

#### An Improved Stochastic Send-on-Delta Scheme for Event-Based State Estimation

Thelander Andrén, Marcus; Cervin, Anton

2016

Document Version: Publisher's PDF, also known as Version of record

Link to publication

Citation for published version (APA):

Thelander Andrén, M., & Cervin, A. (2016). An Improved Stochastic Send-on-Delta Scheme for Event-Based State Estimation. Poster session presented at Reglermöte 2016, Göteborg, Sweden.

Total number of authors:

General rights

Unless other specific re-use rights are stated the following general rights apply:

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

• Users may download and print one copy of any publication from the public portal for the purpose of private study

- You may not further distribute the material or use it for any profit-making activity or commercial gain
  You may freely distribute the URL identifying the publication in the public portal

Read more about Creative commons licenses: https://creativecommons.org/licenses/

Take down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

**LUND UNIVERSITY** 

**PO Box 117** 221 00 Lund +46 46-222 00 00

Download date: 18. May. 2025



### An Improved Stochastic Send-on-Delta Scheme for Event-Based State Estimation

Marcus Thelander Andrén Anton Cervin

Department of Automatic Control, Lund University marcus.thelander\_andren@control.lth.se anton@control.lth.se



### Introduction

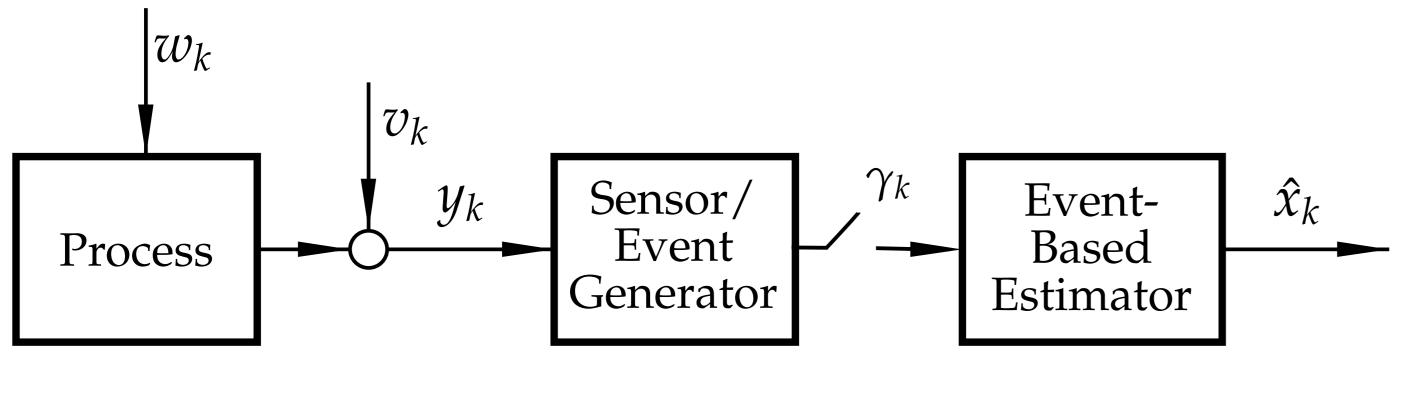
Event-based sensing and communication holds the promise of lower resource utilization and/or better performance for remote state estimation applications in e.g networked control systems (NCS).

However, the problem of designing an optimal event-based state estimator often becomes untractable due to nonlinear measurements. This complexity is avoided with stochastic event-triggering.

In this work [1], we extend the work on stochastic triggering in [2] by proposing a simple predictor in the sensor to further improve the estimation performance.

