



# Explicit MPC

Based on **Explicit Model-Predictive Control** by **Alberto Bemporad**

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# Outline

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- Explicit & Implicit definition
- Implicit MPC vs Explicit MPC
- Explicit MPC
  - Advantages
  - Multi-parametric programming
  - Piecewise Affine functions
  - Methodology
  - Limitations
  - Applications
- Case Study

# MPC

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- **Definition:** An MPC uses linear plant, disturbance, and noise models to estimate the controller state and predict future plant outputs.
  - **Objective:** Using the predicted plant outputs, the controller solves a quadratic programming optimization problem to determine optimal manipulated variable adjustments.

which has 2 approaches:

- Implicit MPC
- Explicit MPC



# Explicit & Implicit definition

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- **Implicit MPC:** Traditional approach, in which MPC requires the solution of a quadratic program (QP) online to compute the control action, often restricting its applicability to slow processes.
- **Explicit MPC:** Explicit MPC completely removes the need for on-line solvers by precomputing the control law off-line, so that online operations reduce to a simple function evaluation.

# Implicit MPC vs Explicit MPC

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# Implicit MPC vs Explicit MPC

- The differences between two can be summarized as following:

	Implicit MPC	Explicit MPC
Problem size	Large	Small
KKT solver	Online matrix inverse	Off-line factorization
Active set update	Heuristics	Sequential
Memory storage	Small	Large

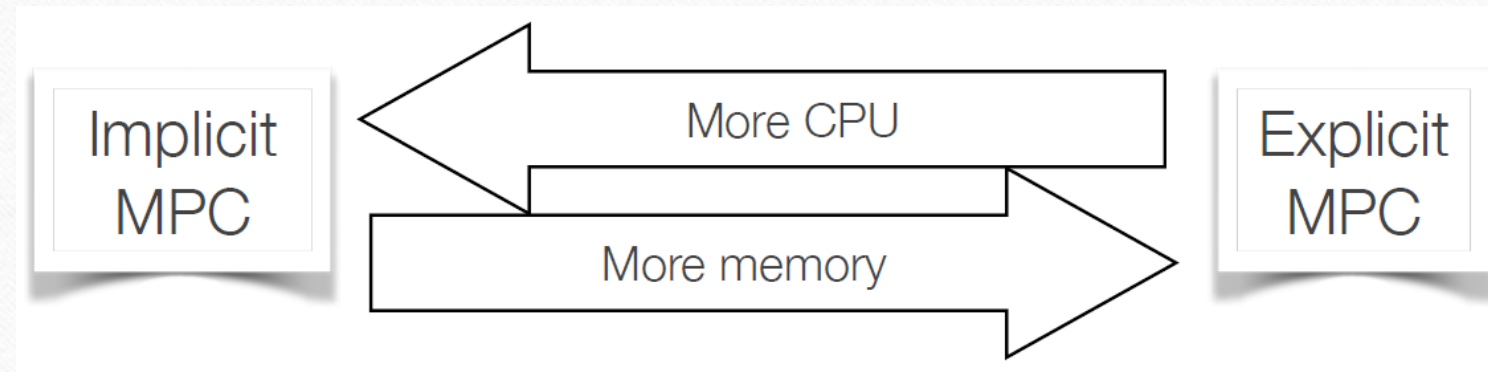
	Vars	Constr.	States
Small	$\leq 6$	15	8
Large	$\approx 500$	3000	2000



# Implicit MPC vs Explicit MPC

In Implicit MPC, there involves online solvers. Hence, requires larger processors.

Whereas, Explicit MPC need not process online but store a number of off-line algorithms. Thus, greater storage capacity is required



# Implicit MPC vs Explicit MPC

	Implicit MPC (active-set method)	Explicit MPC (incremental regionless)
Memory storage	$H, F, G, w, E$	$G, w, E$ primal optimizer, dual optimizer
KKT solver	Matrix inversions	Matrix/vector multiplication
Active set update	Identical algorithm	



