead, a large prediction horizon is used to mimic the infinite-horizon controller and, thereby, to inherit its stability properties.

A major factor in the development of the NMPC controller was the (very) low simulation time of the employed MSWC plant model (to which the low order of this model obviously contributed): as a consequence of this, the use of more sophisticated optimal control problem solution methods, such as the simultaneous approach [5], could be circumvented. Alternatively, the use of stability constraints, to reduce the prediction horizon and thereby the NMPC computation time (which, arguably, is one of the main reasons for using stability constraints), could be circumvented.

A final comment here is that no integral action is incorporated in the NMPC controller used for the simulations discussed here because no constant unknown disturbances and (for this controller) no model/plant mismatch are present in these simulations. When this is the case, no significant offsets in the CVs are obtained with an NMPC controller as long as the optimal control problem solver does not provide a persistent deviation from the optimal solution.

4 Comparison of the controllers

4.1 Setup of the simulations

All controllers had to solve the combustion control problem defined in section 2. More specific, their aim was to minimize the deviations of the CVs from their setpoints, which were defined to be 16 for ϕ_{st} and 6 for O_2. As all controllers were capable of delivering offset-free control with respect to these setpoints, the variation in the corresponding CVs was equivalent to their variation around these setpoints. As mentioned in section 2, constraints did not play a role in the simulations.

The model that was used in the simulations as the plant to be controlled was the same as that used in the NMPC controller, see section 3.1, with disturbance realizations thought to be chosen with realistic characteristics (using experience with data obtained from control projects at large-scale MSWC plants).

The LMPC controller had to solve the same (least-squares, inequality constrained) optimal control problem as that of the NMPC controller (same setpoints and weightings, etc.). It was equipped with integral action to remove offsets due to model/plant mismatch. This integral action was not implemented in the usual way of adding integrating disturbances that asymptotically close the gap between real and estimated outputs but by adapting the setpoints via integrators operating on the observed differences between real outputs and their setpoint counterparts. For details about the conventional and NMPC controller, one is referred to the discussions in sections 2 resp. 3. To determine the performances of the LMPC and NMPC controllers for the perfect information case, both these controller were provided each sample time with the true one-sample-time-ahead initial states and disturbances.

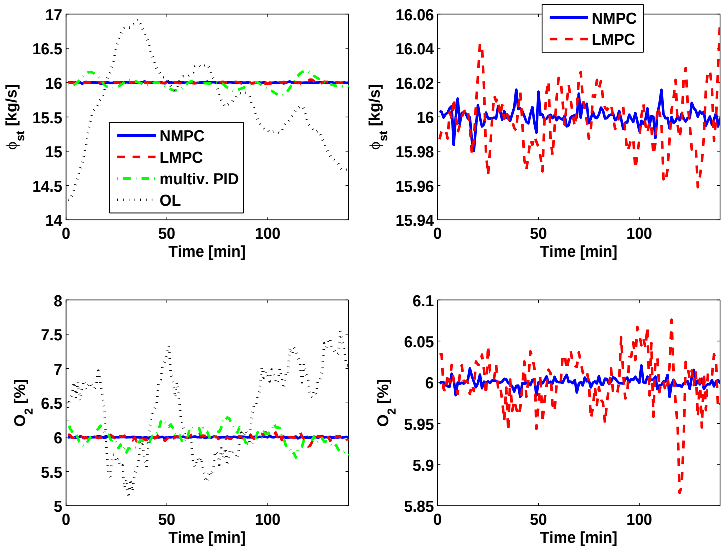

Figure 3: Open- & closed-loop MSWC CVs ϕ_{st} and O_2: right-hand figures are detailed versions of corresponding left-hand figures for LMPC and NMPC case.

All simulations were carried out on a 2.33 GHz dual core processor computer. The sample time of model and controllers was 1 minute. The NMPC computation time was well below this sample time. More specific, this computation time was typically in the order of 15-30 seconds with the remark that the uppr bounds on the iterations to be performed by the SQP solver were set rather high.

4.2 Results

From the simulations it followed that, for the considered perfect information case, an NMPC based MSW combustion controller clearly outperforms a conventional or LMPC based such controller. In fact, it almost manages to keep the CVs ϕ_{st} and O_2 "flat". See figure 3 and table 1 for typically encountered performance plots and figures.

Table 1: Standard deviations open- & closed-loop MSWC CVs ϕ_{st} and O_2.

	open-loop	**conventional controller**	**LMPC**	**NMPC**
STD(ϕ_{st})	2.0	0.10	0.016	0.005
STD(O_2)	2.0	0.19	0.050	0.006

A particular observation with respect to the MVs corresponding to these simulations (which for reasons of space are not depicted here) is that those corresponding to the NMPC controller much more heavily fluctuated than those corresponding to the conventional and LMPC based controller (sometimes even hitting an MV constraint). It apparently much more exploits the MV space to reduce the fluctuations in the CVs (as expected).

It must be noted that both the conventional and LMPC based combustion controller also perform quite well, with notably the last one performing much better than the first one, considering that the standard deviations encountered with conventional controllers at large scale MSWC plants typically are much larger: e.g. 0.68 for ϕ_{st} and 0.39 for O_2 for the MSWC plant considered in [4]. Nevertheless, the NMPC based controller manages to significantly improve on these performances. It must also be noted that the good disturbance rejection performance of the LMPC based controller is mainly due to the added integral action: without it, the performance gets much worse, more specific of the same order as that of the conventional controller (Also, due to the absence of integral action, offsets are obtained in the CVs).

5 Conclusions

Via simulations on an assumably realistic low order first-principles model and unser assumably realistic disturbances, it has been shown that NMPC is inherently capable of outperforming LMPC and conventional, i.e. multivariable PID, controllers with respect to the MSWC plant control problem of suppressing the large disturbances acting on such plants. As a result, NMPC allows for a significant improvement in the economic operation performance of MSWC plants.

The simulations were performed with perfect state and disturbance information available to the MPC controllers. Further research, including model error, measurement noise and state estimation issues, is needed to determine the true performances of these controllers.

In a more general sense, the results also show that not only severe nonlinearity of the plant to be controlled is a motivation for applying NMPC but also the large size of its disturbances, if present, even if the nonlinearity of the plant is not severe. The results also show that MPC, while being mostly used for setpoint tracking purposes, may also provide added value for disturbance rejection control problems.

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