# The Remote Estimation Problem

Compute optimal estimates both with and without transmission:



### **Process:**

$$x_{k+1} = Ax_k + w_k$$

$$y_k = Cx_k + v_k$$

$$w_k \sim \mathcal{N}(0, Q)$$

$$v_k \sim \mathcal{N}(0, R)$$

### **Two Cases:**

$$\gamma_k = \begin{cases}
1 \implies \text{Transmission} \\
0 \implies \text{No transmission}
\end{cases}$$

### The MMSE Estimator

Bayes' theorem gives case dependent Kalman filter:

### Time Update:

### Measurement Update:

$$\hat{x}_{k}^{-} = A\hat{x}_{k-1}$$

$$\hat{x}_{k} = \hat{x}_{k}^{-} + K_{k}[\gamma_{k}y_{k} + (1 - \gamma_{k})S_{l}y_{k-l} - \hat{y}_{k}^{-}]$$

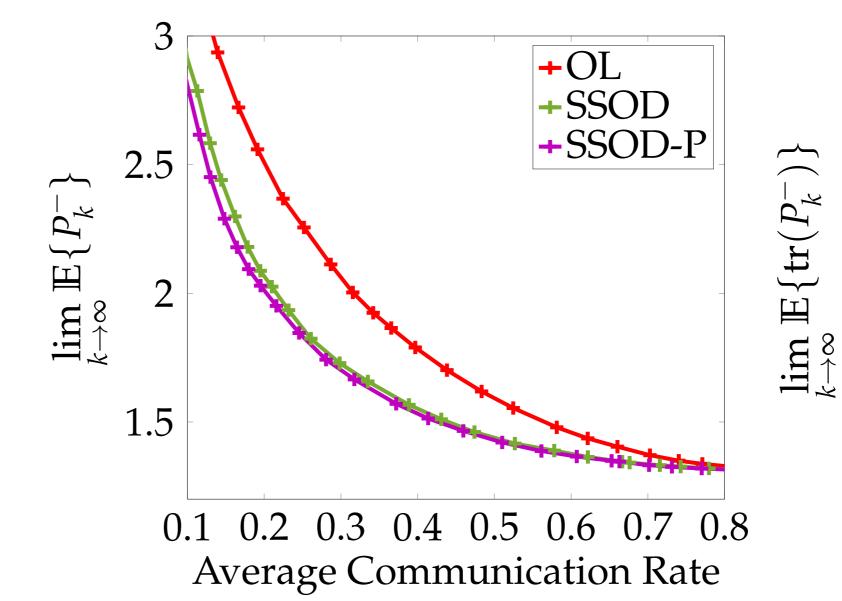
$$\hat{y}_{k}^{-} = C\hat{x}_{k}^{-}$$

$$P_{k} = (I - K_{k}C)P_{k}^{-}$$

$$\hat{y}_{k}^{-} = C\hat{x}_{k}^{-}$$
 $P_{k} = (I - K_{k}C)P_{k}^{-}$ 
 $P_{k}^{-} = AP_{k-1}A^{T} + Q$ 
 $F_{k}^{-} = AP_{k}C^{T}[CP_{k}^{-}C^{T} + R + (1 - \gamma_{k})Y^{-1}]^{-1}$ 

# Numerical Performance Comparison

Performance of SSOD and OL depends on process, while SSOD-P takes the process configuration into account:



0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 Average Communication Rate

3.5

Slow  $1^{st}$ -order process:

