Efficient Holistic Control: Self-Awareness across Controllers and Wireless Networks

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Abstract
Process automation is embracing wireless sensor-actuator networks (WSANs) in the era of Industrial Internet. Despite the success of WSANs for monitoring applications, feedback control poses significant challenges due to data loss and stringent energy constraints in WSANs. Holistic control adopts a cyber-physical system approach to overcome the challenges by orchestrating network reconfiguration and process control at run time. Fundamentally, holistic control leverages self-awareness across control and wireless boundaries to enhance the resiliency of wireless control systems. In this article, we explore efficient holistic control designs to maintain control performance while reducing the communication cost. The contributions of this work are five-fold: (1) We introduce a holistic control architecture that integrates low-power wireless bus (LWB) and two control strategies, rate adaptation and self-triggered control, specifically proposed to reduce communication cost; (2) We present two online rate selection approaches, namely, heuristic and optimal rate selections; (3) We design novel wireless network mechanisms to support rate adaptation and self-triggered control, respectively, in a multi-hop WSAN; (4) We build a real-time network-in-the-loop simulator that integrates MATLAB/Simulink and a three-floor WSAN testbed to evaluate wireless control systems; (5) We empirically explore the tradeoff between communication cost and control performance under alternative holistic control approaches. Our case studies show that rate adaptation and self-triggered control offer advantages in control performance and energy efficiency, respectively, in normal operating conditions. The advantage in energy efficiency of self-triggered control, however, may diminish under harsh physical and wireless conditions due to the cost of recovering from data loss and physical disturbances.

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Process automation is embracing wireless sensor-actuator networks (WSANs) in the era of Industrial Internet. Despite the success of WSANs for monitoring applications, feedback control poses significant challenges due to data loss and stringent energy constraints in WSANs. Holistic control adopts a cyber-physical system approach to overcome the challenges by orchestrating network reconfiguration and process control at run time. Fundamentally, holistic control leverages self-awareness across control and wireless boundaries to enhance the resiliency of wireless control systems. In this article, we explore efficient holistic control designs to maintain control performance while reducing the communication cost. The contributions of this work are five-fold: (1) We introduce a holistic control architecture that integrates low-power wireless bus (LWB) and two control strategies, rate adaptation and self-triggered control, specifically proposed to reduce communication cost; (2) We present two online rate selection approaches, namely, heuristic and optimal rate selections; (3) We design novel wireless network mechanisms to support rate adaptation and self-triggered control, respectively, in a multi-hop WSAN; (4) We build a real-time network-in-the-loop simulator that integrates MATLAB/Simulink and a three-floor WSAN testbed to evaluate wireless control systems; (5) We empirically explore the tradeoff between communication cost and control performance under alternative holistic control approaches. Our case studies show that rate adaptation and self-triggered control offer advantages in control performance and energy efficiency, respectively, in normal operating conditions. The advantage in energy efficiency of self-triggered control, however, may diminish under harsh physical and wireless conditions due to the cost of recovering from data loss and physical disturbances.

CCS Concepts: • Networks → Sensor networks; • Computer systems organization → Sensor networks.

Additional Key Words and Phrases: industrial wireless control, multi-hop mesh network, network reconfiguration, network-in-the-loop simulation, cyber-physical systems, rate adaptation

1 INTRODUCTION

Wireless sensor-actuator networks (WSANs) are being adopted in industrial process automation for their advantages in reducing deployment and maintenance cost. While existing WSANs are usually used for monitoring, it remains challenging to support feedback control loops over WSANs, which is referred to as wireless networked control system (WNCS) [1]. First, compared with traditional networked control systems (NCSs) with wired networks, the control performance of WNCS can be compromised by data losses due to dynamic channel conditions in WSANs. This is largely unacceptable because control performance is closely related not only to the factory’s profits, but also machine operator’s safety and the environment. Second, a wireless device that requires a power cord is often impractical in industry settings (e.g., ABB [2] and Emerson [3]). In practice, an independent and reliable power supply – battery – is often mandatory, but with the disadvantage of their finite energy. Given the difficulty to replace batteries in harsh industrial environments, to ensure a reliable connection between the control center and the sensors and actuators despite the long distance, the key to the design of field devices and wireless standards (e.g. WirelessHART) is to maximize the battery life of the devices such that they could be battery powered for 4 to 10 years. Therefore, it is crucial to improve

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the energy efficiency of WSANs while maintaining control performance in a WNCS. Finally, WNCS must be resilient to both disturbance to the physical plant and external interference to the wireless networks. Therefore, a practical and dependable industrial WNCS must meet the following requirements: (1) control performance, which brings economic benefits; (2) energy efficiency, which reduces maintenance cost; and (3) resiliency, which prevents accidents.

Traditionally, the wireless network and the physical process are managed separately in a WNCS at run time. The lack of coordination between network and plant management forces conservative designs that trade energy for control performance. For example, a WNCS may rely on high sampling rates to guarantee control performance under worst-case conditions, even though the same sampling rates may result in excessive communication cost under normal conditions. Conversely, a less conservative design may result in a fragile system vulnerable to physical disturbance and/or wireless interference. In contrast to the traditional approach, the holistic control approach aims to enhance the resiliency and efficiency of WNCS by cojoining network reconfiguration and process control [4].

In this work we explore efficient holistic control designs to maintain control performance at low energy cost. We develop holistic control approaches that incorporate two alternative strategies, rate adaptation (RA) and self-triggered control (ST). We note that RA introduces adaptation in a traditional time-driven control framework, while ST is a representative event-driven control approach. Exploring both strategies in holistic control allow us to investigate the design tradeoff involved in holistic control design. Specifically, the contributions of this work are five-fold.

- We introduce a new holistic control architecture that integrates multi-hop wireless networks running the Low-power Wireless Bus (LWB) protocol and two alternative control strategies, RA and ST;
- We present two online RA approaches based on heuristics and optimal rate selections, respectively, and establish stability of the resultant closed-loop control system;
- We design robust network adaptation mechanisms to support RA and ST, respectively, in multi-hop LWB networks;
- We build RT-WCPS, a real-time network-in-the-loop simulator that integrates MATLAB/Simulink and a physical WSAN testbed to evaluate wireless control systems;
- We empirically explore the tradeoff between communication cost and control performance under alternative holistic control approaches.

Our case studies show that RA and ST offer advantages in control performance and energy efficiency, respectively, in normal operating conditions. The advantage in energy efficiency of ST, however, may diminish under harsh physical and wireless conditions due to the cost of recovering from data loss and physical disturbance.

The rest of the article is organized as follows: Sec. 2 reviews related works on WNCS designs. Sec. 3 introduces the system architecture of holistic control systems. Secs. 4 and 5 detail the control and network designs of RA and ST. Sec. 6 presents the real-time wireless cyber-physical simulator (RT-WCPS), and Sec. 7 analyzes the experimental results.

2 RELATED WORK

WNCSs comprise distributed sensors, actuators, and controllers communicating through wireless networks. Due to the benefits of flexibility and low deployment and maintenance cost, WNCSs are expanding their applications over industry processes, autonomous warehouses and smart factories [5]. However, WNCSs face serious challenges due to the inherent dynamics in wireless conditions and limited energy resources in wireless networks [6]. The problem of resilient and efficient wireless control has been investigated in the fields of control theory, wireless networks, and more recently network-control co-designs [1].

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In control theory, state observers [7] (e.g., extended Kalman filter) have been introduced to handle packet loss and communication latency in WNCSs. To reduce communication cost, aperiodic control has been proposed as an alternative to periodic control. Examples include event-triggered control [8, 9] and self-triggered control [10]. However, existing implementation of aperiodic control was based on a single-hop wireless network [11] instead of the multi-hop WSANs that are widely adopted in process industries due to their flexibility and scalability in industrial environments. Supporting aperiodic control on a multi-hop WSAN is challenging because industrial WSAN standards usually employ TDMA protocols for predictable communication. The aperiodic communication triggered by aperiodic control is incompatible with the periodic, time-driven nature of communication in industrial multi-hop WSANs.

In wireless networks, given the latency, packet delivery, and energy consumption bounds by control designers, network designs can achieve optimized energy-efficiency [12], reliability [13], load balancing [14], and real-time performance [15] under various wireless channel conditions and network topologies. Breath [12] is proposed to minimize the energy cost while ensuring a desired packet delivery rate and delay of the WSAN by adjusting routing, MAC, radio power and sleeping discipline. SchedEX [13] is proposed to minimize delay while providing reliability guarantees by producing the TDMA schedule. QU-RPL [14] achieves load balancing and improves end-to-end reliability based on queue utilization. Blink [15] supports hard real-time communication in multi-hop WSAN at low energy cost. However, few of those protocols are cognizant of control performance directly. Better network performance does not always imply good control performance of the physical plant. Indeed, the internal properties of the physical plant, such as its stability, inherently influence the impact of improvements in network communication on control performance.

