Multiple-Model Approach to Fault Detection and Identification

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Outline

- Overview of Techniques for FDI
- Multiple-Model (MM) Approach
- Interacting MM (IMM) Approach to FDI
- Hierarchical IMM for FDI
- IMM with Maximum Likelihood Estimation (IM^3L) for FDI
- Simulation Evaluation
- Conclusions

Goals

- Fault Detection
- Fault Identification
- Fault Estimation
- State Estimation
- Early Warning

Techniques for FDI

Conventional:

- **Physical Redundancy**
  Hardware redundancy, expensive
- **Analytical Redundancy**
  Model-based,
  Detects faults based on residual signal
  Many ways to generate residual: diagnostic observers, parity relation, parameter estimation, etc.

Limitation: Most do not deal with state estimation

- **Multiple-Model Method**

Multiple-Model Method

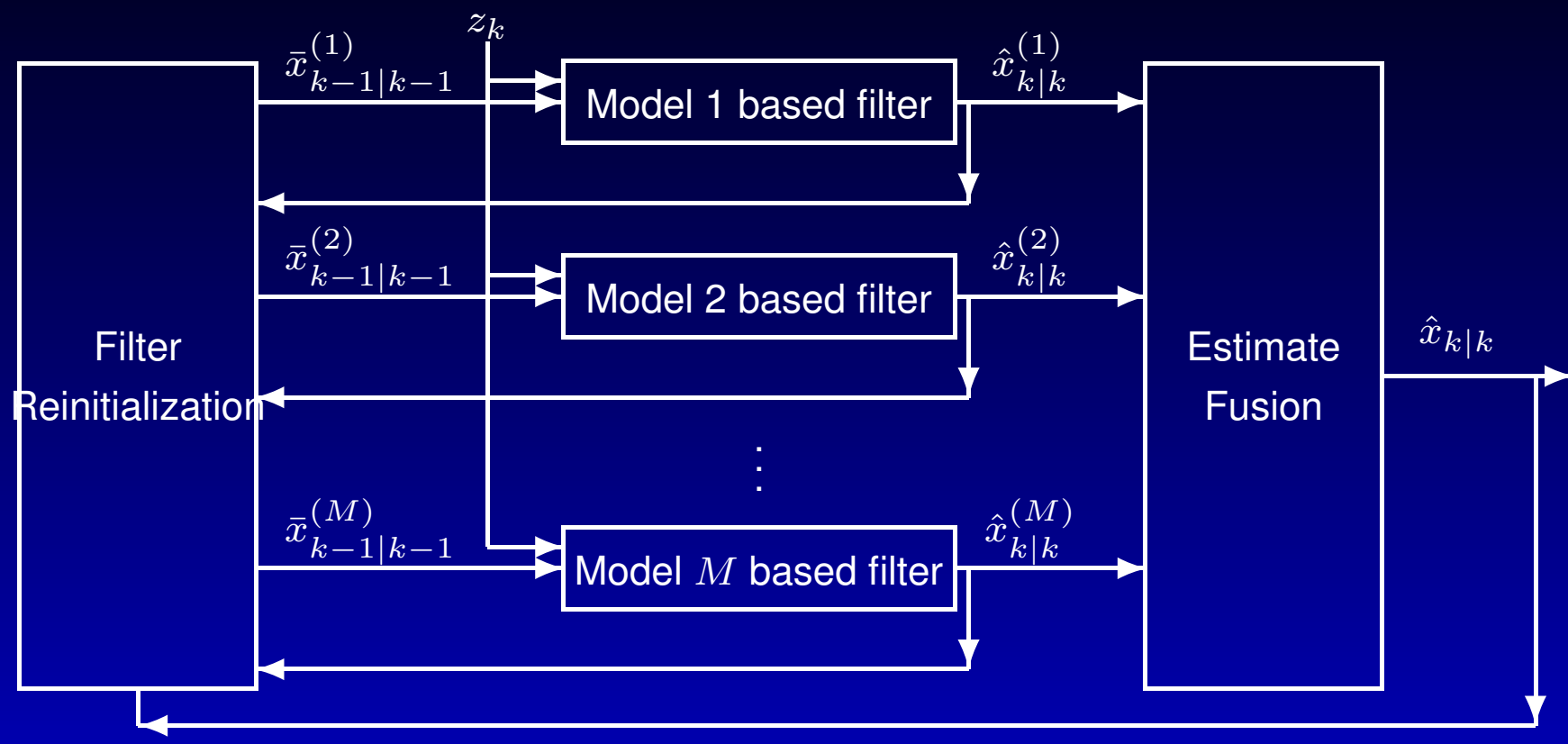
MM estimation for hybrid system

- System mode $\Rightarrow$algorithm model $\Rightarrow$model-based filter
- Mode jump $\Rightarrow$model switching

Two unique features:

- Run a filter bank in parallel at each time and each filter is based on a particular system mode
- Fuse estimates from single-model based filters to yield overall state estimate

Multiple-Model Method



- **Autonomous**: (Magill, 1965, Lainiotis, 1971)
- **Interacting**: GPB (Ackerson and Fu, 1970); IMM (Blom & Bar-Shalom, 1988)
- **Variable Structure**: (Li and Bar-Shalom, 1996; Li, 1998)

IMM-FDI

Dynamic model for system subject to failures

$$x_{k+1} = F_k^j x_k + G_k^j u_k + T_k^j w_k^j$$
$$z_k = H_k^j x_k + v_k^j$$

Pros: State Estimation, Soft Decision (Early Warning)
Cons: Computational Complexity

Found great success in target tracking, etc.

Modeling of Failures

Introduce an effectiveness factor α $(0 \leq \alpha \leq 1)$ to represent extent of failure

- *no failure*: $\alpha = 1$
- *total (hard) failure*: $\alpha = 0$
- *partial (soft) failure*: $0 < \alpha < 1$
- *Sensor failure*: multiply respective row of H matrix by α.
  Soft sensor failures can also be modeled differently, e.g., by changing elements of mean or covariance of measurement noise.
- *Actuator failure*: multiply respective column of G matrix by α

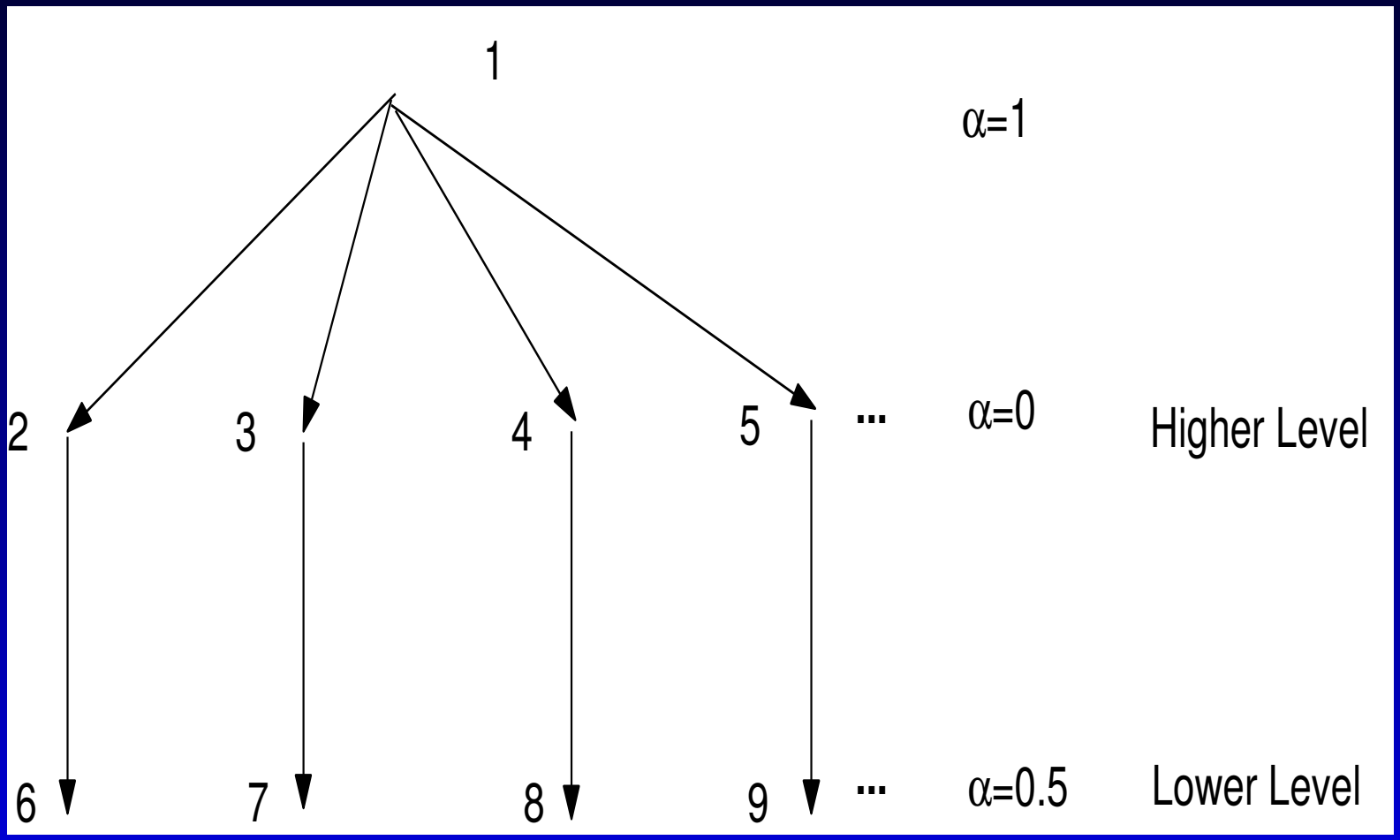
Fault detection rule

Model probabilities are used as indication of a failure since it measures how likely each fault is at a given time