$$A = 0.95, C = 1$$
  
 $Q = 0.8, R = 1$ 

Highly oscillatory  $2^{nd}$ -order process

+OL

+SSOD

+SSOD-P

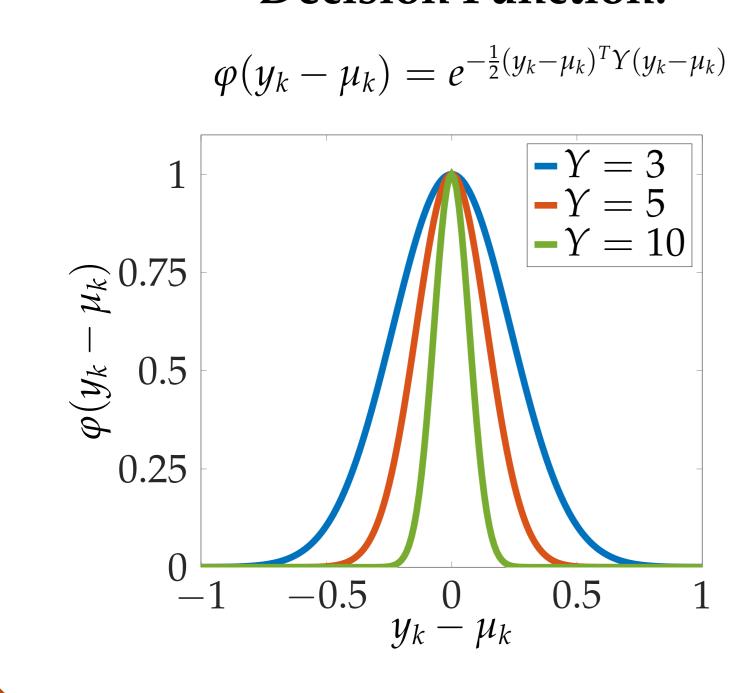
$$A = \begin{bmatrix} -0.85 & -0.35 \\ 0.35 & -0.85 \end{bmatrix}, C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

$$Q = \text{diag}(10^{-3}, 1), \quad R = 0.1$$

# Stochastic Event-Triggering

Trigger transmission with certain probability:

## **Decision Function:**



### **Event-Generator:**

$$\zeta_k \sim \mathcal{U}(0,1)$$

$$\gamma_k = \begin{cases} 1, & \text{if } \zeta_k > \varphi(y_k - \mu_k) \\ 0, & \text{else} \end{cases}$$

