An Observer to Detect Infrequently-Occurring Disturbances in Grinding Operations

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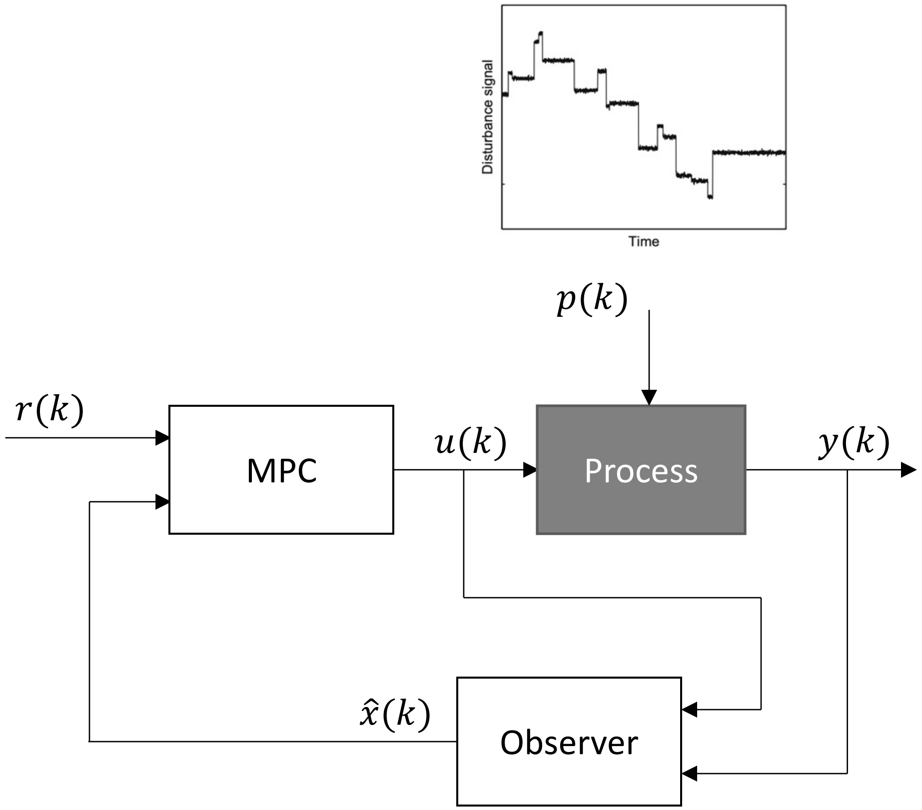
Introduction

Research objective

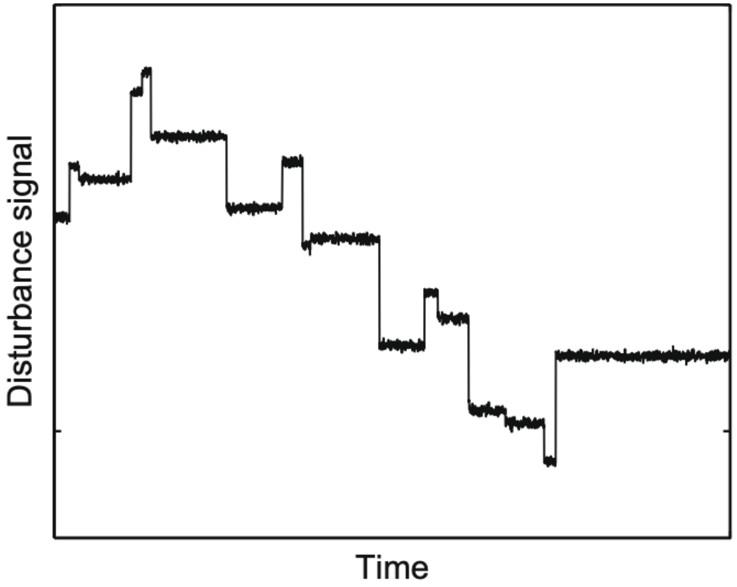


The goal is to design improved control systems by modelling realistic disturbances encountered in mineral processing operations

Introduction

Literature review

- Major upsets are often due to *deterministic disturbances* such as sudden step changes.
- Two types of disturbance:
  - *Persistent*
  - *Infrequently occurring*
- When both types are present, the former will dominate the estimated noise model.



(c) Abrupt step changes of random duration and magnitude.

See MacGregor et al. (1984), Eriksson and Isaksson (1996), Wong and Lee (2009).

Figure from Wong and Lee (2009)

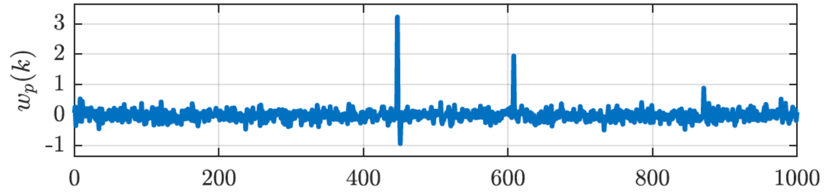
The classical control design approach neglects infrequently occurring disturbances

