

# State-Aware Multiple Access for Networked Control Systems



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# Outline

- 1 Introduction to NCS
- 2 Problem Formulation
- 3 Design of State-based Schedulers
  - Structural Analysis
  - Steady State Performance Analysis
  - Stability Analysis
- 4 Conclusions



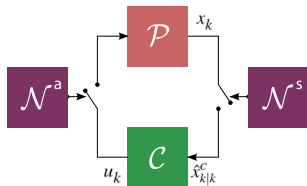
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- Wireless is a broadcast medium:

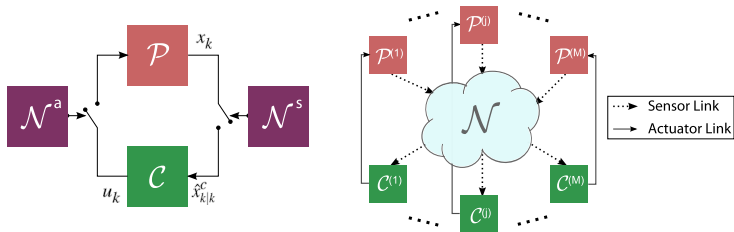


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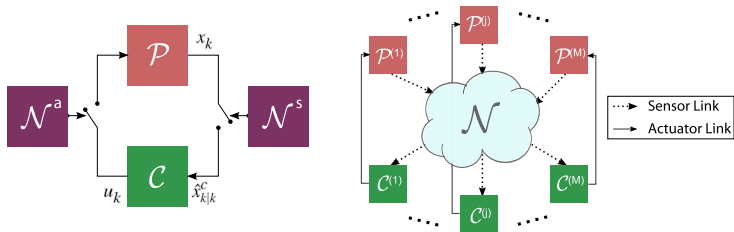


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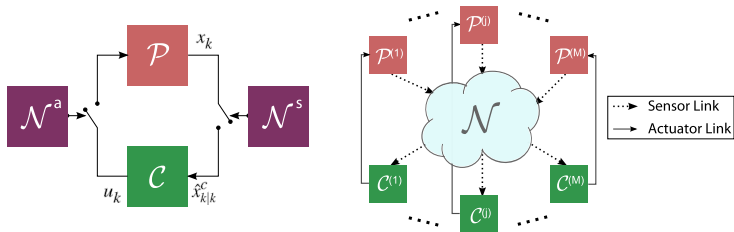


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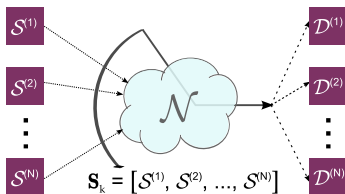
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# Multiple Access (MA) Protocols

## Contention-free MA

- Transmissions guaranteed
- Requires scheduling
- Ill-suited to frequently changing networks



## Contention-based MA

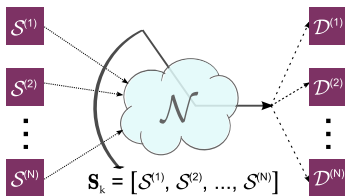
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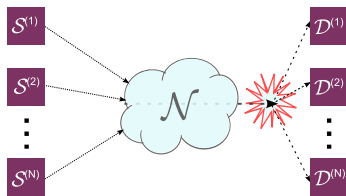
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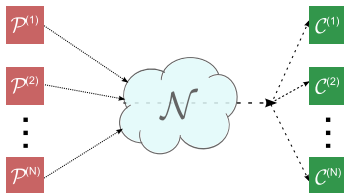
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## New MA for NCS

- Distributed mechanism
- Randomness in access is minimized
- Transmissions probabilistically guaranteed.

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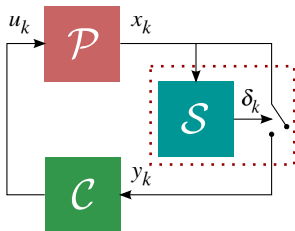
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# State-Aware MA

- Channel access depends on current state
- Realization of state-aware MA:
  - \* modifying existing protocols / introducing new protocols
  - \* adjusting queue lengths

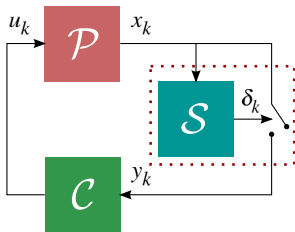


State-based Scheduler selects packets to send to the medium access controller (MAC).