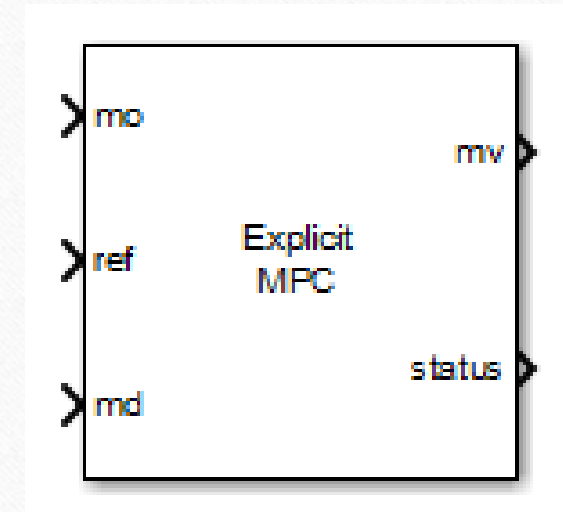
# Explicit MPC Simulink Block

The Explicit MPC Controller block uses the following input signals:

- Measured plant outputs (mo)
  - Reference or setpoint (ref)
  - Measured plant disturbance (md), if any
- Measured plant outputs are obtained from Implicit approach.

Hence, to create an **Explicit MPC controller**:

- first **Traditional (Implicit) MPC controller** is designed.
- then an **Explicit MPC Controller** is generated based on this traditional controller design.



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  - **Advantages**
  - Multi-parametric programming (Linear and Quadratic)
  - Piecewise Affine functions
  - Methodology (MPLP and MPQP)
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# Advantages of Explicit MPC

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- It can be noted that Explicit MPC:
  - Does off-line and simpler computations.
  - Requires fewer run-time computations, thus useful for system with low sample rates.
  - Requires processors of less computational capacity.



# MPC Problem

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- In practical, an MPC should have a QP solution method:
  - embedded in the control hardware
  - the method must be fast enough to provide a solution within short sampling intervals
  - require simple hardware, limited memory to store the data defining the optimization problem and the code implementing the algorithm itself
  - a simple program code
  - and a good **worst-case** estimates of the execution time to meet real-time system requirements

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# Multi-parametric programming

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- MPC takes a different approach to meet the above requirements, where Multi-Parametric Quadratic Programming is proposed to pre-solve the QP off-line, therefore converting the MPC law into a continuous and **Piecewise-Affine Function** of the parameter vector (Bemporad et al. 2002b).



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**Definition 1** We say a function  $L : \mathbb{R}^m \rightarrow \mathbb{R}^n$  is linear if (1) for any vectors  $\mathbf{x}$  and  $\mathbf{y}$  in  $\mathbb{R}^m$ ,  $L(\mathbf{x} + \mathbf{y}) = L(\mathbf{x}) + L(\mathbf{y})$ , and (2) for any vector  $\mathbf{x}$  in  $\mathbb{R}^m$  and scalar  $a$ ,  $L(a\mathbf{x}) = aL(\mathbf{x})$ .

**Definition 4** We say a function  $A : \mathbb{R}^m \rightarrow \mathbb{R}^n$  is affine if there is a linear function  $L : \mathbb{R}^m \rightarrow \mathbb{R}^n$  and a vector  $\mathbf{b}$  in  $\mathbb{R}^n$  such that  $A(\mathbf{x}) = L(\mathbf{x}) + \mathbf{b}$  for all  $\mathbf{x}$  in  $\mathbb{R}^m$ .

$$\begin{aligned} \min_{u_0, \dots, u_{N-1}} \quad & \sum_{k=0}^{N-1} \{ \|Qx_k\|_2 + \|Ru_k\|_2 \} + \|Px_N\|_2 \\ & x_{k+1} = Ax_k + Bu_k, \quad k = 0, \dots, N-1 \\ & x_0 = x(t) \\ & H_u u_k \leq k_u, \quad k = 0, \dots, N-1 \\ & H_x x_k \leq k_x, \quad k = 0, \dots, N-1 \\ & H_N x_N \leq k_N \end{aligned}$$

PWA model

$$\begin{aligned} \min_z \quad & \sum_{k=0}^{N-1} \{ \|Qx_k\|_2 + \|Ru_k\|_2 \} + \|Px_N\|_2 \\ & x_{k+1} = f_{PWA}(x_k, u_k), \quad k = 0, \dots, N-1 \\ & x_0 = x(t) \\ & H_u u_k \leq k_u, \quad k = 0, \dots, N-1 \\ & H_x x_k \leq k_x, \quad k = 0, \dots, N-1 \\ & H_N x_N \leq k_N \end{aligned}$$