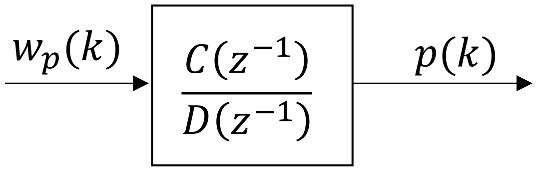
Disturbance Model

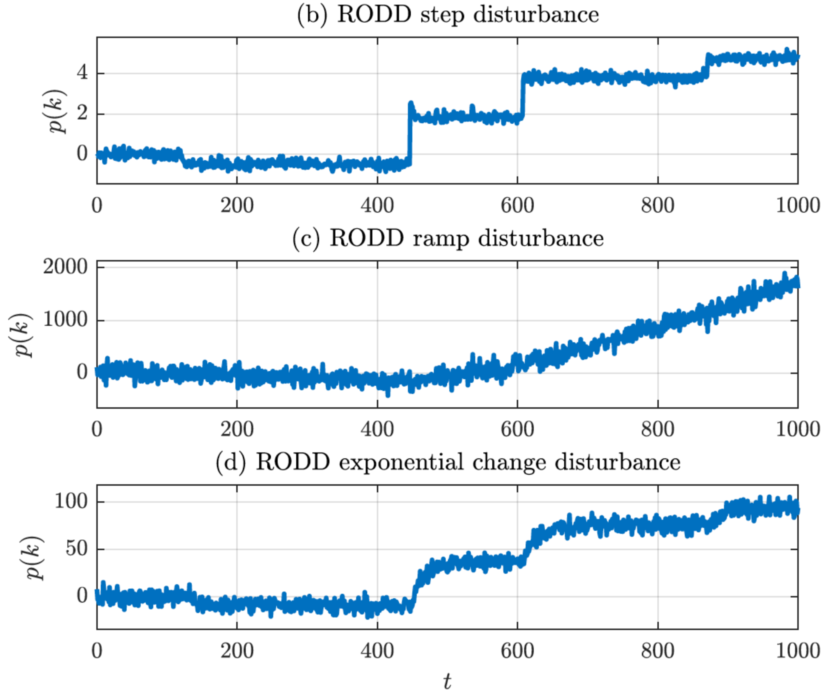
Randomly occurring deterministic disturbance (RODD) model

$$w_p(k) = \begin{cases} \mathcal{N}(0, \sigma_w^2) & \text{with prob.} \quad 1-\epsilon \\ \mathcal{N}(0, b^2\sigma_w^2) & \text{with prob.} \quad \epsilon \end{cases}$$

(a) Random shocks







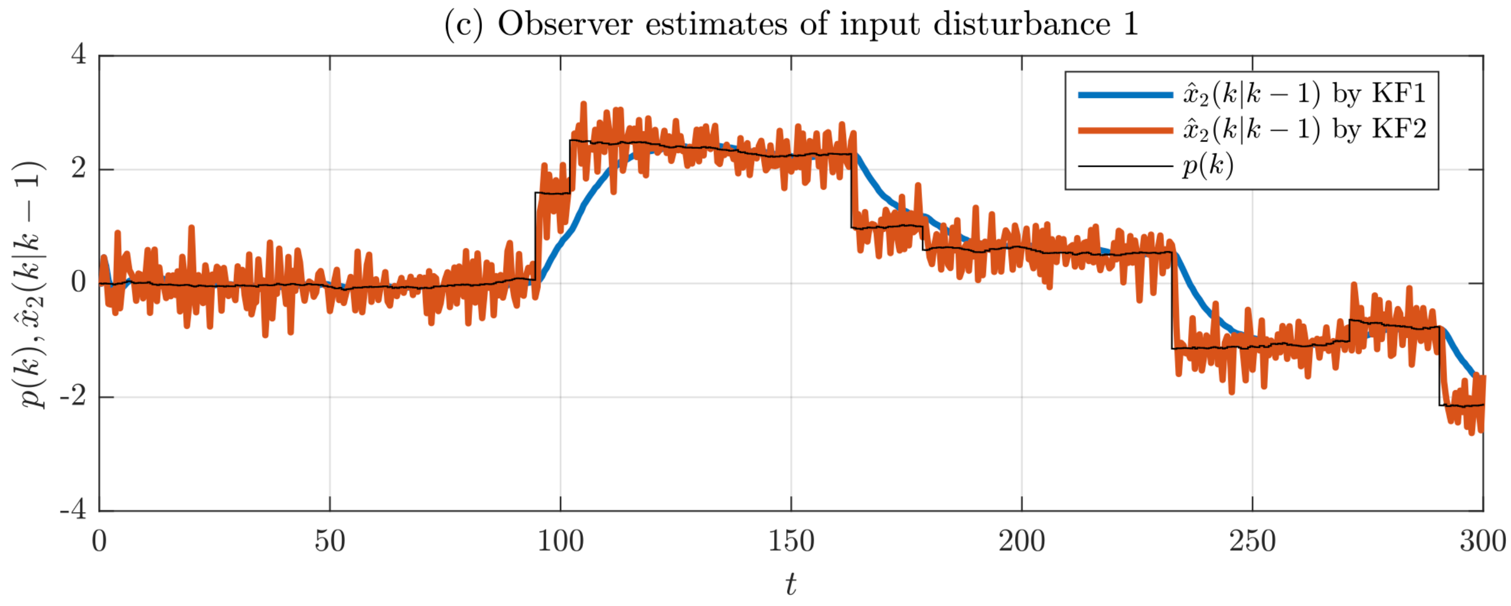
ϵ is small (e.g. 0.01)
b is high (e.g. 100)

MacGregor et al. (1984), Robertson and Lee (1995).