Recent effort on network-control co-design aims to jointly optimize the network and control at design time. Previous works on sampling rate optimization [16–20] exploit the freedom of sampling rates to optimize control performance under various network protocols and system settings. For wired control, Li et al. [16] minimize useful information loss under network bandwidth constraints. Our project differs from this work in the objective of optimizing control performance while lowering energy cost of WSAN. Goswami et al. [17] handle both real-time and control performance constraints by modeling ECUs over a FlexRay bus. While the work is based on a wired network, FlexRay shares similarities to LWB used in our system in their TDMA-based scheduling approach. Our project differs from the work in our focus on online rate adaptation, while Goswami et al. tackled the optimization problem of offline optimization. Furthermore, we also address self-triggered control approaches and network adaptation protocols.

For wireless control, Demirel et al. [18] design packet forwarding policies over an unreliable and energy-constrained WSAN; Saifullah et al. [19] optimize sampling rates under the end-to-end deadline constraints of data flows in a WirelessHART mesh network; Kim et al. [20] focus on control over IEEE 802.11 networks. Asymmetric routing [21] enhances control performance and network efficiency by applying different routing strategies to sensing and actuation data flows since sensing and actuation can have different levels of robustness to packet loss. However, all these efforts focus on offline designs instead of online adaptation, which limits the resiliency and efficiency of WNCS operating in dynamic conditions (e.g., under network interference and physical disturbance; under transient state or steady state). Online rate optimization has been investigated in [22–24] for different objectives. Specifically, Bai et al. [22] minimize tracking error under the constraints of network capacity and delay requirement; Bao et al. [23] optimize the control performance over noisy channels under total bit-rate constraint; Colandairaj et al. [24] adapt sampling rates using a static sampling policy based on control performance and network performance in an IEEE 802.11b network.

This article considers the energy cost of WSANs, and the design and implementation of the network reconfiguration mechanisms for RA over a multi-hop WSAN under the LWB protocol, which are not addressed by these previous works. In prior work [4], we proposed the concept of holistic control that co-joins network management and physical
control at run time. As a simple proof of concept, we presented a holistic control example that adjusts the numbers of
transmissions (Tx's) based on physical states. In this article, we generalize the designs of holistic control by incorporating
more sophisticated control approaches, namely RA and ST. The new control approaches require more sophisticated
network reconfiguration mechanisms that are both efficient and robust. Furthermore, the alternative control approaches
(time-driven vs. event-driven) allow us to explore the design tradeoff involved holistic control in multi-hop WSANs.

It is challenging to conduct experiments on industrial control systems in the field, especially under cyber and physical
disturbances. Lab-scale equipment, on the other hand, is usually too small for realistic cyber-physical experiments,
particularly for multi-hop wireless networks. Therefore, simulation tools are of vital importance to WNCS. Truetime [25]
is a MATLAB/Simulink-based tool, which enables simulations of CPU scheduling, communication and control algorithms.
NCSWT [26] integrates MATLAB/Simulink and NS-2 for modeling and simulation of NCSs. Neither of the native
wireless simulations of Truetime nor the NS-2 simulator can accurately model the probabilistic and irregular packet
receptions of WSANs [27, 28]. WCPS [29] integrates MATLAB/Simulink and TOSSIM [30] specifically designed to
emulate complex temporal link dynamics of WSANs. However, given the complexity of wireless communication in
physical environments, simulators cannot always capture the real-world behavior of WSANs. Network-in-the-loop
simulations have recently been developed to address the limitation of wireless simulations by incorporating physical
network. Baumann et al. [32–34] integrate two real inverted pendulums and a 13-node multi-hop WSAN testbed,
achieving sampling rates of tens of millisecond. However, the physical plants in laboratory settings used in those
experiments cannot represent large-scale industrial processes and are limited to the specific lab-scale physical plants.
In this work, we design and implement a general network-in-the-loop simulator which integrates MATLAB/Simulink
simulations and a 70-node WSAN testbed.

3 WIRELESS CONTROL SYSTEM ARCHITECTURE

Fig. 1 depicts the holistic wireless control architecture. The holistic controllers (1) control the physical plants by
communicating with sensors and actuators through a multi-hop WSAN, and (2) reconfigure the WSAN based on control
needs at run time. Multiple control loops share the same WSAN. As shown in Fig. 1, at time t, a sensor sends its
measurements yt to a remote holistic controller over the multi-hop WSAN. A state observer [7] estimates the state of the
plant. Based on the estimated state ̂xt, the holistic controller generates both (1) the control commands (ut) and (2) the
network reconfiguration signal (Rt or Tn). Two instances of holistic controller, namely RA and ST, are introduced. For
RA (or ST), the control commands ut and the updated sampling rate R(t or next event time Tn) generated by the holistic
controller are sent to the WSAN through flooding. For the control commands, the actuator receives ut and applies ̂ut to
the physical plant. If ̂ut fails to be delivered by the deadline, the actuator reuses the control input received in the last
period, ̂ut−1. For network reconfiguration, every node in the network reconfigures its communication schedule based
on Rt or Tn. The details of control and network designs for RA and ST are presented in Sec. 4 and Sec. 5, respectively.
3.1 Physical control system

In this article, control design and analysis are performed for the physical plant which can be modelled as a linear time-invariant system (LTI) as follows

\[ x_{t+1} = Ax_t + Bu_t, \quad y_t = Cx_t, \]  

(1)

where \( t \) is the time index, \( x_t \in \mathbb{R}^n \) is the state vector, \( u_t \in \mathbb{R}^m \) is the input vector, \( y_t \in \mathbb{R}^p \) is the output vector, \( A \in \mathbb{R}^{n \times n} \), \( B \in \mathbb{R}^{m \times n} \), and \( C \in \mathbb{R}^{p \times n} \). We assume that the pair \((A, B)\) is controllable and that the pair \((A, C)\) is observable. This implies the existence of a linear state feedback controller \( u_t = Kx_t \) which renders the closed-loop control system asymptotically stable. Note that the proposed wireless network reconfiguration mechanisms however are not limited to LTI systems, and are applicable to nonlinear and time-varying systems.

The stability analysis of the resultant control system can be conducted by using the Lyapunov theory. System (1) is stable if there exists a positive definite Lyapunov function [35]

\[ V(x_t) = x_t^T Px_t, \]  

(2)

such that

\[ V(x_{t+1}) - V(x_t) = x_t^T ((A + BK)^T P(A + BK) - P)x_t = -x_t^T Qx_t, \]  

(3)

where \( P, Q \) are positive definite matrices. In other words, \( P \) and \( Q \) satisfy the discrete-time Lyapunov equation:

\[ (A + BK)^T P(A + BK) - P = -Q. \]  

(4)

3.2 Wireless sensor-actuator network

3.2.1 Low-Power Wireless Bus (LWB). The WSAN extends the LWB [36] protocol to support data communication and network reconfiguration for holistic control. LWB is based on Glossy [37], a fast-flooding protocol that exploits the constructive interference among concurrent transmissions of radios compatible with the IEEE 802.15.4 standard. The flooding process is entirely driven by radio events, i.e., a transmission is triggered by completing a packet reception, which drastically speeds up the process and provides microsecond-level WSAN synchronization. Under LWB, nodes take turns to flood their packets in a time-triggered fashion using Glossy flooding according to a single global schedule. A sink node is responsible for disseminating the schedule to all the nodes in the network. Thus, the multi-hop many-to-all communication can be regarded as a single communication resource (shared bus) that runs on a single clock [15].

Adopting LWB as the underlying communication protocol brings significant benefits. Thanks to Glossy flooding, communication in LWB is topology independent. Besides, LWB is a wireless protocol that provides deterministic end-to-end latency given a global schedule [36], which largely simplifies the analysis of system stability over the multi-hop WSAN. Additionally, fast Glossy flooding achieves propagation latency within 10 ms over 100 nodes (8 hops, 3 Txs). We can take the advantage to realize fast network reconfiguration by quickly flooding network configurations across the entire network, an important feature as network reconfiguration is a key element of holistic control.

