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Technical report CSE02-016

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If you want to cite this report, please use the following reference instead:
T.J.J. van den Boom, B. Heidergott, and B. De Schutter, "Complexity reduction in MPC for stochastic max-plus-linear discrete event systems by variability expansion," *Automatica*, vol. 43, no. 6, pp. 1058–1063, June 2007. doi:10.1016/j.automatica.2006.11.023

Control Systems Engineering
Faculty of Information Technology and Systems
Delft University of Technology
Delft, The Netherlands
Current URL: https://www.dcsc.tudelft.nl

* This report can also be downloaded via https://pub.bartdeschutter.org/abs/02_016.html

Complexity reduction in MPC for stochastic max-plus-linear discrete event systems by variability expansion ⋆

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Abstract

Model predictive control (MPC) is a popular controller design technique in the process industry. Recently, MPC has been extended to a class of discrete event systems that can be described by a model that is "linear" in the max-plus algebra. In this context both the perturbations-free case and for the case with noise and/or modeling errors in a bounded or stochastic setting have been considered. In each of these cases an optimization problem has to be solved on-line at each event step in order to determine the MPC input. This paper considers a method to reduce the computational complexity of this optimization problem, based on variability expansion. In particular, it is shown that the computational load is reduced if one decreases the level of "randomness" in the system.

Key words: Discrete event dynamic system, model predictive control, stochastic disturbance, complexity, variability expansion.

1 Introduction

Model predictive control (MPC) [4,8] is a well-established technology for the control of multivariable systems in the presence of input, output and state constraints. Usually, MPC uses (non)linear discrete-time models. However, the attractive features mentioned above have led us to extend MPC to discrete event systems (DES). The class of DES essentially consists of man-made systems that contain a finite number of resources (such as machines, communications channels, or processors) that are shared by several users (such as product types, information packets, or jobs) all of which contribute to the achievement of some common goal (the assembly of products, the end-to-end transmission of a set of information packets, or a parallel computation) [1]. In this paper we focus on the class of DES with synchronization but no concurrency. Such DES can be described by a model that is "linear" in the max-plus algebra [1,2,7], and therefore they are called max-plus-linear (MPL) DES.

In [13] an MPC controller has been developed for the uncertain MPL DES and there it was also shown that under quite general conditions the resulting MPC optimization problem is a convex optimization problem. However, for many practical situations, the computational complexity will increase significantly as the prediction horizon and the system order increase.

In this paper, we will present a novel approach to the approximate calculation of stochastic integrals, called variability expansion [5]. Since variability expansion is an analytical method and does not resort to simulation, it is, in principle, possible to compute higher moments of performance characteristics of stochastic systems. We combine this general method with MPL systems, which enables us to solve the MPC optimization problem for MPL DES very efficiently. An extended version of this paper, including additional proofs and examples can be found at [14].

The paper is organized as follows. In Section 2 we introduce max-plus algebra and stochastic MPL DES. In Section 3 we give a short overview of the MPC algorithm for MPL DES. Section 4 introduces the method of variability expansion and describes how the complexity of the MPC optimization problem for MPL DES can be reduced significantly by using this method. Finally, Section 5 gives a worked example and a comparison of com-

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putational performance for the new method and previous methods.

2 Stochastic max-plus-linear systems

In this paper we consider MPL DES that include stochastic uncertainty (see also [13]). Define $\varepsilon = -\infty$ and $\mathbb{R}_\varepsilon = \mathbb{R} \cup \{\varepsilon\}$, and let the system matrices of such a system be given by $A(k) \in \mathbb{R}_\varepsilon^{n_x \times n_x}$, $B(k) \in \mathbb{R}_\varepsilon^{n_x \times n_u}$, $C(k) \in \mathbb{R}_\varepsilon^{n_y \times n_x}$; then the system is described by a state space model of the form

$$x_i(k) = \max\Big(\max_{j=1,\ldots,n_x} (A_{ij}(k) + x_j(k-1)) \,, \max_{j=1,\ldots,n_u} (B_{ij}(k) + u_j(k)) \Big) \,, \quad i = 1, \ldots, n_x, \quad (1)$$

$$y_\ell(k) = \max_{j=1,\ldots,n_x} (C_{\ell j}(k) + x_j(k)) \,, \quad \ell = 1, \ldots, n_y \,. \quad (2)$$

The index k in (1)–(2) is called the event counter. The state $x(k)$ typically contains the time instants at which the internal events occur for the kth time, the input $u(k)$ contains the time instants at which the input events occur for the kth time, and the output $y(k)$ contains the time instants at which the output events occur for the kth time.