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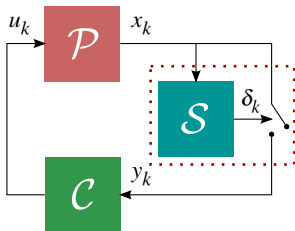


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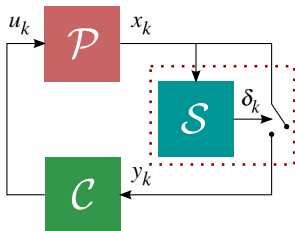


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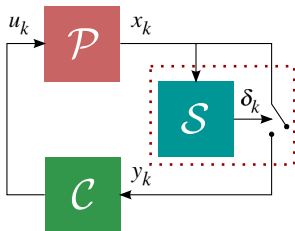


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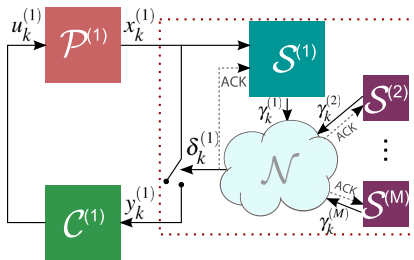
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# A Network of State-based Schedulers

- State-based Scheduler: local scheduler that selects packets to send to the MAC
- MAC cannot anticipate the packets, resorts to Random Access (RA)
- RA determined by Contention Resolution Mechanism (CRM)

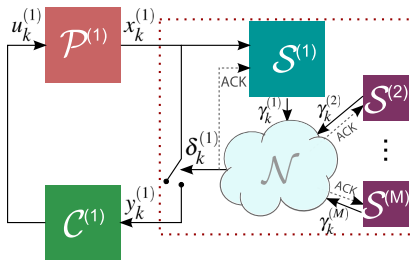


How do we design a network of event-triggered systems?



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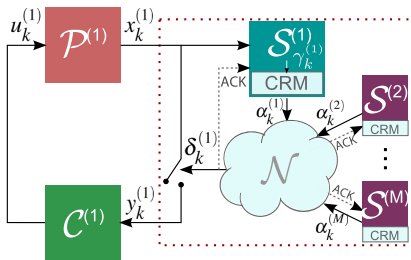
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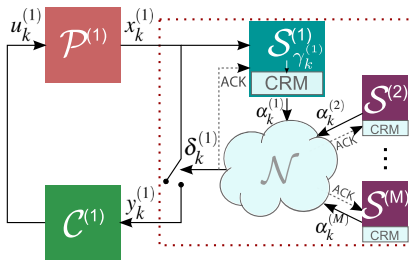
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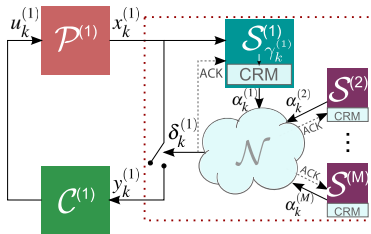


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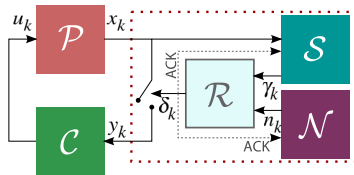
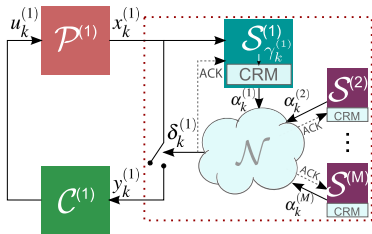
- Multiple Access on the Sensor Link



- $\mathcal{P}$  : Plant
- $\mathcal{C}$  : Controller
- $\mathcal{S}$  : State-based Scheduler
- $\mathcal{N}$  : Network
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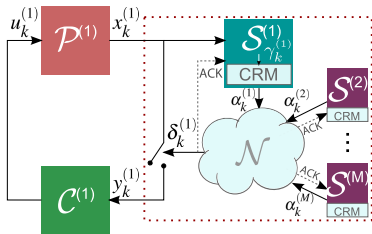


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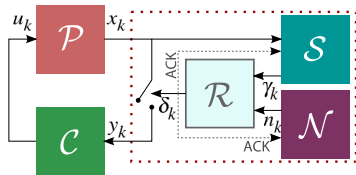
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# Problem Formulation