$$\mu_k^j = \begin{array}{l} \max_i \mu_k^i > \mu_T \Rightarrow H_j : \text{fault } j \text{ occurred} \\ \max_i \mu_k^i < \mu_T \Rightarrow H_1 : \text{no fault} \end{array}$$

Model Probability: Soft Decision

Hierarchical Structure



- **Higher level**

N+1 filters for one normal and N total sensors/actuators failure models

- **Lower levels**

N model sets, each for a specific sensor/actuator failure at the higher level
to test how severe a fault is (by estimating α value)

A lower level is activated only when the corresponding fault is declared at higher level

α and state estimates

$$\widehat{\alpha}_k \triangleq E[\alpha_k | z^k] = \sum_{j=1}^{n} \alpha^j \mu_k^j$$

$$\widehat{x}_{k|k} \triangleq E[x_k | z^k] = \sum_{j=1}^{n} \widehat{x}_{k|k}^j \mu_k^j$$

IM^{3}L

Key

- Estimate α value based on maximum likelihood estimation (MLE)
- Generate a new failure model with $\hat{\alpha}$ and have an improved state estimate based on $\hat{\alpha}$
- **MLE** chooses as the estimate the "most likely" value of the true parameter given data

HIMM vs. IM^{3}L

- Same mechanism for fault detection
- Different estimators of α

$$\widehat{\alpha}_k = \arg\max_{\alpha_k} f(z_k | z^{k-1}, \alpha_k)$$

$$\widehat{\alpha}_k \triangleq E[\alpha_k | z^k] = \sum_{j=1}^{n} \alpha^j \mu_k^j$$

HIMM = hierarchical IMM

HAMM = hierarchical AMM

Simulation Evaluations

Aircraft model: Vertical Takeoff and Landing (VTOL)

The linearized model of VTOL can be described by

$$x(k+1) = Fx(k) + Gu(k) + w(k)$$
$$z(k) = Hx(k) + v(k)$$

where $x = [V_h,\, V_v,\, q,\, \theta]^T$, $u = [\delta_c,\, \delta_l]^T$.
V_h = horizontal velocity
V_v = vertical velocity,
q = pitch rate,
θ = pitch angle
δ_c = collective pitch control
δ_l = longitudinal cyclic pitch control

Performance Indices

false alarm (FA),
missed detection (MD),
correct detection and identification (CDI),
incorrect fault identification (IFI),
no mode detection (NM),
RMS velocity errors,

RMS α errors

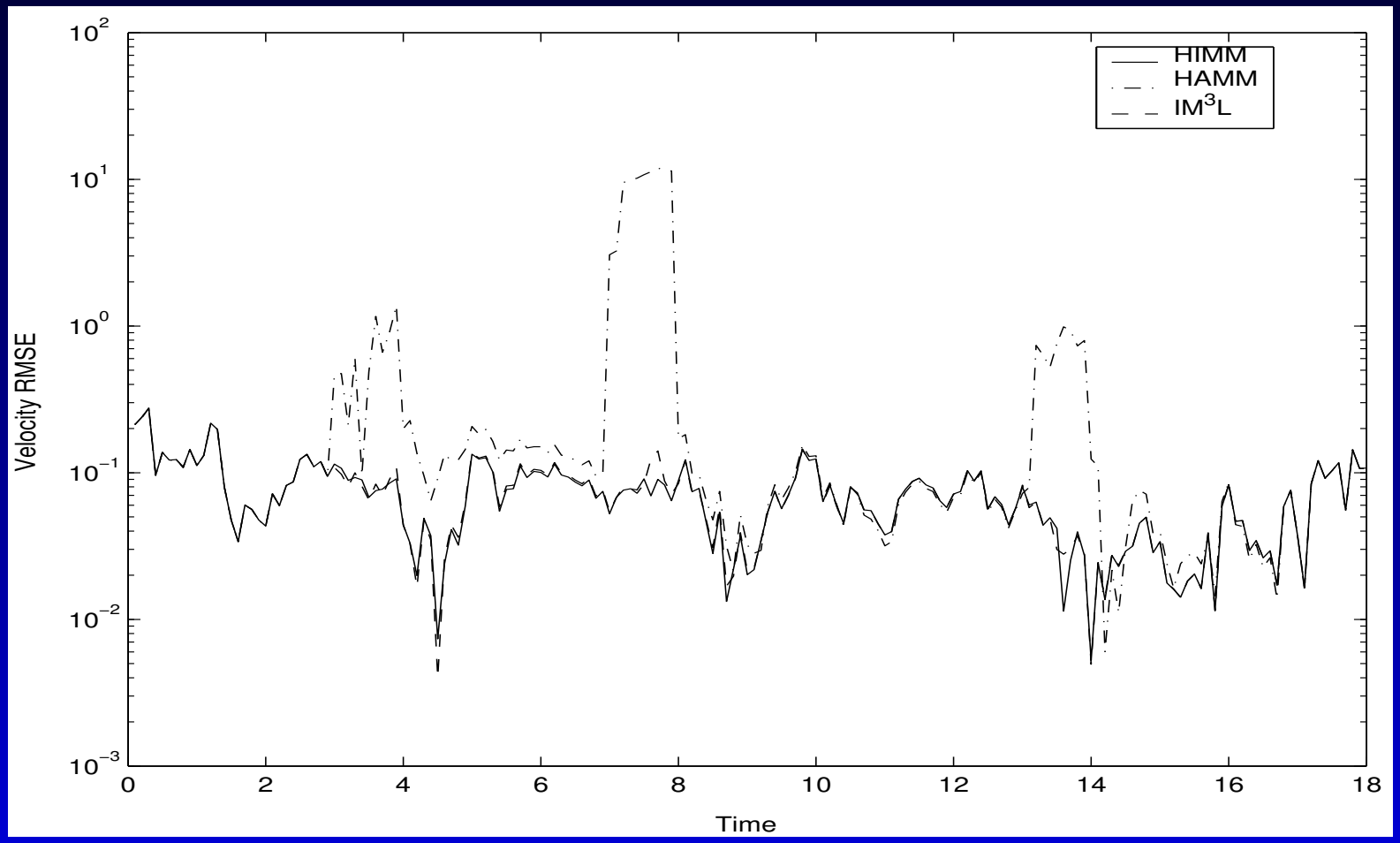
Sequential sensor failures

α/k	V_h Failure	V_v Failure	q Failure	Intended Cases
Case1	10% $[30, 40]$	20% $[70, 80]$	20% $[130, 140]$	small α
Case2	30% $[30, 40]$	30% $[50, 60]$	40% $[130, 140]$	large α
Case3	10% $[30, 40]$		70% $[30, 40]$	half failure
Case4	same as Case1	except Q, R	increased	robustness

Detection ranges

α	Total Failure	Half Failure	No Failure
HIMM1	$[0, 0.3)$	$[0.3, 0.5)$	$[0.5, 1]$
HIMM2	$[0, 0.25]$	$(0.25, 0.75)$	$[0.75, 1]$