The RODD model can be used to simulate common disturbances encountered in industrial operations

Observer Design

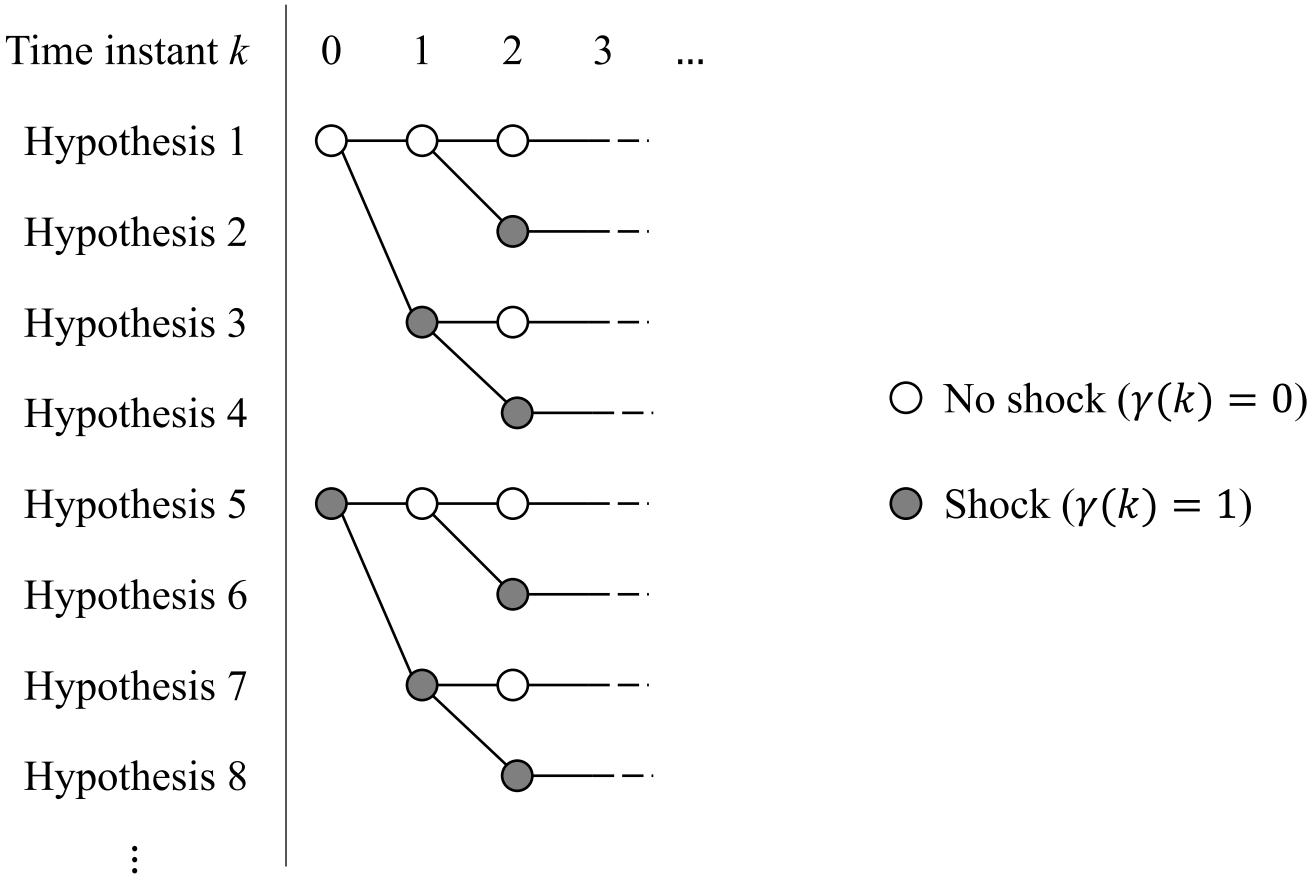
Single filter estimation problem



A single Kalman filter cannot effectively estimate a RODD due to the inevitable trade-off between the tracking response and the sensitivity to noise

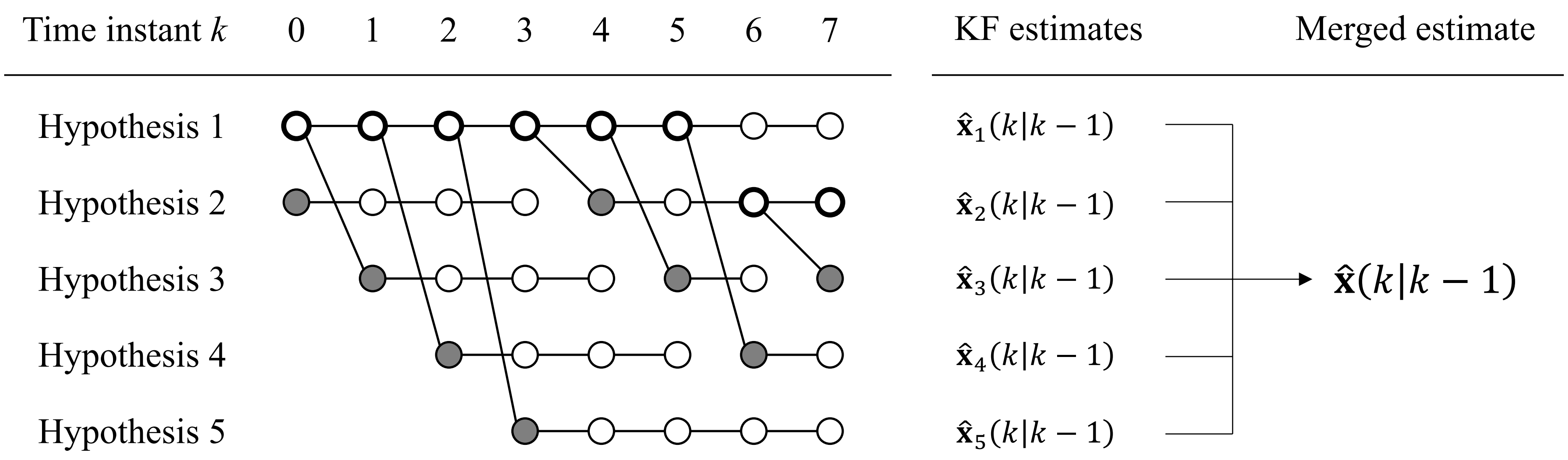
Observer Design

Multiple-model observers – hypothesis branching



Observer Design

Multiple-model observers – sequence pruning



○ No shock ($\gamma(k) = 0$)