## Plant $\mathcal{P}$ :

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

$$w_k \sim \mathcal{N}(0, R_w), \quad x_0 \sim \mathcal{N}(0, R_0).$$

## State-based Scheduler $\mathcal{S}$ :

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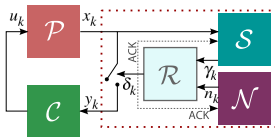
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$$J = \mathbb{E} \left[ x_N^T Q_0 x_N + \sum_{s=0}^{N-1} (x_s^T Q_1 x_s + u_s^T Q_2 u_s) \right]$$

$$\gamma_k, n_k, \delta_k \in \{0, 1\}$$



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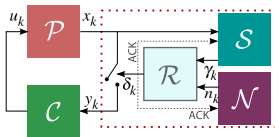
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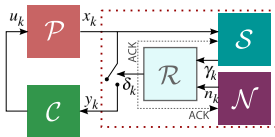
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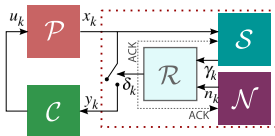
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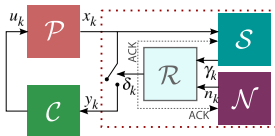
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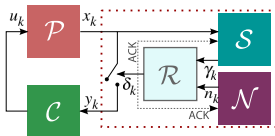
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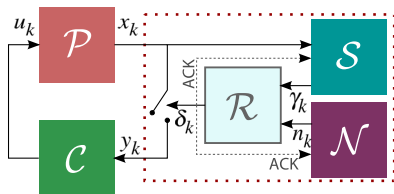
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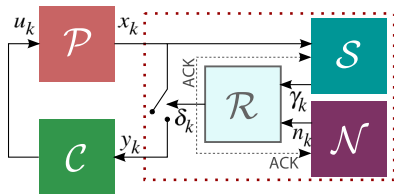
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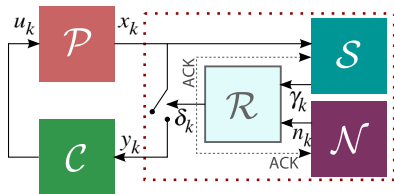
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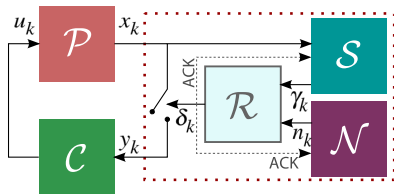
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# Dual Effect Property

## Theorem

*For the closed-loop system given by  $\{\mathcal{P}, \mathcal{S}(f), \mathcal{C}(g)\}$ , the control signal has a dual effect of order  $r = 2$ .*

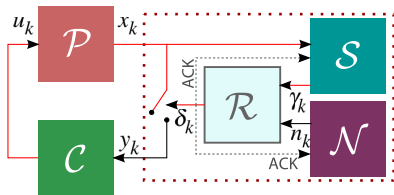
■ Proof:

■ State Estimator:

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■ Consequence: Design of  $\{\mathcal{S}, \mathcal{O}, \mathcal{C}\}$  are coupled!



# Dual Effect Property

## Theorem

*For the closed-loop system given by  $\{\mathcal{P}, \mathcal{S}(f), \mathcal{C}(g)\}$ , the control signal has a dual effect of order  $r = 2$ .*

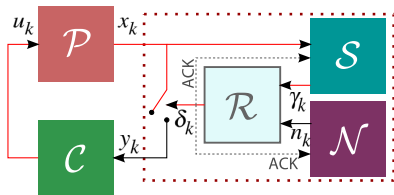
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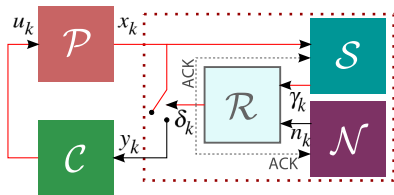
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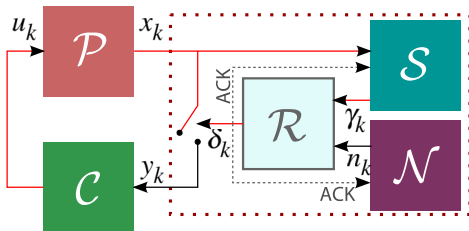


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# Conditions for Certainty Equivalence

## Corollary

*The optimal controller for the system  $\{\mathcal{P}, \mathcal{S}(f), \mathcal{C}(g)\}$ , with respect to the cost  $J$ , is certainty equivalent if and only if the scheduling decisions are not a function of the applied controls.*

