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Special Topic: Logical System Control

Communication and control co-design for heterogeneous industrial IoT over state-dependent Markov fading channels

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Heterogeneous Industrial Internet of Things (IIoT) systems are pivotal to Industry 4.0, where wireless control systems and mobile agents are integrated via edge computing to orchestrate collaborative and flexible operations. However, this integration induces intricate couplings between these two subsystems. In particular, agent motion near the wireless links causes severe shadow fading, undermining closed-loop stability [1]. This fading is inherently state-dependent and time-varying; moreover, shadowing and multipath render the channel states temporally correlated [2]. Conversely, control loops under favorable channel conditions transmit opportunistically, inducing a trade-off between wireless energy efficiency and control performance. This necessitates a communication-control co-design to ensure the stability and long-term efficiency of heterogeneous IIoT systems. For overviews of wireless control in smart manufacturing and communication-control co-design, see [3, 4].

Several studies have developed channel models that correlate the temporal channel variations with the mobile agents' locations. In [5], the state dependence was captured by conditioning packet-success probabilities on the agent's MDP state. Furthermore, Ref. [6] characterized a generalized state-dependent shared fading channel, and formulated the co-design problem as the optimization of a logic-based stochastic switched system. To account for temporal correlation, a state-dependent Markov model was introduced in [7]. However, the study was confined to a single control loop, leaving the shared wireless medium unmodeled—let alone the transmission scheduling required to coordinate medium access among loops. To bridge these gaps, this study proposes a multi-frequency multi-level state-dependent Markov channel, allowing channels to be time-varying and correlated across both time and frequency. We then derive necessary and sufficient conditions for mean-square stability, expressed in terms of heterogeneous system dynamics and fading channel statistics. Building on these conditions, we formulate the communication-control co-design as a bilinear matrix inequality problem, which can be efficiently solved via a block coordinate descent scheme. Notations, preliminaries and remarks are provided in Appendixes A–C, respectively.

System model and problem formulation. Consider a heterogeneous IIoT framework with two subsystems; see Figure 1. (i) A multi-loop control system Σ_x modeling p independent industrial plants that share q ($q < p$) wireless frequency channels; (ii) an MDP Σ_s modeling the stochastic high-level dynamics of a mobile agent that coordinates with the plants.

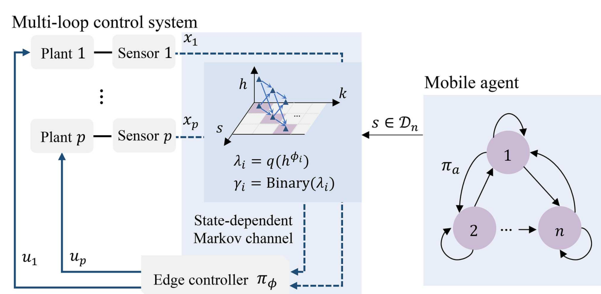

Figure 1 (Color online) A heterogeneous IIoT over state-dependent Markov fading channels.

The model of each plant i is given by a linear time-invariant system $x_i(k+1) = A_i x_i(k) + B_i u_i(k)$, where $x_i(k) \in \mathbb{R}^{n_i}$ and $u_i(k) \in \mathbb{R}^{m_i}$ denote the state and control input at time k, respectively. At each time k, every plant is measured by its associated sensor, which is scheduled to transmit its measurements to an edge controller for control law calculation. The wireless link is subject to time-varying packet dropouts induced by channel conditions. We model system Σ_x as the following switched system:

$$\Sigma_x:\ x_i(k+1) = A_{i,\gamma_i(k)} x_i(k),\ i = 1, 2, \ldots, p,$$

where $\gamma_i(k)$ is a binary mode indicating, for plant i at time k, whether the transmission succeeds or fails, $A_{i,1} = A_i - B_i K_i$ is the closed-loop matrix induced by the state-feedback law $u_i(k) = -K_i x_i(k)$ (e.g., an LQR design), $A_{i,0} = A_i$ corresponds to open-loop evolution under a zero-input policy [8].

The high-level dynamics of the agent is modeled by an MDP $\Sigma_s = (\mathcal{D}_n, S_0, \mathcal{D}_m, P)$, where $\mathcal{D}_n$ is the state space with initial values $S_0 \subseteq \mathcal{D}_n$, $\mathcal{D}_m$ is the action space, and $P : \mathcal{D}_n \times \mathcal{D}_m \times \mathcal{D}_n \to [0, 1]$ is the transition probability among states. Specifically, for

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$s, s' \in \mathcal{D}_n$ and $a \in \mathcal{D}_m$, we denote $P_{s',s}(a) = \mathbb{P}\{s(k+1) = s' | s(k) = s, a(k) = a\}$ with $\sum_{s'\in\mathcal{D}_n} P_{s',s}(a) = 1$ for all s, a.