● Shock ($\gamma(k) = 1$)

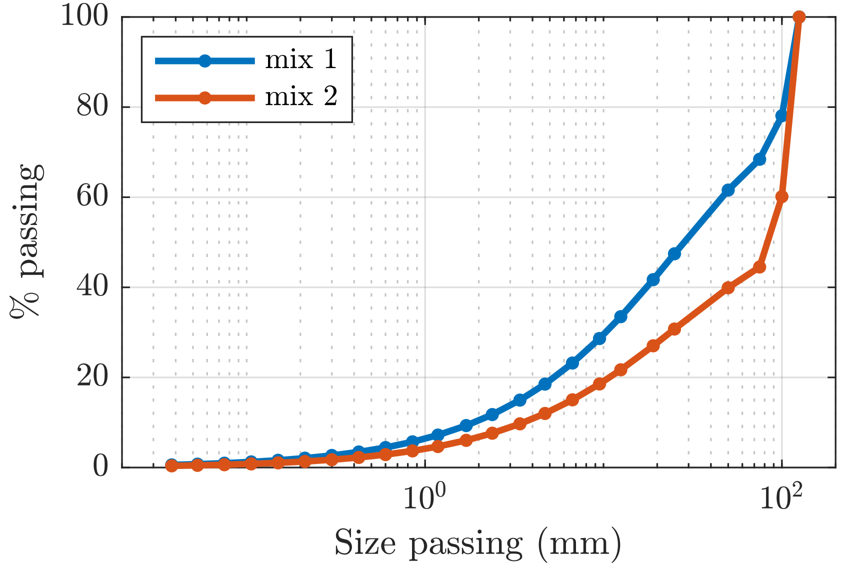
○ Most likely hypothesis at time k

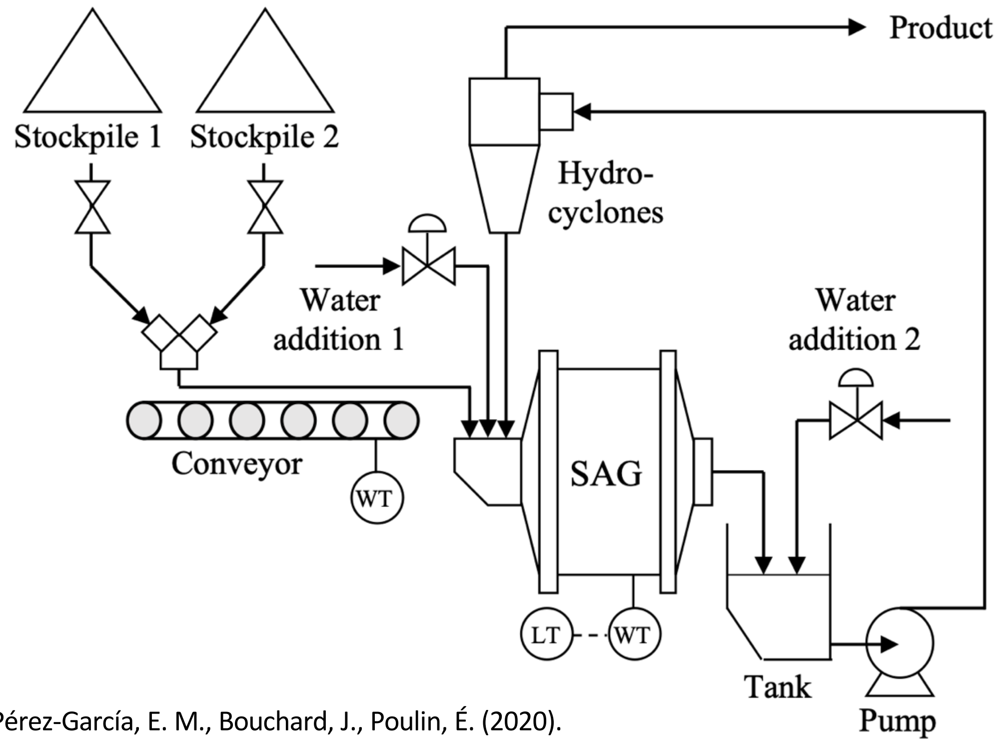
$$\hat{\mathbf{x}}(k|k-1) = \sum_{i=1}^{n_f} \hat{\mathbf{x}}_i(k|k-1)\Pr(\Gamma_i(k)|\mathrm{Y}(k))$$

Andersson, P. (1985), Gustafsson, F. (1993), Eriksson and Isaksson (1996).

Grinding Simulator

Simulated grinding process with switching ore feed





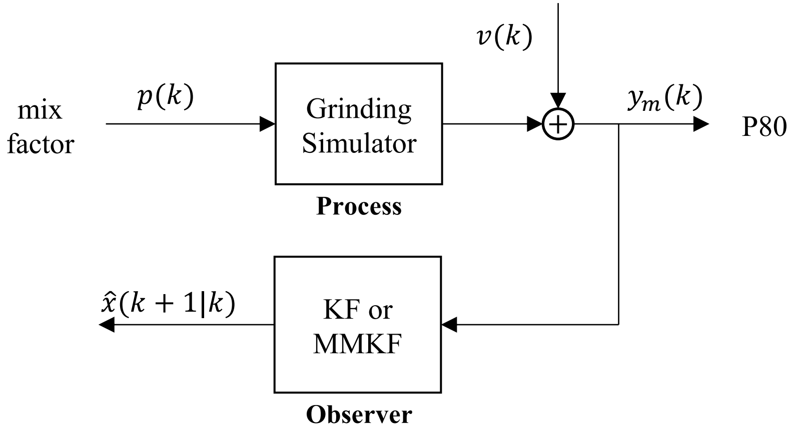
Pérez-García, E. M., Bouchard, J., Poulin, É. (2020).

