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Resilient architecture for network and control co-design under wireless channel uncertainty in cyber-physical systems

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Abstract
In this paper, we propose a resilient architecture for network and control co-design, Wireless-Simplex (W-Simplex), which can ensure control performance by adaptively tuning the network and control parameters against wireless channel uncertainty in cyber-physical systems. To the best of our knowledge, there has been no research into resilient network and control co-design in response to the unreliable wireless channel. Our key observation is that rate adaptation may cause significant degradation in control performance or even system instability. This performance degradation is contrary to the intuition that rate adaptation provides a reliable link under wireless channel uncertainty. We explain the cause of this phenomenon and resolve the situation by proposing a resilient co-design algorithm in an optimization framework. Our simulation study with ns-2 shows the effectiveness of the proposed scheme to provide resilience of cyber-physical systems against wireless channel uncertainty.

1 | INTRODUCTION

Recently, the convergence of cyber and physical spaces[1-5] has turned traditional embedded systems into cyber-physical systems (CPSs), which primarily features tight integration between computational and physical systems by means of networking. In CPS, various embedded devices with computational components are networked to monitor, sense, and actuate physical elements in the real world. Consequently, CPS can be effectively decomposed into three main parts: cyber elements representing software, physical entities composed of various real-world systems, and networks connecting the cyber and physical world.[*]

Among many desirable characteristics of CPS, resilience is one of the most crucial features. Generally speaking, resilience is to maintain an accepted level of operational normalcy in response to disturbances.[6] By considering the three elements of CPS, the major challenges for resilient CPS are as follows: *(i)* software errors in the cyber systems; *(ii)* model uncertainty and disturbances in the physical systems; and *(iii)* wireless channel uncertainty in networks.[†]

In the literature, *(i)* is studied, and the Simplex architecture is proposed for resilience against software errors.[7] More recently, the L1Simplex architecture is presented by Wang et al[8] to address both software and physical failures,

[*]One may argue that a network is simply a combination of software and hardware. However, in terms of CPS, it is more effective to consider that the physical system is the interested real-world system, the cyber is a software managing the physical, and the network is rather a vehicle for information exchange between the two.
[†]We do not explicitly consider resilience against attacks, which will be a subject of future work.

which resolves *(i)* and *(ii)* simultaneously. However, existing studies on network and control co-design do not explicitly address the issue of *(iii)* wireless channel uncertainty. Consequently, we need a resilient network and control co-design architecture against unreliable wireless channel.

In this paper, we pay attention to wireless channel uncertainty and propose a resilient network and control co-design architecture, which can make the system resilient against the adverse effect of wireless channel uncertainty. In particular, our main contributions are as follows.

- We show that rate adaptation for maintaining a robust network link under wireless channel uncertainty may cause degradation of control performance or even instability.
- In order to overcome performance degradation, we incorporate the PHY data rate into the network and control co-design formulation.
- We propose Wireless-Simplex (W-Simplex) that can adaptively tune the network and control parameters for resilience against wireless channel uncertainty.

In wireless communications, it is well known that adaptive modulation and coding or so-called rate adaptation can enhance the communication link against a time-varying, uncertain wireless channel.[9-11] However, in terms of control performance in networked control, rate adaptation may result in severe performance degradation or even system instability, which has never been properly addressed in any previous work. Consequently, we need to understand this phenomenon and resolve the situation for providing resilience in CPS.

The remainder of this paper is organized as follows. In Section 2, we show the control performance of a wireless networked system without and with rate adaptation. Under poor channel condition, we first show that networked control without any rate adaptation simply fails due to severe packet loss, which is obvious. Then, we demonstrate that networked control *with* rate adaptation still gives unstable behavior of the physical system. The overall problem formulation is given in Section 3. We explain the conventional network and control co-design problem. Then, we extend the formulation by considering rate adaptation and propose a resilient co-design architecture in Section 4. We evaluate the performance of the proposed scheme in Section 5. Related work is given in Section 6. Finally, our conclusion follows in Section 7.

2 | MOTIVATION: WHAT HAPPENS TO CONTROL PERFORMANCE UNDER WIRELESS CHANNEL UNCERTAINTY?

In this section, we show control performance degradation of a wireless networked control system due to wireless channel uncertainty. First, Figure 1 shows control performance *without* any rate adaptation when the wireless channel becomes poor.[‡] In this Figure, the y-axis corresponds to the controlled system output, which should track the reference in the steady state. In this case, since the packet reception ratio is seriously reduced because of the lower signal-to-interference-noise ratio as soon as the channel becomes worse, it is obvious that control performance shows instable behavior, as shown in Figure 1.

Now, we consider the situation with rate adaptation when the data rate changes from 11 Mb/s to 1 Mb/s in order to maintain a reliable link against wireless channel degradation. In this case, even though the link is kept reliable without any significant packet drops, the simulation result in Figure 2 still shows severe oscillating instability. This phenomenon is contrary to our intuition that rate adaptation provides a robust link against wireless channel uncertainty.

In fact, this degradation of control performance results from the excessive network delay caused by contention. Rate adaptation lowers the data rate when the channel condition becomes poor. A lower data rate increases the effective network traffic load, which induces more contention. Accordingly, the network delay becomes larger, and the control and network parameters are no longer valid and may fail to give stable behavior, as shown in Figure 2. In the following sections, we will give a more rigorous explanation on this phenomenon and present a resilient co-design framework.

[‡]Details of the simulation environment can be found in Section 5.

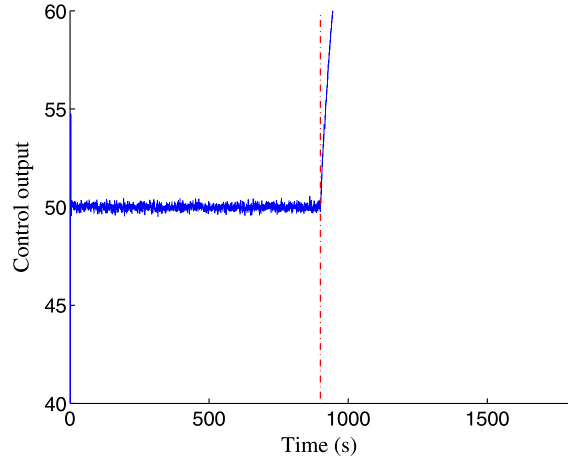

FIGURE 1 Output of the control system with a reference of 50 without any rate adaptation when the wireless channel condition becomes poor at 900 seconds