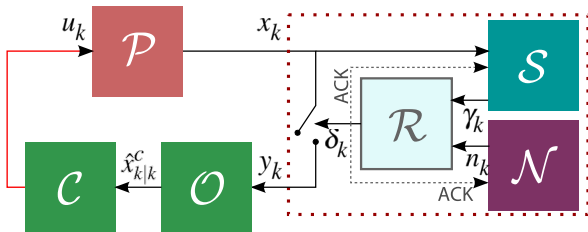


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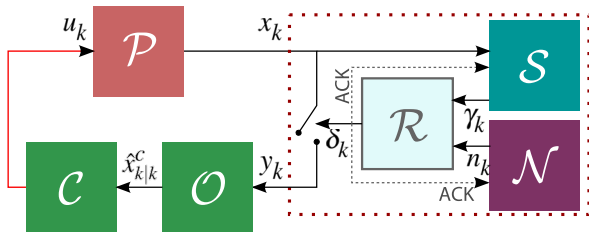




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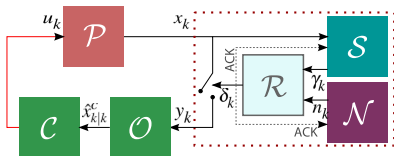
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$$\hat{x}_{k|\tau_k} = A^{k-\tau_k} x_{\tau_k} + \sum_{s=1}^{k-\tau_k} A^{s-1} B u_{k-s} + \mathbb{E} \left[ \sum_{s=1}^{k-\tau_k} A^{s-1} w_{k-s} \mid \dot{f}_k, \dots, \dot{f}_{\tau_k+1} = 0 \right] \cdot \mathbb{P}(\gamma_k=0 \mid \delta_k=0)$$

■ Symmetric Scheduler:

$$\gamma_k = f^{\text{sym}} \left( \sum_{s=1}^{k-\tau_k-1} A^{s-1} w_{k-s} \right);$$

$$f^{\text{sym}}(-r) = f^{\text{sym}}(r)$$



## Proposition: Symmetric Scheduler

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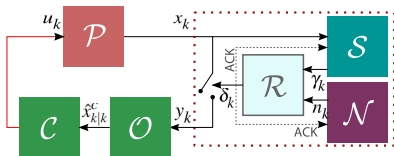
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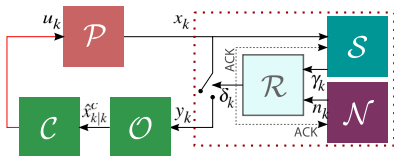
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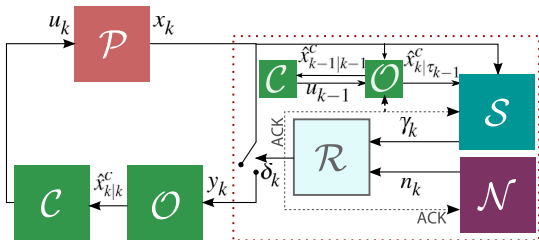
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## Theorem

For the system  $\{P, S, O, C\}$ , using the dual predictor architecture results in a MMSE estimate and certainty equivalence.



■ Scheduler  $S$ :

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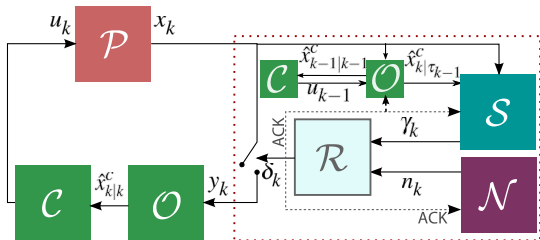
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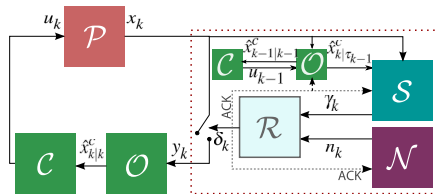
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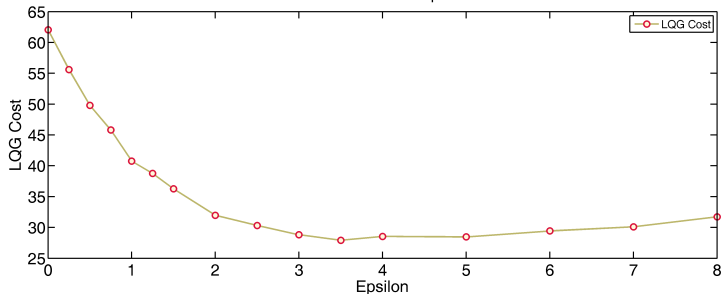
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# Simulation Results