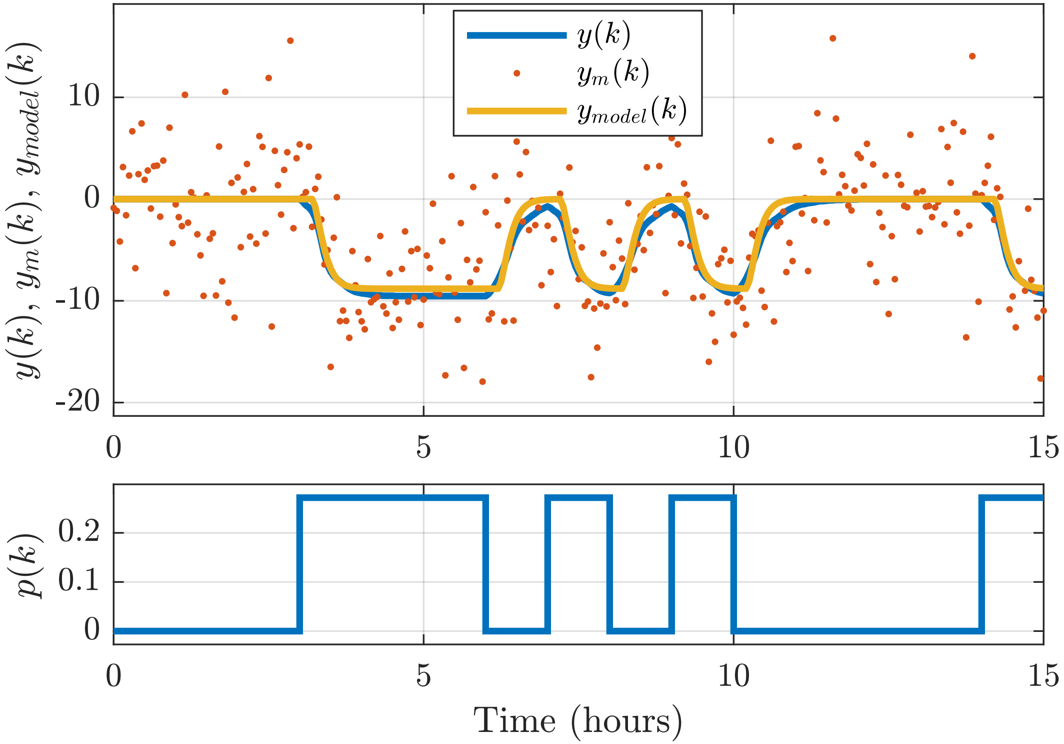
Variations in run-of-mine ore properties are the main source of disturbances to the grinding process

Observer Design

System identification

- SISO system with switching input disturbance



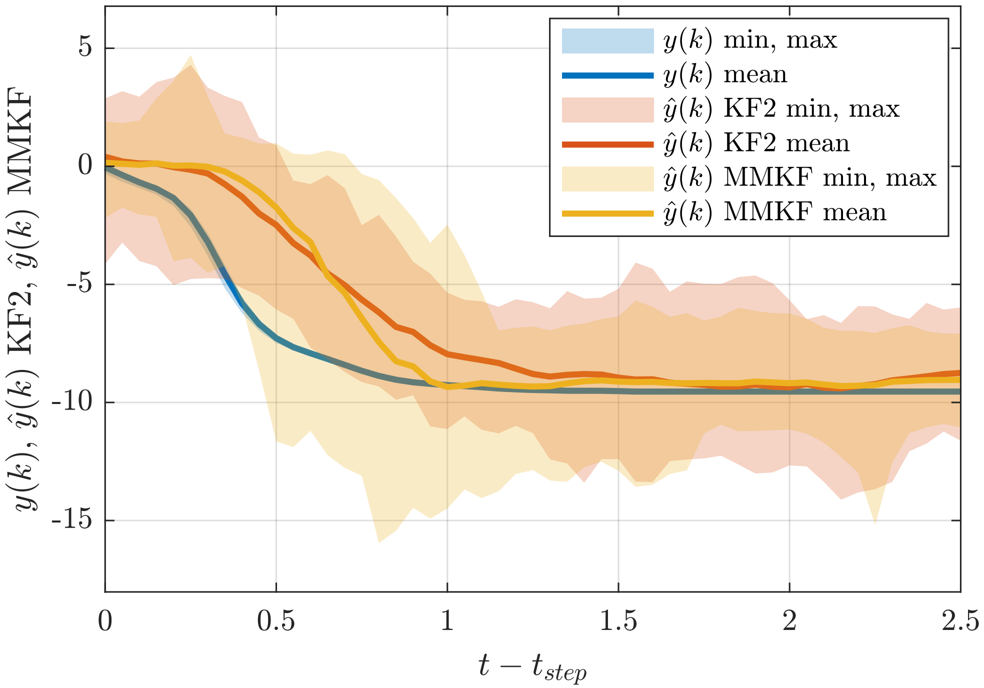


A linear model of the dynamic response of the grinding circuit was identified from a sample of input-output data

Simulation Results

Monte Carlo Simulations

Metric	KF1	KF2	MMKF
$\text{MSE}(\hat{y}(k), y(k))$ overall	11.0	3.7	3.5
$\text{MSE}(\hat{y}(k), y(k))$ transient	21.1	7.7	11.2
$\text{MSE}(\hat{y}(k), y(k))$ steady state	7.9	2.5	1.1
$\text{Var}(\hat{y}(k))$ steady state	1.8	1.9	0.5



The multi-model observer has a better performance in steady state than the best single Kalman filter while responding quickly to the infrequent step changes

Conclusions

- Traditional control design does not consider *infrequent, abrupt disturbances*
- These types of disturbances can be represented by the *randomly-occurring deterministic disturbance* (RODD) model
- A multi-model observer with sequence pruning produces better estimates of step changes than a standard Kalman Filter
- The computational complexity of the multi-model observer is a consideration for practical implementation.