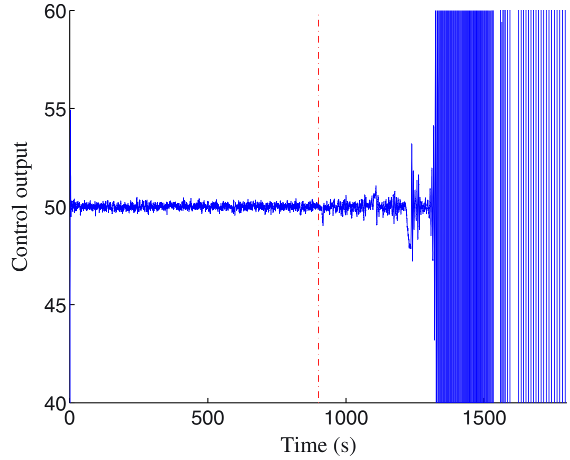

FIGURE 2 Output of the control system with a reference of 50 when the data rate adapts from 11 Mb/s to 1 Mb/s due to channel degradation at 900 seconds

3 | PROBLEM FORMULATION

3.1 | Conventional network and control co-design

In the traditional digital control, a smaller sampling period gives better control performance though the performance saturates at a certain point. In the meantime, the performance of networked control initially improves as the sampling period decreases. However, since network traffic is inversely proportional to the sampling period, more contention will occur as the sampling period becomes smaller. Consequently, at a certain point, the network delay will become significant enough to degrade the control performance and may even cause instability. This performance comparison is illustrated in Figure 3. Consequently, unlike traditional digital control, we need to carefully co-design network and control in networked control systems in order to satisfy both network and control performance.

We give the conventional optimization formulation of network and control co-design in CPS. The overall structure of CPS in the form of a networked control system is described in Figure 4. There are N physical systems and N controllers, where N is an integer. The physical systems periodically send sensed data to the controllers over a wireless network.[§]

Each controller $C_n, n = 1, \dots, N$, has a sampling period of s_n, which defines how often sensed data is sampled and transmitted to the controller. In addition, network delay $d_n, n = 1, \dots, N$, of each feedback loop is represented as $d_n(\mathbf{s}, \mathbf{V}, \delta)$,

[§]Here, we assume that controllers are directly connected to the actuators of the physical systems while sensors are connected to the controllers over a network as in other related works.[13-15]

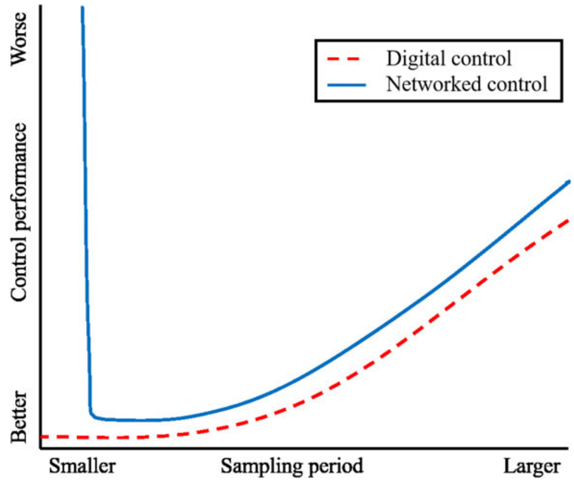

FIGURE 3 Performance comparison of digital control and networked control[12]

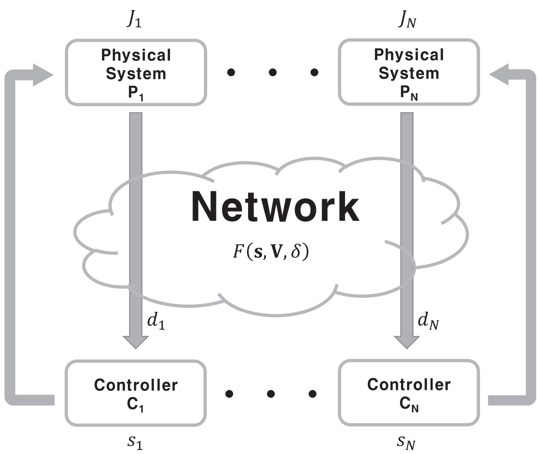

FIGURE 4 Overall networked control structure of a cyber-physical system

where $\mathbf{s}$ and $\mathbf{V}$ are respectively the set of the sampling periods and the network parameters such as contention window size and retransmission count, and δ includes the network setup such as network topology and the number of nodes. In a similar manner, packet loss probability l_n, $n = 1, \dots, N$, of each feedback loop is represented as $l_n(\mathbf{s}, \mathbf{V}, \delta)$. For each physical system P_n, the control performance is represented by the control cost of $J_n = J_n(s_n, d_n(\mathbf{s}, \mathbf{V}, \delta), l_n(\mathbf{s}, \mathbf{V}, \delta))$, which is a function of its own sampling period s_n, network delay d_n, and packet loss probability l_n. Here, since d_n and l_n are functions of $\mathbf{s}$ and $\mathbf{V}$, J_n depends not only on its own sampling period but also on those of others through d_n and l_n.

Hence, the conventional co-design problem can be formulated in an optimization framework as follows:

$$\begin{aligned} &\min_{\mathbf{s},\mathbf{V}} \quad F(\mathbf{s}, \mathbf{V}, \delta) \\ &\text{s.t.} \quad J_n(s_n, d_n(\mathbf{s}, \mathbf{V}, \delta), l_n(\mathbf{s}, \mathbf{V}, \delta)) \le J_n^{\text{th}}, n = 1, \dots, N. \end{aligned} \tag{1}$$

Here, $F(\mathbf{s}, \mathbf{V}, \delta)$ denotes an objective function for network performance such as network energy consumption, and J_n^{th} is a pre-specified threshold of control cost of the nth physical system.

In fact, the problem of network and control co-design has been substantially investigated in the control systems community.[12,16-18] However, most of these studies focus on system stability or control performance while networks are simply modeled as a source of delay and loss. For example, the conventional optimization formulation of (1) does not include rate adaptation, which is the cause of the control performance degradation shown in Figure 2.