- 20 scalar plants
- $A = 1, R_w = 1$  and  $T = 10$
- $p_\alpha = \{1, 0.75, 0.5\}$
- $N = 10, Q_0 = Q_1 = Q_2 = 1$
- Best  $\epsilon = 3.5$



LQG Cost versus Epsilon





# Outline

- 1 Introduction to NCS
- 2 Problem Formulation
- 3 Design of State-based Schedulers
  - Structural Analysis
  - Steady State Performance Analysis
  - Stability Analysis
- 4 Conclusions



# Event-triggered and CRM Abstraction

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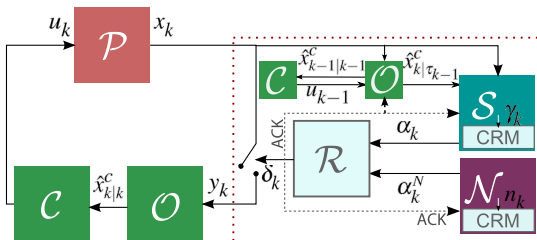
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$p$ -persistent CSMA

$$\mathbb{P}(\alpha_k = 1 | \gamma_k = 1) = p\alpha$$

$$\delta_k = \alpha_k(1 - \alpha_k^N)$$



What is the probability of a successful transmission, i.e.,  $\mathbb{P}(\delta_k^{(i)} = 1)$ ?



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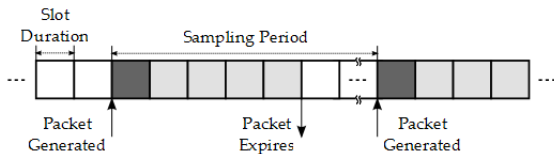
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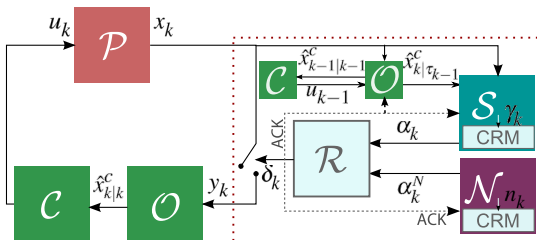
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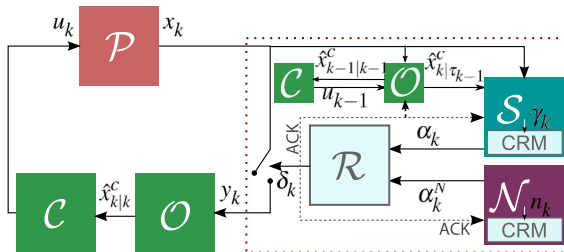
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# Understanding the Problem Setup

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The scheduler output  $\gamma_k$  is correlated to the traffic  $n_k$ .

- **Need for Joint Analysis:**





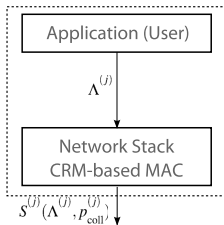
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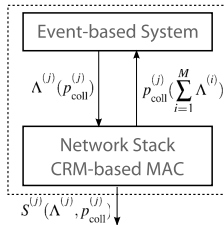
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Typical Networked System



Networked Control System





# Joint CRM & Event-based Markov Model

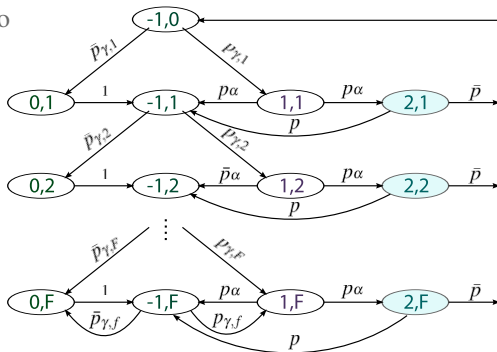
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- Index  $s$ :