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# MPQP

## Algorithm 1

- 1 Let  $X \subseteq \mathbb{R}^n$  be the set of parameters (states);
  - 2 execute **partition**( $X$ );
  - 3 for all regions where  $z$  is a convex set, compute s
  - 4 end.
- procedure partition**( $Y$ )
- 1.1 let  $x_0 \in Y$  and  $\epsilon$  th
  - 1.2 if  $\epsilon \leq 0$  then exit;
  - 1.3 For  $x = x_0$ , compu the QP (13);
  - 1.4 Determine the set of active constraints when  $z = z_0$ ,  $x = x_0$ , and build  $\tilde{G}$ ,  $\tilde{W}$ ,  $\tilde{S}$ ;
  - 1.5 If  $r = \text{rank } \tilde{G}$  is less than the number  $\ell$  of rows of  $\tilde{G}$ , take a subset of  $r$  linearly independent rows, and redefine  $\tilde{G}$ ,  $\tilde{W}$ ,  $\tilde{S}$  accordingly;
  - 1.6 Determine  $\tilde{\lambda}(x)$ ,  $z(x)$  from (17) and (18);
  - 1.7 Characterize the CR from (19) and (20);
  - 1.8 Define and partition the rest of the region as in Theorem 3;
  - 1.9 For each new sub-region  $R_i$ , **partition**( $R_i$ );
- end procedure.**

$$Hz + G'\lambda = 0, \lambda \in \mathbb{R}^q,$$

$$\lambda_i(G^i z - W^i - S^i x) = 0, i = 1, \dots, q,$$

$$\lambda \geq 0,$$

$$Gz \leq W + Sx,$$

$$\max_{x,z,\epsilon} \epsilon$$

$$\text{subj. to } T^i x + \epsilon \|T^i\| \leq Z^i \quad (14)$$

$$Gz - Sx \leq W$$

$$\min_{U \triangleq \{u_t, \dots, u_{t+N_u-1}\}} \left\{ J(U, x(t)) = x'_{t+N_y|t} P x_{t+N_y|t} + \sum_{k=0}^{N_y-1} [x'_{t+k|t} Q x_{t+k|t} + u'_{t+k} R u_{t+k}] \right\}$$

subj. to

$$\begin{aligned} y_{\min} &\leq y_{t+k|t} \leq y_{\max}, \quad k = 1, \dots, N_c \\ u_{\min} &\leq u_{t+k} \leq u_{\max}, \quad k = 0, 1, \dots, N_u \\ x_{t|t} &= x(t) \\ x_{t+k+1|t} &= A x_{t+k|t} + B u_{t+k}, \quad k \geq 0 \\ y_{t+k|t} &= C x_{t+k|t}, \quad k \geq 0 \\ u_{t+k} &= K x_{t+k|t}, \quad N_u \leq k < N_u \end{aligned}$$

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$$z = -H^{-1}G'\lambda$$

$$\begin{aligned} V_z(x) &= \min_z \frac{1}{2} z' H z \\ \text{subj. to } &Gz \leq W + Sx(t), \end{aligned} \quad (13)$$

# MPQP

## Algorithm 1

- 1 Let  $X \subseteq \mathbb{R}^n$  be the set of parameters (states).
- 2 execute **partition**( $X$ );
- 3 for all regions where  $z(\cdot)$  is a convex set, compute  $s$
- 4 end.

**procedure** **partition**( $Y$ )

- 1.1 let  $x_0 \in Y$  and  $\epsilon$  threshold;
  - 1.2 if  $\epsilon \leq 0$  then exit;
  - 1.3 For  $x = x_0$ , compute the QP (13);
  - 1.4 Determine the set of active constraints when  $z = z_0$ ,  $x = x_0$ , and build  $\tilde{G}$ ,  $\tilde{W}$ ,  $\tilde{S}$ ;
  - 1.5 If  $r = \text{rank } \tilde{G}$  is less than the number  $\ell$  of rows of  $\tilde{G}$ , take a subset of  $r$  linearly independent rows, and redefine  $\tilde{G}$ ,  $\tilde{W}$ ,  $\tilde{S}$  accordingly;
  - 1.6 Determine  $\tilde{\lambda}(x)$ ,  $z(x)$  from (17) and (18);
  - 1.7 Characterize the CR from (19) and (20);
  - 1.8 Define and partition the rest of the region as in Theorem 3;
  - 1.9 For each new sub-region  $R_i$ , **partition**( $R_i$ );
- end procedure.**

$$Hz + G'\lambda = 0, \lambda \in \mathbb{R}^q,$$

$$\lambda_i(G^i z - W^i - S^i x) = 0, i = 1, \dots, q,$$

$$\lambda \geq 0,$$

$$Gz \leq W + Sx,$$

For inactive constraints,  $\check{\lambda} = 0$ .