Sensor failures: small α



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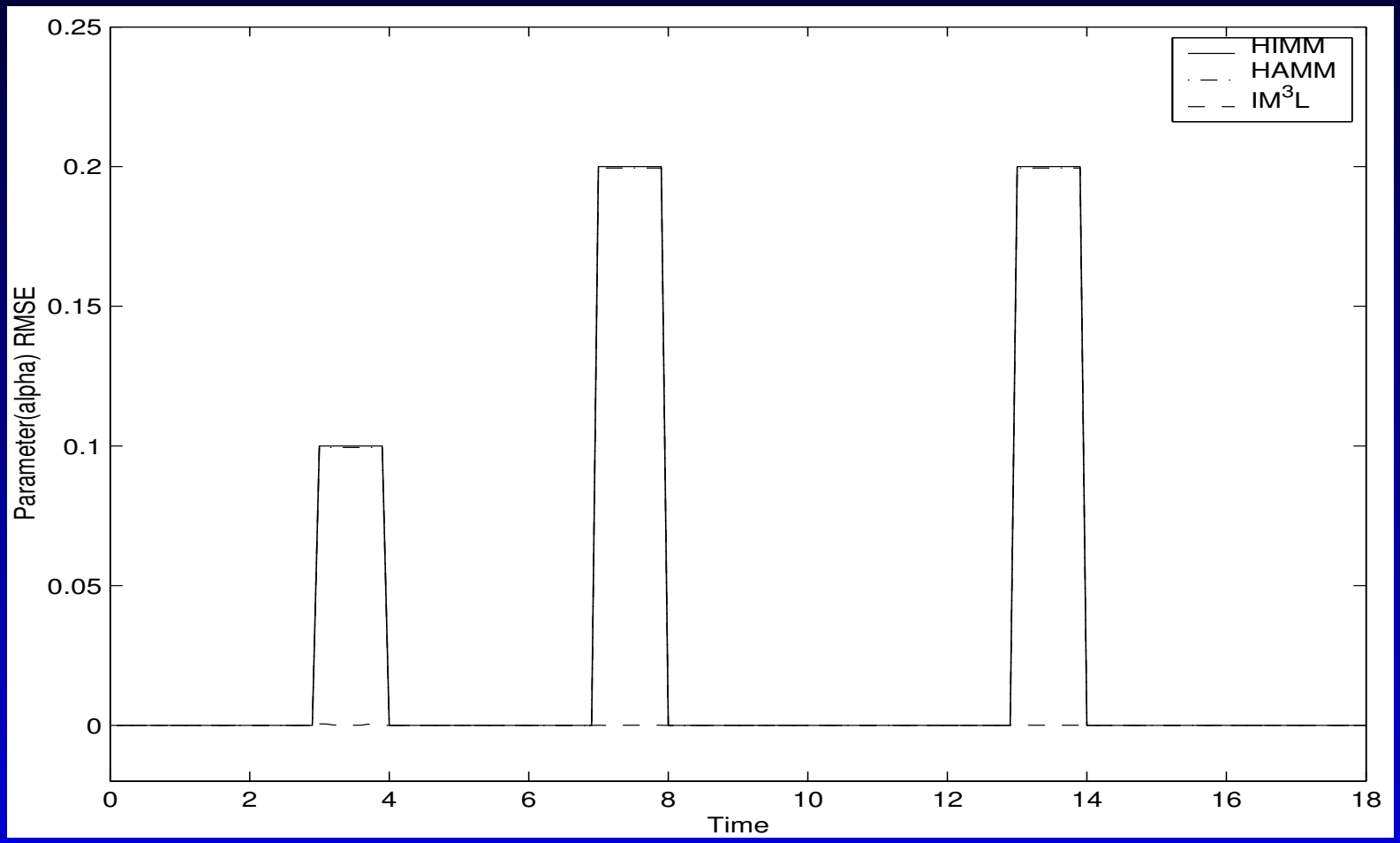
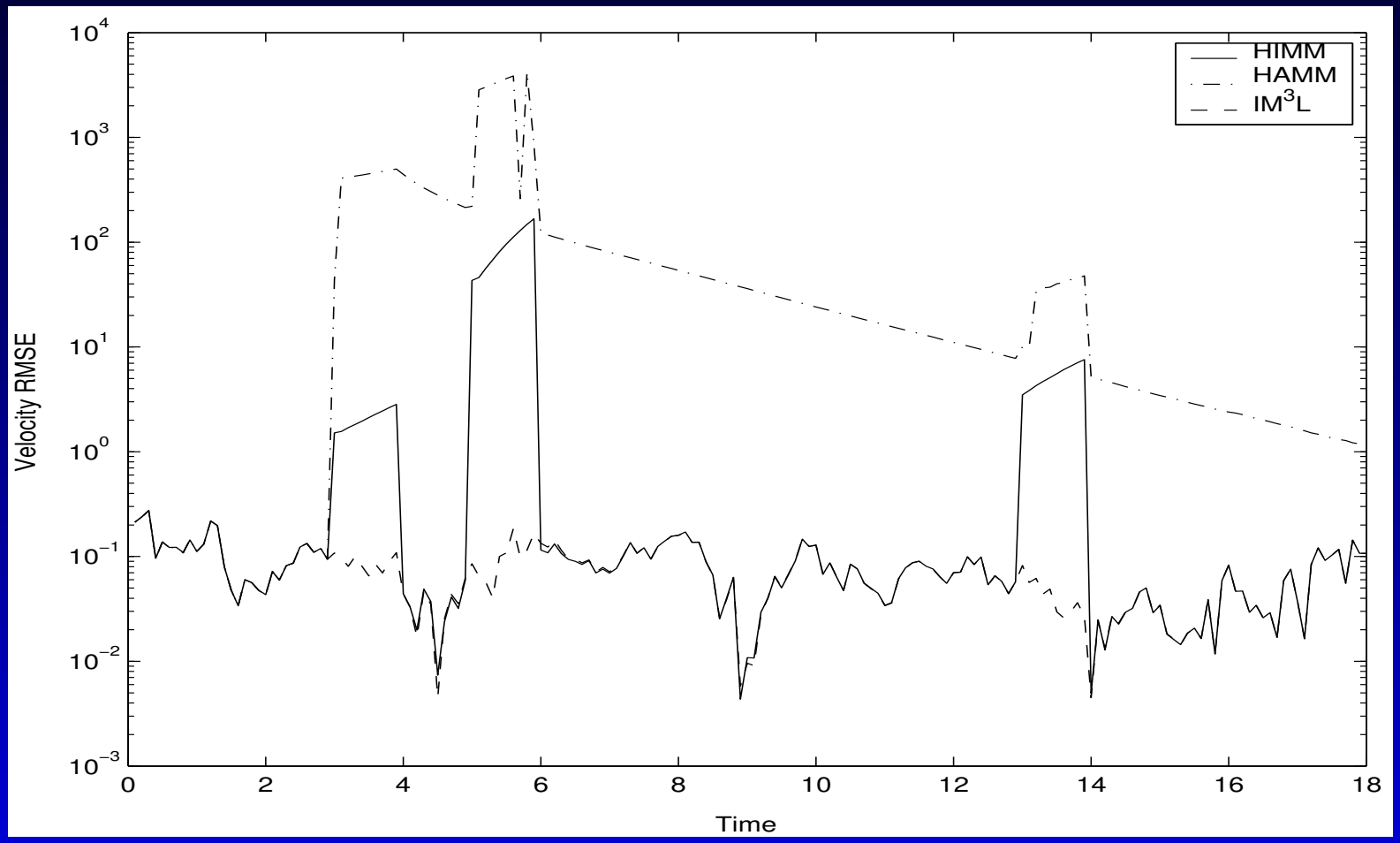


