Research Article

Model Predictive Control with a Relaxed Cost Function for Constrained Linear Systems

David Sotelo, Antonio Favela-Contreras, Viacheslav V. Kalashnikov, and Carlos Sotelo

Tecnologico de Monterrey, Escuela de Ingenieria a y Ciencias, Monterrey, Mexico

Correspondence should be addressed to Antonio Favela-Contreras; antonio.favela@tec.mx

Received 5 September 2019; Accepted 4 March 2020; Published 31 March 2020

Copyright © 2020 David Sotelo et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The Model Predictive Control technique is widely used for optimizing the performance of constrained multi-input multi-output processes. However, due to its mathematical complexity and heavy computation effort, it is mainly suitable in processes with slow dynamics. Based on the Exact Penalization theorem, this paper presents a discrete-time state-space Model Predictive Control strategy with a relaxed performance index, where the constraints are implicitly defined in the weighting matrices, computed at each sampling time. The performance validation for the Model Predictive Control strategy with the proposed relaxed cost function uses the simulation of a tape transport system and a jet transport aircraft during cruise flight. Without affecting the tracking performance, numerical results show that the execution time is notably decreased compared with two well-known discrete-time state-space Model Predictive Control strategies. This makes the proposed Model Predictive Control mainly suitable for constrained multivariable processes with fast dynamics.

1. Introduction

Model Predictive Control (MPC) for linear systems is now a well-established discipline providing stability, feasibility, and robustness [1–6]. Due to its inherent ability to take into account constraints and deal with multi-input multi-output variables [7–10], it has been applied in a wide range of applications, including chemical processes, industrial systems, energy, health, environment, and aerospace [11–16]. In [17], a robust MPC strategy is presented to handle the trajectory tracking problem for an underactuated two-wheeled inverted pendulum vehicle. Moreover, based on an MPC scheme, in [18], a control strategy is designed to an unmanned aerial vehicle for its automatic carrier landing system. Nevertheless, the computation complexity makes the multivariable MPC ineffectual for high speed applications where the controller must execute in a few milliseconds [19–23]. Moreover, the problem becomes much more complicated solving such an online constrained optimization problem by computing a numerical solver [24–26]. Several MPC techniques are used to overcome these problems. For instance, in [27], an explicit model predictive control moves major part of computation offline, which makes it enable to be implemented in real time for wide range of fast systems. Also, in [28], to reduce the online computational time, all the state trajectories are included in the optimal control problem as the constraints in the prediction horizon, then only a quadratic programming problem is solved. In [29], based on a mixed integer quadratic programming problem, the control input is calculated at each discrete time. In contrast to common MPC approaches, where an optimization toolbox is required, this work presents a relaxed performance index, in which the weighting matrices are computed online using the concept of Taylor series expansion and standard inverse distance weighting (IDW) functions. Then, tracking performance under input-output constraints is well obtained, lighter computation load is achieved, and execution time to solve a Quadratic Program (QP) is reduced. Thus, a computationally efficient constrained MPC for discrete-time state-space multivariable systems is obtained.

The paper is organized as follows. Section 2 gives the preliminaries of the proposed MPC strategy. Section 3 describes the proposed relaxed cost function. Section 4
presents a tape transport system and a jet transport aircraft as study cases. Simulation results show the performance of the proposed MPC strategy and the execution time improvement compared with two well-known MPC strategies. Finally, Section 5 discusses the conclusions. Acknowledgments and the list of references finish the paper.

2. Model Predictive Control Based on Discrete-Time State Space Model

This section presents a brief review of MPC based on discrete-time state-space model. The original controller is proposed by Alamir in [7]. In this previous work, considering the predictions of the states, the control action is obtained through the solution of a constrained optimization problem by using a cost function with constant weighting matrices. At each sampling time, an optimal control problem is solved whose results are computationally expensive. The system dynamics is denoted by the Linear Time Invariant (LTI) State-Space Model taking the following structure:

\[ x(k + 1) = Ax(k) + Bu(k), \]
\[ y_r(k) = C_r x(k), \]
\[ y(k) = C y(k), \]