Let $h(k) = [h^1(k) \cdots h^q(k)]^\top \in \mathcal{H}$ denote the joint channel quality state, where $h^j(k) \in \mathcal{D}_{l^j}$ represents the quality of frequency j with l^j levels, and $\mathcal{H} = \mathcal{D}_{l^1} \times \cdots \times \mathcal{D}_{l^q}$. We generalize the shadow fading channel model in [5–7] to the multi-frequency multi-level state-dependent Markov model.

Definition 1. Given the MDP Σ_s and the channel state space $\mathcal{H}$, the multi-frequency multi-level state-dependent Markov channel consists of the following two components.

(i) Packet-success law. For each $i = 1, \dots, p$,

$$\mathbb{P}\{\gamma_i(k) = 1 | \phi(k) = \phi, h(k) = h\} = \begin{cases} 0, & \phi_i \prod_{i'\neq i}[\phi_i - \phi_{i'}] = 0, \\ q(h^{\phi_i}), & \text{otherwise}, \end{cases} \tag{1}$$

where $\phi(k) = [\phi_1(k) \cdots \phi_p(k)]^\top$, $\phi_i(k) \in \{0, 1, \dots, q\}$ indicates transmission on frequency $j = 1, 2, \dots, q$, and silence for $j = 0$, $q(h^j) \in [0, 1]$ denotes the probability of successful decoding on frequency j.

(ii) Channel-state evolution. For all $s \in \mathcal{D}_n$, and $h, h' \in \mathcal{H}$,

$$\mathbb{P}\{h(k+1) = h' | h(k) = h, s(k) = s\} = H_{h',h}(s), \tag{2}$$

where $H_{h',h}(s)$ denotes the transition probability from channel state h to h' given MDP state s.

A distinctive feature of the above model is that the channel conditions experienced by the control loops vary with spatio-temporal dynamics. Such a feature invalidates the traditional methods that design communication and control policies separately [4], posing challenges of hybrid states and a shared medium with interference and contention.

Our objective in this study is to co-design optimal transmission scheduling policy π_ϕ and mobile agent's control policy π_a to minimize the average expected joint cost

$$J_{\text{joint}} = \lim_{t\to\infty} \frac{1}{t} \mathbb{E}\left\{ \sum_{k=0}^{t-1} c(s(k), h(k), \phi(k), a(k)) \right\},$$

where $c(s(k), h(k), \phi(k), a(k))$ denotes the joint stage cost, subject to the mean-square stability of system Σ_x.

Main results. For the system Σ_x, the switching signal $\gamma_i(k)$ is governed by the logical dynamics Σ_s via the state-dependent Markov channel (1) and (2), yielding a hybrid system with logical states $s(k)$, $h(k)$, and the continuous state $x_i(k)$. The stability of interest is partial stability with respect to the continuous component. To analyze it, we use the semi-tensor product to encode logical states as vectors $\vec{s}(k)$, $\vec{h}(k)$ [9], and define the merged state $y_i(k) = \vec{s}(k) \ltimes \vec{h}(k) \ltimes x_i(k)$. Due to page limitation, preliminaries and all proofs are deferred to Appendixes B and D.

Theorem 1. Multi-loop control system Σ_x with the state-dependent Markov channel (1) and (2) is mean-square stable, if and only if the merged stochastic switched system

$$\Sigma_y\colon\ y_i(k+1) = F_{i,\sigma(k)}(k) y_i(k),\ i = 1, 2, \dots, p \tag{3}$$

is mean-square stable, where $F_{i,\sigma(k)}(k)$ is a random matrix taking values in $\mathbb{R}^{nn_il \times nn_il}$, $l = \prod_{j=1}^q l^j$, and $\sigma(k) \in \mathcal{D}_{m(q+1)^p}$ encodes the communication-control policy with $\vec{\sigma}(k) = \vec{\phi}(k) \ltimes \vec{a}(k)$.

Order the Cartesian product $\mathcal{D}_n \times \mathcal{H} = \{[s_a\ h_b]^\top : a = 1, \dots, n, b = 1, \dots, l\}$ lexicographically. θ_r denotes its r-th element. The following result provides necessary and sufficient conditions for the mean-square stability of system Σ_x.