Remark 1 *Recurrence relations (1) and (2) can be written in a concise way using max-plus-algebra [1,2,7]. To see this, let* $x \oplus y = \max(x, y)$ *and* $x \otimes y = x + y$ *for* $x, y \in \mathbb{R}_\varepsilon$. *For matrices* $A \in \mathbb{R}_\varepsilon^{n \times m}$ *and* $B \in \mathbb{R}_\varepsilon^{m \times l}$, *their* $\otimes$*-product is defined by* $[A \otimes B]_{ij} = \bigoplus_{k=1}^{m} A_{ik} \otimes B_{kj} = \max_{k=1,\ldots,m}(A_{ik} + B_{kj})$. *In the same vein,* $\oplus$*-addition of matrices* $A \in \mathbb{R}_\varepsilon^{n \times m}$ *and* $B \in \mathbb{R}_\varepsilon^{n \times m}$ *is defined by* $[A \oplus B]_{ij} = A_{ij} \oplus B_{ij} = \max(B_{ij}, A_{ij})$. *With these definitions, the system equations (1) and (2) become*

$$x(k) = A(k) \otimes x(k-1) \oplus B(k) \otimes u(k)$$
$$y(k) = C(k) \otimes x(k) \,.$$

The system equations become thus linear in the max-plus algebra, and therefore the system is called a max-plus linear system.

The entries of system matrices $A(k)$, $B(k)$ and $C(k)$ are uncertain due to modeling errors or disturbances. Usually fast changes in the system matrices will be considered as noise and disturbances, whereas slow changes or permanent errors are considered as model mismatch. In this paper both features will be treated within one single framework. The uncertainty caused by disturbances and errors in the estimation of physical variables, can be gathered in the uncertainty vector $e(k)$. In this paper we assume that the uncertainty has stochastic properties. Hence, $e(k)$ is a stochastic variable. We assume that $e(k)$ captures the complete event-varying aspect of the system.

Now we will describe how the entries of $e(k)$ enter the system. Let $\mathcal{S}_{\text{mpns}}$ be the set of max-plus-nonnegative-scaling functions, i.e., functions f of the form $f(z) = \max_{i=1,\ldots,m}(\mu_i + \nu_{i,1} z_1 + \ldots + \nu_{i,n} z_n)$, with variable $z \in \mathbb{R}_\varepsilon^n$ and constants $\nu_{i,j} \in \mathbb{R}^+$ and $\mu_i \in \mathbb{R}$, where $\mathbb{R}^+$ is the set of nonnegative real numbers. If we want to stress that f is a function of z we will denote this by $f \in \mathcal{S}_{\text{mpns}}(z)$.

Note that the system matrices of an MPL model usually consist of sums or maximizations of internal process times, transportation times, etc. (see, e.g., [1] or Section 5). Since the entries of $e(k)$ directly correspond to the uncertainties in the duration times, and using the fact that the set $\mathcal{S}_{\text{mpns}}$ is closed under the operations max, +, and scalar multiplication by a nonnegative scalar [12], we know that the entries of the uncertain system matrices belong to $\mathcal{S}_{\text{mpns}}$: $A(k) \in \mathcal{S}_{\text{mpns}}^{n_x \times n_x}(e(k))$, $B(k) \in \mathcal{S}_{\text{mpns}}^{n_x \times n_u}(e(k))$, $C(k) \in \mathcal{S}_{\text{mpns}}^{n_y \times n_x}(e(k))$. System (1)–(2) with such system matrices will be called a stochastic MPL DES. Some results for the analysis of stochastic MPL DES can be found in [10,11].