3.2.2 Implicit scheduling of multi-rate LWB. Unlike prior work [15] which uses a centralized scheduler node to operate scheduling algorithms, we tailored LWB for implicit scheduling. All nodes schedule themselves based on information from holistic controllers, such as flooding rates or next event timers of each control loop. We define a data flow of WSAN as \( f_{i,j} \), which transmits data from a source node \( s_{i,j} \) to a destination node \( d_{i,j} \), where \( i \in \{1, 2, ..., n\} \) is the control loop index, and \( j \in \{1, 2, ..., m_i\} \) is the flow index of the control loop \( i \) (\( l_i \)). Accordingly, \( n \) is the number of control loops, and \( m_i \) is the number of data flows in \( l_i \). For example, the control loop \( l_1 \) has two data flows \( f_{1,1} \) and \( f_{1,2} \).
among which $f_{1,1}$ is a sensing flow transmitting measurements from a sensor node ($s_{1,1}$) to a controller node ($d_{1,1}$), and $f_{1,2}$ is an actuation flow transmitting control command from a controller node ($s_{2,2}$) to an actuator ($d_{1,2}$). A MIMO control loop can have multiple sensing and actuation flows. The update rate of control commands in the control loop $i$ is denoted as $R_i$. The operation period of $i$ is $T_i = \frac{1}{R_i}$. We assume the rates of the flows in one control loop are equal.

In implicit scheduling of data flows, each node stores a static global schedule of all data flows, denoted by entries $f_{i,j}(t_{i,j}, d_{i,j}, t_{i,j})$. $t_{i,j}$ is the relative time slot reserved for flow $f_{i,j}$ in LWB period $T = \frac{1}{R}$. LWB operates at the highest rate of all the control loops, $R = \max_{1 \leq i \leq n} R_i$. Fig. 2 shows a simple static schedule. We assume there are three control loops and each loop has one flow. All loops have the same rate $R$. Let $R_1 = R_2 = R_3 = \frac{1}{T}$. Then, the rate of LWB is $R = \frac{1}{T}$. Therefore, we get the static schedule entries: $f_{1,1}[2, 1, 1], f_{2,1}[3, 4, 2], f_{3,1}[4, 1, 3]$. In each period $T$, the synchronization message $S$ is flooded by the sink node in the beginning of every period, followed by three data slots assigned for three flows.

**Fig. 2.** LWB with static global schedule. ($f_{1,1}, node2 \rightarrow node1, \frac{1}{T} Hz; f_{2,1}, node3 \rightarrow node4, \frac{1}{T} Hz; f_{3,1}, node4 \rightarrow node1, \frac{1}{T} Hz$)

This static schedule is calculated assuming each control loop runs at its highest candidate rate. The static schedule can be calculated offline using any scheduling algorithm, e.g., EDF or RM. In practice, industrial process control systems usually run at sampling rates lower than 1 Hz [38]. By adopting fast Glossy flooding (flooding a packet over 100 nodes within 10 ms [37]), WSAN can guarantee the schedulability of tens of data flows, which suggests the feasibility of the static schedule. We refer interested readers to [15, 39] for network designs with tighter real-time requirements.

To implement multi-rate LWB using implicit scheduling, besides the static global schedule, the only information that all nodes need are the rates of all the control loops $R_i$. In order to make the implicit scheduling work properly, the potential $T_i$ of all the loops should be set to integral multiples of the shortest period $T$. Then each node can independently decide whether to flood $f_{i,j}$ or sleep at $t_{i,j}$ within the time interval $[(k-1)T, kT], k = 1, 2, 3, \ldots$, depending on $R_i$. Fig. 3 shows an example of the implicit scheduling with the static schedule in Fig. 2, where $R_1 = \frac{1}{T}, R_2 = \frac{1}{7T},$ and $R_3 = \frac{1}{7T}$. All nodes flood $f_{1,1}$ at the first data slot of every period $T$, flood $f_{2,1}$ at the second data slot every other period $T$, and flood $f_{3,1}$ at the third data slot every $4T$. They sleep at the rest blank data slots.

**Fig. 3.** Implicit scheduling. ($f_{1,1}, node2 \rightarrow node1, \frac{1}{T} Hz; f_{2,1}, node3 \rightarrow node4, \frac{1}{7T} Hz; f_{3,1}, node4 \rightarrow node1, \frac{1}{7T} Hz$)

In implicit scheduling, since each node stores the static schedule, the network reconfiguration commands can be generated by any source nodes in WSAN distributively, in contrast to centralized scheduling in which the whole schedule is sent by the sink in the beginning of each period $T$. We will present how network reconfiguration signals, such as $R_i$, are disseminated in Sec. 4.2 and 5.2.

### 3.3 Holistic management

As shown in Fig. 4, we develop a holistic control architecture that bridges the gap between the plant control and WSAN management. Based on the current status of physical plants and WSAN, the holistic controller generates two kinds of commands at the same time, one for dynamically adjusting the network configuration, and the other for operating the physical plants. In the following two sections, we focus on two specific efficient holistic control designs: rate adaptation and self-triggered control over a multi-hop mesh network.
We propose two online RA strategies. First is a heuristic-based RA which selects rate based on physical states and described by (7). We set this upper bound as the trigger of succeeding rate increases.

Based on (5), we have

Given a customized state error bound, denoted as \( s_e \), we set the rate increasing threshold \( V_{th} = \lambda_1 ||s_e||^2 \). Furthermore, we adopt a more stringent decreasing threshold \( V_{Dth} = \lambda \alpha_1 ||s_e||^2, \lambda \in (0, 1) \). If \( V(x_t) \) remains below \( V_{Dth} \) for a customized time interval \( \tau \), the control system is regarded in good condition. Given (3),

\[
V(x_{t+1}) - V(x_t) \leq -\beta ||x_t||^2, \tag{6}
\]

where \( \beta \) is the smallest eigenvalue of \( Q \). Given (5) and (6), we can get the upper bound of the ideal Lyapunov function, described by (7). We set this upper bound as the trigger of succeeding rate increases.

\[
V(x_{t+1}) \leq (1 - \beta/\alpha_2) V(x_t). \tag{7}
\]

The heuristic RA algorithm of a holistic controller is presented in Alg. 1, and its complexity is \( O(1) \).
4.1.2 Optimal rate adaptation. A disadvantage of the aforementioned heuristics-based RA is that it requires hand tuning that can be challenging for complex control systems. Furthermore, it does not offer a systematic way to balance control system performance and communication cost, the two important and conflicting concerns in wireless control systems. Henceforth, we formulate rate selection as an optimization problem. The objective of the optimization problem is to minimize a cost function that incorporates both control performance and communication cost.

As described in Sec. 3.2.2, each candidate period of a feedback control loop is an integral multiple of the smallest sampling period $T$. Let $T_s = n_s T$ be the least common multiple of all candidate periods of a feedback control loop. In order to compare the control performance resulting from different rates, we rewrite all possible systems with different sampling rates in the slowest time frame $T_s$ in a process referred to as lifting [40].

By lifting the system in the slowest time frame $T_s$, the system is given by

$$x_{t+n_s T} = A_{d_1}^{n_s} x_t + \left[A_{d_1}^{n_s-1} B_{d_1} \cdots B_{d_1}\right] \begin{bmatrix} u_{t,1} \\ \vdots \\ u_{t+(n_s-1)T,1} \end{bmatrix}$$

where $u_{t+iT,1}$ is the control input during time interval $[t+iT, t+(i+1)T]$, and $A_{d_1} = e^{A_c T}$, $B_{d_1} = \int_0^T e^{A_c (T-r)} B_{c} dr$, where $A_c$ and $B_c$ are the system matrices of the original continuous system dynamics $\dot{x} = A_c x + B_c u$. For the lowest sampling rate $1/T_s$, the corresponding system does not need lifting and has the dynamics

$$x_{t+n_s T} = A_{d_1}^{n_s} x_t + B_{d_1} u_{t,n_s}$$

where $u_{t,n_s}$ is defined over $[t, t+n_s T)$, and $A_{d_1} = e^{n_s A_c T}$, $B_{d_1} = \int_0^{n_s T} e^{A_c (n_s T-r)} B_{c} dr$. To make a fair evaluation for systems resultant from different rates, we rewrite the slowest system (9) as follow

$$x_{t+n_s T} = A_{d_1}^{n_s} x_t + \left[A_{d_1}^{n_s-1} B_{d_1} \cdots B_{d_1}\right] \begin{bmatrix} u_{t,n_s} \\ \vdots \\ u_{t+(n_s-1)T,n_s} \end{bmatrix} = A_{d_1}^{n_s} x_t + \sum_{i=0}^{n_s-1} A_{d_1}^{i} B_{d_1} u_{t,n_s}$$

where $u_{t,n_s} = u_{t+iT,n_s}$, $i \in \{0, \ldots, n_s - 1\}$, and $A_{d_1} = A_{d_1}^{n_s}$. Finally, we can rewrite the system dynamics of loop $i$, depending on the rate $R_i$, as follows

$$x_{t+n_s T} = A_{d_1}^{n_s} x_t + \sum_{i=1}^{n_s-1} A_{d_1}^{i} B_{d_1} u_{t+iT,1}, \text{ if } R_i = 1/T$$

$$x_{t+n_s T} = A_{d_1}^{n_s} x_t + \sum_{i=1}^{n_s-1} A_{d_1}^{i} B_{d_1} u_{t+iT,k}, \text{ if } R_i = 1/(kT)$$

$$x_{t+n_s T} = A_{d_1}^{n_s} x_t + \sum_{i=1}^{n_s-1} A_{d_1}^{i} B_{d_1} u_{t,n_s}, \text{ if } R_i = 1/T_s$$