Sensor failures: large α



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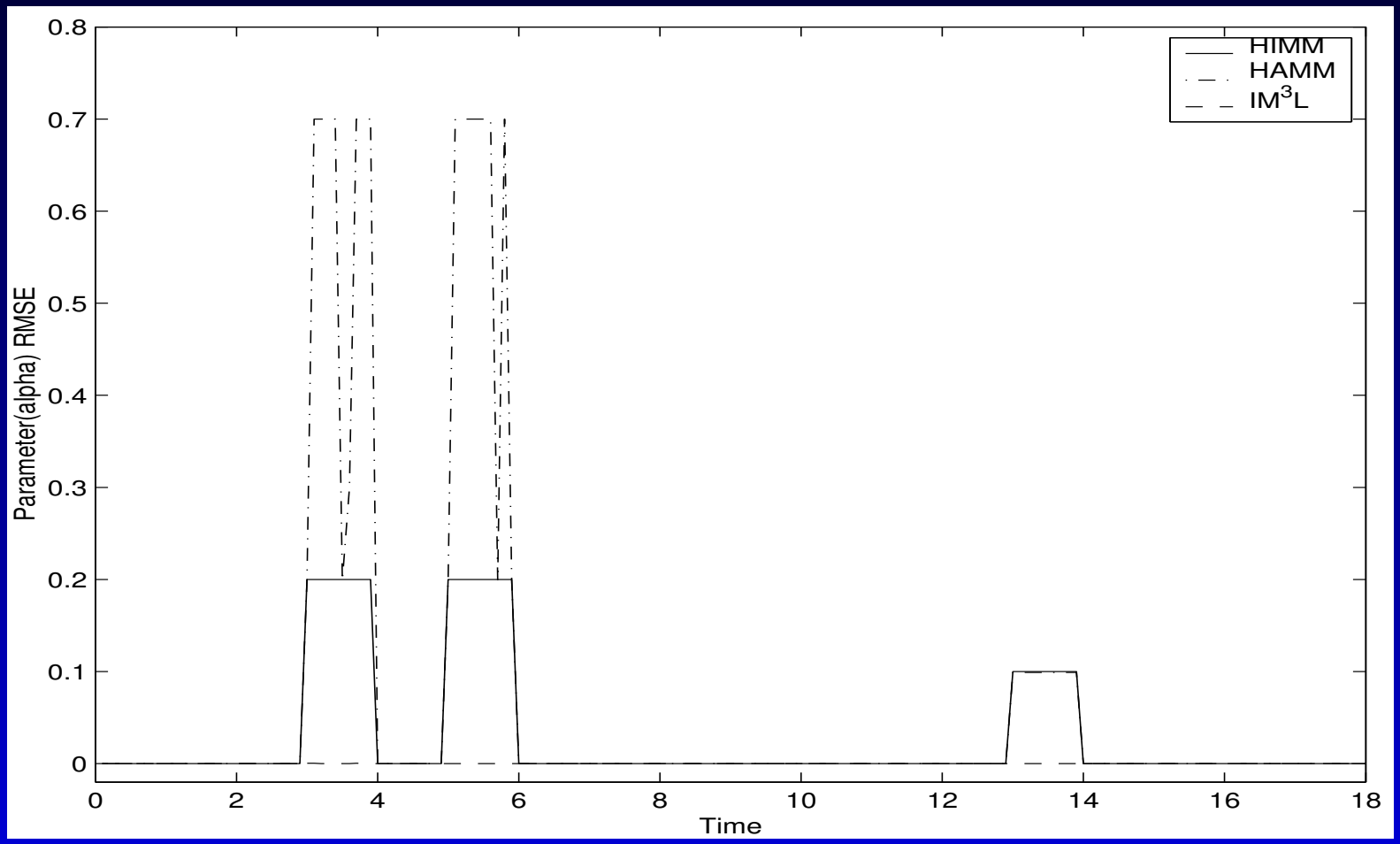
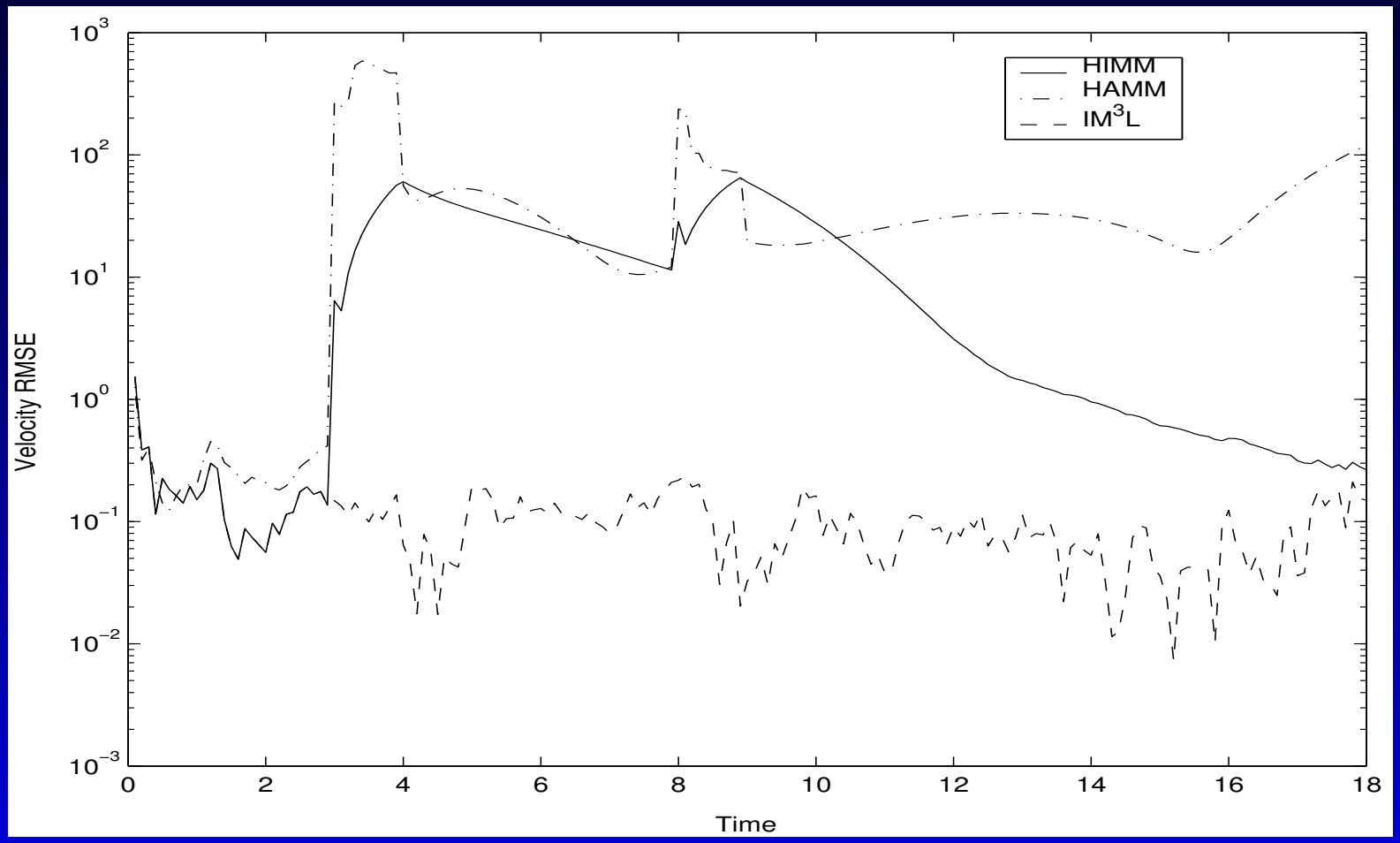