Without any rate adaptation, the packet loss probability l_n in (1) will become larger with a poor channel condition, which may result in degradation of control performance or system instability, as shown in Figure 1. In case of rate adaptation, let $\mathbf{s}^*$ and $\mathbf{V}^*$ denote the solution to (1). When rate adaptation lowers the PHY data rate due to a poor channel condition, the region of the sampling period for system stability will become smaller because of increased network contention,

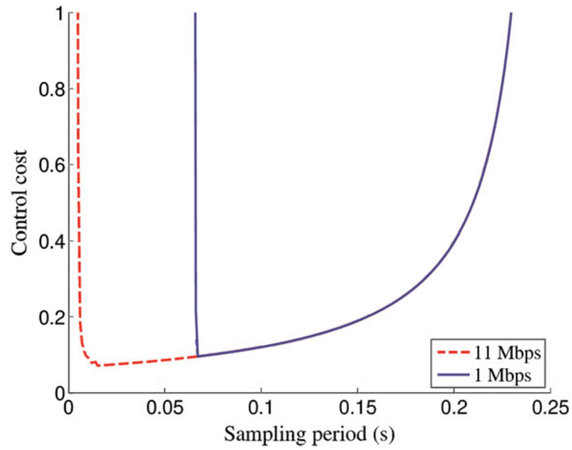

FIGURE 5 Control cost for the data rate of 1 Mb/s and 11Mb/s

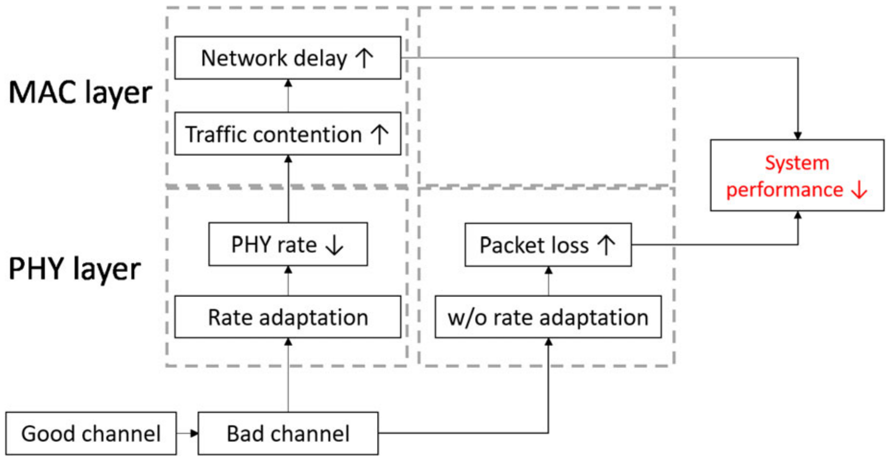

FIGURE 6 Performance degradation with and without rate adaptation

as shown in Figure 5.[¶] This phenomenon occurs because the network delay d_n is a decreasing function of the data rate. From Figure 5, for example, $\mathbf{s}^*$ is set to 0.05 seconds when the data rate is 11 Mb/s, then the physical system will become unstable once the data rate changes into 1 Mb/s. Figure 6 explains why rate adaptation causes the performance degradation. Consequently, for system resilience, we need to explicitly include the effect of wireless channel uncertainty in (1).

3.2 | Network and control co-design with rate adaptation

We extend (1) in order to incorporate the effect of rate adaptation. Let r_n denote the PHY data rate of the feedback loop n. Then, among a finite set of values, r_n is selected depending on random channel condition denoted by ξ, ie, $r_n = r_n(\xi)$. Consequently, for a given value of r_n, network and control co-design can be formulated as the following constrained optimization:

$$\begin{aligned} \min_{\mathbf{s},\mathbf{V}} \quad & F(\mathbf{s}, \mathbf{V}, r_n(\xi), \delta) \\ \text{s.t.} \quad & J_n(s_n, d_n(\mathbf{s}, \mathbf{V}, r_n(\xi), \delta)) \le J_n^{\text{th}}, n = 1, \ldots, N. \end{aligned} \tag{2}$$

Here, with an assumption that rate adaptation keeps the packet loss probability l_n negligible, we no more include l_n in the formulation.

[¶]It should be noted that Figure 5 is a simulation result, whereas Figure 3 is a conceptual illustration. Details of the simulation environment can be found in Section 5.

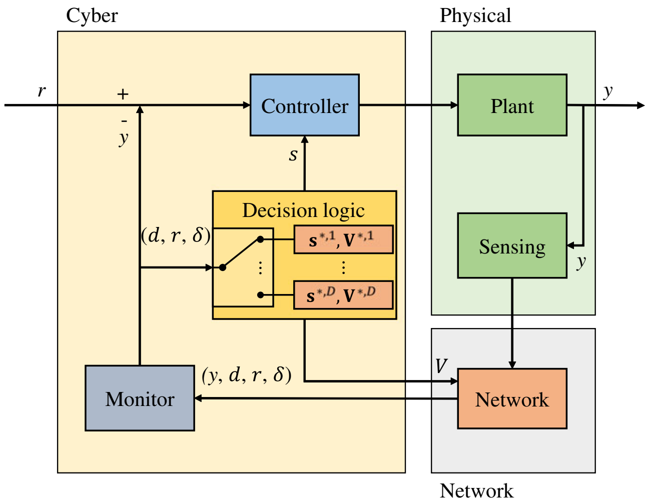

FIGURE 7 Wireless-Simplex architecture for network and control co-design

Since $r_n(\xi)$ changes according to the channel condition ξ, fixed values of $\mathbf{s}$ and $\mathbf{V}$ cannot guarantee the required control performance as already shown in Figure 2. Consequently, we need a high-level architecture that can adaptively tune $\mathbf{s}$ and $\mathbf{V}$ for different values of $r_n(\xi)$ in order to keep the system resilient to the uncertain wireless channel.

4 | W-SIMPLEX: RESILIENT ARCHITECTURE FOR NETWORK AND CONTROL CO-DESIGN

In this section, we propose a resilient architecture that can adaptively tune the network and control parameters against wireless channel uncertainty. In a nutshell, we adopt the idea of the Simplex architecture,[7] which is a switching architecture between a high performance algorithm and high assurance one for resilience under software errors.

4.1 | W-Simplex: network and control co-design against wireless channel uncertainty

Similarly as in the Simplex architecture, we consider a switching architecture for the PHY data rate $r_n(\xi)$. The basic idea is as follows: The values of $\mathbf{s}$ and $\mathbf{V}$ need to be appropriately tuned according to $r_n(\xi)$. Hence, once the data rate is determined according to the channel condition, $\mathbf{s}$ and $\mathbf{V}$ are switched to proper values in order to satisfy both the network and control performance given in (2). In other words, if $r_n(\xi)$ is selected in a finite set of $\{r^1, \dots, r^D\}$, we solve (2) to get the solution of $\mathbf{s}^*$ and $\mathbf{V}^*$ for each r^i, $i = 1, \dots, D$, in advance. Then, for each value of $r_n(\xi)$, $\mathbf{s}$ and $\mathbf{V}$ are switched to the corresponding $\mathbf{s}^*$ and $\mathbf{V}^*$. The overall W-Simplex architecture is given in Figure 7.