Based on (11), the states and inputs of systems with all candidate rates are lifted to the lowest rate. We are now ready to formulate rate selection as an optimization problem. Let us evaluate the cost function over a horizon of $N$ sample periods corresponding to the lowest sample rate, i.e., the horizon for performance evaluation lasts $N T_s$ seconds. Since each loop can select its rate individually, we can formulate $n$ independent optimization problems, where $n$ is the number of feedback control loops. Coordination between different control loops is part of our future work. The optimization problem for loop $i$ has decision variables of an $N$-dimensional vector $R_i(k)$, where its $k$th element $R_i(k)$ represents the sample rate during the time interval $[t + (k-1)T_s, t + kT_s]$. Finally, the cost function is defined as a
weighted combination of control performance and communication cost:
\[
J(x_t, R_i) = \sum_{j=0}^{N-1} \{x_{t+j}^T T_\tau x_{t+j}(R_i(j)) + e_1 u_{t+j}^T (R_i(j)) + e_2 R_i(j)\},
\]
(12)
where \(x_{t+j}\) is predicted based on (11) given \(x_t\) and control law, \(x_{t+j}(R_i(j))^T W_Q x_{t+j}(R_i(j)) + e_1 u_{t+j}^T (R_i(j)) + e_2 R_i(j)\) represents control performance including state cost and control cost, \(W_Q, W_R\) set relative weights of state deviation and control effort, \(x_{t+j}\) denotes \(x_{t+j}^T T_\tau x_{t+j}\), and
\[
u_{t+j} = \begin{cases} 
[u_{t+j} T_\tau, \ldots, u_{t+j} T_\tau (n_s-1) T_\tau, 1]^T, & \text{if } R_i(j) = 1/T \\
\vdots \\
[u_{t+j} T_\tau, n_s, \ldots, u_{t+j} T_\tau (n_s-1) T_\tau, n_s]^T, & \text{if } R_i(j) = 1/T_\tau 
\end{cases}
\]
In (12), the communication cost is linearly proportional to sampling rate \(R_i(j)\). Constant \(e_1\) is to weight state error versus control cost, and \(e_2\) is to weight control performance versus communication cost. When \(e_2\) approaches 0, which means that network energy cost is ignored, the WNCS is prone to stay at the fastest sampling rate to achieve better control performance. We define this scenario as cheap network in analogy with cheap control, which is the case \(W_R = 0\) when evaluate control performance. As a result, the optimization problem of loop \(i\) can be written as follows
\[
\begin{align*}
\text{minimize} & \quad J(x_t, R_i) \\
\text{subject to} & \quad R_i = [R_i(1), \ldots, R_i(N)]^T, \text{ with } R_i(k) \in \{R_{L,i}, \ldots, R_{U,i}\} \\
& \quad x_{t+j} = \begin{cases} 
A_{d1}^{n_s} x_{t+j-1} + \sum_{l=1}^{n_s-1} A_{dl}^{n_s} B_{dl} u_{t+j-1} x_{t+j-1}, & \text{if } R_i(j) = 1/T \\
\vdots \\
A_{d1}^{n_s} x_{t+j-1} + \sum_{l=1}^{n_s-1} A_{dl}^{n_s} B_{dl} u_{t+j-1} x_{t+j-1}, & \text{if } R_i(j) = 1/T_\tau 
\end{cases} \\
& \quad u_t = K x_t.
\end{align*}
\]
The optimization problem (13) has \(N\) integer decision variables. Since the decision variables \(R_i(j)\) belongs to a finite set of candidate rates, the optimal rate adaptation problem is an integer programming problem, which could be computationally expensive to solve at every sampling period. To reduce the computational complexity, we simplify (13) by assuming that the control system stays at the same rate over the horizon, i.e., \(R_i(1) = \cdots = R_i(N) = R_i\). Accordingly, the cost function is given by
\[
J(x_t, R_i) = \sum_{j=0}^{N-1} \{x_{t+j}^T T_\tau x_{t+j}(R_i) + e_1 u_{t+j}^T (R_i) + e_2 R_i\}.
\]
(14)
The simplified optimization problem takes the following formulation
\[
\begin{align*}
\text{minimize} & \quad J(x_t, R_i) \\
\text{subject to} & \quad R_i \in \{R_{L,i}, \ldots, R_{U,i}\} \\
& \quad x_{t+j} = \begin{cases} 
A_{d1}^{n_s} x_{t+j-1} + \sum_{l=1}^{n_s-1} A_{dl}^{n_s} B_{dl} u_{t+j-1} x_{t+j-1}, & \text{if } R_i = 1/T \\
\vdots \\
A_{d1}^{n_s} x_{t+j-1} + \sum_{l=1}^{n_s-1} A_{dl}^{n_s} B_{dl} u_{t+j-1} x_{t+j-1}, & \text{if } R_i = 1/T_\tau 
\end{cases} \\
& \quad u_t = K x_t.
\end{align*}
\]
(15)
Although the simplified optimization problem (15) is an integer programming problem, for each loop \( i \) it has only one scalar decision variable \( R_i \) (instead of \( N \) in (13)). Furthermore, the number of candidate rates is usually small in practice, which significantly reduces the computation complexity. We solve the optimization problem by brute force search. Note that the system matrices of rate lifting can be calculated offline. Given a horizon of \( N \), \( M \) candidate rates, and 
\[
 n_s = \left\lceil \frac{T}{T_i} \right\rceil, \text{ the computation complexity is } O(MNn_s).
\]
We also evaluate the computation cost in MATLAB/Simulink on a 2.5 GHz Intel Core i7 processor. The settings of the experiments are the same as in Sec. 7.2.2 (\( n_s = 2^{M-1} \)). Fig. 5 shows the execution time of solving (15) for 2000 times. As shown in Fig. 5A, with candidate rates \( M = 3 \), the median and worst-case execution time when horizon \( N < 25 \) is below 1 ms and 2.1 ms, respectively. As shown in Fig. 5B, with \( N = 10 \), the median and worst-case execution time when \( M \leq 6 \) is below 4 ms and 11 ms, respectively. The execution time is negligible compared with the 1 s sampling period. These results show that the problem (15) is online solvable.

**Remark 4.1.** Since we target industrial process control systems with sampling rates lower than 1 Hz [38], we tailor the rate selection for our WSAN design with an assumption of the existence of “worst-case-guaranteed” schedule in Sec. 3.2. Hence there is no network resource/schedulability constraint, and the rate selections of multiple loops can be done individually.

For systems with schedulability constraints, we can provide schedulability guarantee by generalizing the optimal RA problems (13) and (15) to incorporate schedulability constraints. We replace the objective function in [19] Eq.(8) by 
\[
 \sum_{i=1}^{N} f(x_i, R_i) \] 
and adding system dynamic constraints (11) of all loops. Since we apply LWB, as studied in [15], the real-time scheduling constraints can be simplified from multi-processor task scheduling in [19] to uni-processor case. However, given that the configuration space of the corresponding centralized optimization problem is much larger than (13) and (15), and the introduce of schedulability constraints, the resultant optimization problem can be computationally expensive to solve online. In addition, this approach requires centralized management of the control loops. Extending our work to consider schedulability constraint is part of future work.