3 Model predictive control for stochastic MPL systems

In [3,12,13] the MPC framework has been extended to MPL models (1)–(2) as follows. Just as in conventional MPC [4,8] we define at each event step k a cost criterion $J(k)$ in the event period $[k, k + N_\text{p} - 1]$:

$$J(k) = \sum_{j=0}^{N_\text{p}-1} \sum_{i=1}^{n_y} I\!E[\eta_i(k+j)] - \lambda \sum_{j=0}^{N_\text{p}-1} \sum_{\ell=1}^{n_u} u_\ell(k+j) \quad (3)$$

where N_p is the prediction horizon, λ is a weighting parameter, and where $I\!E[\eta_i(k)]$ denotes the expected value of the ith "tardiness" $\eta_i(k)$, given by $\eta_i(k) = \max(\, y_i(k) - r_i(k) \,,\, 0 \,)$, in which $r(k)$ is the due date for output signal $y(k)$. Note that this choice of $J(k)$ favors on-time delivery and penalizes late delivery.

Define the vectors

$$\tilde{u}(k) = [\; u^T(k) \;\; \cdots \;\; u^T(k+N_\text{p}-1) \;]^T,$$
$$\tilde{r}(k) = [\; r^T(k) \;\; \cdots \;\; r^T(k+N_\text{p}-1) \;]^T,$$
$$\tilde{y}(k) = [\; y^T(k) \;\; \cdots \;\; y^T(k+N_\text{p}-1) \;]^T,$$
$$\tilde{e}(k) = [\; e^T(k) \;\; \cdots \;\; e^T(k+N_\text{p}-1) \;]^T.$$

The aim is now to compute an optimal input sequence $u(k), \ldots, u(k + N_\text{p} - 1)$ that minimizes $J(k)$ subject to some linear constraints on the inputs and outputs (e.g.,

minimal and maximal input or output rates [1], hard due dates) of the form [3]

$$A_{\text{constr}}(k)\tilde{u}(k) + B_{\text{constr}}(k)\mathbb{E}[\tilde{y}(k)] \leq c_{\text{constr}}(k) \ . \quad (4)$$

As the $u(k)$'s correspond to consecutive event occurrence times, we have to add the condition

$$\Delta u(k+j) = u(k+j) - u(k+j-1) \geq 0 \quad \text{for } j = 0, \ldots, N_{\text{p}} - 1. \quad (5)$$

Furthermore, in order to reduce the number of decision variables and the corresponding computational complexity we introduce a control horizon N_{c} ($\leq N_{\text{p}}$) and we impose the additional condition that the input rate should be constant from event step $k + N_{\text{c}} - 1$ on:

$$\Delta u(k+j) = \Delta u(k+N_{\text{c}}-1), \text{ for } j = N_{\text{c}}, \ldots, N_{\text{p}}-1. \quad (6)$$

MPC uses a receding horizon principle. This means that after computation of the optimal control sequence $u(k), \ldots, u(k + N_{\text{c}} - 1)$, only the first control sample $u(k)$ will be implemented, subsequently the horizon is shifted one event step, the state and/or model is updated with new information of the measurements, and the optimization is restarted.

The MPL-MPC problem for event step k can be defined as:

$$\min_{\tilde{u}(k)} \ J_{\text{out}}(k) + \lambda J_{\text{in}}(k) \quad \text{s. t. (1), (2), (4), (5) and (6).}$$

In order to compute the optimal MPC input signal, we need the expected value of the signals $\eta_i(k+j)$ and $y_i(k+j)$. We will now consider the computation of $\mathbb{E}[\eta_i(k+j)]$ and $\mathbb{E}[y_i(k+j)]$. In [13] it is shown that $\eta_i(k+j)$ and $y_i(k+j)$ are max-plus-nonnegative-scaling functions of the variable $w(k) = \left[-\tilde{r}^T(k) \ x^T(k-1) \ \tilde{u}^T(k) \right]^T$.

Proposition 2 *[13] Consider a signal $v(k)$ that is a max-plus-nonnegative-scaling function of $w(k)$ and $\tilde{e}(k)$:*

$$v(k) = \max_{j=1,\ldots,n_v} \left(\alpha_j + \beta_j^T w(k) + \gamma_j^T \tilde{e}(k) \right) \ , \quad (7)$$

where $\alpha_j \in \mathbb{R}_\varepsilon$, $\beta_j \in (\mathbb{R}^+)^{n_w}$, $\gamma_j \in (\mathbb{R}^+)^{n_{\tilde{e}}}$, and $\tilde{e}(k) \in \mathbb{R}^{n_{\tilde{e}}}$ is a stochastic variable with probability density function p. If we define the sets $\Phi_j(w(k))$, $j = 1, \ldots, n_v$ such that