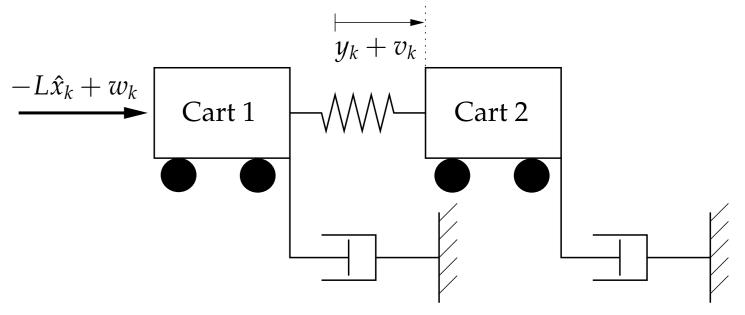
### **Property of Scheme:**

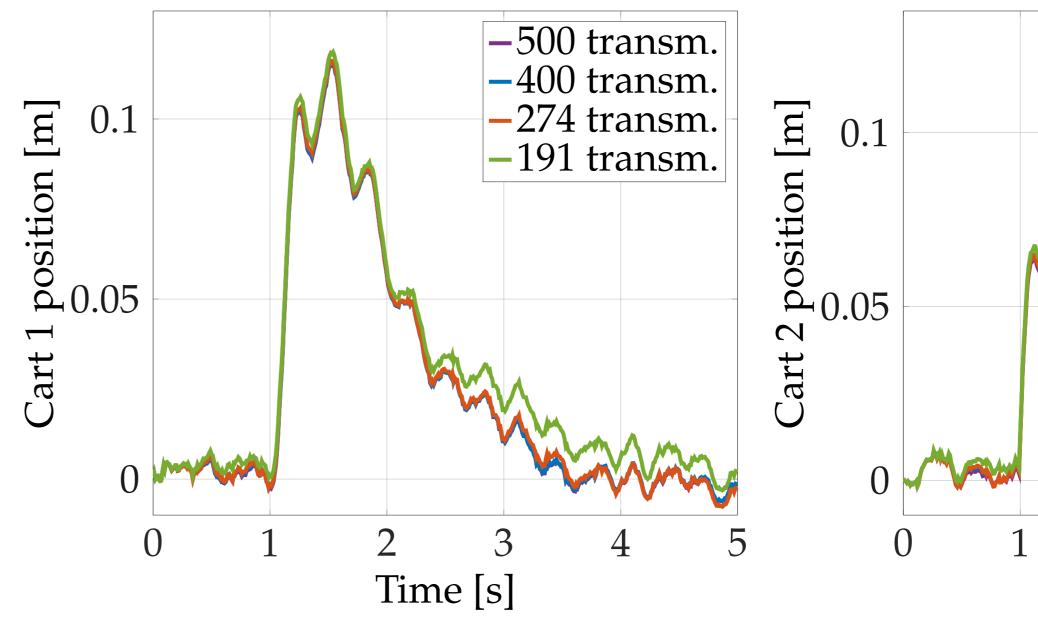
$$\Pr(\gamma_k=0)=\varphi(y_k-\mu_k)$$

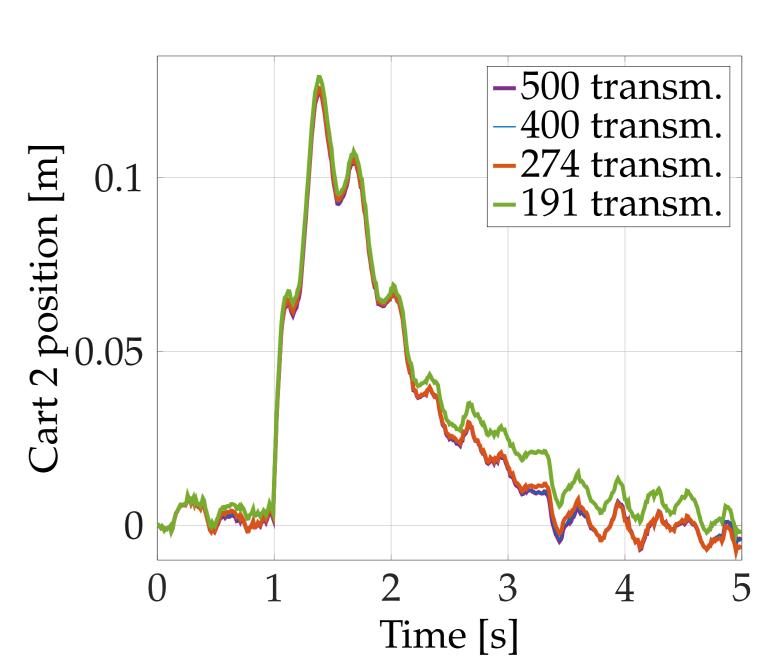
# Simulation Study

Position control of two carts with state-feedback and SSOD-P:

- System discretized with time step 0.01 s
- Impulse in cart 1 velocity at time 1 s
- Degradation in control performance small even at low communication rates







# A Simple Prediction

Proposed  $\mu_k$  in [2] with no estimator-to-sensor feedback are:

Open-Loop (OL
$$\mu_k = 0$$

Open-Loop (OL): Stoch. Send-on-Delta (SSOD):

 $\mu_k = y_{k-l}$  (Transmit l steps ago)

Based on stationarity, we instead propose:

### Stoch. Send-on-Delta with Simple Prediction (SSOD-P):

$$\mu_k = \mathbb{E}\{y_k|y_{k-l}\} = S_l y_{k-l}$$

$$S_l = CA^l\Sigma C^T[C\Sigma C^T + R]^{-1}, \quad \Sigma = \text{Cov}(x_k)$$
 in stationarity

### Conclusions

- Stochastic Triggering enables simple remote estimator design
- We propose a simple sensor prediction for improved performance
- Prediction implies a scaling of last transmitted value
- Scaling factors can be pre-computed offline
- Proposed scheme compares well in numerical examples

### Acknowledgments

This work has been supported by the Swedish Research Council. The authors are members of the LCCC Linnaeus Center and the ELLIIT Excellence Center at Lund University.

### References

[1] M. Thelander Andrén and A. Cervin Event-Based State Estimation Using an Improved Stochastic Send-on-Delta Sampling Scheme In 2nd Int. Conf. on Event-Based Control, Communication and Signal Processing (EBCCSP) (Accepted), Krakow, Poland, June, 2016.

[2] Shi, D., Shi, L. and Tongwen, C. Event-Based State Estimation – A Stochastic Perspective Springer, 2016.