### 4.1.3 Stability analysis

Deploying the aforementioned RA algorithms renders the closed-loop control system being a switched system, whereas the switch is governed by the RA algorithm. Since it is difficult, if not impossible, to formulate the analytic formula of the switching sequence, we borrow the stability result for switched systems with arbitrary switching. Stability analysis tools for switched systems can be found in [42] and references therein. This work performs stability analysis and control design based on a well-received result: if there exists a common Lyapunov function for all subsystems, then the stability of the switched system is guaranteed under arbitrary switching. It is revealed that the construction of such a common Lyapunov function among all candidate rates can be formulated as a Linear Matrix Inequality (LMI) problem: solves for \( P \) satisfying

\[
 (A(R_i) + B(R_i)K)^\top P(A(R_i) + B(R_i)K) - P < 0, \quad \forall R_i \in \{R_{i,1}, \ldots, R_{i,s}\}
\]  

where \( A(R_i) \) and \( B(R_i) \) are discretized system matrices of loop \( i \) corresponding to the sample rate \( R_i \). If there is a feasible solution for the LMI problem (16), then \( V(x_t) = x_t^\top Px_t \) is the common Lyapunov function of all candidate rates, and the stability is established.
The aforementioned stability analysis, in a deterministic setting, provides a strategy to search for a common Lyapunov function $V(x_t)$ that is used in Sec. 4.1.1. As described in Sec. 3.2.1, the latency bound of LWB is deterministic [36, 37]. In our test cases, the latency is shorter than one sampling period. Stability analysis under network latency of below one sampling period is well studied. We refer interested readers to [32, 43]. The stability analysis can be generalized to take indeterministic network latency and packet loss into account, which consequently leads to stochastic stability. Stability analysis under different network scenarios has been intensively studied in control community, and are not the focus of this article. We refer interested readers to stability analysis addressing network latency [43, 44] and packet loss with different distribution patterns [45, 46]. Despite the simplifications, our stability analysis provides practical guidance towards balancing the closed-loop control performance and network rate in real-world scenarios involving network latency and packet loss, as shown in case studies under network and physical interference in Secs. 7.4-7.6.

**Remark 4.2.** The existence of a single common Lyapunov function (16) for all candidate rates is a conservative but easy-to-check stability condition. The relaxation of conservativeness has been intensively studied in control community, and leads to numerous results [47-49]. For example, work [47] proposed to replace the single common Lyapunov function with a switched Lyapunov function, and established a sufficient condition of stability as stated in the following theorem.

**Theorem 4.3** ([47], Thm. 4). If there exist symmetric matrices $S(R_i)$, matrices $G(R_i)$ and $U(R_i)$ such that $V(R_i, R_j)$

\[
\begin{pmatrix}
G(R_i) + G(R_j)^T & (A(R_i)G(R_i) + B(R_i)U(R_j))^T \\
A(R_i)G(R_i) + B(R_i)U(R_j) & S(R_j)
\end{pmatrix} > 0
\] (17)

then the gain of state feedback control

\[
K(R_i) = U(R_i)G(R_i) \forall R_i \in \{R_{i,1}, \ldots, R_{i,s}\}
\] (18)

stabilizes the system.

The results in [47] shows the tradeoff between a single Lyapunov function for simplicity and a switched Lyapunov function that is less conservative but numerically hard to check.

### 4.2 Network reconfiguration

In this section, we present a run-time RA protocol for a mesh WSAN. Packet loss has non-negligible impacts on WNCS, especially in the process of network reconfiguration. In the end of this section, we discuss packet loss recovery of RA.

**4.2.1 Candidate rates selection.** Sec. 4.1 considers how to adjust the rate of each loop. The candidate rates are also important design factors. To ensure that the rate transient processes work properly, the potential rates of each loop need to be designed intentionally. First, according to Sec. 3.2.2, when the offline scheduler schedules data flow $f_{i,j}$, it reserves time slots for fastest rate $R$. Second, the candidate periods of all the loops should be integral multiples of the shortest period $T = \frac{1}{R}$. Third, to ensure that the RA works properly with packet loss recovery, which will be discussed later in Sec. 4.2.3, the candidate rates of each loop should be harmonic, e.g., $(\frac{1}{2}, \frac{1}{3}, \frac{1}{5})$ or $(\frac{1}{2}, \frac{1}{3}, \frac{1}{6})$. Schedule examples for candidate rates of $(\frac{1}{2}, \frac{1}{3}, \frac{1}{5})$ are shown in Table 1. A filled unit indicates that a packet is sent in that time slot. In addition, according to Sec. 4.1.3, in order to guarantee stability, a common Lyapunov function should exist by solving the LMI problem formulated by subsystems induced by all candidate rates.

**4.2.2 Network reconfiguration based on piggyback.** The holistic controller of $l_i$ adopts a piggyback mechanism to disseminate a newly computed $R_i$ for data flows $f_{i,j}, j = 1, 2, \ldots, m_i$. The holistic controller of $l_i$ piggybacks $R_i$ with the
known in advance, which requires the network to reserve resource for unknown events. The ST relaxes this requirement.

### 5.1 Control design

Introduce control design and network design of ST.

### 5.2 Self-Triggered Control

Self-triggered control (ST) [10], an aperiodic event-driven control design, improves the efficiency of the network. The first single-hop wireless network protocol for aperiodic control is presented in [11]. However, due to the lack of network protocol, aperiodic control designs have not been adopted in multi-hop mesh networks. In this section, we respectively introduce control design and network design of ST.

#### 5.1 Control design

In event-triggered control, trigger condition is checked in every sampling period. The time of actuation event cannot be known in advance, which requires the network to reserve resource for unknown events. The ST relaxes this requirement by predicting the future events based on system models. Intuitively, ST triggers sensing and actuation events only when...
certain control performance is predicted to be lost. The self-triggered strategy we present in this article is motivated by [11]. Since a decreasing Lyapunov function \( V(x_t) = x_t^T P x_t \) is the certificate of stability (\( P \) is achieved in Sec. 4.1.3), the desired control performance is defined by a decreasing function \( S(x_t) \), upper bounding the evolution of Lyapunov function \( V(x_t) : V(x_t) \leq S(x_t) \). Provided that \( V(x_t) \leq S(x_t) \) holds and \( S(x_t) \) is decaying over time, the closed-loop system is stabilized \([10, 11]\). The predicted time of the next sensing and actuation events is \( t_k = \min \{ t \geq t_{k-1} | V(x_t) - S(x_t) \geq 0 \} \).

Here, we adopt a feasible decreasing \( S(x_t) \), as follows:

\[
S(x_t) = V(x_{t_{k-1}}) e^{-\gamma V(x_{t_{k-1}})^\delta (t-t_{k-1})}.
\]

(19)

We induce the term \( \gamma V(x_{t_{k-1}})^\delta, \gamma, \delta > 0 \), which makes the decreasing rate of \( S(x_t) \) adapt to the value of the Lyapunov function (state error). That is, when \( V(x_{t_{k-1}}) \) is large, which indicates severe state error, the \( S(x_t) \) decreases faster. Therefore, the sensing and actuation events are more likely to be triggered. On the other hand, when \( V(x_{t_{k-1}}) \) is small, which indicates the current states are close to equilibrium point, the \( S(x_t) \) decreases slower. The sensing and actuation events are unnecessary and less likely to be triggered.

Please note that unlike event-triggered control, the trigger condition of which is checked in every sampling period, self-triggered control checks the trigger condition based on predictions based on system model, which makes it less resilient to disturbance. In order to provide robustness guarantees of the self-triggered control, an upper bound of the inter-transmission interval should be customized based on \([11, 50, 51]\).

### 5.2 Network protocol for self-triggered control

#### 5.2.1 Self-triggered transmissions

Due to the predictive nature of ST, the network knows \textit{a priori} when the event will be triggered by the holistic controllers. Therefore, nodes know the next time when they should wake up and flood data. Within the inter-transmission interval, the nodes sleep. In this way, the energy costs of nodes can be reduced compared with periodic control at the highest rate.

Similar to the network protocol of RA, the holistic controller uses the piggyback mechanism to disseminate a newly computed time of next transmission \( T_{n_i} \) for all data flows of \( i \). Again, \( T_{n_i} \) should be integer multiples of \( T \). The holistic controller piggybacks \( T_{n_i} \) with the actuation command. Therefore the data field of the actuation packet is \([i, T_{n_i}, Da_{ai}]\). Because of flooding, all nodes in the network can receive this update. In a node, each data flow has an event timer. Once a node receives a \( T_{n_i} \), it will set the value of \( Timer_{i,j} \) to \( T_{n_i} \) and start counting down from the next period. If the \( Timer_{i,j} \) expires, the node will wake up and flood in the pre-assigned relative slots \( t_{i,j} \) within \( T \). Fig. 6 shows an example of self-triggered transmissions based on LWB. At the first period, \( f_{2,1} \) is flooded, and node 3, which is the source of \( f_{2,1} \), receives and floods \( T_{n_2} = 3T \) at slot that is assigned for \( f_{2,1} \). Therefore, the next \( f_{2,1} \) is reserved and transmitted \( 3T \) later at the fourth period. At the second period, \( f_{1,1} \) and \( f_{3,1} \) are transmitted, and \( T_{n_1} = T, T_{n_3} = 2T \), respectively. Therefore, the next \( f_{1,1} \) is reserved and transmitted at the third period, and \( f_{3,1} \) at the fourth period.