Now, the remaining issue is how to obtain models for the control cost, network delay, and network performance. In the subsequent sections, we derive these models.

4.2 | Control cost

In this section, in order to solve a given constrained optimization in (2), we model the control cost J_n of the nth networked control system. Since the analysis applies for all the systems $n = 1, \dots, N$, we omit subscript n for simplicity.

It is assumed that the physical system is modeled as a single-input–single-output linear system. Specifically,

$$\begin{aligned} \dot{x}(t) &= Ax(t) + B_1u(t) + B_2w(t), \\ y(t) &= Cx(t), \\ u(t) &= Kx(t), \end{aligned} \tag{3}$$

where $x(t) \in \mathbb{R}^m$ is the state of the physical system, the dimension of which is m, $u(t) \in \mathbb{R}$ is the control input, $w(t) \in \mathbb{R}$ is disturbance, and $y(t) \in \mathbb{R}$ is the output, respectively. The disturbance $w(t)$ is assumed to be a zero-mean white Gaussian process whose power spectral density is given by a constant W. The matrices A, B_1, B_2, and C define the physical system dynamics and are in appropriate dimensions. A state feedback control is assumed with gain matrix K, designed to yield $(A - B_1K)$ to be Hurwitz matrix for stability.

Since the system is driven by a random disturbance, we define the control performance by the expected value of $y(t)^2$, ie,

$$J = E\left[y^2(t)\right] = CE\left[x(t)x(t)^T\right]C^T,$$

which gives a measure of the deviation of y from a desired value of 0. This can be achieved by calculating the covariance of the state, ie, $E[x(t)x(t)^T]$. Measuring the deviation of y from any nonzero desired value can also be done by an appropriate coordinate change. Qualitatively speaking, the control cost J is the variance of output in control. A larger value of J means that the system state deviates more around the reference in the steady state. Hence, the larger the value of J is, the worse the control performance becomes.

Discretizing system (3) with sample period s yields the following difference state equation:

$$\begin{aligned} x[k+1] &= \Phi x[k] + \Gamma u[k] + \gamma[k], \\ y[k] &= Cx[k], \\ u[k] &= Kx[k], \end{aligned}$$

where

$$\begin{aligned} \Phi &= e^{As}, \\ \Gamma &= \int_0^s e^{A\tau} d\tau B_1, \\ \gamma[k] &= \int_0^s e^{A(s-\tau)} B_2 w(\tau) d\tau. \end{aligned}$$

Then, the closed-loop system dynamics in discrete-time are written as

$$\begin{aligned} x[k+1] &= \Phi_{CL} x[k] + \gamma[k], \\ y[k] &= Cx[k], \end{aligned} \tag{4}$$

where $\Phi_{CL} = \Phi - \Gamma K$ is a closed-loop state matrix.

The network induced delay is denoted by d_n in Section 3. As it may be natural for a discrete-time control system, we assume that d_n is a multiple of the sampling period s and given by $d_n = k_d \cdot s$ for a positive integer k_d. Then, the control system including the delay can be written as

$$\begin{aligned} x[k+1] &= \Phi x[k] - \Gamma K x[k-k_d] + \gamma[k], \\ y[k] &= Cx[k], \end{aligned}$$

which, in turn, can also be rewritten as follows:

$$\begin{aligned} X[k+1] &= \Phi_d X[k] + F\gamma[k], \\ y[k] &= C_d X[k], \end{aligned} \tag{5}$$

where

$$\begin{aligned} X[k] &= \left[x^T[k]\, x^T[k-1]\, \cdots\, x^T[k-k_d]\right]^T, \\ F &= [I_{m\times m}\, 0_{m\times m}\, \cdots\, 0_{m\times m}]^T, \\ C_d &= [C\, 0_{1\times m}\, \cdots\, 0_{1\times m}], \end{aligned}$$

and

$$\Phi_d = \begin{bmatrix} \Phi & 0_{m\times m} & \cdots & -\Gamma K \\ I_{m\times m} & 0_{m\times m} & \cdots & 0_{m\times m} \\ \vdots & \ddots & \ddots & \vdots \\ 0_{m\times m} & \cdots & I_{m\times m} & 0_{m\times m} \end{bmatrix}.$$

Denote the state covariance matrix of system (4) without delay $(d = 0)$ by

$$P[k] = E\left[x[k]x^T[k]\right].$$

Then, it is obtained by solving the following Lyapunov equation:

$$P[k+1] = \Phi_{CL} P[k] \Phi_{CL}^T + Q,$$

where

$$Q = \int_0^s e^{A\tau} B_2 W B_2^T e^{A^T\tau} d\tau.$$

If all eigenvalues of the matrix Φ_{CL} are inside the unit circle and there exists the positive definite matrix P that is the solution of

$$P = \Phi_{CL} P \Phi_{CL}^T + Q,$$

then $P[k]$ is given by P in the steady state. Thus, the control cost J is defined as follows:

$$J = CPC^T.$$

For the case of the system of (5), the equation for the covariance matrix P_d (subscript d denotes the delay) is given by

$$P_d[k+1] = \Phi_d P_d[k] \Phi_d^T + Q_d, \tag{6}$$

where $P_d[k] = E[X[k]X^T[k]]$, and $(k_d + 1)m$-dimensional square matrix Q_d is given by

$$Q_d = \begin{bmatrix} Q & 0_{m\times m} & \cdots & 0_{m\times m} \\ 0_{m\times m} & 0_{m\times m} & \cdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ 0_{m\times m} & \cdots & \cdots & 0_{m\times m} \end{bmatrix}.$$

In (6), if all eigenvalues of the matrix Φ_d are inside the unit circle and there exists the positive definite matrix P_d that is the solution of

$$P_d = \Phi_d P_d \Phi_d^T + Q_d,$$

then the control cost is given by

$$J_d = C_d P_d C_d^T.$$

4.3 | Network delay model

In this section, we model the network delay in a similar manner as in related co-design studies.[13,14,19] Unlike homogeneous network models used in the previous work, we adopt a heterogeneous network model, in which each network node can have different values of network parameters.[20]

We consider IEEE 802.11 WLAN as the network between the physical systems and the controllers. Let the network consist of N nodes with packet arrival rates of λ_n, $n = 1, \dots, N$. The utilization and collision probability of each node are respectively denoted by ρ_n and p_n, $n = 1, \dots, N$. Then, the average backoff window of node n can be represented as

$$\overline{W}_n = \frac{1 - p_n - p_n(2p_n)^m}{1 - 2p_n} \frac{\mathrm{CW}_{\min}}{2},$$

where m is the maximum number of retransmission and $\mathrm{CW}_{\min}$ is the minimum of the contention window size.