Sensor failures: half failure



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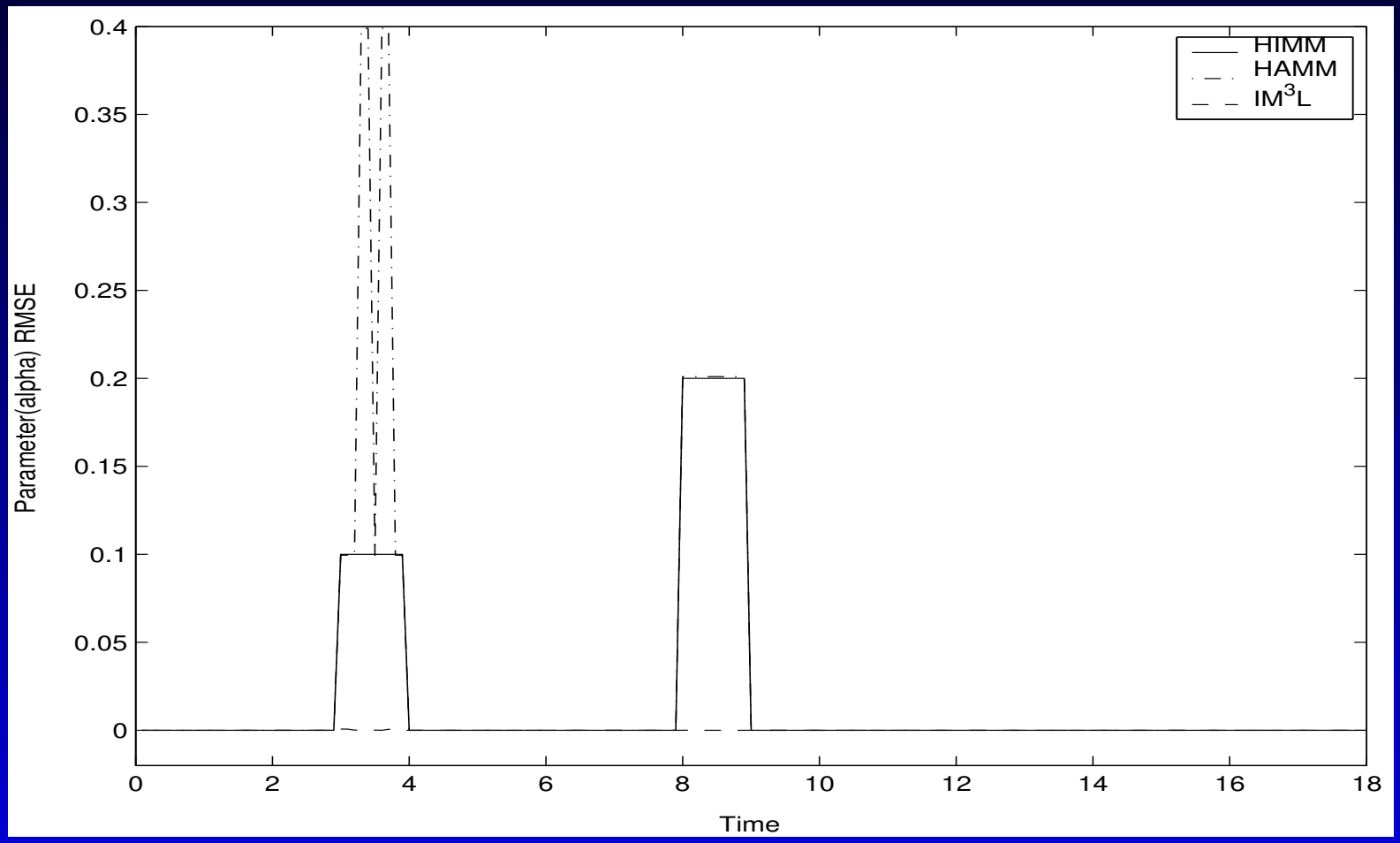
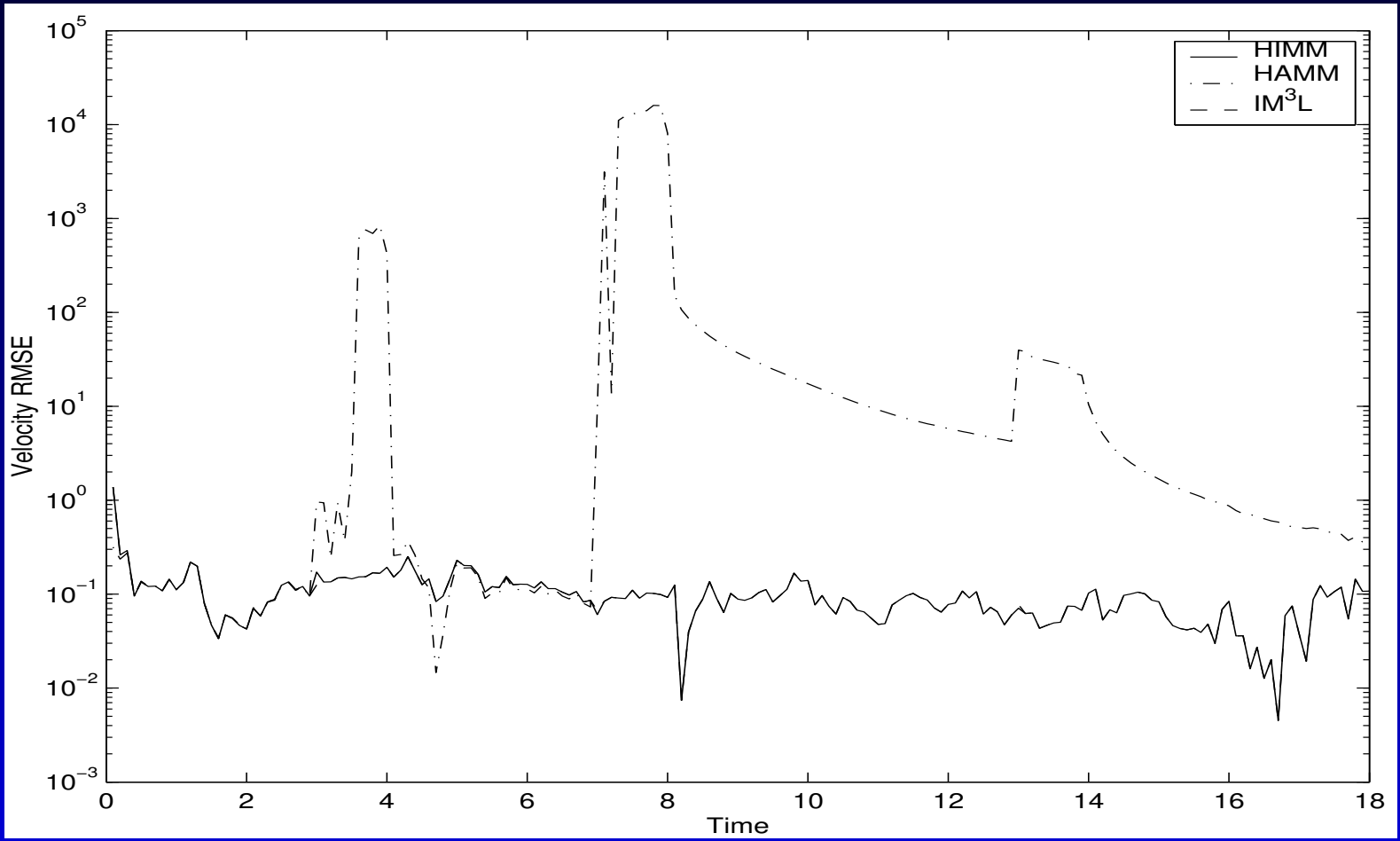


Sensor failures: increased Q/R



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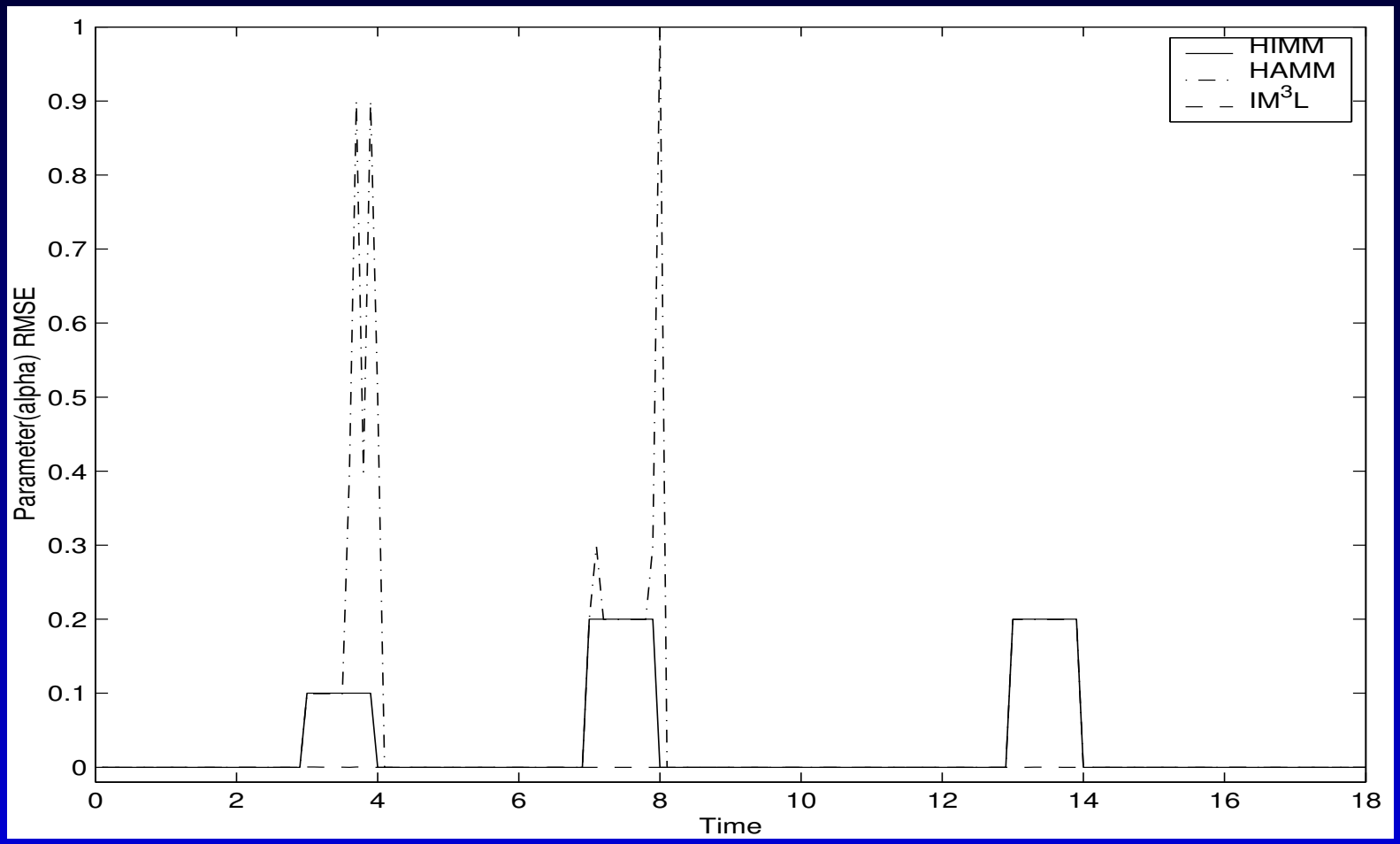