![Self-triggered transmission based on LWB (f1,1, node2 → node1; f2,1, node3 → node4; f3,1, node4 → node1)](image)

#### 5.2.2 Why not event-triggered transmissions

We adopt ST instead of event-triggered control. In event-triggered control, trigger conditions are checked every sampling period. Source node is aware of whether the event is triggered in current period, and it does not flood if the trigger condition is not violated. However, other nodes in mesh WSAN do not know the trigger time in advance, they still wake up and keep listening in case certain events are triggered in current period.
Therefore, event-trigger control systems over a multi-hop mesh network cannot reduce duty cycle of the network. As shown in Fig. 7, at the first period, the source node of $f_{1,1}$, node 3, notices the event is triggered. It floods $f_{2,1}$ in the second relative time slot. Since all other nodes are listening, they receive and forward $f_{2,1}$. Different from ST, all nodes keep awake in the first and third relative time slots in case the trigger conditions of $f_{1,1}$ and $f_{3,1}$ are violated.

5.2.3 Packet loss recovery for ST. If all nodes receive $T_{n1}$, and are synchronized well, they wake up and flood $f_{i,j}$ at the same time. However, unlike rate adaptation based on LWB, which can self-recover from packet loss, self-triggered transmissions based on LWB are less resilient to packet loss. If a node fails to receive $T_{n1}$, it is possible that it will not wake up at the right time for the next transmission and will become unsynchronized with other nodes for $f_{i,j}$ forever. Table 3 shows an example of the impact of packet loss on flow $f_{1,1}$, when a holistic controller predicts a series of inter-transmission intervals ($T_{n1}$). \{1, 0, /\} in brackets following $T_{n1}$ indicate that the node receives a packet, loses a packet, and remains sleeping, separately, correspond to its inter-transmission interval $T_{n1}$. In this example, the update inter-transmission time $T_{n1} = T$ is received by nodes 2 and 3, but fails to arrive at node 4 in first period ($t_{1,1}$) due to packet loss. Hence, the nodes 2 and 3 schedule next transmissions in the second period ($t_{1,1} + T$), while node 4 uses last $T_{n1} = 2T$ and schedules next transmission in the third period ($t_{1,1} + 2T$). In the second period, nodes 2 and 3 receive new $T_{n1} = 2T$, and schedule the next transmissions in the fourth period ($t_{1,1} + 3T$). Node 4 sleeps at this period and loses the updated inter-transmission time again. If the system goes on like this, node 4 becomes unsynchronized with other nodes and loses all packets. Therefore, it is of vital importance to come up with effective and efficient strategies to recover from packet loss. We propose the following packet loss recovery strategy: if a node wakes up but does not receive a packet with $T_{n1}$, it should re-awake at the highest rate $R$, until another packet with $T_{n1}$ is received.

6 REAL-TIME WCPS

To experiment with wireless control over real-world WSANs, we develop a real-time wireless cyber-physical simulator (RT-WCPS). In this section, we first present the architecture of RT-WCPS. Then we analyze its real-time performance.

6.1 Architecture of RT-WCPS

RT-WCPS integrates MATLAB/Simulink Desktop Real-time (SLDRT) [52] and a 3-floor WSAN testbed [53, 54]. The architecture of RT-WCPS is shown in Fig. 8. Note that this figure shows the architecture of one wireless control loop. Several control loops can share the same WSAN.

SLDRT is used to simulate the physical part of the WNCS: physical plants, controllers, state observers, and physical disturbance. In practice, industrial plants usually operate continuously or at very high rates. However, the wireless communication and controller execute at a relatively low rate because of the communication and computation latencies. Therefore, SLDRT modules are operated at different rates in our design.
The 3-floor WSAN testbed is deployed on the 3rd to 5th floors of Jolley Hall at Washington University in St. Louis, as shown in Fig. 9. It consists of 70 TelosB motes. Each mote is equipped with Chipcon CC2420 radio compliant with the IEEE 802.15.4 standard and a TI MSP430 microcontroller. 40 Raspberry Pis with a backplane network are used for the measurement and management of the wireless network [6].

The interfaces between SLDRT and WSAN are socket connections between the PCs that run SLDRT and the Pis, and serial connections between the Pis and the end nodes. In this way, the end nodes $s_{i,j}$, $d_{i,j}$ of the sensing and actuation flows $f_{i,j}$ can be any nodes in the testbed.

### 6.2 Real-time network-in-the-loop simulation

Both SLDRT and the 3-floor WSAN testbed operate in real-time. To evaluate the real-time performance of the RT-WCPS, we measure the latency caused by each module. In our design, sensing and actuation flows have the same overhead like oil refinery and mining, sampling periods of which are usually longer than those of RT-WCPS. Please note that the node is less than 26 ms (2.6%). More than 966 ms is reserved for communication over the WSAN in each period, among which around 175 ms is utilized for transmissions in this example. The results validate the real-time performance of RT-WCPS. Please note that 26 ms overhead is acceptable when we use RT-WCPS to simulate industrial processes like oil refinery and mining, sampling periods of which are usually longer than 1 s [38]. However, it is not acceptable
in faster sampling period of tens of milliseconds. We will work on shortening this overhead in the future. We refer
interested readers to [15, 32, 39] for network and WNCS designs with tighter time requirements.

7 EVALUATION

In this section, we describe systematic trials of our wireless control designs using RT-WCPS. On the physical side, to
represent an industrial process system, we use up to five 4-state load positioning systems that share the same WSAN.
On the WSAN side, we evaluate the proposed network protocols over a 70-node WSAN tested [53, 54].

Because the state observer provides robust and theoretically sound protection against loss of sensing information [7, 56,
57], the WNCSs are more sensitive to packet loss on the actuation side of WSAN [21]. Thus, we focus on comprehensive
actuation-network-in-the-loop simulations. We then empirically evaluate the tradeoff between rate adaptation (RA)
and self-triggered control (ST) in communication cost and control performance under different operating conditions.

7.1 Systems settings

7.1.1 Physical system settings. We run simulations of a realistic load positioning system [58, 59], which positions a
load (L) using a motor with a ballscrew transmission. The motor is attached rigidly to a movable base platform (B). The
load positioning is a 4-state nonlinear system as described in [59]. When the system is operated at low rates as in real
industrial applications, the stiffness of the ballscrew and the potential energy stored in it are neglected in the model.
The system can be simplified as a 4-state linear system [58]:

\[ \dot{x}_t = A_c x_t + B_c u_t, \quad y_t = C_c x_t, \quad (20) \]

where

\[ A_c = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -d_L (\frac{1}{m_L} + \frac{1}{m_B}) & -k_B/m_B & d_B/m_B & 0 \\ 0 & 0 & 1 & 0 \\ \frac{d_L}{m_B} & \frac{k_B}{m_B} & - \frac{d_B}{m_B} & 0 \end{bmatrix}, \quad B_c = \begin{bmatrix} 0 \\ \frac{1}{m_L} + \frac{1}{m_B} \\ 0 \\ - \frac{1}{m_B} \end{bmatrix}, \]

and \( C_c = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix} \). Here, \( d_L, m_L, d_B, m_B, \) and \( k_B \) are parameters of the load and base platforms, such as the
mass, damping, and stiffness. The state vector is defined as \( x_t = [x_L(t) \dot{x}_L(t) x_B(t) \dot{x}_B(t)]^T \), where \( x_L \) is the displacement
of the load relative to the base platform, \( x_B \) is the absolute displacement of the base platform, and \( \dot{x}_L \) and \( \dot{x}_B \) are the
speeds of the relative and absolute movements. We will stabilize the states of the load positioning system to the origin.