$$\forall \tilde{e}(k) \in \Phi_j(w(k)) : \ v(k) = \alpha_j + \beta_j^T w(k) + \gamma_j^T \tilde{e}(k)$$

and $\bigcup_{j=1}^{n_v} \Phi_j(w(k)) = \mathbb{R}^{n_{\tilde{e}}}$, then the expected value of $v(k)$ is given by

$$\mathbb{E}[v(k)] = \sum_{j=1}^{n_v} \int \ldots \int_{\tilde{e} \in \Phi_j(w)} \left(\alpha_j + \beta_j^T w(k) + \gamma_j^T \tilde{e} \right) p(\tilde{e}) \, d\tilde{e}$$

where $d\tilde{e} = d\tilde{e}_1 \, d\tilde{e}_2 \ldots d\tilde{e}_{n_{\tilde{e}}}$. Furthermore, the function $\mathbb{E}[v(k)]$ is convex in $w(k)$ and a subgradient $g_v(w(k))$ of $\mathbb{E}[v(k)]$ is given by

$$g_v(w(k)) = \sum_{\ell=1}^{n_v} \beta_\ell^T \int_{\tilde{e} \in \Phi_\ell(w(k))} \cdots \int p(\tilde{e}) \, d\tilde{e} \ .$$

Now consider the MPL-MPC problem for event step k. First note that $\eta_i(k+j)$ and $y_i(k+j)$ depend on $\tilde{e}(k)$ and can both be written as a function $v(\tilde{e}(k))$ of the form (7), and that, because of Proposition 2, $\mathbb{E}[\eta_i(k+j)]$ and $\mathbb{E}[y(k+j)]$ are convex in $w(k)$. This means that $J_{\text{out}}(k)$ and $J(k)$ are convex in $\tilde{u}(k)$. Hence

Lemma 3 *If the linear constraints are monotonically nondecreasing as a function of $\mathbb{E}[\tilde{y}(k)]$ (in other words, if $[B_{\text{c}}]_{ij} \geq 0$ for all i, j), constraint (4) becomes convex in $\tilde{u}(k)$.*

Note that convex optimization problems can be solved using reliable and efficient optimization algorithms, based on, e.g., interior point methods [9,15].

4 Variability expansion

The algorithm described in the previous section has a complexity that is growing fast with an increasing number of stochastic variables $n_{\tilde{e}}$ due to the numerical integration that is required when computing the expected values of $\eta_i(k+j)$ and $y_i(k+j)$. In this section we will approximate the expected value of $v(\tilde{e}(k))$ using the method of variability expansion. To this end, we assume that the entries of $\tilde{e}(k)$ are independent and identically distributed (i.i.d) and we introduce an artificial parameter θ. We replace with probability $1-\theta$ the ith entry of random vector $\tilde{e}(k)$ by its mean. The result is denoted by $\tilde{e}_\theta(k)$. The parameter θ allows controlling the level of randomness in the system, and letting θ go from 0 to 1 increases the level of stochasticity in the system.

The main idea of variability expansion is the following. Considering $\mathbb{E}[v(\tilde{e}_\theta(k))]$ as a function in θ, it can be developed into a Taylor series in θ that converges to the true function on $\mathbb{R}$; for a proof we refer to the Appendix. Note that only $\theta \in [0, 1]$ has an interpretation in terms of our model. In particular, if we denote the value of $d^m/d\theta^m \, \mathbb{E}[v(\tilde{e}_\theta(k))]$ for $\theta = 0$ by $d^m/d\theta^m \, \mathbb{E}[v(\tilde{e}_0(k))]$,

[1] For a manufacturing system the input (output) rate corresponds to the rate at which raw material/external resources (finished products) are fed to (leave) the system.

then $I\!E[v(\tilde{e}(k))] = I\!E[v(\tilde{e}_1(k))]$, the "true" expected value of $v(\tilde{e}(k))$, is given by

$$I\!E[v(\tilde{e}(k))] = \sum_{m=0}^{M} \frac{1}{m!} \frac{d^m}{d\theta^m} I\!E[v(\tilde{e}_0(k))] + R_M(k)\,,$$

where, for $M < n_{\tilde{e}}$,

$$R_M \leq \frac{1}{(M+1)!} \sup_{\theta\in[0,1]} \left| \frac{d^{M+1}}{d\theta^{M+1}} I\!E[v(\tilde{e}_0(k))] \right|$$