$$\tilde{\lambda} = -(\tilde{G}H^{-1}\tilde{G}')^{-1}(\tilde{W} + \tilde{S}x) \quad (17)$$

$$z = -H^{-1}G'\lambda \quad \rightarrow \quad z = H^{-1}\tilde{G}'(\tilde{G}H^{-1}\tilde{G}')^{-1}(\tilde{W} + \tilde{S}x) \quad (18)$$

# MPQP

## Algorithm 1

- 1 Let  $X \subseteq \mathbb{R}^n$  be the set of parameters (states).
- 2 execute **partition**( $X$ );
- 3 for all regions where  $z(\cdot)$  is a convex set, compute  $z(x)$ .
- 4 end.

**procedure** **partition**( $Y$ );

- 1.1 let  $x_0 \in Y$  and  $\epsilon$  th
  - 1.2 if  $\epsilon \leq 0$  then exit;
  - 1.3 For  $x = x_0$ , compute  $z(x)$  using the QP (13);
  - 1.4 Determine the set of active constraints  $V_z(x) = \min_z \frac{1}{2} z' H z$  at  $x = x_0$ , and build  $\tilde{G}$ ,  $\tilde{W}$ ,  $\tilde{S}$ .
  - 1.5 If  $r = \text{rank } \tilde{G}$  is less than  $n$ , take a subset of  $r$  linearly independent rows of  $\tilde{G}$ , redefine  $\tilde{G}$ ,  $\tilde{W}$ ,  $\tilde{S}$  accordingly;
  - 1.6 Determine  $\tilde{\lambda}(x)$ ,  $z(x)$  from (17) and (18);
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  - 1.8 Define and partition the rest of the region as in Theorem 3;
  - 1.9 For each new sub-region  $R_i$ , **partition**( $R_i$ );
- end procedure.**

$$Hz + G'\lambda = 0, \lambda \in \mathbb{R}^q,$$

$$\lambda_i(G^i z - W^i - S^i x) = 0, i = 1, \dots, q,$$

$$\lambda \geq 0,$$

$$Gz \leq W + Sx,$$

$$V_z(x) = \min_z \frac{1}{2} z' H z$$

$$\text{subj. to } Gz \leq W + Sx(t),$$

(13)

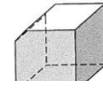
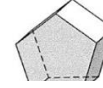
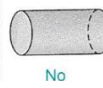
$$z = -H^{-1}G'\lambda$$

$$GH^{-1}\tilde{G}'(\tilde{G}H^{-1}\tilde{G}')^{-1}(\tilde{W} + \tilde{S}x) \leq W + Sx \quad (19)$$

$$\tilde{\lambda} = -(\tilde{G}H^{-1}\tilde{G}')^{-1}(\tilde{W} + \tilde{S}x) \quad (17)$$



# MI



## Algorithm 1

- 1 Let  $X \subseteq \mathbb{R}^n$  be the set of parameters (states);
- 2 execute **partition**( $X$ );
- 3 for all regions where  $z(x)$  is the same and whose union is a convex set, compute such a union as in [9];
- 4 end.

**procedure** **partition**( $Y$ )

- 1.1 let  $x_0 \in Y$  and  $\epsilon$  the solution to the LP (14);
  - 1.2 if  $\epsilon \leq 0$  then exit; (no full dimensional CR is in  $Y$ )
  - 1.3 For  $x = x_0$ , compute the optimal solution  $(z_0, \lambda_0)$  of the QP (13);
  - 1.4 Determine the set of active constraints when  $z = z_0$ ,  $x = x_0$ , and build  $\tilde{G}$ ,  $\tilde{W}$ ,  $\tilde{S}$ ;
  - 1.5 If  $r = \text{rank } \tilde{G}$  is less than the number  $\ell$  of rows of  $\tilde{G}$ , take a subset of  $r$  linearly independent rows, and redefine  $\tilde{G}$ ,  $\tilde{W}$ ,  $\tilde{S}$  accordingly;
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  - 1.8 Define and partition the rest of the region as in Theorem 3;
  - 1.9 For each new sub-region  $R_i$ , **partition**( $R_i$ );
- end procedure.**