Theorem 2. For a given policy pair (π_ϕ, π_a), the following statements are equivalent:

(i) The system Σ_x is mean-square stable;

(ii) $\rho(G_i) < 1$ for all $i = 1, 2, \dots, p$;

(iii) For each $i = 1, 2, \dots, p$, there exists $P_i \in \mathbb{H}^{nn_il, nl}$ with $P_i \succ 0$, such that $P_i - \mathbf{T}_i(P_i) \succ 0$.

Here, $G_i = \sum_{\phi,a} (\Pi^{(a)} D^{(\phi,a)}) \otimes \bar{F}_{i,(\phi,a)}$, $[\Pi^{(a)}]_{r',r} = \Pi(\theta_{r'} | \theta_r, a)$, $D^{(\phi,a)} = \operatorname{diag}(\mathbb{P}\{\phi, a|\theta_1\}, \dots, \mathbb{P}\{\phi, a|\theta_{nl}\})$, where $\Pi(\theta'|\theta, a) = P_{s',s}(a) H_{h',h}(s)$, $\mathbb{P}\{\phi, a|\theta\} = \pi_\phi(\phi|s, h)\pi_a(a|s)$ with $\theta = [s\ h]^\top$, $\theta' = [s'\ h']^\top$, and $\bar{F}_{i,(\phi,a)} = \mathbb{E}\{F_{i,(\phi,a)}(k) \otimes F_{i,(\phi,a)}(k)\}$. Moreover, $\mathbf{T}_i(P_i) = (\mathbf{T}_{i,\theta_1}(P_i), \mathbf{T}_{i,\theta_2}(P_i), \dots, \mathbf{T}_{i,\theta_{nl}}(P_i))$, $\mathbf{T}_{i,\theta}(P_i) = \sum_{\theta',\phi,a} \Pi(\theta|\theta', a) \mathbb{P}\{\phi, a|\theta'\} \bar{F}_{i,(\phi,a)}(P_{i,\theta'})$, and $\bar{F}_{i,(\phi,a)}(P_{i,\theta'}) = \mathbb{E}\{F_{i,(\phi,a)}(k) P_{i,\theta'} F^\top_{i,(\phi,a)}(k)\}$.

With the stability conditions derived in Theorem 2, we have the following result on the co-design problem.

Theorem 3. The optimal stationary policy pair $(\pi^\star_\phi, \pi^\star_a)$ is given by any optimal solution to the following bilinear matrix inequality problem:

$$\begin{aligned}
\mathbf{P}:\ & \min_{\pi_\phi, \pi_a, \mu, \{P_{i,\theta}\}} \sum_{\theta=(s,h),\phi,a} c(\theta, \phi, a)\mu(\theta)\pi_\phi(\phi|\theta)\pi_a(a|s) \\
\text{s.t.}\ & \sum_\phi \pi_\phi(\phi|s, h) = 1, \pi_\phi(\phi|s, h) \geqslant 0,\ \forall s, h, \\
& \sum_a \pi_a(a|s) = 1, \pi_a(a|s) \geqslant 0,\ \forall s, \\
& \sum_\theta \mu(\theta) = 1, \mu(\theta) \geqslant 0, \mu(\theta) = \sum_{\theta',a} \Pi(\theta|\theta', a)\mu(\theta')\pi_a(a|s'), \\
& P_{i,\theta} - \sum_{\theta',\phi,a} \Pi(\theta \mid \theta', a)\pi_\phi(\phi|\theta')\pi_a(a|s')\bar{F}_{i,(\phi,a)}(P_{i,\theta'}) \succeq \varepsilon I, \\
& P_{i,\theta} \succeq \varepsilon I, \forall\, i = 1, \dots, p,\ \forall \theta,
\end{aligned}$$

where $\varepsilon > 0$, and $\mu(\theta)$ is the stationary distribution of the state $\theta = (s, h)$.

Due to the block-multiconvex structure, optimization problem $\mathbf{P}$ can be solved by a block coordinate descent scheme: we cyclically minimize the objective over the blocks $\{P_{i,\theta}\}$, π_ϕ and π_a, while enforcing the linear balance equations to update the stationary distribution μ. Each block subproblem is convex (linear or semi-definite), thus can be handled by standard solvers such as MOSEK or SDP 3.

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Supporting information Appendixes A–D. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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