and $R_M = 0$ otherwise. A closed-form expression for the mth order derivative $d^m/d\theta^m I\!E[v(\tilde{e}_0(k))]$ can be obtained as follows. Set for $0 \leq m \leq n_{\tilde{e}}$ and $i_1 < i_2 < \ldots < i_m$:

$$V(i_1, i_2, \ldots, i_m) = I\!E[v(\tilde{e}_\theta(k, i_1, i_2, \ldots, i_m))]$$

where $[\tilde{e}_\theta(k, i_1, i_2, \ldots, i_m)]_j$ equals the mean value of the jth element of $\tilde{e}_0$ for $j \notin \{i_1, i_2, \ldots, i_m\}$ and $[\tilde{e}(k)]_j$ for $j \in \{i_1, i_2, \ldots, i_m\}$, and where $V(0) = v(\tilde{e}_0(k))$. This means that $V(i_1, i_2, \ldots, i_m)$ is the estimation of v in the case where only the elements $[\tilde{e}(k)]_j$ for $j \in \{i_1, i_2, \ldots, i_m\}$ are stochastic, and the elements $[\tilde{e}(k)]_j$ for $j \notin \{i_1, i_2, \ldots, i_m\}$ are fixed to their mean.

For $m \leq n_{\tilde{e}}$, set

$$\mathbf{V}(m) = \sum_{i_1=1}^{n_{\tilde{e}}-m} \sum_{i_2=i_1+1}^{n_{\tilde{e}}-m+1} \cdots \sum_{i_m=i_{m-1}+1}^{n_{\tilde{e}}} V(i_1, i_2, \ldots, i_m)\,.$$

The term $\mathbf{V}(m)$ yields the total effect of making m out of $n_{\tilde{e}}$ variables stochastic.

Lemma 4 *Provided that $\tilde{e}(k)$ has a bounded support, the nth order derivative of $I\!E[v(\tilde{e}_\theta(k))]$ with respect to θ is for any $\theta \in \mathbb{R}$ given by*

$$\frac{d^n}{d\theta^n} I\!E[v(\tilde{e}(k))] = n! \sum_{l=0}^{n} \binom{n_{\tilde{e}} - l}{n - l} (-1)^{n-l} \mathbf{V}(l)\,,$$

for $n \leq n_{\tilde{e}}$, and zero otherwise.

Proof: We give a sketch of the proof; for details see [6]. Note that $\tilde{e}(k)$ can be written as $f(X_1, \ldots, X_{n_{\tilde{e}}})$ for some measurable mapping f and i.i.d. random noise variables X_i. We formalize variability expansion as follows. Choose $l \in \{0,1\}^{n_{\tilde{e}}}$, let X_i following the "true" distribution if $l_i = 1$ and let $X_i = a$ (with probability one) if $l_i = 0$. This is easily achieved be replacing those X_i in f for which $l_i = 1$ by a . The thus modified mapping f is denoted by f_l. Next, let the elements of l be independently distributed with $\mathbb{P}(l_i = 1) = 1 - \theta$ and $\mathbb{P}(l_i = 0) = \theta$, where $\mathbb{P}(\cdot)$ denotes probability. It then holds that

$$I\!E[v(\tilde{e}_\theta(k))] = I\!E[f(X_1(\theta), \ldots, X_{n_{\tilde{e}}}(\theta))]$$

$$= \sum_{l\in\{0,1\}^{n_{\tilde{e}}}} I\!E[f_l(X_1, \ldots, X_{n_{\tilde{e}}})]\,(1-\theta)^{\sum_{i=1}^{n_{\tilde{e}}} l_i} \theta^{n_{\tilde{e}} - \sum_{i=1}^{n_{\tilde{e}}} l_i}.$$

Note that the sum on the right-hand side of the above equation is finite and we may interchange the order of higher-order differentiation and summation. Since the distribution of l is a polynomial in θ of order $n_{\tilde{e}}$, it is infinitely differentiable and its derivatives of order $n_{\tilde{e}}+1$ and higher vanish. Taking (higher-order) derivatives and regrouping the positive and negative parts, proves the claim. □

By Lemma 4, $I\!E[v(\tilde{e}_\theta(k))]$ is infinitely many times differentiable with respect to θ. Moreover, the derivatives vanish for sufficiently high order, which implies that $I\!E[v(\tilde{e}_\theta(k))]$ as a function of θ can be represented on $\mathbb{R}$ by its Taylor series developed at $\theta = 0$. This train of thoughts leads to the following approximation for $I\!E[v(\tilde{e}(k))]$.