There are two kinds of plants. For the first kind, denoted as PLANT1, \( d_L = 15, m_L = 100, d_B = 10, m_B = 10, \)
\( k_B = 5, \) and \( K = [-1.9393 - 13.1373 0.0842 - 13.0264] \). For the second kind, denoted as PLANT2, \( d_L = 10, m_L = 15, \)
\( d_B = 3, m_B = 5, k_B = 2, \) and \( K = [-1.0076 - 0.6317 - 0.1954 - 0.3814] \). The second kind of plants have lower mass
and damping, therefore their response time is shorter than that of PLANT1. In holistic controller, we discretize the
continuous-time models (20) using step-invariant transformation at its corresponding sampling period \( T_j \):

\[ A_{T_j} = e^{A_c T_j}, \quad B_{T_j} = \int_0^{T_j} e^{A_c \tau} d\tau B_c. \]

For each control loop, given the discrete-time model, \( K, \) and \( Q, \) we can get \( P, \alpha_1, \alpha_2, \) and \( \beta \) according to (16), (5), and
(6), respectively. For all loops, \( Q = I_4, W_Q = I_4, W_R = 1, \gamma = 1, \) and \( \delta = 2. \) We will adjust and evaluate some parameter
selections of RA, such as \( V_{ith}, \lambda \) and \( \tau \) of heuristic RA algorithm, and \( e_2 \) of the optimal RA problem.

7.1.2 WSAN settings. The network protocols for RA and ST use Contiki [60]. The LWB operates at the rate \( R = 1 \) Hz.
The global static schedule has one synchronization slot, with a length of 25 ms, and 2-5 data slots, with lengths of 18 ms.
70 nodes participate in the transmissions. The synchronization packet is disseminated by the sink node (node 164) every 1 s. The synchronization packet size is 6 bytes, and the data packets are 25 bytes. Each data slot is used to transmit the control command \( u_t \) and network reconfiguration signals \( R \) or \( Tn \) of each control loop. Fig. 9 shows the source and destination pairs of five actuation flows over 3-floor WSAN. The Tx power is 0 dbm, and the retransmission number is 3.

### 7.1.3 RT-WCPS settings

We simulate the WNCs using RT-WCPS, which integrates a 70-node WSAN and SLDRT. We simulated two control loops sharing a WSAN for statistical results from Sec. 7.3 to Sec. 7.6. Loop \( l_1 \) controls a PLANT1. Loop \( l_2 \) controls a PLANT2. The SLDRT modules of two loops are shown in Fig. 11. Each loop has its own holistic controller, and the controllers and the actuators communicate via actuation flows sharing the same WSAN. And we simulate five control loops sharing a WSAN to show the scalability of RT-WCPS in Sec. 7.7. Loops \( l_1, l_3, \) and \( l_5 \) control 3 PLANT1s separately. Loops \( l_2 \) and \( l_4 \) control 2 PLANT2s.

![Fig. 11. SLDRT modules of RT-WCPS.](image)

As presented in Sec. 6.1, modules in Fig. 11 operate at different rates. The physical plants run at 100 Hz. Kalman filters and actuators run at 1 Hz. The “worst-case-guaranteed” WSAN and controllers run at 1 Hz, and WSAN and controllers can adjust their rates and operate ST during runtime, based on control needs. In RA, we choose candidate rates: 1 Hz, 0.5 Hz, 0.25 Hz, which are reasonable rates for our load positioning systems with time constants of roughly 30 s. And they are also typical rates in industrial process control [38]. In order to provide robustness guarantees of the self-triggered control [11], we set the upper bound of the inter-transmission interval as 10 s.

### 7.2 Evaluation of optimal and heuristic rate adaptation algorithms

We first evaluate the online heuristic RA. Fig. 12 shows how heuristic RA works. Take PLANT1 as an example. We introduce physical disturbance by injecting a constant bias into the actuator from 120 to 140 s, as shown in plot (a). Plot (b) shows the Lyapunov function \( V(x_t) \). The two dashed lines, from upper to lower, are the thresholds for increase and decrease of rate. Plot (c) shows the sampling rate adaptation. \( Tn \) indicates the time till the next packet Tx, i.e., sampling period in RA. Plots (d) and (e) show the control command \( u_t \) and physical states \( x_t \), respectively. During the transient (0 – 60 s and 120 – 160 s), the control performance is poor, which is reflected by a large value of \( V(x_t) \). When \( V(x_t) \) is above the increase threshold, the holistic controller increases the rate. When \( x \) is approaching the origin (80 – 120 s and 170 – 200 s), as indicated by the decreases of \( V(x_t) \), and \( V(x_t) \) is below the decrease threshold for \( \tau = 10 \) s, the rate of the WSAN decreases shown in (c).

Fig. 13 shows the impact of parameter tuning in heuristic rate selection, i.e., the increased threshold \( V_{th, inc} \), decreased threshold coefficient \( \lambda \), and the test time interval \( \tau \). Each marker in this figure is obtained by carrying out 20 rounds of simulations. We use the mean absolute error (MAE) as the metric of control performance, and the number of...
7.2.2 Optimal rate selection. We evaluate the optimal rate selection. Fig. 14 shows how optimal rate selection works. Plot (b) shows the values of objective function $J$ of three candidate rates and the optimal rate solution of the optimization problem (15). During the transient processes around 0 – 50 s and 125 – 150 s, the control performance dominates $J$. Therefore high sampling rate minimizes $J$. While when the system is stable during 80 – 120 s and 180 – 200 s, the communication cost dominates $J$. Thus low rate minimizes $J$. In this way, optimal rate selection facilitates a systematic balance between energy cost and control performance through adjusting the weight ($\epsilon_2$) in $J$. Fig. 15 shows the relationship between MAE, communication cost, and $\epsilon_2$. Each marker is obtained by 20 rounds of simulations. Larger $\epsilon_2$ reduces energy cost at the cost of control performance and vice versa. Considering the diminishing return of MAE improvement, proper $\epsilon_2$ could be chosen to achieve small MAE at the cost of reasonable network energy cost.

7.2.3 Comparison between optimal and heuristic approaches. The optimal rate selection is able to systematically balance energy and control performance. It does not need any threshold compared to heuristic rate selection. However, since packets sent through WSAN as the metric of energy cost. The value of X-axis is the mean of total number of packets. As described in Sec. 4.1.1, $V_{th} = \alpha_1 ||x_{se}||^2$, $V_{th} = \lambda \alpha_1 ||x_{se}||^2$. Thus, the intuition is that smaller $V_{th}$ makes rate increase more often, and smaller $\lambda$ and longer $\tau$ make rate decrease less often. We can see that with fixed $\tau$ and $\lambda$, the MAE decreases at the cost of more network energy consumption as $V_{th}$ becomes smaller. There is a diminishing return of control performance improving as increase of energy cost. Fig. 13A shows that $\lambda$ mostly does not affect the trajectory of curves, which indicate relationship between MAE and network energy cost. With fixed $V_{th}$ and $\tau$, MAE decreases at more energy cost when $\lambda$ is smaller. The same impact holds for $\tau$ in Fig. 13B that MAE decreases at more energy cost when $\tau$ is longer.
we propose to adapt the rate at run-time, computational complexity of the algorithms matters. Optimal rate selection problem is an integer programming problem. Its computational complexity is higher than the heuristic approach with the complexity of $O(1)$. Fig. 16 compares the performance of optimal and heuristic RA approaches. The markers on the lower left of the figure indicate better performance that can achieve smaller MAE with less energy cost. We can see that the optimal rate selection has slightly better performance than the best envelop of the heuristic approach. The envelop is achieved by arbitrarily tuning combinations of parameters 90 times as shown in Fig. 13. On the other hand, tuning $\epsilon_2$ in optimal RA is more efficient to balance energy and control performance. However, we can also see that the advantage of optimal rate selection is less remarkable when the requirement of control performance is stringent, as shown in the right bottom part of Fig. 16. Since we have a specific and stringent requirement on control performance, i.e., $||x_\epsilon||^2 = 0.1$, $\lambda = 0.1$ and $\tau = 10$ s, we choose to adopt heuristic rate selection in the rest of sections.

### 7.3 Normal network and physical conditions

We then run network-in-the-loop simulations. We evaluate the WNCSs under normal conditions. The WSAN operated on IEEE 802.15.4’s channel 26. The average packet delivery ratio is 99.15%. And there is no physical disturbance. We present the results of five sets of network-in-the-loop simulations under the different management approaches:

1. RA: Fig. 17A shows the response curves of loop 1. In plot (b), each dot indicates Txs of one packet, and the y-axis of the dot is the time till the next Tx. When $x$ is approaching the origin, as indicated by the decreases of $V(x_1)$, and $V(x_2)$ is below the decrease threshold for $\tau = 10$ s, the rate of the WSAN starts to decrease, as shown in (b). The rate changes from 1 Hz (1 Tx every 1 s), to 0.5 Hz (1 Tx every 2 s) at $t = 53$ s, then to 0.25 Hz (1 Tx every 4 s) at $t = 64$ s.