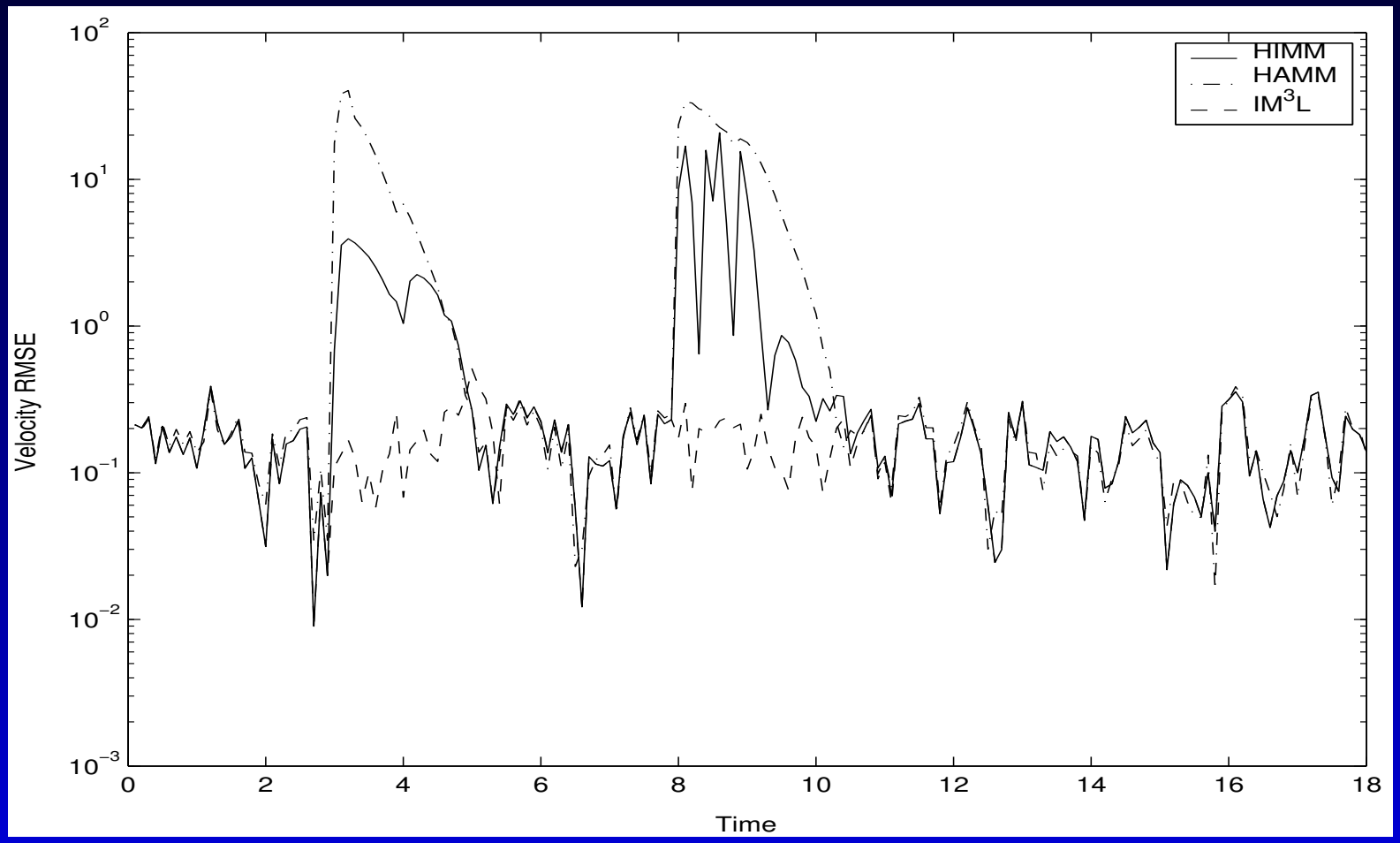
Sensor fail	%	MD	FA	CDI	NMD	IFI	Flops
Case 1	HIMM	0	0	100	0	0	1.135
	HAMM	0	0	100	0	0	0.933
	IM^3L	0	0	100	0	0	1.071
Case 2	HIMM	0	0	100	0	0	1.135
	HAMM	8.33	0	90.56	0	1.11	0.892
	IM^3L	0	0	100	0	0	1.071
Case 3	HIMM	0	0	99.44	0.56	0	1.139
	HAMM	0	0.12	98.17	0.04	1.67	0.937
	IM^3L	0	0	99.44	0.56	0	1.097
Case 4	HIMM	0	0	99.92	0.08	0	1.127
	HAMM	1.11	1.11	93.34	0	4.44	0.925
	IM^3L	0	0	99.92	0.08	0	1.063

Sequential actuator failures

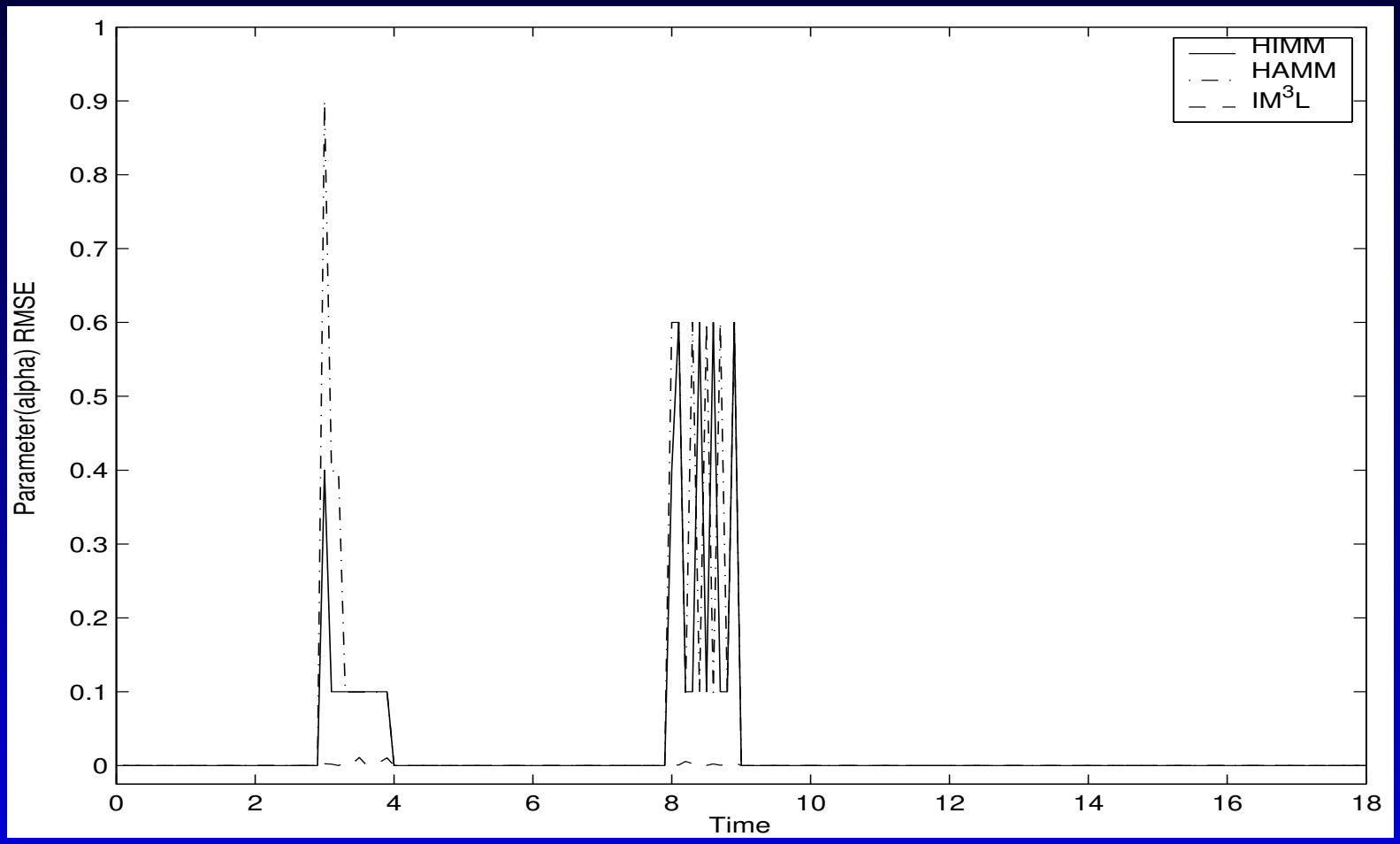
Scenarios

α/k	δ_c Failue	δ_l Failure	
Case1	10% $[30, 40]$	40% $[80, 90]$	Q tuned for HA
Case2	same as Case1	except untuned Q	
Case3	20% $[30, 40]$	60% $[80, 90]$	half failure
Case4	same as Case1	except Q,R increased	robustness