Future Research

- Determine the potential benefits of improved disturbance observers in multivariable feedback control scenarios
- Data from operating plants is needed to determine the characteristics of real disturbances
- Investigate nonlinear system identification approaches to estimate disturbance parameters from data—e.g. sequential Monte Carlo methods (Schön et al., 2015)
- Other types of disturbance models may be worth investigating—e.g. the hidden Markov model approach (Wong and Lee, 2009).

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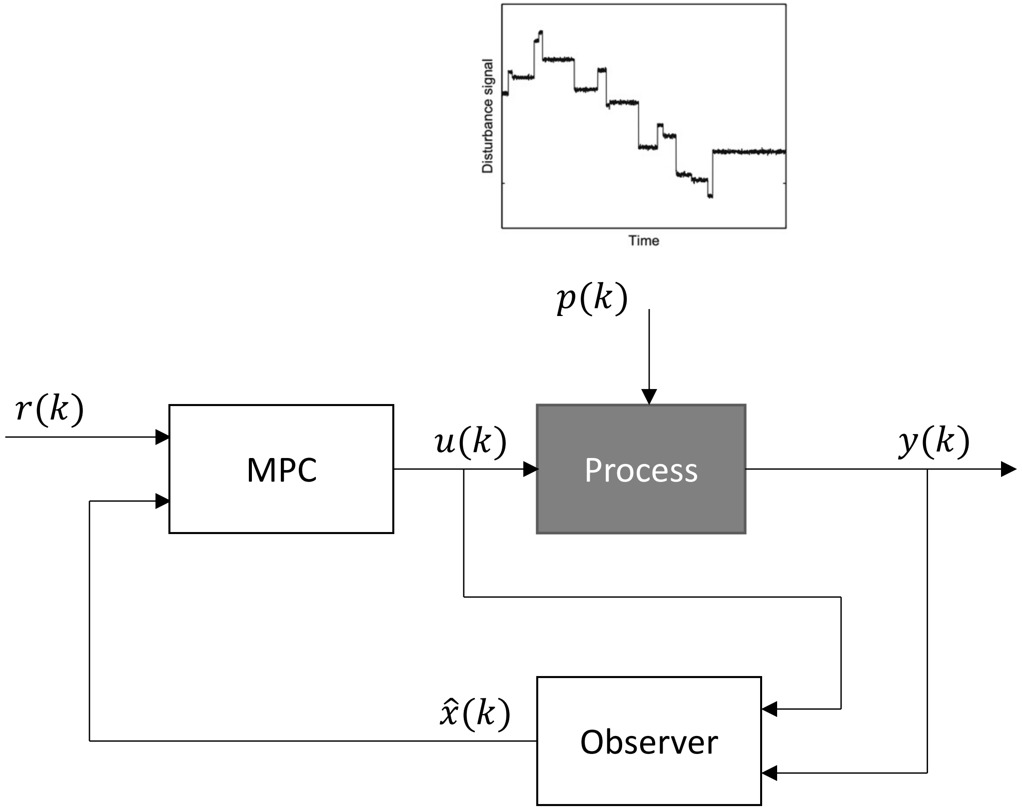
- Wong, W. C., Lee, J. H. (2009). Realistic disturbance modeling using Hidden Markov Models: Applications in model-based process control. Journal of Process Control, 19, 1438–1450.

Thank You



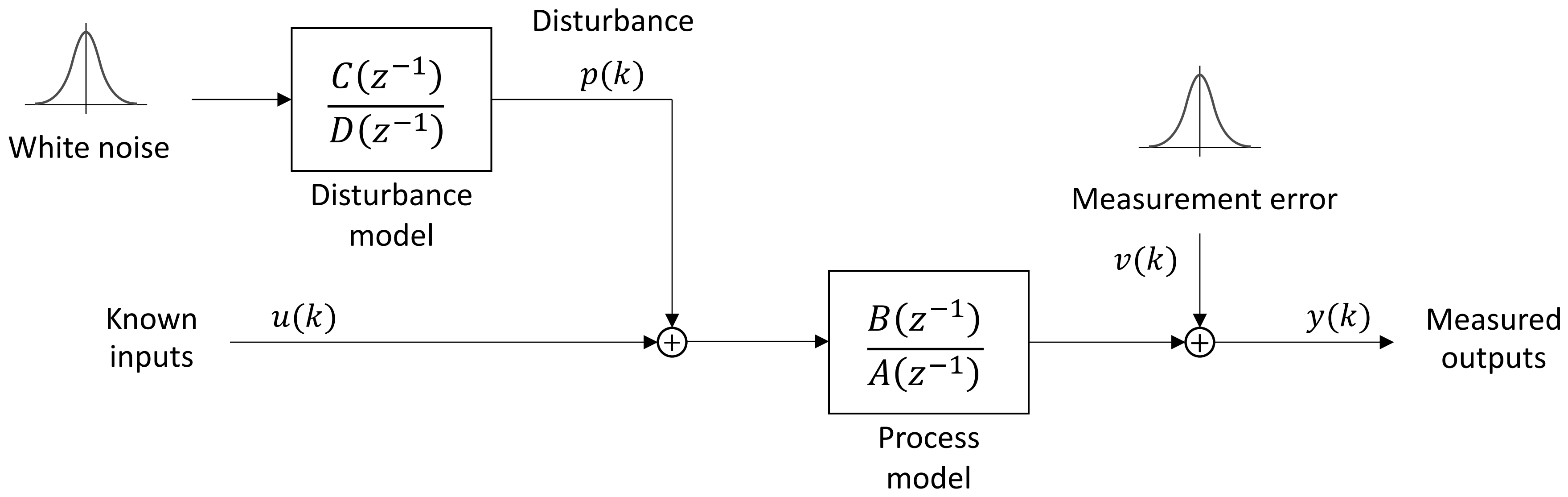
- Code repository:

