



Thesis Seminar Adaptive Task Scheduling for Cyber-Physical Control Systems

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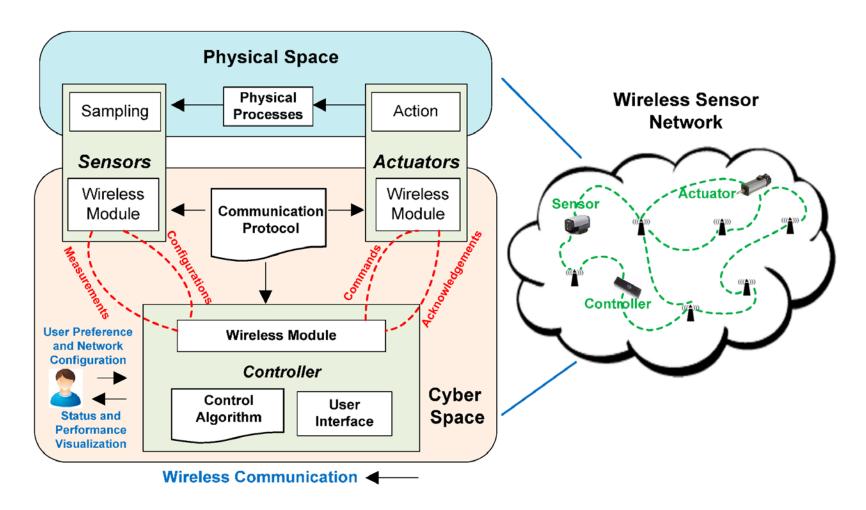
Background

- Cyber-Physical Control Systems (CPCS)
- Basic elements: Computation, Control and Communication
- i.e. large scale embedded systems with network connectivity



Background

Example 1: Wireless Sensor Network (WSN)



Background

Example 2: Autonomous driving



Background

Requirements of Cyber-Physical Control Systems (CPCS):

- System should be flexible
- High robustness and resilience
- Long-term deployment subject to ageing and degradation

Traditional scheduling systems cannot fully satisfied!

Thesis Contributions

Research questions:

- How could a cyber-physical control system (CPCS) be more robust to timing uncertainties, especially in a long term?
- 2. How could **online information** and **cloud computing** be utilized to improve the **resilience** of a CPCS?



Thesis Contributions

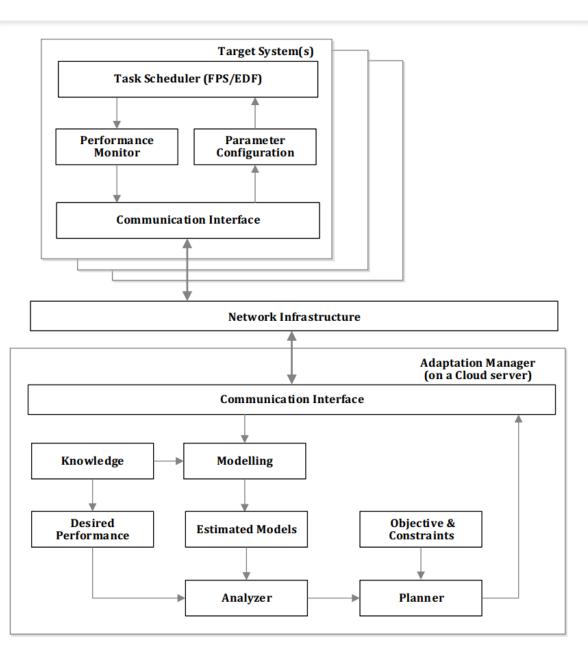
Adaptive

TAsk

Scheduling

(ATAS)

Framework



Thesis Contributions

In this thesis, we have made the following contributions:

- 1. Trend Analysis of Worst-Case Execution Times
- 2. Period Adaptation
- 3. A Dual-Period Task Model

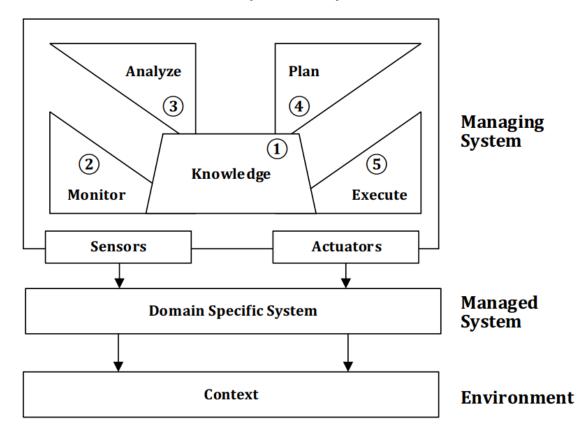
For this seminar, I will focus on the period adaptation.