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- $p_{\gamma,d}$ : scheduler probability,
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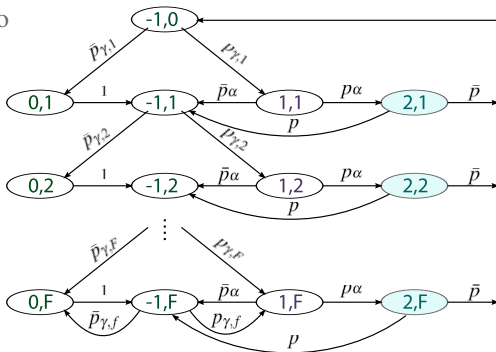
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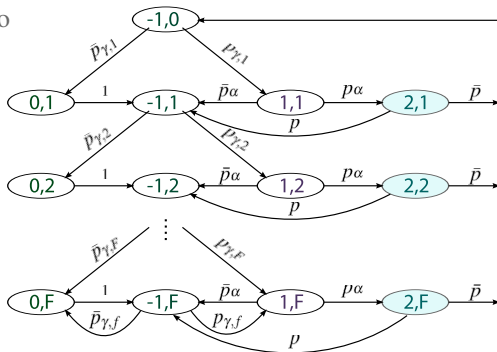
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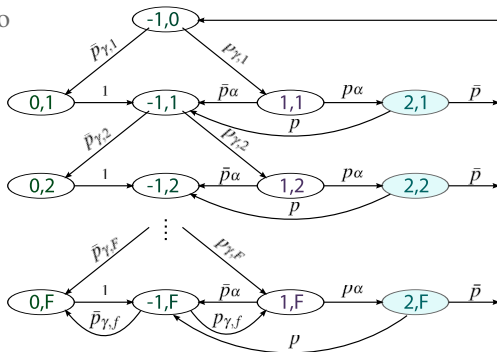
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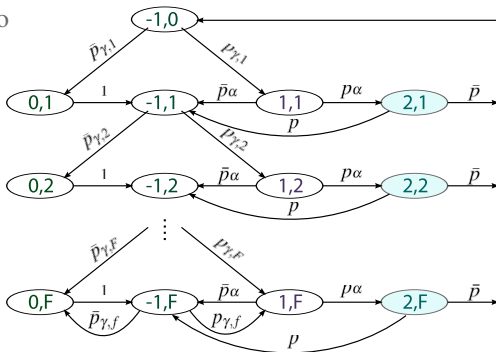
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Key Assumption: Bianchi's conditional independence

The conditional probability of a busy channel for a node that attempts to transmit is given by an independent probability  $p$  for each node.



# Steady State Performance Analysis

## Theorem

*For the closed loop system given by  $\{\mathcal{P}, \mathcal{S}(\tilde{f}), \mathcal{R}, \mathcal{C}\}$ , the probability of a successful transmission in steady state is given by*

$$\mathbb{P}(\delta_k^{(j)} = 1) = (1 - p^{(j)}) \cdot p_{TX}^{(j)}, \quad (1)$$

### ■ Proof:

Sampling instants:

$$\sum_{i=0}^{\infty} p_i^{(j)} = 1$$

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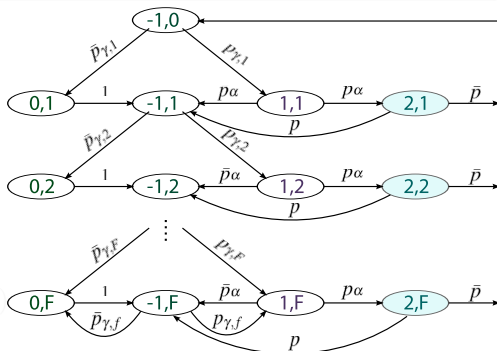
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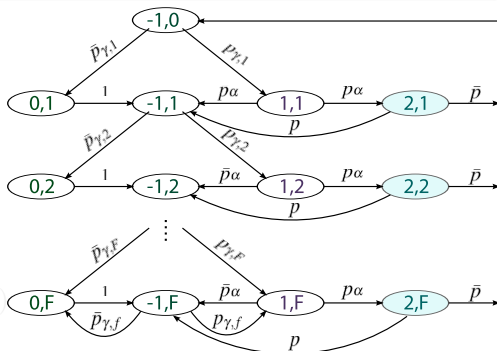
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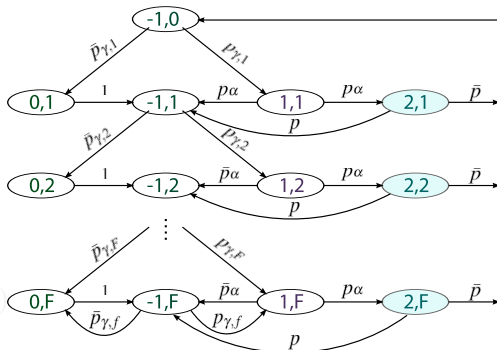
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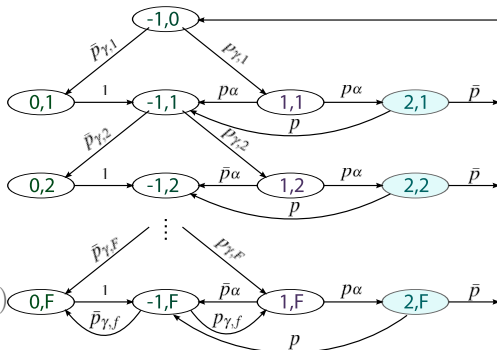
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# Simulation Example

