

# Modeling Round-off Error in the Fast Gradient Method for Predictive Control

Ian McInerney<sup>a</sup>, Eric C. Kerrigan<sup>a,b</sup>, George A. Constantinides<sup>a</sup>

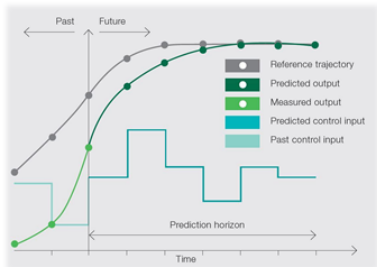
<sup>a</sup>Department of Electrical and Electronic Engineering, Imperial College London

<sup>b</sup>Department of Aeronautics, Imperial College London

# Outline

- 1 Preliminaries
- 2 Generic round-off error model
- 3 Parametric round-off error model
- 4 Conclusions

# Model Predictive Control



$$\min_{u,x} \frac{1}{2} x_N' P x_N + \frac{1}{2} \sum_{k=0}^{N-1} x_k' Q x_k + u_k' R u_k$$

$$\text{s.t. } x_{k+1} = A x_k + B u_k, \quad k = 0, \dots, N-1$$

$$x_0 = \bar{x}_0$$

$$E u_k \leq c_u, \quad k = 0, \dots, N-1$$



$$\min_u \frac{1}{2} u' H u + \bar{x}_0' J' u$$

$$\text{s.t. } u \in \mathbb{K} := \{u : G u \leq g\}$$

## Fast Gradient Method

- Accelerated first-order optimization solver
- Project onto the constraint set
- Necessary condition for stability:  $\lambda(H) \in (0, 1)$

### Algorithm

```
for  $i = 0$  to  $l_{max} - 1$  do  
   $f^{(i)} := Hy^{(i)} + J\bar{x}_0$  ▷ Gradient  
   $t^{(i)} := y^{(i)} - f^{(i)}$  ▷ Update  
   $u^{(i+1)} := \pi_{\mathbb{K}}(t^{(i)})$  ▷ Projection  
   $y^{(i+1)} := (1 + \beta)t^{(i+1)} - \beta t^{(i)}$  ▷ Acceleration  
end for
```

## Fixed-Point Arithmetic

- Quantize  $\mathbb{R}$  into  $\mathbb{Z}$  by multiplying by a scale factor and rounding

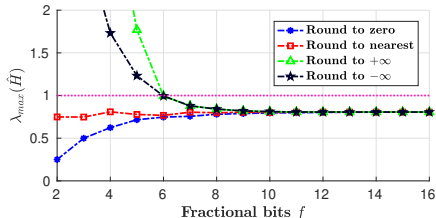
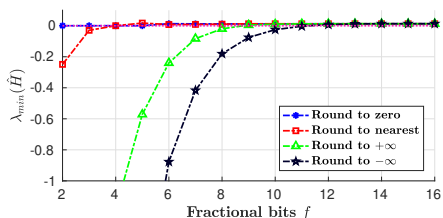
$$\underbrace{18020.017052}_{\mathbb{R}} \xrightarrow{\times 10^5} \underbrace{18020}_{\text{integer}} \underbrace{01705}_{\text{fraction}}_{\text{Fixed-point}}$$

- Only requires integer computations in hardware
- Introduces  $\epsilon_f$  round-off error

Model rounding action as an additive disturbance matrix:

$$\hat{H} = H + E$$

# Rounding Stability Margin



## Rounding Stability Margin ( $\eta$ )

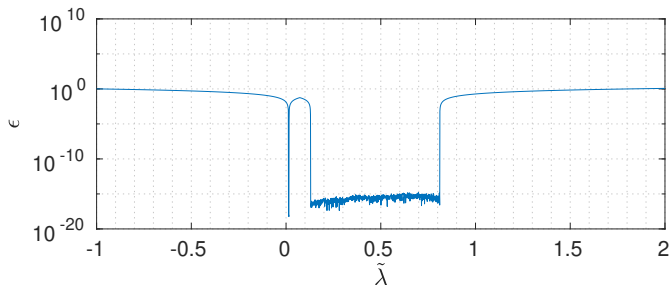
The smallest value of  $\|E\|_2$  that causes the eigenvalues of  $\hat{H}$  to leave the interval  $(0, 1)$ .