where \( x \in \mathbb{R}^n \) is the state vector, \( u \in \mathbb{R}^n \) is the controlled input vector, \( y_r \in \mathbb{R}^n \) is the output vector, \( A \in \mathbb{R}^{n \times n} \) is the state matrix, \( B \in \mathbb{R}^{n \times n} \) is the input matrix, \( \mathbb{R}^{n \times m} \) stands for the input matrix, \( C_r \in \mathbb{R}^{n_r \times n} \) is the output matrix, and \( k \in \mathbb{N} \) denotes the sampling instant number. Hence, as in [7], from (1), the state predictions for the consecutive sampling instants are

\[ x(k + 1) = Ax(k) + Bu(k), \]
\[ x(k + 2) = A^2 x(k) + A1B u(k) + Bu(k + 1), \]
\[ \vdots \]

\[ x(k + i) = A^i x(k) + [ A^{i-1}B \ldots AB ] u(k), \]

where \( \Phi \in \mathbb{R}^{m \times m} \) and \( \Psi_i \in \mathbb{R}^{m \times (N n_r)} \) are used to represent the N-step-ahead prediction map for Linear Time Invariant (LTI) systems in a compactness form (2). Thus, system (2) can be reformulated using the following vector-matrix notation:

\[ \bar{x}(k) = \Phi x(k) + \Psi_i \bar{u}(k), \quad \forall i \in \{1, \ldots, N\}, \]

and \( \bar{x}(k) \in \mathbb{R}^{m n_r} \) is the whole state trajectory of \( x = [ x_1 \ x_2 \ \ldots \ x_n ]^T \), \( \bar{u}(k) \in \mathbb{R}^{m n_r} \) concatenates the computed sequence of \( u = [ u_1 \ u_2 \ \ldots \ u_n ]^T \), and \( \bar{y}_r(k) \in \mathbb{R}^{m n_r} \) is the output trajectory of \( y_r = [ y_1 \ y_2 \ \ldots \ y_{n_r} ]^T \) as follows:

\[ \bar{x}(k) = \begin{bmatrix} x(k) \\ x(k + 1) \\ \vdots \\ x(k + N) \end{bmatrix}, \]
\[ \bar{u}(k) = \begin{bmatrix} u(k) \\ u(k + 1) \\ \vdots \\ u(k + N - 1) \end{bmatrix}, \]
\[ \bar{y}_r(k) = \begin{bmatrix} y_r(k) \\ y_r(k + 1) \\ \vdots \\ y_r(k + N) \end{bmatrix}. \]

Now, any candidate sequence of actions \( \bar{u}(k) \) has the corresponding future behavior of the system contained in the state trajectory \( \bar{x}(k) \) and consequently the output trajectory \( \bar{y}_r(k) \).

Defining the projection matrix \( \Pi_i^{(n,N)} \),

\[ \Pi_i^{(n,N)} = \begin{bmatrix} 0_{0 \times (i-1) terms} & I_{n \times i} \ & 0_{0 \times (N-i) terms} \end{bmatrix}, \]

where \( n \) is the vector length, \( N \) corresponds to the prediction horizon, and \( i \) stands for the desired term, then the state, control, and output vectors at a specific instant \( k + i \) can be obtained as follows:

\[ x(k + i) = \Pi_i^{(n,N)} \bar{x}(k), \]
\[ u(k + i - 1) = \Pi_i^{(n,N)} \bar{u}(k), \]
\[ y_r(k + i) = \Pi_i^{(n,N)} \bar{y}_r(k). \]

3. Proposed Relaxed Cost Function

3.1. Development. To find the best sequence of control action, in the present work, the value of the cost function \( J(\bar{u} | x(k), \bar{w}_r(k), u^0) \) is defined over the prediction horizon \([k, k + N]\) as follows:
where considering a past control action value \( u^n \in \mathbb{R}^{n_u} \), the last two terms are added to penalize the rate excursion of the control vector by the weighting matrix \( R \in \mathbb{R}^{n_u \times n_u} \). Moreover, in the first term, the pondering matrix \( Q \in \mathbb{R}^{n_y \times n_y} \) penalizes the error between the output trajectory \( \bar{y}_r(k) \in \mathbb{R}^{n_y} \) and the reference \( \bar{w}_r(k) \in \mathbb{R}^{n_y} \) of the vector \( \bar{w}_r = [w_1, w_2, \ldots, w_n] \), which is expressed as follows:

\[
\bar{w}_r(k) = \begin{bmatrix} w_r(k + 1) \\ w_r(k + 2) \\ \vdots \\ w_r(k + N) \end{bmatrix}
\]
The deviation between the predicted output $\tilde{y}_p$ and the reference $y_p$ is penalized by a function of distance $|\tilde{y}_p - y_p|$. Furthermore, to avoid that the predicted process variable $\tilde{y}_p$ remains close to the lower bound $y_p^{\text{min}}$ or the upper bound $y_p^{\text{max}}$, the min($|\tilde{y}_p - y_p^{\text{min}}|, |\tilde{y}_p - y_p^{\text{max}}|$) term is added. Finally, $y$ term is included in order to increase the penalization while the predicted manipulation variable $\tilde{u}_p$ is close to the upper or lower bounds, $u_p^{\text{max}}$ and $u_p^{\text{min}}$, respectively.