The collision probability of node n in a slot is given by

$$p_n = 1 - \prod_{\substack{i=1 \\ i\neq n}}^{N} \left(1 - \rho_i \frac{(1 - 2p_i)}{1 - p_i - p_i(2p_i)^m} \frac{2}{\mathrm{CW}_{\min}} \right). \tag{7}$$

Here, the utilization of node n, ρ_n is expressed as follows:

$$\rho_n = \sum_{\substack{i=1 \\ i\neq n}}^{N} \lambda_n \rho_i \left[T_{S_i} + T_{C_i} \frac{p_i}{2(1 - p_i)} \right] + \lambda_n \left[\overline{W}_n + T_{S_n} + T_{C_n} \frac{p_n}{2(1 - p_n)} \right], \tag{8}$$

where T_{S_i} and T_{C_i} are the length of node i's packet and collision in the unit of backoff slots, respectively. We can now numerically solve a system of equations (7) and (8) because they are $2N$ equations with $2N$ variables.

In order to obtain the delays experienced by a packet at each node, the system is modeled as a discrete time $G/G/1$ queue. We first calculate the number of backoff slots that the labeled node has to wait between two successful transmissions. The probability that node n experiences i backoff slots is given as follows:

$$\begin{aligned}P[\mathrm{BO}_n = i] = \rho_n \big[&(1-p_n)U_{1,\mathrm{CW}_{\min}}(i) + p_n(1-p_n) \\ &\times \left[U_{1,\mathrm{CW}_{\min}} * U_{1,2\mathrm{CW}_{\min}}(i)\right] + \cdots + p_n^m(1-p_n) \\ &\times \left[U_{1,\mathrm{CW}_{\min}} * U_{1,2\mathrm{CW}_{\min}} * \cdots * U_{1,2^m\mathrm{CW}_{\min}}(i)\right] \\ &+p_n^{m+1}(1-p_n)\left[U_{1,\mathrm{CW}_{\min}} * \cdots * U_{1,2^m\mathrm{CW}_{\min}} * U_{1,2^m\mathrm{CW}_{\min}}(i)\right] + \cdots\big],\end{aligned}$$

with the corresponding probability generating function $\mathrm{BO}_n(z)$, where $U_{a,b}$ denotes the uniform distribution between a and b, and $*$ represents the convolution operation.

To compute the service time experienced by a packet at the labeled node, we derive how many of the backoff slots corresponds to collision or successful transmission by other nodes.
The probability that any of backoff slots experienced by node n is active, q_n, is given as follows:

$$q_n = 1 - \prod_{\substack{i=1 \\ i \neq n}}^{N} \left(1 - \frac{\rho_i}{W_i}\right). \tag{9}$$

The probability that any of backoff slots experienced by node n is collision, q_{n_c}, is given by

$$q_{n_c} = \frac{1 - \prod_{\substack{i=1 \\ i \neq n}}^{N} \left(1 - \frac{\rho_i}{W_i}\right) - \sum_{\substack{i=1 \\ i \neq n}}^{N} \frac{\rho_i}{W_i} \prod_{\substack{j=1 \\ j \neq i,n}}^{N} \left(1 - \frac{\rho_j}{W_j}\right)}{1 - \prod_{\substack{i=1 \\ i \neq n}}^{N} \left(1 - \frac{\rho_i}{W_i}\right)}.$$

Then, given that a slot contains a successful transmission, the probability that it belongs to node i, $i \neq n$, is obtained as follows:

$$R_n[i] = \frac{\frac{\rho_i}{W_i} \prod_{\substack{j=1 \\ j \neq i,n}}^{N} \left(1 - \frac{\rho_j}{W_j}\right)}{\sum_{\substack{i=1 \\ i \neq n}}^{N} \frac{\rho_i}{W_i} \prod_{\substack{j=1 \\ j \neq i,n}}^{N} \left(1 - \frac{\rho_j}{W_j}\right)}.$$

The probability that a successful transmission by other nodes adds v slots to the service time of the labeled node is

$$\tilde{l}_n(v) = \sum_{\substack{i=1 \\ i \neq n}}^{N} R_n[i] l_i(v),$$

and the contribution of an arbitrary number of successful transmissions, say, j, is given by

$$P\left[\sum^{j} \text{pkt time} = u\right] = \tilde{l}_n * \tilde{l}_n * \cdots * \tilde{l}_n(u) = \tilde{l}_n^{(j)}(u),$$

where $\tilde{l}_n^{(j)}()$ represents the j-fold convolution of $\tilde{l}_n(v)$.

The probability mass function of the service time Y for node n is given by

$$P[Y_n = s] = \sum_{i}^{\infty} \sum_{j}^{i} \sum_{k}^{j} \left[\tilde{l}_n^{(j-k)}(u) \binom{i}{j} q_n^j (1-q_n)^{i-j} \times \binom{j}{k} q_{n_c}^k (1-q_{n_c})^{j-k} P[\mathrm{BO}_n = i] I(s)\right],$$

where $I(s)$ is an indicator function, which is equal to one when $s = u + i + kT_C$ and zero otherwise.

Now, the probability generating function of the final service time, $B_n(z)$ can be obtained by the convolution of the channel access time $Y_n(z)$ and the length of the served packet L_n, which is represented as follows:

$$B_n(z) = Y_n(z) L_n(z).$$

Here, $a_n(k)$ denotes the probability that k packets arrive in a slot at node n with the corresponding probability generating function $A_n(z)$. Finally, the mean of the network delay d_n is given by

$$d_n = B'_n(1) + \frac{[A'_n(1)]^2 B''_n(1) + A''_n(1)B'_n(1)}{2A'_n(1)\left[1 - A'_n(1)B'_n(1)\right]}.$$

4.4 | Network performance objective

Now, we consider the network-wide energy consumption as the objective function $F(\mathbf{s}, \mathbf{V}, r_i(\xi), \delta)$. Let SE and QNE denote the event that a slot is empty and the queue is not empty, respectively. Then, $P[SE]$ can be represented as

$$P[SE] = 1 \times (1 - \rho) + \rho P[SE|QNE].$$

Here, $P[SE|QNE]$ can be further approximated by $(\overline{W} - 1)/\overline{W}$. Therefore, we have

$$P[SE] = (1 - \rho) + \rho \frac{\overline{W} - 1}{\overline{W}} = 1 - \frac{\rho}{\overline{W}}.$$

Consequently, network energy consumption of all the nodes can be calculated as

$$F = \sum_{i=1}^{N} \frac{\rho_i}{\overline{W}_i}.$$

5 | PERFORMANCE EVALUATION

In this section, we carry out simulation study to validate the effectiveness of the proposed architecture of W-Simplex.