# Rounding Stability Margin

## Computation

Assuming  $\lambda(H) \in (0, 1)$ , use the  $\epsilon$ -pseudospectrum of  $H$  at  $\tilde{\lambda} = \{0, 1\}$ .

$$\left\| (\tilde{\lambda}I - H)^{-1} \right\| \geq \frac{1}{\epsilon} \xleftrightarrow{\text{Equivalently}} \tilde{\lambda} \in \lambda(H + E) \text{ with } \|E\| \leq \epsilon$$



## Generic Rounding Model

Model

$$E_g := \begin{bmatrix} \pm\epsilon_f & \pm\epsilon_f & \dots \\ \pm\epsilon_f & \pm\epsilon_f & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

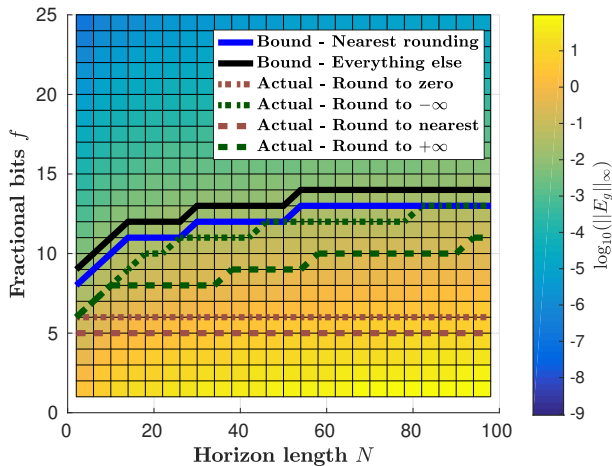


Fractional Bits Sufficient for  $\lambda(\hat{H}) \in (0, 1)$

$$f = \begin{cases} \lceil -\log_2 \left( \frac{\eta}{mN} \right) \rceil - 1 & \text{if using round to nearest,} \\ \lceil -\log_2 \left( \frac{\eta}{mN} \right) \rceil & \text{otherwise.} \end{cases}$$



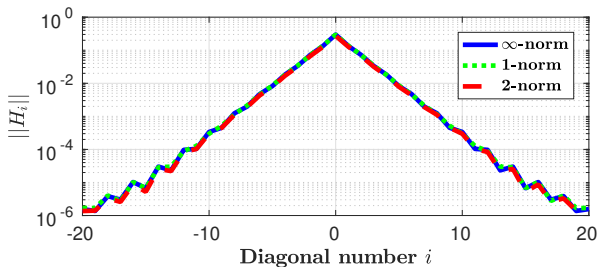
# Results



# Hessian Structure

## Toeplitz Components

$$H_i = \begin{cases} B'(A^i)'PB & \text{if } i > 0, \\ B'PB + R & \text{if } i = 0, \\ B'PA^{|i|}B & \text{if } i < 0. \end{cases}$$



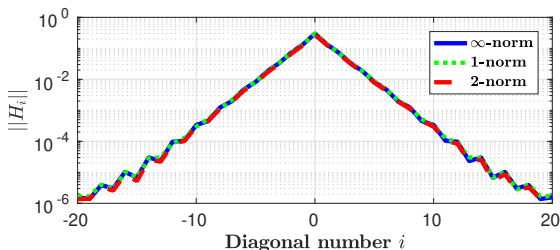
# Parametric Rounding Model

## Idea

Split round-off error model into two parts:  $E_p := E_G + E_T$ , with

$$(E_G)_i := \begin{cases} E_g & \text{if } i < k, \\ 0 & \text{otherwise,} \end{cases} \quad (E_T)_i := \begin{cases} H_i & \text{if } |i| \geq k, \\ 0 & \text{otherwise.} \end{cases}$$