The penalization at the input $R \in \mathbb{R}^{n_u \times n_u}$ is defined:

$$R = \begin{bmatrix} r_1 & \cdots & 0 \\ \vdots & \ddots & 0 \\ 0 & \cdots & r_q \end{bmatrix},$$  \hspace{1cm} (21)

where $r_q = y + |\delta u_q - \delta u_q^0|, \forall q \in \{1, \ldots, n_u\}$.

The first term is included to avoid that the predicted manipulated variable $\tilde{u}_p$ remains close to the upper or lower bounds, $u_p^{\text{max}}$ and $u_p^{\text{min}}$, while the second term is added to reduce the large excursion between the increment of the predicted manipulated variable $\delta u_q$ and the increment of the previous manipulated variable $\delta u_q^0$.

The resulting optimization problem $P(x(k))$ expressed as the cost function $J(\tilde{u} | x(k), \tilde{w}_p(k), u_p)$ is minimized at each instant $k$ by a sequence of future actions $\tilde{u}_p^{\text{opt}}(x(k))$ respecting all the constraints. As it is described, $Q$ and $R$ are defined as functionals of constraints depending on the current state $x(k)$, the desired trajectory $\tilde{w}_p(k)$, and the past controlled input $u_p$. Thus, the matrices $H, F_i, i = 1, 2, 3$ are computed online looking for relaxing the optimization problem.

3.3. Algorithm for the Proposed MPC Strategy. The algorithm used for the proposed discrete-time state-space constrained MPC strategy consists of:

1. Define the linear time-invariant mathematical model of the physical system in state-space representation (equation (1))
2. Compute the matrices $\Phi_i$ and $\Psi_i, \forall i \in \{1, \ldots, N\}$ used to represent the N-step-ahead prediction map for LTI systems (equation (4))
3. Estimate the manipulation $\tilde{u}_p$ (equation (18)) and the output $\tilde{y}_p$ (equation (19)) at the next sampling instant, using Taylor series expansion
4. Compute the weighting matrices $Q$ (equation (20)) and $R$ (equation (19)) based on the proposed functions
5. Compute the online matrices $H, F_i, i = 1, 2, 3$ of the proposed performance index (equation (12))
6. Obtain the control law $\tilde{u}_p^{\text{opt}}(x(k))$ (equation (14)) and apply to the system the first action of the best sequence control action $K_{MPC}(x(k))$ (equation (15))
7. At the next sampling instant ($k = k + 1$), the reference $w_r$, the bounds $y_p^{\text{min}}, y_p^{\text{max}}, u_p^{\text{min}},$ and $u_p^{\text{max}},$ the measurements of the outputs $y$, and the state variables $x(k)$, are updated, and the MPC optimization problem is solved again (equation (17)); the algorithm goes to step 3.

4. Simulation and Results

The present work and the MPC strategies in [7, 31] are developed using the same computational platform for its evaluation. Hence, to solve the optimization problem in [7, 31], quadprog toolbox from MATLAB® is used. MATLAB® codes for the following study cases are available: MPC Matlab Files_MPE.

4.1. Example 1: Tape Transport System. The tape drive system consists of two reels to supply and file data. Here, the data transfer rate is proportional to the tape transport speed. Thus, the tape drive mechanism must be able to rapidly transport a fragile tape with an accurate tension regulation. Figure 1 shows the schematic of a tape transport system where its components and variables involved are the tape stiffness and the damping denoted by $K$ and $D$, the reel radii and the inertia represented as $r$ and $J$, the motor torque constant $K_t$, and the viscous friction coefficient denoted by $\beta$.