■  $\mathcal{P}$ :  $x_{k+1} = x_k + u_k + w_k, w_k \sim \mathcal{N}(0, 1)$

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Parameter	Simulation	Analysis
$\mathbb{P}(\delta_k = 1)$	0.1840	0.1872
$p_1$	0.5937	0.5944
$p_2$	0.5655	0.5620
$p_3$	0.5367	0.5277
$p_4$	0.5076	0.4917
$p_5$	0.4778	0.4542



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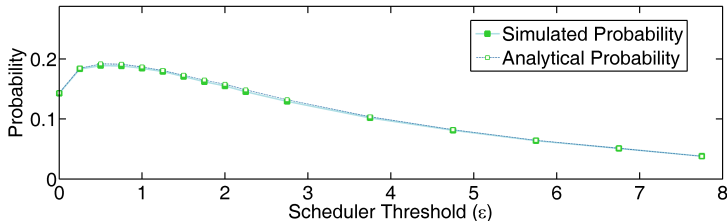
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$$x_{c,k} = \begin{cases} \mathbb{E}[x_k | \mathbb{I}_{\tau_{k-1}}^c] & d_k < F \\ x_{k-F} & d_k \geq F \end{cases}$$

■ Parameters:  $M = 10, \epsilon = 1, p_\alpha = 0.2,$   
 $R = 5, p_{\gamma,d} = [0.3171 \quad 0.5138]$

Parameter	Simulation	Analysis
$\mathbb{P}(\delta_k = 1)$	0.1840	0.1872
$p_1$	0.5937	0.5944
$p_2$	0.5655	0.5620
$p_3$	0.5367	0.5277
$p_4$	0.5076	0.4917
$p_5$	0.4778	0.4542

Probability of a Successful Transmission versus Scheduler Threshold





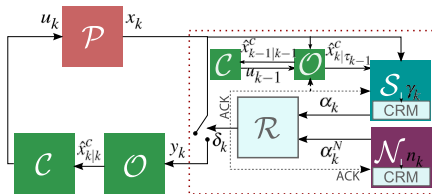
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# Lyapunov Mean Square Stability

- Let us consider infinite horizon LQG cost; we can now analyze stability of a closed-loop system in this network.



- Since Certainty Equivalence holds, we can translate the LMSS property from the state to the estimation error.
- There exists a constant  $\varsigma$ , with  $0 < \varsigma < \zeta$ , such that the above condition is equivalent to  $\limsup_{k \rightarrow \infty} \mathbb{E}[P_{k|k}] \leq \varsigma$ .



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The state is said to possess mean square stability if given  $\zeta > 0$ , there exists  $\xi(\zeta) > 0$  such that  $|x_0| < \xi$  implies

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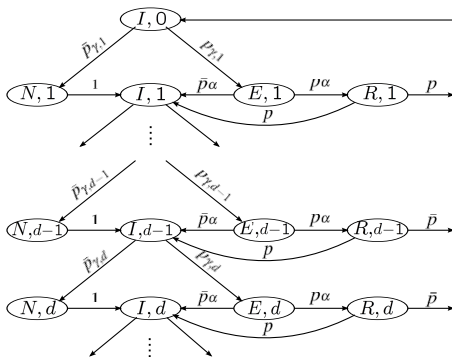
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# Markov Model

## Assumptions:

- Bianchi's conditional probability holds
- Network is in steady state

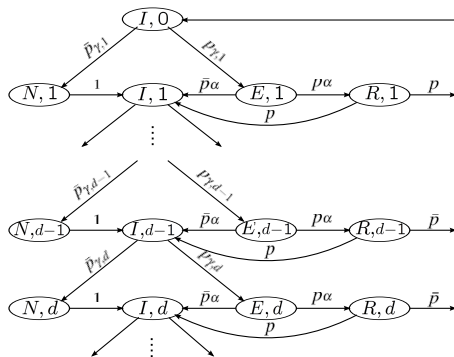


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The network is said to be in steady state when the states  $(S, d)$ ,  $\forall S \in \{I, N, E, R\}, d \geq 0$ , are recurrent, or  $p < 1$ .