$$\begin{aligned} I\!E[v(\tilde{e}(k))] &= \sum_{l=0}^{M} \left(\sum_{n=l}^{M} \binom{n_{\tilde{e}} - l}{n - l} (-1)^{n-l} \right) \mathbf{V}(l) + R_{M+1} \\ &= \sum_{l=0}^{M} c_l^M \mathbf{V}(l) + R_{M+1}\,. \end{aligned}$$

We summarize our analysis in the following theorem.

Theorem 5 *Let $\tilde{e}(k)$ has bounded support. For $M \in \mathbb{N}$, the Taylor polynomial for $I\!E[v(\tilde{e}(k))]$ of degree M is given by*

$$I\!E[v(\tilde{e}(k))] = \sum_{l=0}^{M} c_l^M\, \mathbf{V}(l) + R_M(k)\,,$$

with $R_M(k) = 0$ for $M \geq \tilde{n}_{\tilde{e}}$.

By Theorem 5 it holds that

$$I\!E[v(\tilde{e}(k))] \approx \sum_{l=0}^{M} c_l^M\, \mathbf{V}(l)\,. \tag{8}$$

The subgradient $\nabla_{\tilde{u}} I\!E[v(\tilde{e}(k))]$ can be computed using the same weighted summation. For example, the approximate subgradient for $M \leq n_{\tilde{e}}$ becomes:

$$\nabla_{\tilde{u}} I\!E[v(\tilde{e}(k))] \approx \sum_{l=0}^{h} c_l^M\, \nabla_{\tilde{u}} \mathbf{V}(l)\,.$$

The values of $\mathbf{V}$ and $\nabla_{\tilde{u}}\mathbf{V}$ can be computed using Proposition 2. Because of the dramatic reduction in

number of stochastic variables, these values are computed much faster than a full estimation of $v(\tilde{e}(k))$ and $\nabla_{\tilde{u}} I\!E[v(\tilde{e}(k))]$.

5 Example: A production system

Consider the production system in Figure 1. This system consists of two machines M_1 and M_2 and operates in batches. The raw material is fed to machine M_1

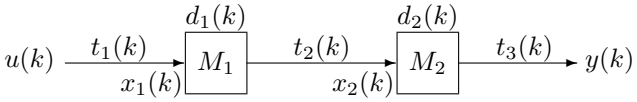

Fig. 1. A production system.

where preprocessing is done. Afterwards the intermediate product is fed to machine M_2 and finally leaves the system. We assume that each machine starts working as soon as possible on each batch, i.e., as soon as the raw material or the required intermediate product is available, and as soon as the machine is idle (i.e., the previous batch of products has been processed and has left the machine).

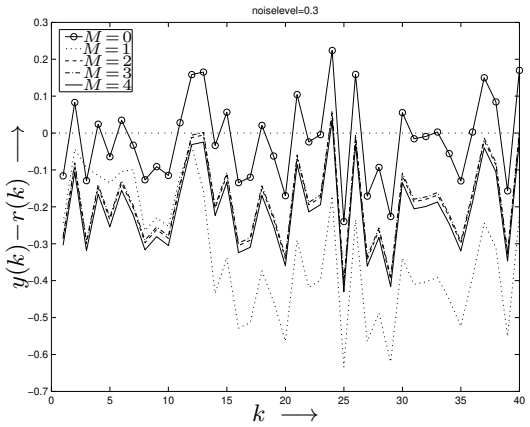

Fig. 2. The due date error $y(k)-r(k)$ for MPC with an Mth order approximation, $M \in \{0,1,2,3,4\}$ and a noise level $\alpha = 0.3$.