Assuming there is no force loss across the head, the tape tension $T = T_1 = T_2$ [42]. Although the physical model of the process contains nonlinearities, in (22), a simplified state-space model is presented in continuous time [42–44]:

$$\dot{x}(t) = A_t x(t) + B_t u(t),$$

$$y(t) = C_t x(t),$$

$$A_t = \begin{bmatrix} -D \frac{r_1^2}{J_1} + \frac{r_2^2}{J_2} & \frac{B_1 r_1}{J_1} - K r_2 - D \frac{B_2}{J_2} & 0 \\ \frac{r_1}{J_1} & -\frac{\beta}{J_1} & 0 \\ \frac{r_2}{J_2} & 0 & \frac{\beta}{J_2} \end{bmatrix},$$

$$B_t = \begin{bmatrix} K_t \frac{r_1}{J_1} & 0 \\ 0 & K_t \frac{r_2}{J_2} \end{bmatrix},$$

$$C_t = \begin{bmatrix} 0 & \frac{r_1}{2} & \frac{r_2}{2} \\ 1 & 0 & 0 \end{bmatrix}.$$ 

The model has three states, $x = [T \omega_1 \omega_2]^T$, where $T$ is the tension tape in $N$; meanwhile, $\omega_1$ and $\omega_2$ represent the
supply and take-up reel in rad/s, respectively. Moreover, the system has two inputs \( \mathbf{u} = [u_1 \ u_2]^T \) that represent the voltages applied to the reel motors in volts, and two outputs \( \mathbf{y} = [y_1 \ y_2]^T \) which stand for the tape speed \( \nu_w \) at the read-write head in m/s and the tape tension \( T \), respectively. The control strategy described in the present work is simulated using parameters from the tested tape system described in [42, 45, 46], whose parameters are summarized in Table 1. Considering that the motors are nominally identical, for both motors, it is used as the same motor torque constant \( K_t \) and viscous friction coefficient \( \beta \) [45, 46].

Discretizing (23) with a sampling time \( \tau = 0.1 \) s and considering a prediction horizon \( N = 10 \) with a tuning parameter \( \alpha = 3.7 \), the simulation results are shown in Figure 2. It is divided in two main parts, the first part corresponds to the outputs and the inputs of the system using the MPC with the relaxed cost function, while the second part shows the coefficients of the weighting matrices \( Q \) and \( R \). As it is shown, computing the coefficient values \( q_1 \) and \( q_2 \), the constrained tape speed \( y_1 \) and tape tension \( y_2 \) present a good performance. Here, \( y_1 \) do not present overshoot and has a maximum settling time of 0.1 seconds while \( y_2 \) has a maximum overshoot of 3% and a settling time of 0.3 seconds. On the contrary, the motor voltages \( u_1 \) for the supply reel and \( u_2 \) for the take-up reel remains inside their lower and upper bounds by using the computed coefficient values \( r_1 \) and \( r_2 \). Here, the values of \( r_1 \) are lower than the values of \( r_2 \), due to the rates of the manipulations.

In order to see the closed-loop stability of the system, the stability indicator \( S_N \) is defined as in [7]:

\[
S_N := \max_{j \in \{1, \ldots, n\}} |\lambda_j(A - BK_N)|, \tag{23}
\]

where \( \lambda_j \) stands for the eigenvalues of the system for \( j \in \{1, \ldots, n\} \) and \( K_N = \prod_{i=1}^{n} N_i \), \( H^{-1}[F_j \mathbf{x}(k)] \) is the closed-loop gain. Figure 3 shows that the system remains stable during the test. Finally, Table 2 is presented to compare the execution time between the present work and previous works [7, 31].

As it can seen, the total execution time is reduced, by taking advantage of the relaxed cost function. Here, the computation of \( \mathbf{u}(k) \) is 1.924 seconds and 2.148 seconds faster than the computation of the manipulations using [7, 31] MPCs strategies. Henceforth, the percentage consumption of time to obtain the control actions is notably decreased.