Where  $k$  is the diagonal beyond which all blocks in  $\hat{H}_i$  are 0



# Parametric Rounding Model

## Fractional Width Selection

Choose  $\epsilon_f$  such that

$$|\epsilon_f| m(2k - 1) + 2 \|\mathcal{P}_{\bar{H}}(k, \cdot)\|_{H_\infty} < \eta,$$

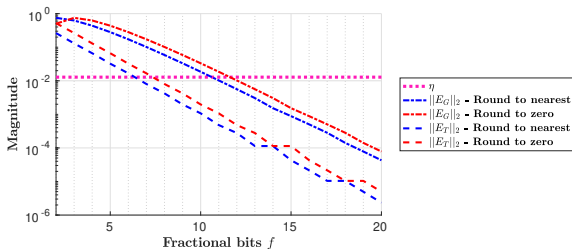
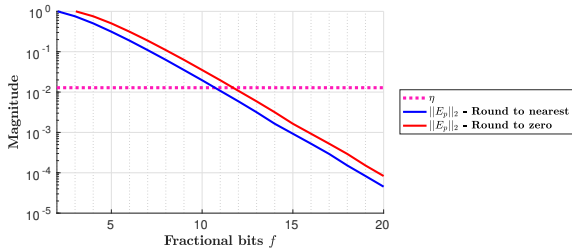
where

$$\mathcal{P}_{\bar{H}}(n, z) := z\mathcal{G}_P(z) - B'P\mathcal{P}_n(z)B \quad \forall z \in \mathbb{T},$$

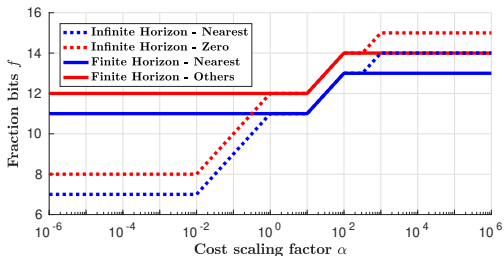
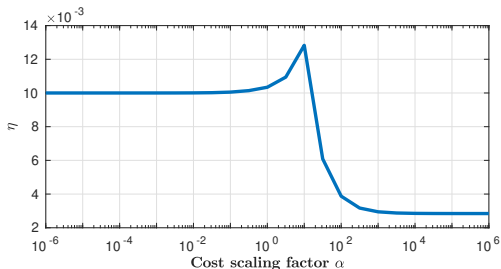
$$\mathcal{G}_P := \begin{cases} x^+ = Ax + Bu \\ y = B'Px \end{cases},$$

$$\mathcal{P}_n(z) := \sum_{i=0}^{n-1} A^i z^{-i} \quad \forall z \in \mathbb{T}.$$

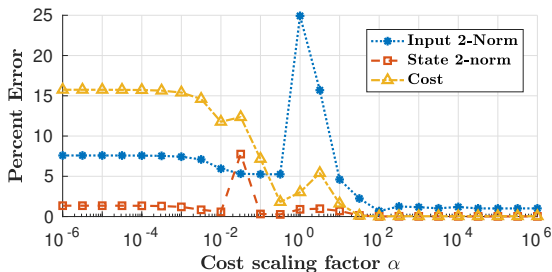
# Results



# Results



## Results



Fractional Length	Logic Resources				Power (mW)	Solve Time ( $\mu$ s)
	LUT	FF	DSP	BRAM		
$f=12$	947	768	4	2	20	532.17
$f=16$	1,136	912	4	2	25	612.17
$f=21$	887	1,033	8	8	43	701.77
$f=26$	993	1,237	12	9	48	701.77

## Conclusions

### Key Contributions

- Compute the Rounding Stability Margin for the Fast Gradient Method using the  $\epsilon$ -pseudospectrum
- Exploit Toeplitz structure to model exact round-off error
- Reduce the fractional bits needed by 30–45%
- Reduction in hardware usage and solution time by up to 77% and 25% respectively

### Future Directions

- Derive sufficient condition for stability of the Fast Gradient Method
- Bound perturbation of optimal vector  $u^*$  when problem is quantized