5.1 | Simulation setup

Our simulator is implemented in ns-2. By putting everything in Section 4 together, we implement an iterative algorithm for solving (2) for each value of the data rate $r_i \in \{r^1, \ldots, r^D\}$, which is given in Algorithm 1. Algorithm 1 iteratively searches an interior point of the sampling period that satisfies the given constraint in (2) and minimizes the network energy consumption. The optimization problem of (2) can be solved from the optimal sampling period values obtained by performing Algorithm 1 on a set of data rate $\mathbf{r}$ and on a set of network parameters $\mathbf{V}$. In order to focus on the control performance rather than the dynamics of a specific rate adaptation algorithm, we implement ideal rate adaptation that immediately adjusts the data rate with perfect knowledge on the channel condition change. We confirmed that ideal rate adaptation can guarantee the packet error rate less than 0.01% through ns-2 simulator. In this manner, we do not need to consider the transient behavior of rate adaptation and can focus on the control performance.

In addition, to clearly show the effect of rate adaptation, we use IEEE 802.11g instead of more recent standards. IEEE 802.11g includes two sets of mandatory modulation schemes that are ERP-DSSS/CCK and ERP-OFDM. The parameter values in IEEE 802.11g are shown in Table 1.

TABLE 1 This is sample table caption

Modulation scheme	Parameter	Value
ERP-DSSS/CCK	PLCP preamble	144 bits
	PLCP header	48 bits
	DIFS	50 μs
	SIFS	10 μs
ERP-OFDM	PLCP preamble	16 μs
	PLCP header	4 μs
	DIFS	50 μs
	SIFS	10 μs

Algorithm 1 Iterative algorithm for solving (2) for a given value of the data rate.

Notations: N: the number of physical systems
$s_{\max}$: maximum allowable sampling period
s: sampling period
$\boldsymbol{J}$: control cost
$\boldsymbol{J}_{\text{th}}$: control cost threshold
$\boldsymbol{F}$: network energy consumption
Inputs: $\lambda_1, \dots, \lambda_N$: packet arrival rate
$\mu_1, \dots, \mu_N$: packet service rate
Initialize: $\text{Left}_k \leftarrow 0, k = 1, \dots, N$
$\text{Center}_k \leftarrow \frac{s_{\max,k}}{2}, k = 1, \dots, N$
$\text{Right}_k \leftarrow s_{\max,k}, k = 1, \dots, N$
while 1 **do**
  for $k = 1$ to N **do**
    if $\lambda_k > \mu_k$ **then**
      $\text{RightShift} \leftarrow 1$
    else if $J(s_k) < J_{\text{th},k}$ **then**
      $\text{LeftShift} \leftarrow 1$
    else
      $s_{\text{temp1}} \leftarrow \frac{\text{Right}_k - \text{Center}_k}{2}$
      $s_{\text{temp2}} \leftarrow \frac{\text{Center}_k - \text{Left}_k}{2}$
      if $F(s_{\text{temp1}}) > F(s_{\text{temp2}})$ **then**
        $\text{LeftShift} \leftarrow 1$
      else
        $\text{RightShift} \leftarrow 1$
      end if
    end if
    if $\text{RightShift} == 1$ **then**
      $s_{\text{temp}} \leftarrow \frac{\text{Right}_k - \text{Center}_k}{2}$
      if $J(s_{\text{temp}}) < J_{\text{th},k}$ **then**
        $\text{Center}_k \leftarrow \frac{\text{Right}_k - \text{Center}_k}{2}$
        $\text{Left}_k \leftarrow 0$
        $\text{Right}_k \leftarrow s_{\max,k}$
      else
        $\text{Right}_k \leftarrow \frac{\text{Right}_k - \text{Center}_k}{2}$
      end if
      $\text{RightShift} \leftarrow 0$
    end if
    if $\text{LeftShift} == 1$ **then**
      $s_{\text{temp}} \leftarrow \frac{\text{Center}_k - \text{Left}_k}{2}$
      if $J(s_{\text{temp}}) < J_{\text{th},k}$ **then**
        $\text{Center}_k \leftarrow \frac{\text{Center}_k - \text{Left}_k}{2}$
        $\text{Left}_k \leftarrow 0$
        $\text{Right}_k \leftarrow s_{\max,k}$
      else
        $\text{Left}_k \leftarrow \frac{\text{Center}_k - \text{Left}_k}{2}$
      end if
      $\text{LeftShift} \leftarrow 0$
    end if
  end for
end while

The value of L, which represents the time to transmit a packet, is defined as

$$L = PLCP_P + PLCP_H + \frac{Packet\ size}{PHY\ rate},$$

where $PLCP_P$ and $PLCP_H$ represent the length of time required to transmit the PLCP preamble and the PLCP header. The PHY data rate includes 1, 2, 5.5, and 11 Mb/s in case of ERP-DSSS/CCK and 6, 9, 12, 18, 24, 36, 48, and 54 Mb/s in case of ERP-OFDM. The value of T_S, which represents the time to access channel and transmit a packet, is defined as

$$T_{S_{DSSS}} = DIFS + CW + 3 \times SIFS + L + RTS + CTS + ACK,$$
$$T_{S_{OFDM}} = DIFS + CW + SIFS + L + ACK,$$

where $T_{S_{DSSS}}$ is T_S in ERP-DSSS/CCK, $T_{S_{OFDM}}$ is T_S in ERP-OFDM, and CW is the average length of contention window size. We consider the modulation scheme in the channel is ERP-DSSS/CCK, which allows for backward compatibility with older 802.11 radios.

5.2 | Control performance under uncertain wireless channel

In Section 2, the control system suffers from performance degradation and oscillating instability when the wireless channel condition becomes poor, even though ideal rate adaptation is used. Here, we show the performance of the proposed architecture of W-Simplex.

We set the control parameter **s** as the set of the sampling periods of all the control system, and the network parameter **V** as the set of the contention window values of all the network nodes.