### Table 1: Tape transport system parameters.

| Symbol | Parameter                      | Value               |
|--------|--------------------------------|---------------------|
| \( K \) | Tape stiffness                 | \( 2 \times 10^7 \) N/m |
| \( D \) | Damping                        | \( 2 \) N s/m^2      |
| \( r_1 \) | Radius of supply reel          | \( 2.12 \times 10^{-3} \) m |
| \( r_2 \) | Radius of take-up reel         | \( 9.75 \times 10^{-3} \) m |
| \( J_1 \) | Moment of inertia of the supply reel | \( 14.2 \times 10^{-6} \) Kg m^2 |
| \( J_2 \) | Moment of inertia of the take-up reel | \( 10.35 \times 10^{-6} \) Kg m^2 |
| \( K_t \) | Motor torque constant          | \( 24.8 \times 10^{-3} \) N m/V |
| \( \beta \) | Viscous friction coefficient   | \( 1.03 \times 10^{-4} \) N m/s rad |

#### 4.2. Example 2: Jet Transport Aircraft.

The Jet Transport Aircraft Boeing 747 in high-lift configuration addresses complex geometries and physical phenomena that make the controller design a difficult process. Figure 4 illustrates the Jet Transport Aircraft with its components and variables involved such as the angles \( \beta \) and \( \phi \) and the angular velocities \( \psi \) and \( \theta \).

Although the physical model of the Boeing 747 is lengthy, in (24), the simplified state-space model during cruise flight at MATCH = 0.8 and \( H = 40,000 \) ft is presented in continuous time [47]:

\[
\dot{x}(t) = A_x x(t) + B_u u(t),
\]

\[
y(t) = C_x x(t),
\]

\[
A_x = \begin{bmatrix}
-0.0558 & -0.9968 & 0.0802 & 0.0415 \\
0.598 & -0.115 & -0.0318 & 0 \\
-3.05 & 0.388 & -0.465 & 0 \\
0 & 0.0805 & 1 & 0
\end{bmatrix}, \tag{24}
\]

\[
B_x = \begin{bmatrix}
0.0729 \\
-4.75 & 0.775 \\
0.153 & 14.3 \\
0 & 0
\end{bmatrix},
\]

\[
C_x = \begin{bmatrix}
0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}.
\]

The model has four states, \( x = [\beta \ \psi \ \theta \ \phi]^T \), where \( \beta \) is the sideslip angle, \( \psi \) stands for the bank angle, and meanwhile \( \psi \) and \( \theta \) represent the yaw and roll rate, respectively. Herein, all the angles are in rad and the angular velocities in rad/s. The system has two inputs \( u = [u_1 \ u_2]^T \): the rudder and the aileron deflections, and two outputs \( y = [y_1 \ y_2]^T \): the yaw rate \( \psi \) and the bank angle \( \phi \).

Using a sampling time \( \tau = 0.2 \) s, system (24) is discretized. Then, a set of changes in the output reference and a series of variations in the constraints are used to test the present work. Considering a prediction horizon \( N = 20 \) and a tuning parameter \( \alpha = 4.5 \), simulation results are shown in Figure 5. Here, using the computed coefficient values \( q_i \) and
they rate $\gamma_1$ has a maximum overshoot of 2.9% with a maximum settling time of 1 second, while the bank angle $\gamma_2$ has a maximum overshoot of 6.6% with a maximum settling time of 1.2 seconds. Moreover, with the computed coefficient values $r_1$ and $r_2$, the rudder deflection $u_1$, and the aileron deflection $u_2$ remains inside their bounds without saturation. Here, the values of $r_2$ are greater than the values of $r_1$, this is because the rate of the manipulation $u_1$ is greater than the rate of the manipulation $u_2$. On the contrary, Figure 6 shows the stability behavior during the test. As it is shown, the system remains stable.

Finally, the execution time comparison between the present work and previous works [7, 31] is shown in Table 3. As it can be seen, the total execution time is considerably reduced due to the relaxed cost function. Here, the computation of $\tilde{u}(k)$ is 6.074 seconds and 3.1558 seconds.
Figure 3: Stability behavior.

Table 2: Execution time comparison with previous works.

| MPC         | Total (s) | Computation of $\bar{u}(k)$ (s) | Percentage consumption (%) |
|-------------|-----------|----------------------------------|---------------------------|
| [5]         | 2.919     | 1.936                            | 66.3                      |
| [22]        | 2.907     | 2.160                            | 74.3                      |
| This work   | 0.892     | 0.012                            | 1.3                       |

Figure 4: Jet transport aircraft. (a) Top view. (b) Front view.

Figure 5: Continued.
Figure 5: Simulation results for jet transport aircraft under the MPC strategy with the relaxed cost function.

Figure 6: Stability behavior.