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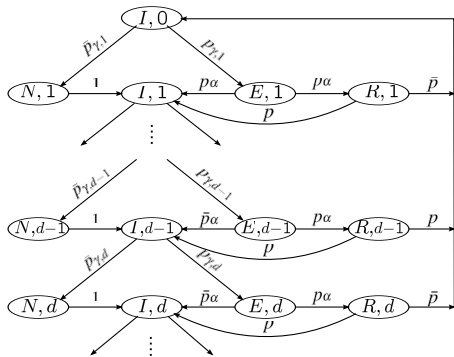
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# Upper Bound for Estimation Error

Estimation Error Covariance:  $\mathbb{E}[P_{k|k}] = \sum_{d=0}^{\infty} P_d \mathbb{P}(d_k = d)$



Theorem: Upper Bound for Estimation Error in the State

$$\hat{\phi}_{(i,d)} = \frac{1}{d} \hat{\phi}_{(i,d-1)} * \phi_N, \hat{\phi}_{(i,0)} = \phi_N. \text{ Then, } \phi_{(i,d)} \geq \hat{\phi}_{(i,d)} \forall d \geq 0.$$



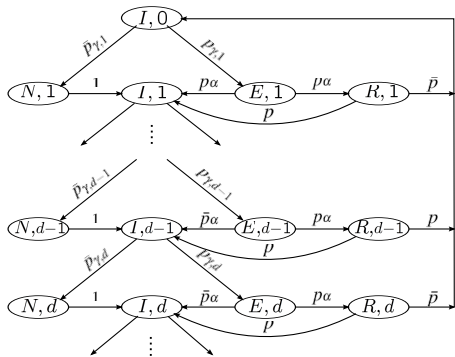
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Evolution of pdf:

$$\phi_{(N,d)} = \begin{cases} \frac{\phi_{(I,d-1)}(\tilde{x})}{\bar{p}_{\gamma,d}} & |\tilde{x}| \leq \epsilon_d, \\ 0 & \text{otherwise,} \end{cases}$$

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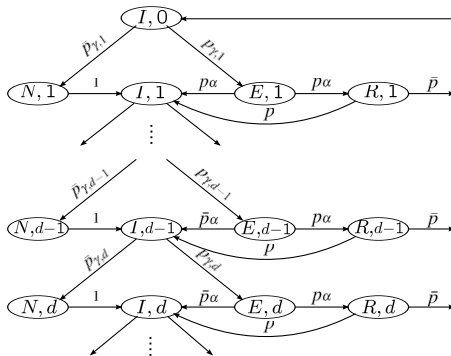


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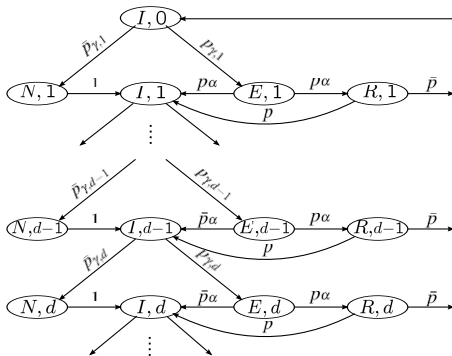


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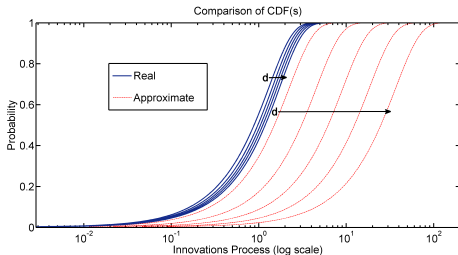


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$\hat{\phi}_{(I,d)} = \frac{1}{a} \hat{\phi}_{(I,d-1)} * \phi_N, \hat{\phi}_{(I,0)} = \phi_N$ . Then,  $\phi_{(I,d)} \succeq \hat{\phi}_{(I,d)} \forall d \geq 0$ .



# Conditions for Stability

Theorem: Conditions for LMSS

Sufficient conditions for LMSS are given by

$$\limsup_{d \rightarrow \infty} \frac{P_{(l,d+1)}}{P_{(l,d)}} < \frac{1}{1+a^2}.$$

- **LMSS versus Steady State:**

LMSS implies network steady state, but network steady state does not imply LMSS.

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Channel access adapted to plant state and network traffic.

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Separation in design of  $\{S, O, C\}$  obtained by limiting the class of permissible schedulers.

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Selecting scheduler thresholds to guarantee stability and optimize performance.



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