  `https://github.com/billtubbs/ifac-2022-mmkf`

ADDITIONAL INFORMATION

Introduction

Disturbance models

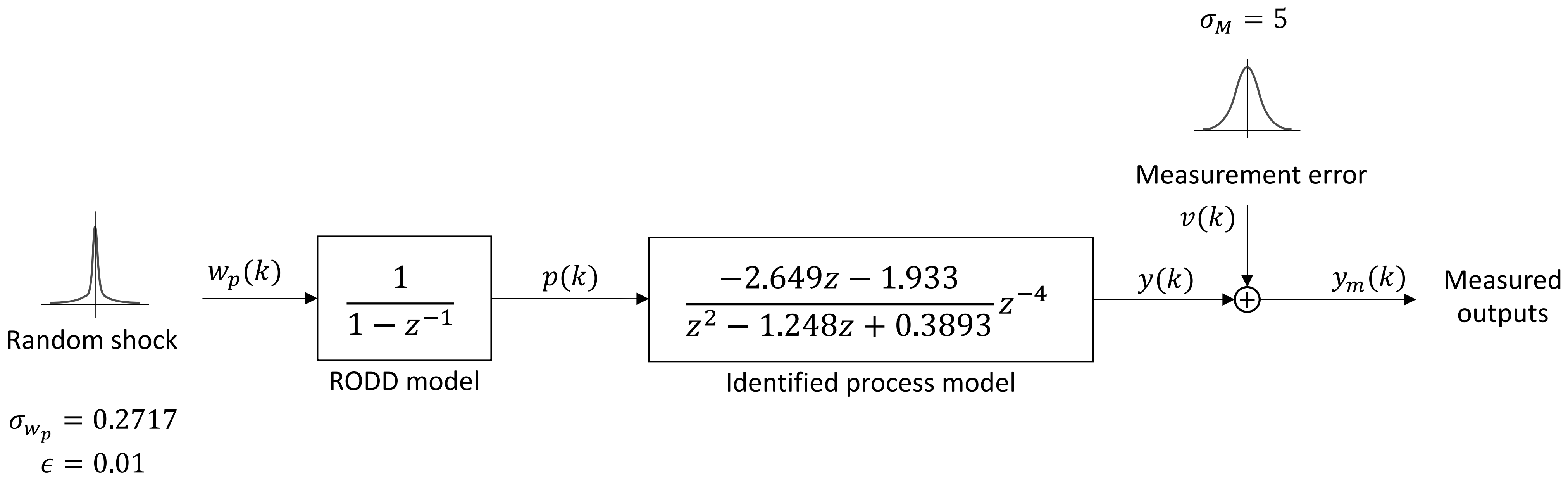


In classical control design, disturbances are modelled with Gaussian random noises

Observer Design

Observer system model

- Linear SISO system with RODD input



The observer model is a randomly-occurring step disturbance model combined with a linear model of the process dynamics

Disturbance Model

Randomly occurring deterministic disturbance (RODD) model

- Binary random variable:

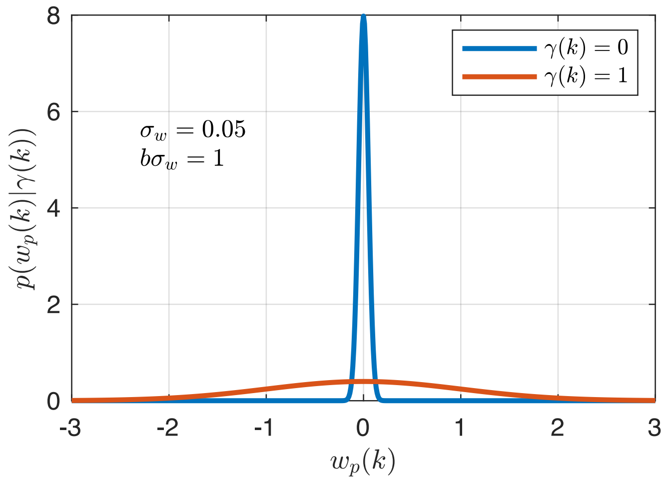
$$\gamma(k) = \begin{cases} 0 & \text{no disturbance} \\ 1 & \text{disturbance} \end{cases}$$

$$\Pr(\gamma(k) = n) = \begin{cases} 1 - \epsilon & \text{for } n = 0 \\ \epsilon & \text{for } n = 1 \end{cases}$$

where ϵ is small (e.g. 0.01)

$\Gamma(k)$:									
0	0	0	1	0	0	0	0	0	0

- Generate *random shock* signal:



$$w_p(k) = \begin{cases} \mathcal{N}(0, \sigma_w^2) & \text{if} \quad \gamma(k) = 0 \\ \mathcal{N}(0, b^2\sigma_w^2) & \text{if} \quad \gamma(k) = 1 \end{cases}$$

where b is high (e.g. 100)

MacGregor et al. (1984), Robertson and Lee (1995)

Observer Design

Augmented system model (state space)

$$\mathbf{x}(k+1) = \begin{bmatrix} 1.248 & -0.779 & 4 & 0 & 0 & 0 & 0 \\ 0.5 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{x}(k) + \begin{bmatrix} \mathbf{w}(k) \\ w_p(k) \end{bmatrix}$$

$$y(k) = \begin{bmatrix} -0.662 & -0.967 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \mathbf{x}(k) + \mathbf{v}(k)$$