Table 3: Execution time comparison with previous works.

|       | MPC Total (s) | Computation of $\tilde{u}(k)$ (s) | Percentage consumption (%) |
|-------|---------------|-----------------------------------|---------------------------|
| [5]   | 8.262         | 6.105                             | 73.9                      |
| [22]  | 4.020         | 3.186                             | 79.2                      |
| This work | 1.808        | 0.031                             | 1.7                       |
seconds faster than the computation of the manipulations using [7, 31] MPCs strategies. Then, as in example 1, the percentage consumption of time to obtain the control actions is notably decreased.

5. Conclusions

This paper presents a discrete-time state-space MPC approach for multivariable systems. Based on the IDW method and the concept of Taylor series expansion, a relaxed performance index with constraints defined in the online weighting matrices is proposed to compute the control action. Thus, as in study cases, the proposed MPC strategy is used to control a tape transport system and a jet transport aircraft during cruise flight.

Simulation results show that the proposed MPC strategy with the relaxed cost function has a good performance, no matter abrupt changes of set-points and constraints occur, even at the same time. Additionally, compared with two well-known discrete-time state-space MPC strategies, there is a significant improvement on the execution time without affecting the tracking performance. The percentage consumption of time to compute the best sequence of control actions $\bar{u}(k)$ is 1.3% for the tape transport system and 1.7% for the jet transport aircraft. Henceforth, it takes almost 0.1 milliseconds for the tape transport system and 0.12 milliseconds for the jet transport aircraft to obtain the manipulation $u(k)$ that minimizes the proposed cost function while respecting the constraints. Thus, the proposed MPC strategy with the relaxed cost function is mainly suitable for constrained multivariable real processes with fast dynamics.

Data Availability

The data of the conducted experiments and simulations are available upon requirement.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The research activities of the third co-author were partially supported by the Mexico National Council for Science and Technologies (CONACYT) with Grants CB-2013-01-221676 and FC-2016-01-1938. The authors also thank the Research Groups of Sensors and Devices, and of Optimization and Data Science of the School of Engineering and Sciences for their support of the development of this work and MSc. Arturo Pinto for his fruitful discussions.

References

[1] R. Heydari and M. Farrokhi, “Robust model predictive control of biped robots with adaptive on-line gait generation,” International Journal of Control, Automation and Systems, vol. 15, no. 1, pp. 329–344, 2017.

[2] S. Riverso, M. Farina, and G. Ferrari-Trecate, “Plug-and-play decentralized model predictive control for linear systems,” IEEE Transactions on Automatic Control, vol. 58, no. 10, pp. 2608–2614, 2013.

[3] R. Zhang, J. Lu, H. Qu, and F. Gao, “State space model predictive fault-tolerant control for batch processes with partial actuator failure,” Journal of Process Control, vol. 24, no. 5, pp. 613–620, 2014.

[4] M. Zhao, C.-C Jiang, and M.-H. She, “Robust contractive economic MPC for nonlinear systems with additive disturbance,” International Journal of Control, Automation and Systems, vol. 16, no. 5, pp. 2253–2263, 2018.

[5] H. Shi, P. Li, J. Cao, C. Su, and J. Yu, “Robust fuzzy predictive control for discrete-time systems with interval time-varying delays and unknown disturbances,” IEEE Transactions on Fuzzy Systems, 2019.

[6] H. Shi, P. Li, C. Su, Y. Wang, J. Yu, and J. Cao, “Robust constrained model predictive fault-tolerant control for industrial processes with partial actuator failures and interval time-varying delays,” Journal of Process Control, vol. 75, pp. 187–203, 2019.

[7] M. Alamir, A Pragmatic Story of Model Predictive Control: Self-Contained Algorithms and Case-Studies, CNRS-University of Grenoble, Grenoble, France, 2013.

[8] I. Chang and J. Bentsman, “Constrained discrete-time state-dependent Riccati equation technique: a model predictive control approach,” in Proceedings of the 52nd IEEE Conference on Decision and Control, pp. 5125–5130, Florence, Italy, December 2013.

[9] B. Zhu, H. Tazvinga, and X. Xia, “Switched model predictive control for energy dispatching of a photovoltaic-diesel-battery hybrid power system,” IEEE Transactions on Control Systems Technology, vol. 23, no. 3, pp. 1229–1236, 2015.

[10] H.-y. Shi, C.-l. Su, J.-t. Cao, P. Li, Y.-l. Song, and N.-b. Li, “Incremental multivariable predictive functional control and its application in a gas fractionation unit,” Journal of Central South University, vol. 22, no. 12, pp. 4653–4668, 2015.