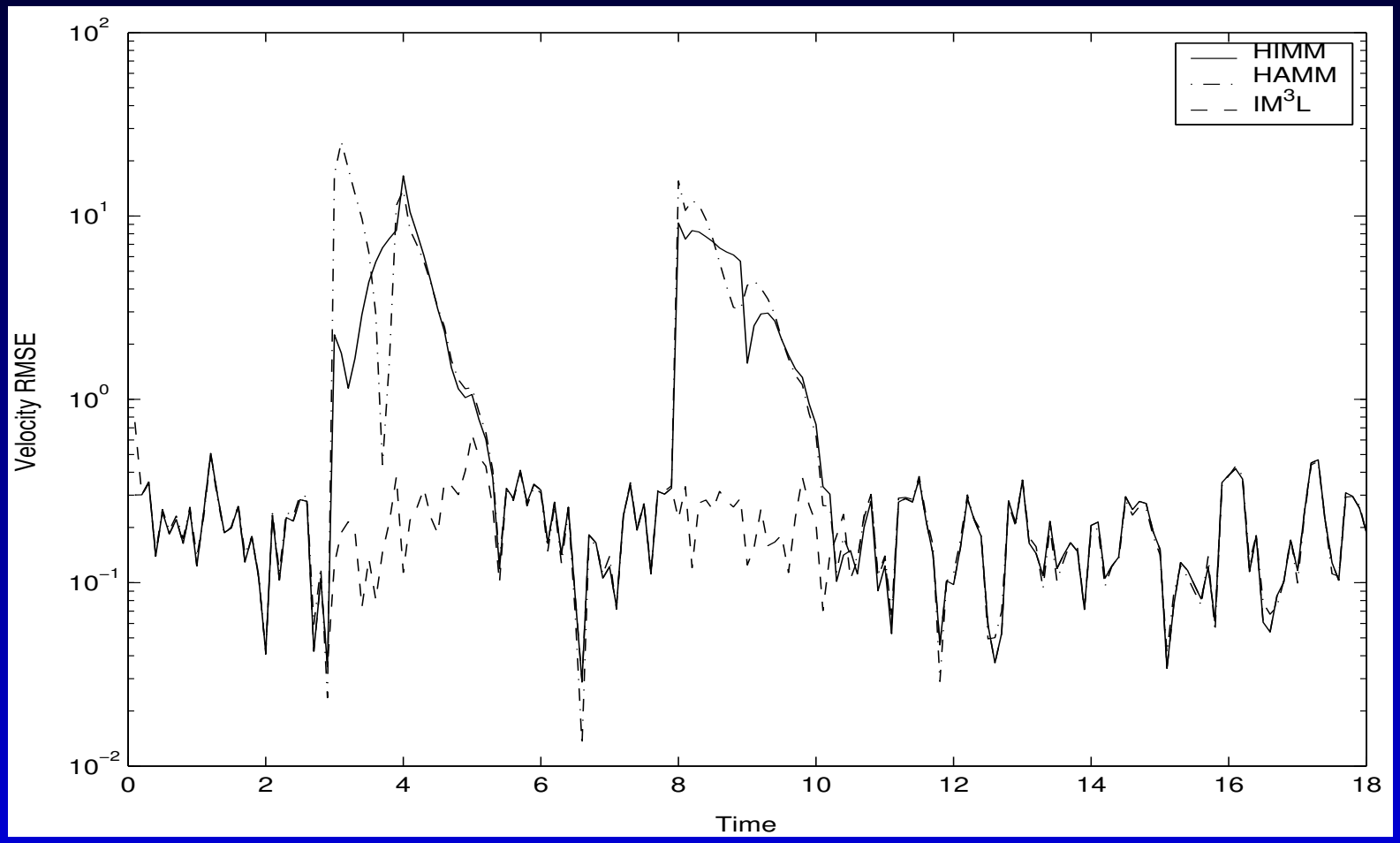
Actuator failures: total failure



Actuator failures: total failure



Actuator failures: half failure



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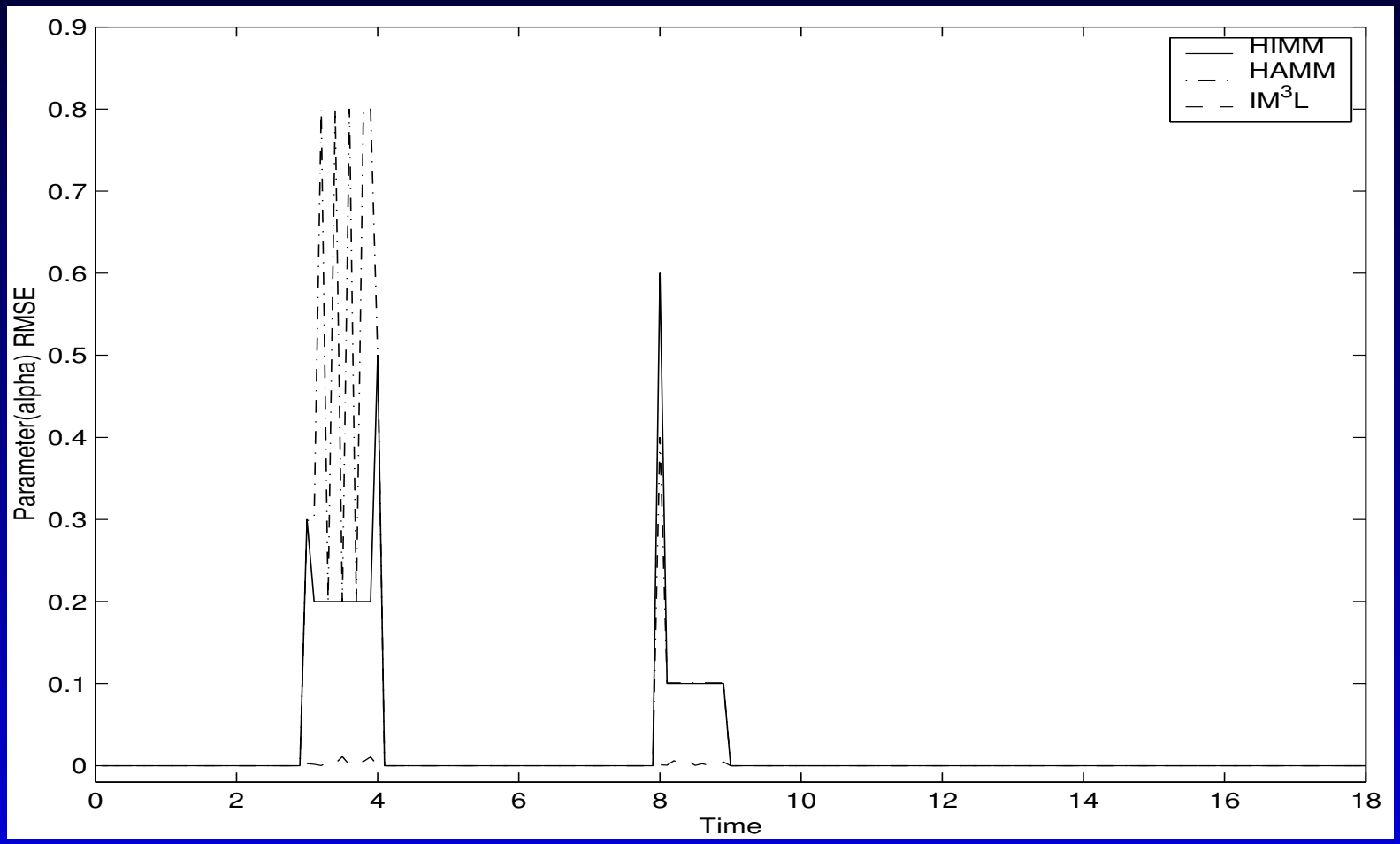
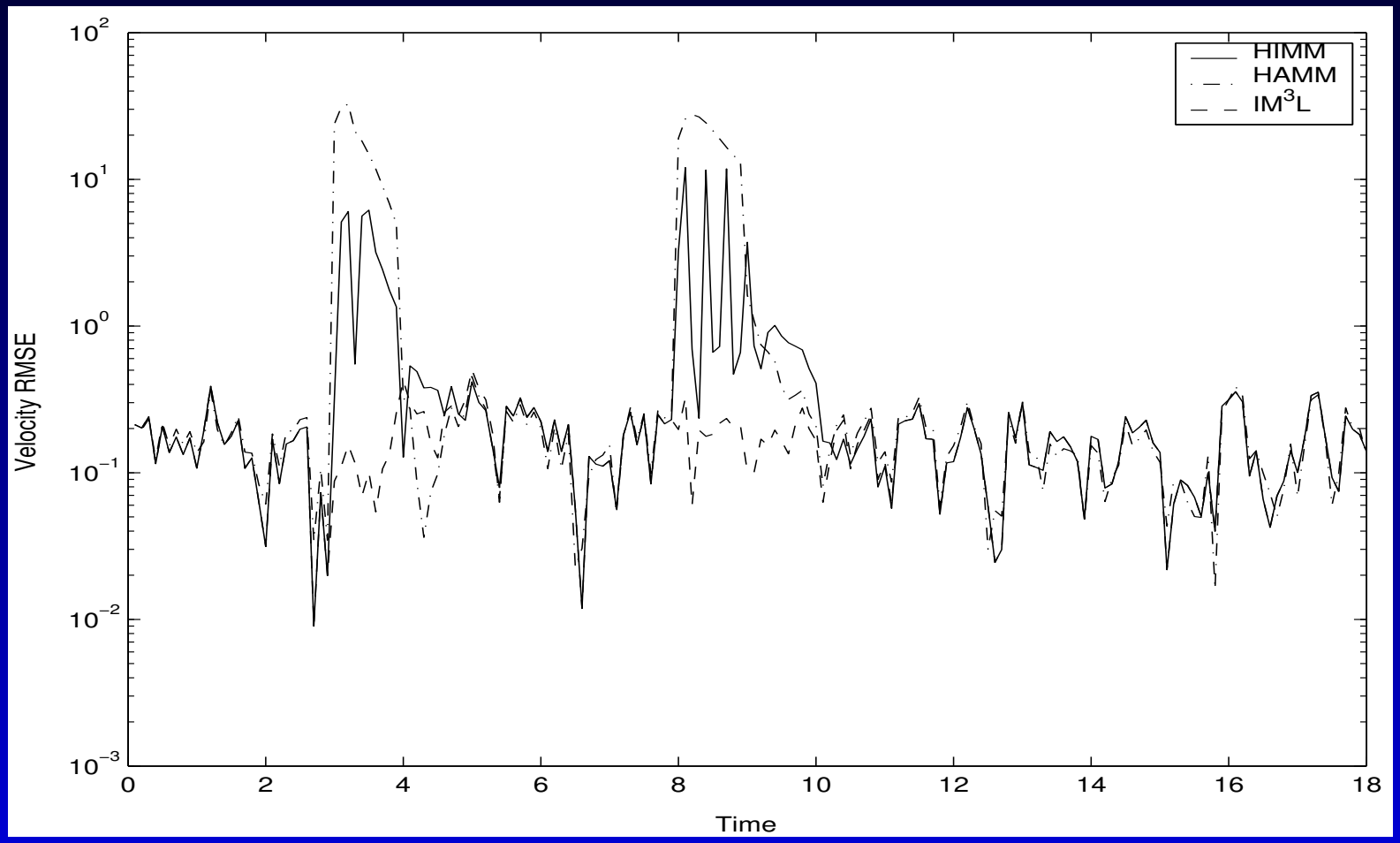
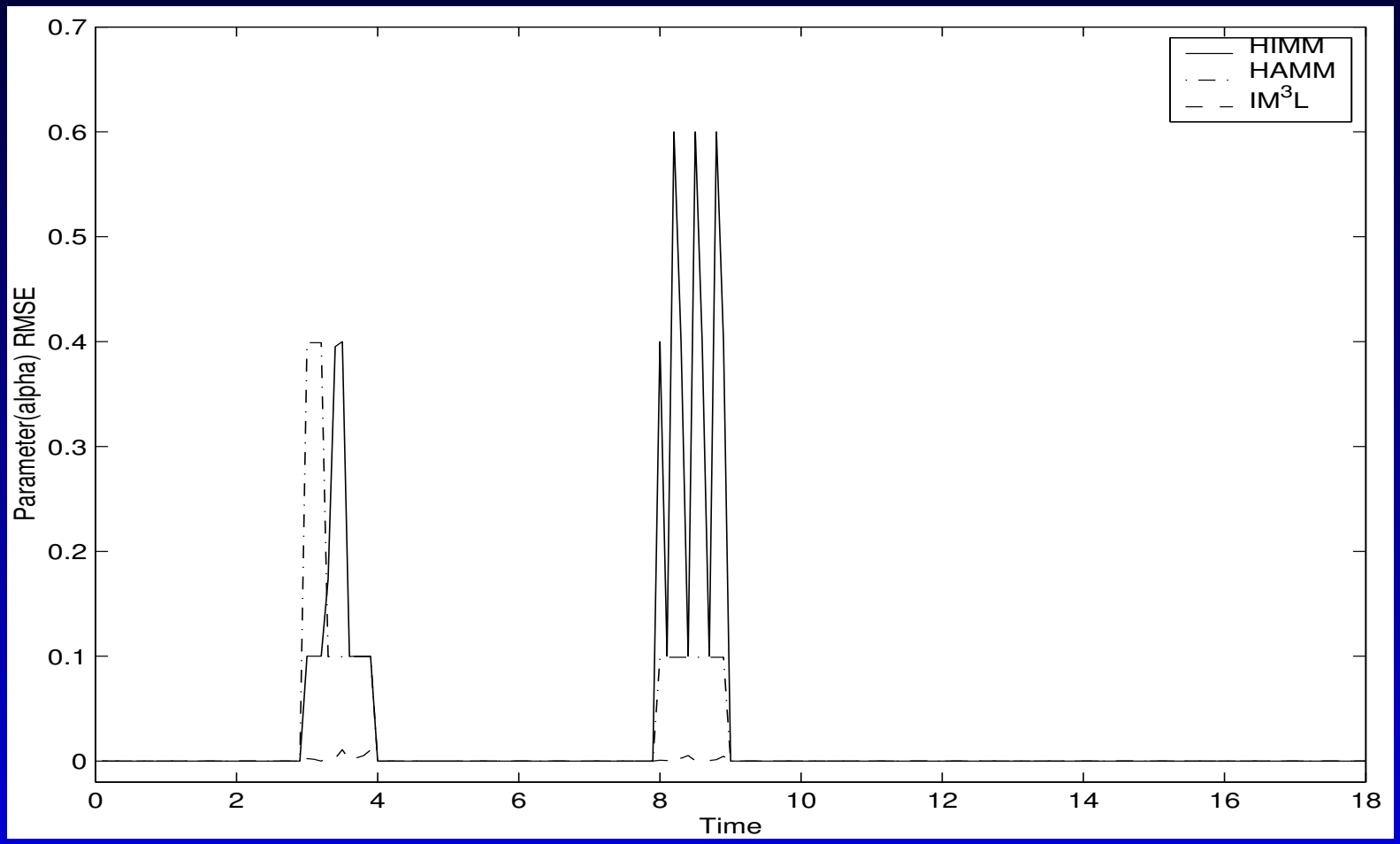


Actuator failures: increased Q/R



Actuator failures: increased Q/R



Actuator fail	%	MD	FA	CDI	NMD	IFI	Flops
Case 1	HIMM	2.78	0	97.22	0	0	1.151
	HAMM	3.89	0	96.11	0	0	0.989
	IM^3L	0	0	100	0	0	1.071
Case 2	HIMM	6.11	0	93.89	0	0	1.142
	HAMM	11.11	0	88.89	0	0	0.922
	IM^3L	0	0	100	0	0	1.096
Case 3	HIMM	0.55	0.57	98.79	0.09	0	1.180
	HAMM	3.33	0.57	96.01	0.09	0	0.999
	IM^3L	0	0.01	99.9	0.09	0	1.099
Case 4	HIMM	4.44	0	95	0.56	0	1.146
	HAMM	0	0	100	0	0	1.014
	IM^3L	0	0	100	0	0	1.089

Conclusions

- IM^{3}L beats HIMM, which beats HAMM
- Performance could be improved if more models are included at lower level.
- IM^{3}L provide accurate $\hat{\alpha}$ and robust state estimation even during the failure
- Model based on $\hat{\alpha}$ is close to truth, verified by residuals histograms (not shown)
- IM^{3}L is applicable to other failures, e.g, multiple, simultaneous system, sensor and actuator failures