Seminar Outline

- 1. Background
- 2. Control Task Timing
- 3. Period Adaptation
- 4. Evaluation
- 5. Conclusion

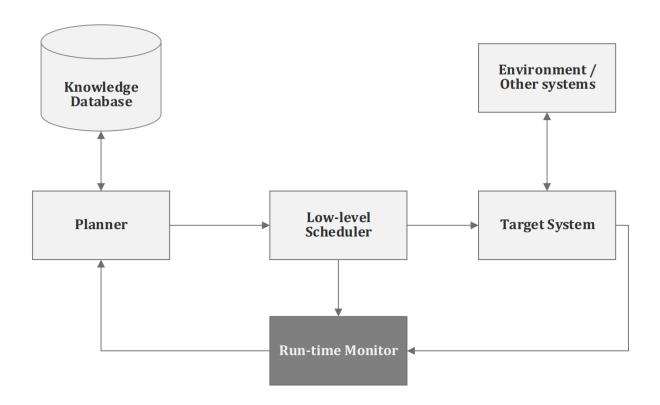
MAPE-K Framework

- An architecture introduced by IBM recently
- Support adaptiveness for computer systems
- Standard framework for self-adaptive systems



Period Adaptation: Structure

- MAPE-K in scheduling
- Focus on control applications

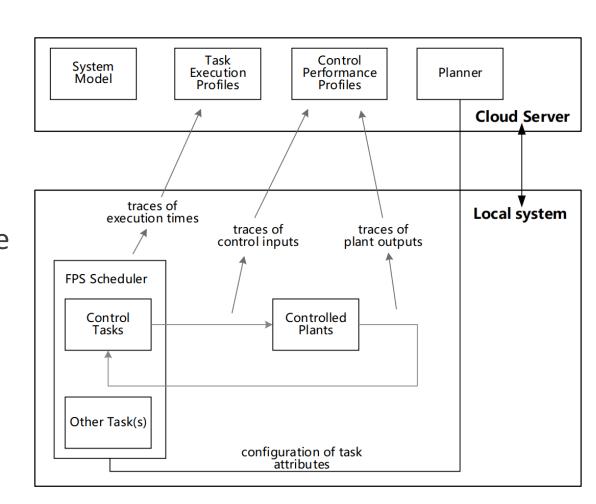


Period Adaptation: Structure

Two sub-systems:

- Local system
- Cloud Server

M, E on the local machine
A, P and K on the cloud



Assumptions

- 1. The embedded computer (local system) consists a uniprocessor and a preemptive scheduler using fixed-priority scheduling (FPS).
- 2. Control tasks are released periodically, i.e., the system applies time-triggered rather than event-triggered controllers.
- 3. All tasks in the complete system are initially schedulable, given the control tasks are using periods that can satisfy control specifications.
- 4. The system has the ability to monitor task execution times (supported by POSIX-RT). The kernel has the ability to change task periods at run-time.
- 5. The system itself has limited resources but has connectivity to a more powerful cloud computer.

Period Adaptation

Observation:

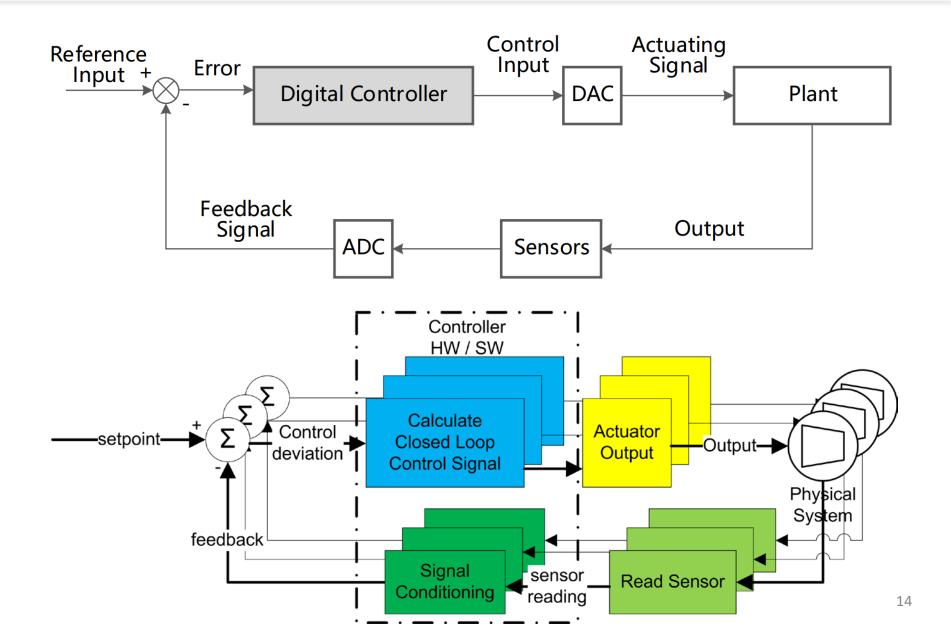
 Task period of a digital controller often have to be conservatively selected.