2. ST: Fig. 17B shows the response curve of ST. In (b), since $V(x_1)$ decreases, the inter-transmission interval changes from 1 s to 10 s at $t = 48$ s. When $V(x_1)$ increases at around 60 s to 90 s, $Tn$ reduces to 1 s as soon as the timer expires.

3. Fixed rate time-driven control: Existing WSANs typically employ time-drive transmissions with fixed rates, so we use three fixed rates of 1 Hz, 0.5 Hz and 0.25 Hz, denoted by 1, 2, 4 in following statistical results.
Next we run each experiment for 20 rounds with different initial values to statistically compare different approaches. Fig. 18 shows the performances of two loops. Both RA and ST can achieve similar control performances with fixed rate of 1 Hz, with a network cost (# of packets) reduction of more than 50%. Loop 2 has network cost reduction of more than 62%, since it has shorter time constant. For both loops, ST is more aggressive in saving network cost than RA.

In reality, the total energy cost of all flows, including the synchronization cost, is of interest. Therefore, we analyze power cost over the WSAN in detail. We collect the time spent in transmitting and listening per node per second using the Energest module [61] provided by Contiki OS. The sum of transmitting and listening time is the radio-on time of the collection period, and the node sleeps in the rest of the period. We adopt the energy model in [62] to estimate the energy cost. Fig. 19A and Fig. 19B show that the energy cost are consistent with duty cycle. Fig. 19A shows the average energy cost of all 70 nodes is consistent with the number of packets going through WSAN. RA and ST save 40% energy, which is higher than energy cost of loop1 and loop2 alone in Fig. 18, since energy estimation includes the cost of synchronization every second. However, in the case of the maximum energy cost, ST costs more than RA, which can be explained by the fact that the node incurs the maximum energy cost due to packet loss. Facing packet loss, the node with the ST transmissions protocol keeps listening at a high energy cost because of its recovery mechanism. Whereas the node with the RA protocol applies self-recovery mechanism without extra energy cost. To verify this difference, we analyze the power cost of two nodes. Node 103 has a higher packet reception ratio than node 124. Fig. 19C shows that ST transmissions are not as efficient as RA for node 124, due to its recovery mechanism. Fig. 20 shows the relationship between MAE and energy cost under normal condition under different management approaches. Each data
point indicates the MAE and energy cost of one round of experiment. Data points of RA and ST are concentrated in the bottom left of the figure, which indicates that those approaches achieve smaller MAE with lower energy cost.

![Energy cost of all WSAN nodes](image)

**Fig. 19. Energy cost under normal condition.**

7.4 Network interference

We operate WSAN over channel 22 (2.460 GHz) of IEEE.802.15.4, and we introduce network interference by continuously sending jamming packets over an overlapping channel 11 (2.462 GHz) of WiFi. The average packet delivery ratio is reduced to 65.9%. Fig. 21 shows the response curves of RA and ST. In Plot (b), each dot indicates that the actuator receives a packet. Both methods stay longer at high rate than in normal condition to compensate the impact of interferences. And both the network protocols can recover from packet drops. Fig. 22 shows the statistical results under network interference. In this case, both RA and ST guarantee the control performance, at the cost of more energy consumption than Sec. 7.3. ST consumes more energy than RA, due to its packet loss recovery mechanism. Fig. 23 shows the relationship between MAE and energy cost under network interference. Data points of RA and ST are concentrated in the bottom middle, which indicates that those approaches achieve smaller MAE with higher energy cost than normal case due to recovery from network interference, but still lower than 1 Hz sampling. The simultaneous increase of both MAE and energy cost can be explained by the intuition of efficient holistic control that poorer system performance will cause the increase of the rates and number of events. On the other hand, no extra energy is cost when the system is in good condition. This trend indicates that network resources are adapted well based on the states of the physical plants.

7.5 Physical disturbance

We introduce physical disturbance by adding a constant bias to actuators from 120 s to 140 s. As shown in Fig. 24, both RA and ST adapt rates to 1 Hz under the physical disturbance. However, the time ST ($t = 130 s$) reacts to the...
disturbance is later than RA \( (t = 126 \text{ s}) \), since ST has longer \( T_n \) (10 s). Fig. 26 shows the statistical results. As shown in Fig. 26A, both RA and ST have similar MAE with a fixed rate of 1 Hz, and can save more than 30% of the energy. However, as shown in Fig. 26B, the ST performs worse than RA within the interference interval. The longer \( T_n \) (10 s) makes ST response to disturbance slower than time-driven management. Fig. 25 shows the relationship between MAE and energy cost under physical disturbance. Data points of RA and ST are concentrated in the bottom left of the figure, which indicates that those approaches achieve smaller MAE with lower energy cost.

7.6 Both network and physical interferences

We run experiments with both network and physical interferences in Sec. 7.4 and Sec. 7.5. Fixed rate of 0.25 Hz causes the instability of the system. Therefore, we do not show the results of 0.25 Hz. Fig. 27 shows the statistical results that both RA and ST guarantee the control performance at the costs of more energy consumption than in Sec. 7.5. ST costs more energy than RA, due to the recovery mechanism. Fig. 28 shows the relationship between MAE and energy cost under both network and physical interferences. Data points RA and ST are concentrated in the bottom left, which indicates that those approaches achieve smaller MAE with lower energy cost. The simultaneous increase of both MAE and energy cost indicate that network resources are allocated properly based on the states of the physical plants.

To summarize, in normal physical and network condition, RA and ST can achieve similar control performance to a conventional fixed rate of 1 Hz, while improving energy efficiency. Besides, ST is more aggressive in energy saving
Efficient Holistic Control: Self-Awareness across Controllers and Wireless Networks

![Diagram](image)

(A) time-driven control with rate adaptation

(B) self-triggered control

Fig. 24. Response curve under physical interference.

![Diagram](image)

(A) time interval of one round: 0 s – 300 s

(B) time interval of physical interference: 120s – 180s

Fig. 25. Relationship between MAE and energy cost under physical disturbance.

![Diagram](image)

Fig. 26. Performance of double loops under physical interference.

![Diagram](image)

Fig. 27. Performance under network and physical interferences.

![Diagram](image)

Fig. 28. Relationship between MAE and energy cost under both network and physical interferences.

than RA. However, when there are interferences, RA has better performance and energy efficiency than ST, because ST has an embedded recovery mechanism, which costs more energy under packet loss, and a longer inter-transmission interval, which makes ST response slowly to disturbance.

7.7 Scalability and flexibility of RT-WCPS

Although above experimental results are based on two control loops, RT-WCPS has the scalability to operate more control loops. In addition, it has the flexibility that end nodes of the data flows can be any nodes in the testbed. As an example, we simulate five control loops sharing a WSAN. Loops $l_1$, $l_3$, and $l_5$ control 3 PLANT1s. Loops $l_2$ and $l_4$ control 2 PLANT2s. Fig. 9 shows the source and destination pairs of five actuation flows over 3-floor WSAN. Table 4 shows the MAEs and energy costs in one round (200 s) of network-in-the-loop simulation under normal condition. Loops $l_1$, $l_3$, and $l_5$ have larger MAEs and are more sensitive to different rates than $l_2$ and $l_4$, since $l_2$ and $l_4$ with lower mass and
RA and ST can achieve similar control performance with fixed rate of 1 Hz, while save energy for more than 47%.

<table>
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<th>Table 4. Performance of five-loop simulation</th>
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8 CONCLUSIONS

Wireless control faces significant challenges due to data loss and energy constraints in WSANs. In this article, we present two efficient holistic control designs for industrial process, rate adaptation (RA) and self-triggered control (ST), that can not only ensure control performance under wireless and physical interferences, but also reduce network energy consumption. Furthermore, we design two network reconfiguration mechanisms based on LWB to support RA and ST in multi-hop WSANs. In addition, we build a real-time network-in-the-loop simulation framework which integrates MATLAB/Simulink and a three-floor WSAN testbed to experiment with wireless control over real-world WSANs. Our empirical studies show that both RA and ST offer advantages in control performance and energy efficiency. The advantage in energy efficiency of ST, however, diminishes under harsh physical and wireless conditions due to the cost of recovering from data loss and physical disturbance.

REFERENCES

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