[11] Y. Wang and S. Boyd, “Fast model predictive control using online optimization,” IEEE Transactions on Control Systems Technology, vol. 18, no. 2, pp. 267–278, 2010.

[12] S.-K. Kim, D.-K. Choi, K.-B. Lee, and Y. J. Lee, “Offset-free model predictive control for the power control of three-phase AC/DC converters,” IEEE Transactions on Industrial Electronics, vol. 62, no. 11, pp. 7114–7126, 2015.

[13] R. Zhang, A. Xue, and F. Gao, “Temperature control of industrial coke furnace using novel state space model predictive control,” IEEE Transactions on Industrial Informatics, vol. 10, no. 4, pp. 2084–2092, 2014.

[14] M. Preindl and S. Bolognani, “Model predictive direct speed control with finite control set of PMSM drive systems,” IEEE Transactions on Power Electronics, vol. 28, no. 2, pp. 1007–1015, 2013.

[15] B. Hredzak, V. G. Agelidis, and M. Minsoo Jang, “A model predictive control system for a hybrid battery-ultracapacitor power source,” IEEE Transactions on Power Electronics, vol. 29, no. 3, pp. 1469–1479, 2014.

[16] H. Shi, C. Su, J. Cao, P. Li, J. Liang, and G. Zhong, “Nonlinear adaptive predictive functional control based on the Takagi-Sugeno model for average cracking outlet temperature of the ethylene cracking furnace,” Industrial Engineering Chemistry Research, vol. 54, no. 6, pp. 1849–1860, 2015.

[17] M. Yue, C. An, and J.-Z. Sun, “An efficient model predictive control for trajectory tracking of wheeled inverted pendulum vehicles with various physical constraints,” International
Z. Fan, J. Li, and M. Deng, "An adaptive inverse-distance weighting spatial interpolation method with the consideration of multiple factors," Geomatics and Information Science of Wuhan University, vol. 6, p. 20, 2016.

D. Shepard, "A two-dimensional interpolation function for irregularly-spaced data," in Proceedings of the of the 23rd ACM National Conference, pp. 517–524, New York, NY, USA, 1968.

G. Y. Lu and D. W. Wong, "An adaptive inverse-distance weighting spatial interpolation technique," Computers & Geosciences, vol. 34, no. 9, pp. 1044–1055, 2008.

D. W. Wang, L. N. Li, C. Hu, Q. Li, X. Chen, and P. W. Huang, "A modified inverse distance weighting method for interpolation in open public places based on wi-fi probe data," Journal of Advanced Transportation, Article ID 7602792, 11 pages, 2019.

M. Lawrynczuk, "Nonlinear predictive control of a boiler-turbine unit: a space-state approach with successive on-line model linearisation and quadratic optimisation," ISA Transactions, vol. 67, pp. 476–495, 2017.

M. Lawrynczuk, "Nonlinear state-space predictive control with on-line linearisation and state estimation," International Journal of Applied Mathematics and Computer Science, vol. 25, no. 4, pp. 833–847, 2015.

W. H. Chen, "Predictive control of general nonlinear systems using approximation," IEEE Proceedings—Control Theory and Applications, vol. 151, no. 2, pp. 137–144, 2004.

R. Errouissi, A. Al-Durra, and S. M. Muyeem, "A robust continuous-time MPC of a DC-DC boost converter interfaced with a grid-connected photovoltaic system," IEEE Journal of Photovoltaics, vol. 6, no. 6, pp. 1619–1629, 2016.

C. Sotelo, A. Favela-Contreras, F. Beltrán-Carbajal, G. Dieck-Assad, P. Rodríguez-Cañedo, and D. Sotelo, "A novel discrete-time nonlinear model predictive control based on state space model," International Journal of Control, Automation and Systems, vol. 16, no. 6, pp. 2688–2696, 2018.

P. D. Mathur and W. C. Messner, "Controller development for a prototype high-speed low-tension tape transport," IEEE Transactions on Control Systems Technology, vol. 6, no. 4, pp. 534–542, 1998.

Y. LU and W. C. Messner, "Robust servo design for tape transport," in Proceedings of the 2001 IEEE International Conference on Control Applications (CCA’01) (Cat. No. 01CH37204), pp. 1014–1019, Mexico City, Mexico, September 2001.

D. Tenne and T. Singh, "Robust feed-forward/feedback design for tape transport," in Proceedings of the of the AIAA Guidance, Navigation, and Control Conference and Exhibit, p. 5119, Providence, RI, USA, August 2004.