**Theorem 3**  
 $\{x \in Y : Ax$   
*Also let*

$$R_i = \left\{ \begin{array}{l} x \\ u = \end{array} \right.$$

$$\left\{ \begin{array}{ll} \begin{array}{l} [-5.9220 \ -6.8883] x \\ \\ 2.0000 \\ \\ 2.0000 \\ \\ -2.0000 \\ \\ [-6.4159 \ -4.6953] x + 0.6423 \\ \\ -2.0000 \\ \\ [-6.4159 \ -4.6953] x - 0.6423 \end{array} & \begin{array}{l} \text{if } \begin{bmatrix} -5.9220 & -6.8883 \\ 5.9220 & 6.8883 \\ -1.5379 & 6.8291 \\ 1.5379 & -6.8291 \end{bmatrix} x \leq \begin{bmatrix} 2.0000 \\ 2.0000 \\ 2.0000 \\ 2.0000 \end{bmatrix} \\ \text{(Region \#1)} \\ \\ \text{if } \begin{bmatrix} -3.4155 & 4.6452 \\ 0.1044 & 0.1215 \\ 0.1259 & 0.0922 \end{bmatrix} x \leq \begin{bmatrix} 2.6341 \\ -0.0353 \\ -0.0267 \end{bmatrix} \\ \text{(Region \#2, \#4)} \\ \\ \text{if } \begin{bmatrix} 0.0679 & -0.0924 \\ 0.1259 & 0.0922 \end{bmatrix} x \leq \begin{bmatrix} -0.0524 \\ -0.0519 \end{bmatrix} \\ \text{(Region \#3)} \\ \\ \text{if } \begin{bmatrix} -0.1259 & -0.0922 \\ -0.0679 & 0.0924 \end{bmatrix} x \leq \begin{bmatrix} -0.0519 \\ -0.0524 \end{bmatrix} \\ \text{(Region \#5)} \\ \\ \text{if } \begin{bmatrix} -6.4159 & -4.6953 \\ -0.0275 & 0.1220 \\ 6.4159 & 4.6953 \end{bmatrix} x \leq \begin{bmatrix} 1.3577 \\ -0.0357 \\ 2.6423 \end{bmatrix} \\ \text{(Region \#6)} \\ \\ \text{if } \begin{bmatrix} 3.4155 & -4.6452 \\ -0.1044 & -0.1215 \\ -0.1259 & -0.0922 \end{bmatrix} x \leq \begin{bmatrix} 2.6341 \\ -0.0353 \\ -0.0267 \end{bmatrix} \\ \text{(Region \#7, \#8)} \\ \\ \text{if } \begin{bmatrix} 6.4159 & 4.6953 \\ 0.0275 & -0.1220 \\ -6.4159 & -4.6953 \end{bmatrix} x \leq \begin{bmatrix} 1.3577 \\ -0.0357 \\ 2.6423 \end{bmatrix} \\ \text{(Region \#9)} \end{array} \right.$$

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# Limitations

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- Though Explicit MPC is faster and uses off-line approach it is capable of handling smaller systems (generally with variables  $<6$ ).
- Requires large storage units.
- Sequential and less dynamic.



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# Applications

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- In literature, it can be seen that Explicit MPC techniques have addressed several industrial problems.
- Explicit MPCs are reported to be most suitable for fast-sampling problems (in the order of 1-50 ms) and relatively small size (1-2 manipulated inputs, 5-10 parameters) such as **automotive domain and electrical power converters**.

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# Conclusion

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- Explicit MPC is a powerful tool to convert an MPC design into an equivalent offline control law that has simpler implementations.
- Implementation of the explicit MPC for solving the QP problem depends on available CPU time, data memory, and program memory and other practical considerations.
- Explicit MPC approach remains convenient for relatively small and offline problems (such as one or two command inputs, short control and constraint horizons, up to ten states).
- For larger problems, and/or problems that are linear time varying, online QP solution methods tailored to conventional Implicit MPC may be preferable.

# References

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# Simulation Results