Key Ideas:

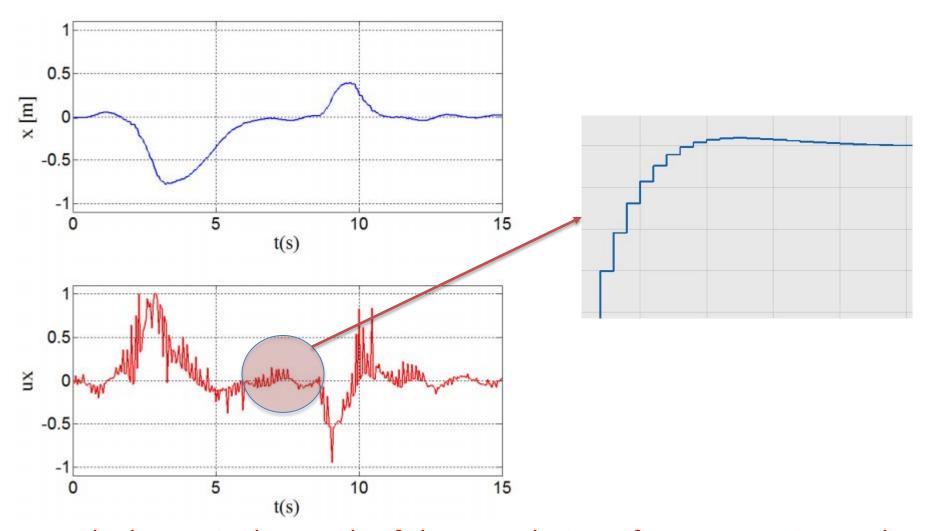
- Partition the taskset into control tasks \(\Gamma\) and non-control tasks \(\Gamma\)no
- Evaluate the new period based on observations and predictions
- Reduce the period of control tasks to save CPU time
- The period is gradually changed so minimal disruption will be created

However, change control task period will affect control performance.