Define $u(k)$ as the time instant at which the system is fed for the kth time, $y(k)$ as the time instant at which the kth product leaves the system, $x_i(k)$ as the time instant at which machine i starts for the kth time, $t_j(k)$ as the transportation time on link j for the kth batch and $d_i(k)$ as the processing time on machine i for the kth batch. We obtain (1)-(2) where the system matrices A, B and C are given by [13]

$$A(k) = \begin{bmatrix} d_1(k-1) & \varepsilon \\ d_1(k-1) + d_1(k) + t_2(k) & d_2(k-1) \end{bmatrix},$$

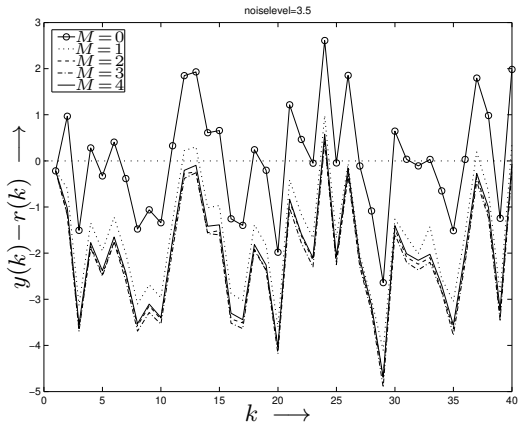

Fig. 3. The due date error $y(k)-r(k)$ for MPC with an Mth order approximation, $M \in \{0,1,2,3,4\}$ and a noise level $\alpha = 3.5$.

$$B(k) = \begin{bmatrix} t_1(k) \\ d_1(k) + t_1(k) + t_2(k) \end{bmatrix},$$

$$C(k) = \begin{bmatrix} \varepsilon & d_2(k) + t_3(k) \end{bmatrix}.$$

Let us now solve the stochastic MPC problem for this perturbed MPL system. Assume that two of the transportation times are constant: $t_1(k) = 0$, $t_3(k) = 0$, and that transportation time $t_2(k)$ and the production times $d_1(k)$ and $d_2(k)$ are corrupted by noise: $d_1(k) = 5 + \alpha\, 0.2\, e_1(k)$, $d_2(k) = 1 + \alpha\, 0.5\, e_2(k)$, $t_2(k) = 1 + \alpha\, 0.6\, e_3(k)$, where α is a nonnegative constant and $e(k) = \begin{bmatrix} e_1(k) & e_2(k) & e_3(k) \end{bmatrix}^T$ is a random signal with probability density function

$$p(e) = \begin{cases} 1/8 \text{ if } \max\limits_{i=1,2,3}(|e_i|) \le 1, \\ 0 \quad \text{if } \max\limits_{i=1,2,3}(|e_i|) > 1. \end{cases} \tag{9}$$

Assume that the initial state is equal to $x(0) = [\,0\ 6\,]^T$, the due date signal is given by $r(k) = 4 + 6 \cdot k$ and the cost criterion (3) is optimized for $N_{\mathrm{p}} = 3$, $N_{\mathrm{c}} = 2$ and $\lambda = 0.1$. With the choice of the cost criterion (3), we can rewrite the stochastic MPC problem into a convex optimization problem. For the computation of the cost criterion we use an Mth order Taylor approximation with $M = 0, 1, 2, 3, 4$.

Next we apply MPC for the Mth order approximation for $M = 0, 1, 2, 3, 4$. The optimal input sequence is computed for $k = 1, \ldots, 40$, and for each k, the first element $u(k)$ of the sequence $\tilde{u}(k)$ is applied to the perturbed system (due to the receding horizon strategy). We perform two experiments with different noise levels $\alpha = 0.3$ and $\alpha = 3.5$. In the experiments, the true system is simulated for a random sequence $e(k)$, $k = 1, \ldots, 40$, satisfying the probability density function (9). The due date

error $y(k)-r(k)$ for MPC is given in Figure 2 for a noise level $\alpha = 0.3$, and in Figure 3 for a noise level $\alpha = 3.5$. The 0th order approximation is in fact equal to the case where no disturbance is taken into account. We see that for $M = 0$ the scheme leads to a frequent violation of the due dates (i.e. the difference signal $y(k) - r(k)$ is frequently positive). We see that for increasing approximation order M the due date error decreases and $y(k)-r(k)$ is below zero most of the time (which means that our product is delivered in time). Furthermore, the approximation seems to converge for increasing M.

	$M=0$	$M=1$	$M=2$	$M=3$	$M=4$
CPU time	1	16.5	470	3810	34900

Table 1
(Scaled) CPU times for different levels in approximation

In Table 1 the (scaled) CPU times are given for the computation of the cost criterion and its subgradient for $M \in \{0, 1, 2, 3, 4\}$. From Table 1 we see that computation time grows dramatically with increasing M. Depending on the application and the available computation interval, we can choose the level of approximation. In general, the above trade-off will give us the best possible approximation of the optimal solution, given the constraints in computation time. For this system $M = 2$ or $M = 3$ is probably sufficient for practical use.