As a control performance metric, we use e^2, the square of the control error e, which is the difference between the system output and the reference. Simply speaking, smaller e^2 implies better control performance. We take into account two types of physical systems, $S1$ and $S2$, which have different system parameters. The system parameters of $S1$ are such that $A = [01; 00]$, $B_1 = B_2 = [0; 1]$, $C = [10]$, $K = [-15\ -\ 8]$, and $W = 1$ and the system parameters of $S2$ are such that $A = [01; 00]$, $B_1 = B_2 = [0; 1]$, $C = [10]$, $K = [-24\ -\ 10]$, and $W = 1$. We assume 20 physical systems, among which the half are $S1$ and the rest half are $S2$. It should be noted that dynamics of both $S1$ and $S2$ are simple, yet effective enough to show unstable behavior under delayed feedback. In fact, the physical system used in simulation is a double integrator, which is representative of many electro-mechanical systems. It will be a subject of future work to investigate the performance of W-Simplex with more specific physical systems.

Figure 8 shows the control performance with a fixed sampling time of 0.05 seconds when the data rate changes from 11 Mb/s to 2 Mb/s due to a poor channel condition at 900 seconds. The upper and lower Figures respectively show the control performance of each type of physical systems. As already expected from Figure 5, the control performance for both types of systems becomes unstable under the data rate of 2 Mb/s.

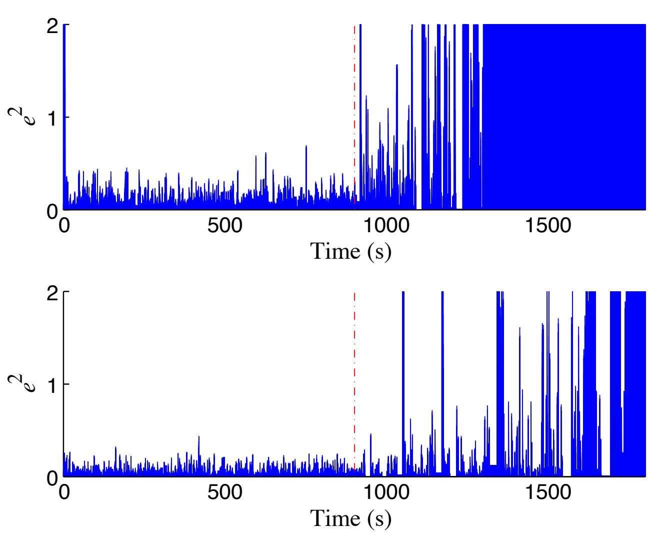

FIGURE 8 Control cost e^2 without Wireless-Simplex when the data rate changes from 11 Mb/s to 2 Mb/s at 900 seconds (upper: S1; lower: S2)

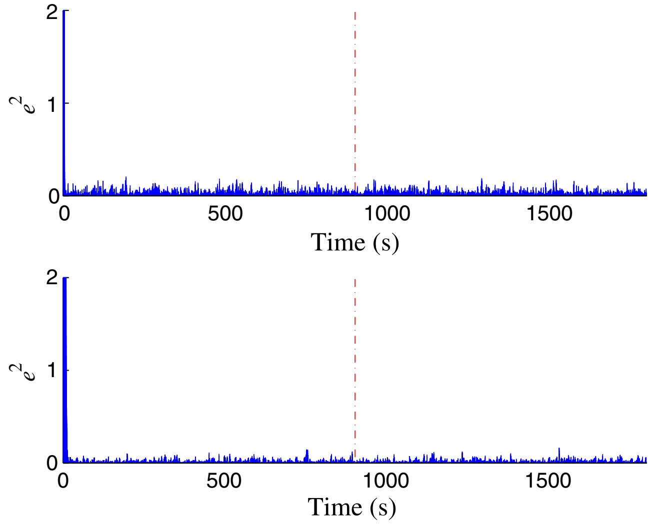

FIGURE 9 Control cost e^2 of Wireless-Simplex when the data rate changes from 11 Mb/s to 2 Mb/s (upper: S1; lower: S2)

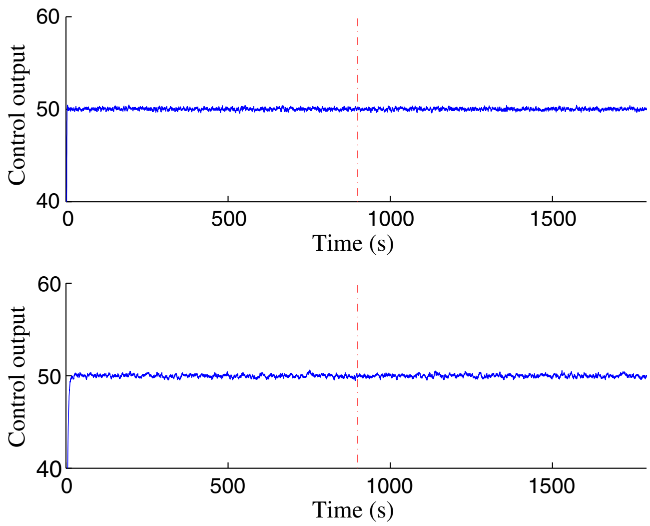

FIGURE 10 Tracking performance of Wireless-Simplex with a reference value of 50 when the data rate changes from 11 Mb/s to 2 Mb/s at 900 seconds

Now, we show the performance of W-Simplex in Figure 9. The sampling periods of $S1$ and $S2$ are respectively tuned to 73.4 ms and 84.9 ms under the PHY data rate of 2 Mb/s. The control cost e^2 of both systems remain quite small values, which implies resilient control performance under wireless channel uncertainty. Figure 10 shows the tracking performance for each type of the physical systems with a reference value of 50. Both types of the systems shows good tracking performance.

Figure 11 shows the control performance of systems when the data rate further changes from 2 Mb/s to 1 Mb/s due to even worse channel condition. The sampling periods of $S1$ and $S2$ are respectively adjusted to 152 ms and 190 ms under the PHY data rate of 1 Mb/s. In this simulation, the lower case of the $S2$ system occasionally shows increased control cost. Nevertheless, we can confirm from Figure 12 that both of the systems remain stable after the data rate change at 900 seconds.

Finally, we show the control cost as a function of the sampling period and the data rate in Figure 13, where we can clearly discover that the sampling periods for stable control performance become larger for lower data rates. Overall, the sampling period is a determining factor for stability of the physical systems while the effect of the network parameter of the contention window is virtually negligible. In fact, the solutions of (2) give that the optimal network parameter of the contention windows remains the same as a value of 32, which implies that the sampling period dominates the control performance, as shown in Figure 13.