Observer Design

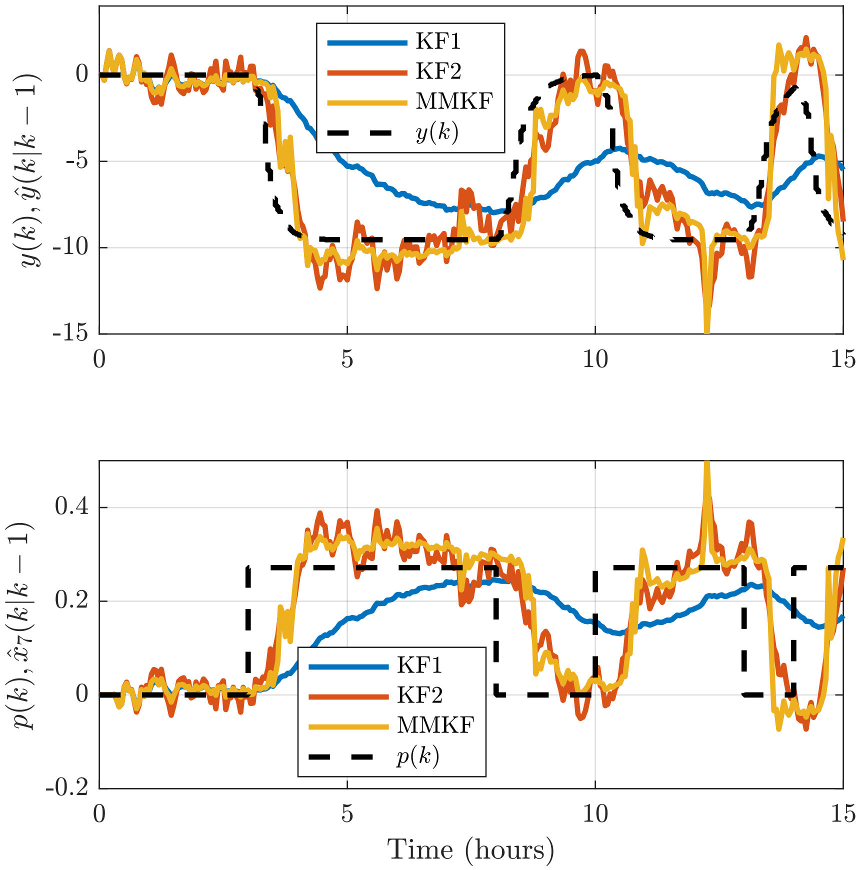
Observer parameters

Label	KF1	KF2	MMKF
Type	Kalman filter	Kalman filter	Multi-model Kalman filter
Parameters			
$\mathbf{Q}$	$\mathbf{Q}_0$	$\mathbf{Q}_{\text{opt}}$	$\{\mathbf{Q}_0, \mathbf{Q}_1\}$
R	5^2	5^2	5^2
$\mathbf{P}(0)$	$\mathbf{P}_0$	$\mathbf{P}_0$	$\mathbf{P}_0$
n_{f}	1	1	20
n_{min}	-	-	18
ϵ	-	-	0.01
σ_{w_p}	-	-	0.2717
b	-	-	100

Simulation Results

Observer estimates

- Kalman filter (KF1) – tuned to the persistent process noise
- Kalman filter (KF2) – tuned to minimize the overall mean-squared error of the estimates
- Multi-model observer (MMKF) reacts quickly to changes with less sensitivity to noise during steady-state.



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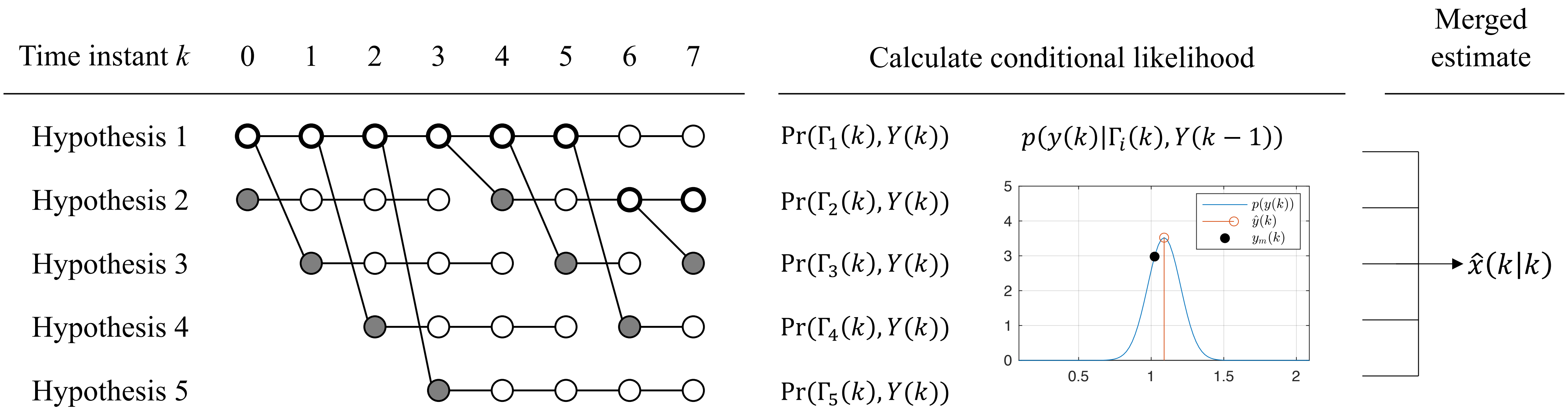
Observer Design

Multiple-model observers – sequence pruning



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● Shock ($\gamma(k) = 1$)

○ Most likely hypothesis at time k

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Andersson, P. (1985), Gustafsson, F. (1993), Eriksson and Isaksson (1996).