6 Discussion

We have discussed complexity reduction in MPC for max-plus linear discrete event systems with stochastic uncertainties. From the MPC framework, a convex optimization problem results if the constraints are a non-decreasing function of the output. With an increasing number of stochastic variables, the computational complexity of the optimization problem increases dramatically due to the numerical integrations required to evaluate the objective function. To tackle this increase of complexity, we use the method of variability expansion. The key idea of this method is to introduce a parameter θ that controls the level of stochasticity in the system. In this paper we have derived explicit expressions for the coefficients in the expansion (and we have provided the proofs that were lacking in [5]). Based on a Taylor expansion in the parameter θ, good approximations for the expectations of the cost criterion and the constraints can be computed, which leads to a significant reduction of the computational complexity of our approach. From the example it becomes clear that if we do not take the stochastic perturbation into account (the case that the approximation order is $M = 0$), the due-date error will often be positive, which means for a production system that the products are finished too late. Even for small M the due-date error is reduced dramatically, and the system can deliver products in time.

Acknowledgements

Research partially funded by the Dutch Technology Foundation STW project "Model predictive control for hybrid systems" (DMR.5675), the European 6th Framework Network of Excellence "HYbrid CONtrol: Taming Heterogeneity and Complexity of Networked Embedded Systems (HYCON)".

References

[1] F. Baccelli, G. Cohen, G.J. Olsder, and J.P. Quadrat. *Synchronization and Linearity*. John Wiley & Sons, (out of print, accessible via www.maxplus.org), New York, 1992.

[2] R.A. Cuninghame-Green. *Minimax Algebra*, volume 166 of *Lecture Notes in Economics and Mathematical Systems*. Springer-Verlag, Berlin, 1979.

[3] B. De Schutter and T. van den Boom. Model predictive control for max-plus-linear discrete event systems. *Automatica*, 37(7):1049–1056, July 2001.

[4] C.E. García, D.M. Prett, and M. Morari. Model predictive control: Theory and practice — A survey. *Automatica*, 25(3):335–348, May 1989.

[5] B. Heidergott. Variablity expansion for performance characteristic of (max,plus)-linear systems. In *Proc. of the Workshop on Discrete Event Systems (WODES'02)*, Zaragoza, Spain, 2002.

[6] B. Heidergott. *Max-Plus Linear Stochastic Systems and Perturbation Analysis*. Springer, New York, 2006.

[7] B. Heidergott, G.J. Olsder, and J. van der Woude. *Max Plus at Work: Modeling and Analysis of Synchronized Systems*. Princeton University Press, Princeton, 2006.

[8] J.M. Maciejowski. *Predictive control with constraints*. Prentice Hall, Pearson Education Limited, Harlow, UK, 2002.

[9] Y. Nesterov and A. Nemirovskii. *Interior-Point Polynomial Algorithms in Convex Programming*. SIAM, Philadelphia, Pennsylvania, 1994.

[10] G.J. Olsder, J.A.C. Resing, R.E. de Vries, M.S. Keane, and G. Hooghiemstra. Discrete event systems with stochastic processing times. *IEEE Transactions on Automatic Control*, 35(3):299–302, March 1990.

[11] J.A.C. Resing, R.E. de Vries, G. Hooghiemstra, M.S. Keane, and G.J. Olsder. Asymptotic behavior of random discrete event systems. *Stochastic Processes and their Applications*, 36:195–216, 1990.

[12] T.J.J. van den Boom and B. De Schutter. MPC for perturbed max-plus-linear systems. *Systems and Control Letters*, 45(1):21–33, January 2002.

[13] T.J.J. van den Boom and B. De Schutter. Model predictive control for perturbed max-plus-linear systems: A stochastic approach. *International Journal of Control*, 77(3):302–309, February 2004.

[14] T.J.J. van den Boom, B. Heidergott, and B. De Schutter. Complexity reduction in MPC for stochastic max-plus-linear systems by variability expansion: Extended report. Internal report, DCSC, Delft University of Technology, 2006.

[15] S.J. Wright. *Primal-Dual Interior Point Methods*. SIAM, Philadephia, Pennsylvania, 1997.