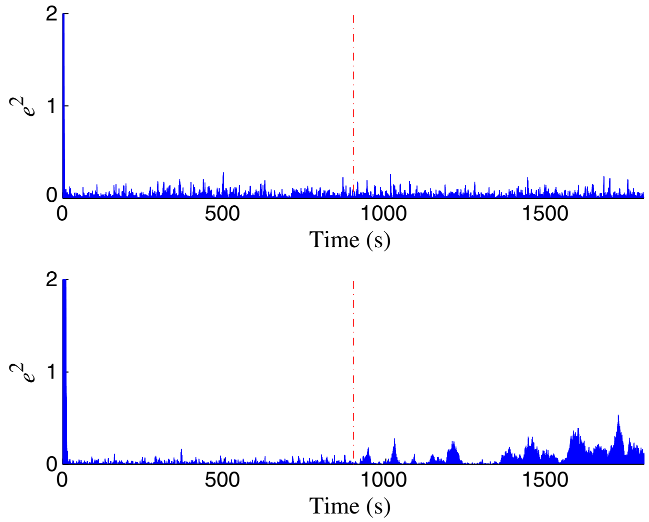

FIGURE 11 Control cost e^2 of Wireless-Simplex when the data rate changes from 2 Mb/s to 1 Mb/s (upper: S1; lower: S2)

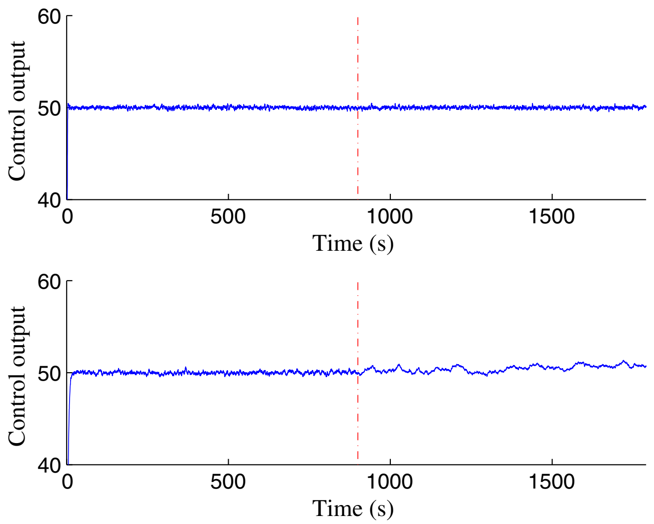

FIGURE 12 Tracking performance of Wireless-Simplex with a reference value of 50 when the data rate changes from 2 Mb/s to 1 Mb/s at 900 seconds

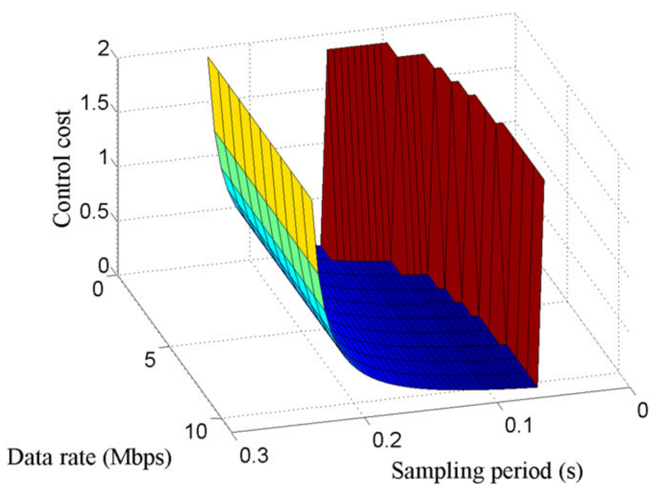

FIGURE 13 Control cost as a function of the sampling period and the data rate

6 | RELATED WORK

There exist extensive works on networked control systems. Hence, we introduce some of recent studies. Interested readers may refer to further information.[18,21,22] Control design for networked control systems has been studied by Wang and Lemmon,[23] Irwin et al,[24] and Mo et al.[25] In the work of Wang and Lemmon,[23] instead of traditional periodic control, event-triggered control schemes are proposed. Irwin et al[24] present a new co-design for CPS with two different predictive control schemes, which are dynamic matrix control and a linear quadratic controller, respectively. Mo et al[25] propose a stochastic model for networked control systems, which considers networked degradations due to transmission delay and packet dropout. However, in these studies, the networks are simply modeled as a source of delay and packet loss, and the details of network protocols are not properly considered.

An optimization formulation for network and control co-design is proposed in the work of Park et al,[13] which corresponds to the conventional co-design framework of (1). In other work of Park et al,[19] a distributed adaptive algorithm is proposed for minimizing power consumption while guaranteeing a given successful packet reception probability and delay constraints in the packet transmission in CPS. The joint optimization of controllers and communication systems is introduced in the work of Sadi et al,[26] which encompasses efficient abstractions of both systems. The objective of the joint optimization is to minimize the power consumption of the communication system. The constraints of the problem are the schedulability and maximum transmit power restrictions of the communication system, and the reliability and delay requirements of the control system to guarantee its stability. These recent studies give network and control co-design methods for CPS. However, the effect of wireless channel uncertainty on quality of control is not considered.

The Simplex architecture is proposed in the work of Sha,[7] which switches between a high performance algorithm and a high assurance one for resolving software errors. The L1Simplex architecture is introduced in the work of Wang et al,[8] which can address both software and physical failures. L1Simplex architecture contains the high-performance controller, the $\mathcal{L}_1$-based high-assurance controller, and the decision logic for controller switching that can efficiently handle a class of software and physical failures. In the work of Yao et al,[27] the NetSimplex is presented, which extends the original Simplex architecture in the work of Wang et al[8] to a networked control environment. NetSimplex addresses the challenge of computing the networked systems's maximum stability region under both network delays and varying parameters.

In summary, even though there have been substantial research on network and control co-design, resilient co-design against wireless channel uncertainty has not been properly addressed so far.

7 | CONCLUSION

In this paper, we have proposed a high-level switching architecture of W-Simplex, which can adaptively tune the network and control parameters for providing resilience against wireless channel uncertainty. In particular, we have shown that rate adaptation may cause severe performance degradation or even instability in networked control systems. We have identified that this phenomenon results from the fact that rate adaptation changes the MAC layer delay, which is a decreasing function of the PHY data rate. In order to resolve the situation, we have incorporated rate adaptation in the conventional co-design framework.

There remain several important issues for future work. It will be an interesting subject of future work to extend the proposed framework by incorporating various cyber-physical attack scenarios.[28] Another direction of future research is to further investigate the mathematical structure of the co-design optimization problem.

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