M. D. Baumgart and L. Y. Pao, "Robust control of nonlinear tape transport systems with and without tension sensors," Journal of Dynamic Systems, Measurement, and Control, vol. 129, no. 1, pp. 41–55, 2007.

M. D. Baumgart and L. Y. Pao, "Robust control of tape transport systems with no tension sensor," in Proceedings of the 2004 43rd IEEE Conference on Decision and Control (CDC) (IEEE Cat. No. 04CH37601), pp. 4342–4349, Nassau, Bahamas, December 2004.

S. Singh and T. R. Murthy, "Simulation of sensor failure accommodation in flight control system of transport aircraft: a modular Approach," World Journal of Modelling and Simulation, vol. 11, no. 1, pp. 55–68, 2015.

Z. Fan, J. Li, and M. Deng, "An adaptive inverse-distance weighting spatial interpolation method with the consideration of multiple factors," Geomatics and Information Science of Wuhan University, vol. 6, p. 20, 2016.

D. Shepard, "A two-dimensional interpolation function for irregularly-spaced data," in Proceedings of the of the 23rd ACM National Conference, pp. 517–524, New York, NY, USA, 1968.

G. Y. Lu and D. W. Wong, "An adaptive inverse-distance weighting spatial interpolation technique," Computers & Geosciences, vol. 34, no. 9, pp. 1044–1055, 2008.

D. W. Wang, L. N. Li, C. Hu, Q. Li, X. Chen, and P. W. Huang, "A modified inverse distance weighting method for interpolation in open public places based on wi-fi probe data," Journal of Advanced Transportation, Article ID 7602792, 11 pages, 2019.

M. Lawrynczuk, "Nonlinear predictive control of a boiler-turbine unit: a space-state approach with successive on-line model linearisation and quadratic optimisation," ISA Transactions, vol. 67, pp. 476–495, 2017.

M. Lawrynczuk, "Nonlinear state-space predictive control with on-line linearisation and state estimation," International Journal of Applied Mathematics and Computer Science, vol. 25, no. 4, pp. 833–847, 2015.

W. H. Chen, "Predictive control of general nonlinear systems using approximation," IEEE Proceedings—Control Theory and Applications, vol. 151, no. 2, pp. 137–144, 2004.

R. Errouissi, A. Al-Durra, and S. M. Muyeem, "A robust continuous-time MPC of a DC-DC boost converter interfaced with a grid-connected photovoltaic system," IEEE Journal of Photovoltaics, vol. 6, no. 6, pp. 1619–1629, 2016.

C. Sotelo, A. Favela-Contreras, F. Beltrán-Carbajal, G. Dieck-Assad, P. Rodríguez-Cañedo, and D. Sotelo, "A novel discrete-time nonlinear model predictive control based on state space model," International Journal of Control, Automation and Systems, vol. 16, no. 6, pp. 2688–2696, 2018.

P. D. Mathur and W. C. Messner, "Controller development for a prototype high-speed low-tension tape transport," IEEE Transactions on Control Systems Technology, vol. 6, no. 4, pp. 534–542, 1998.

Y. LU and W. C. Messner, "Robust servo design for tape transport," in Proceedings of the 2001 IEEE International Conference on Control Applications (CCA’01) (Cat. No. 01CH37204), pp. 1014–1019, Mexico City, Mexico, September 2001.

D. Tenne and T. Singh, "Robust feed-forward/feedback design for tape transport," in Proceedings of the of the AIAA Guidance, Navigation, and Control Conference and Exhibit, p. 5119, Providence, RI, USA, August 2004.

M. D. Baumgart and L. Y. Pao, "Robust control of nonlinear tape transport systems with and without tension sensors," Journal of Dynamic Systems, Measurement, and Control, vol. 129, no. 1, pp. 41–55, 2007.

M. D. Baumgart and L. Y. Pao, "Robust control of tape transport systems with no tension sensor," in Proceedings of the 2004 43rd IEEE Conference on Decision and Control (CDC) (IEEE Cat. No. 04CH37601), pp. 4342–4349, Nassau, Bahamas, December 2004.

S. Singh and T. R. Murthy, "Simulation of sensor failure accommodation in flight control system of transport aircraft: a modular Approach," World Journal of Modelling and Simulation, vol. 11, no. 1, pp. 55–68, 2015.