Digital Control Systems

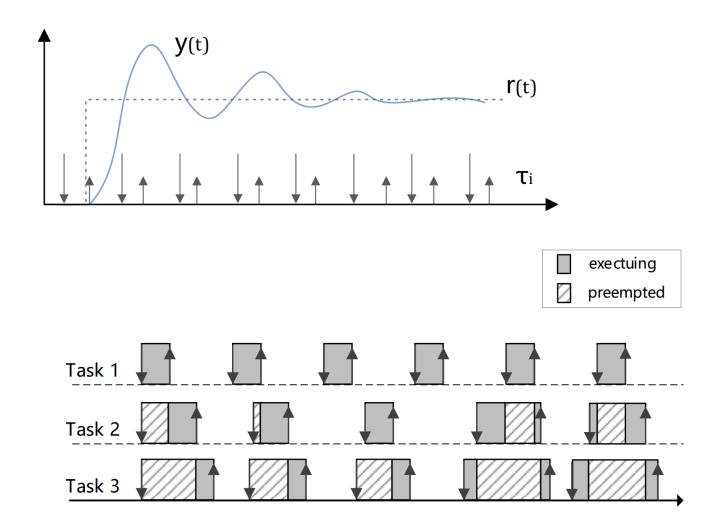


Digital Control Systems

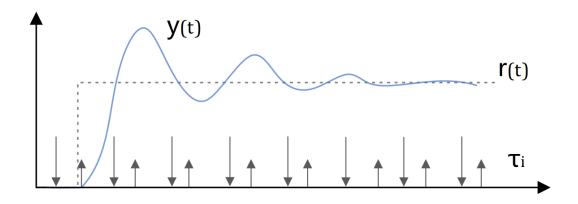


Each change is the result of the completion of a computation task

Control Performance and Timing



Control Performance and Timing

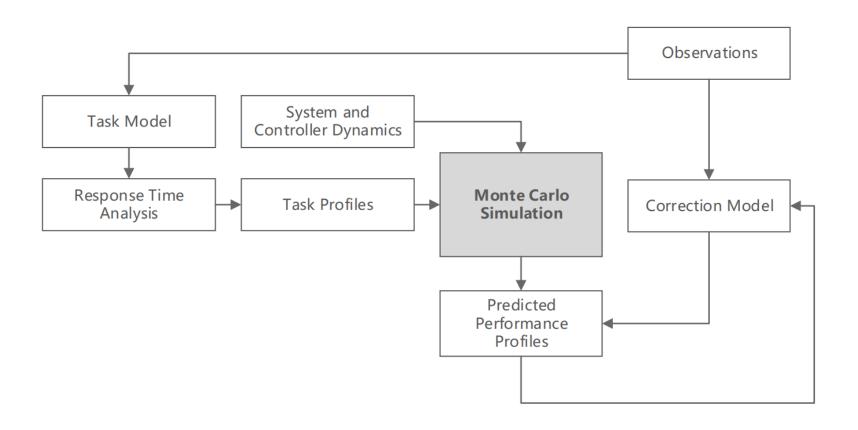


- Generally, larger period produce worse control
- Evaluating control performance: Integral of Absolute Error (IAE)

$$J = \int_0^\infty |r(t) - y(t)| \cdot dt$$
$$= \int_0^\infty |e(t)| \cdot dt$$

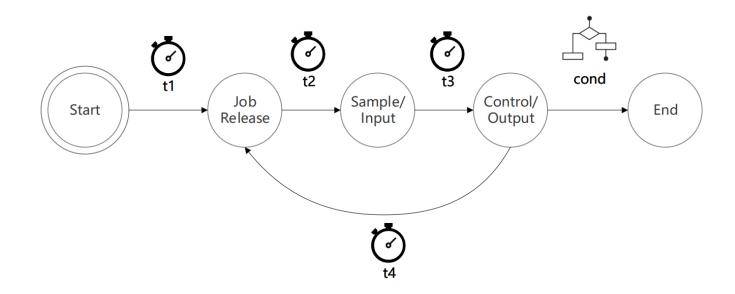
- Control performance will be hard to predict due to timing
- There will also be variations in IAE measurements!

Period Adaptation



- Monte Carlo: prediction based on a large number of experiments.
- a hybrid system = continuous + discrete

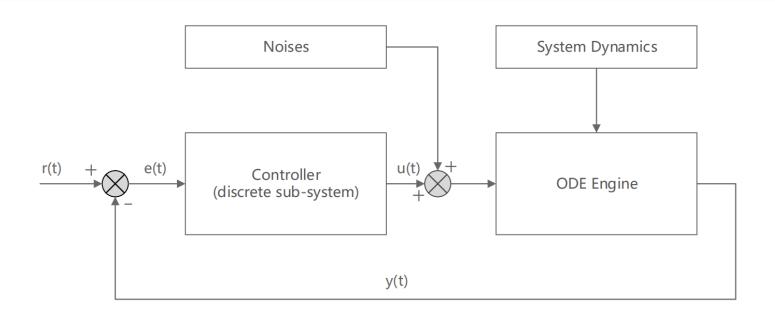
Monte Carlo Simulation – Discrete Model



Execution timing model:

- t1: initial task phasing
- t2: sampling delay
- t3: input-output latency
- t4: task reset time

Monte Carlo Simulation – Continuous Model

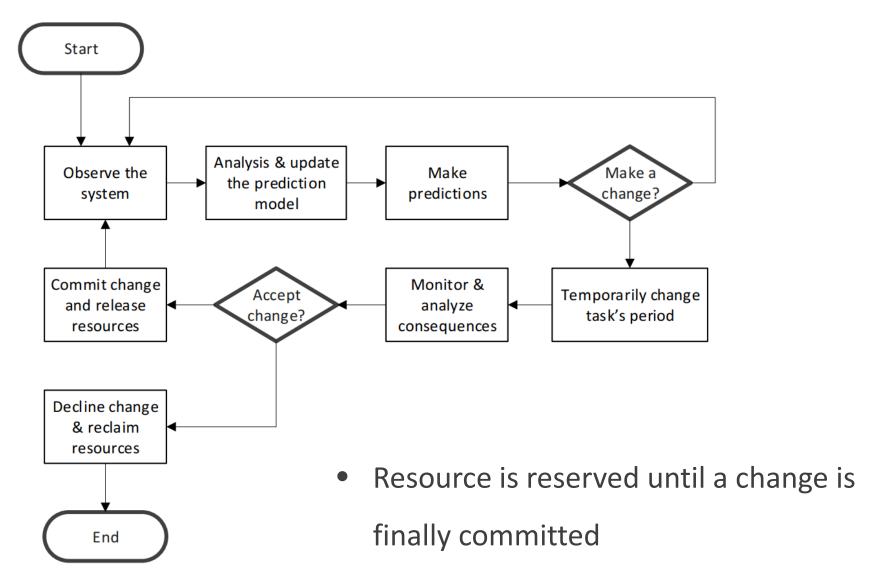


- Controllers: PID, MPC, LQR
- System dynamics equation: state-space

$$u_1(t) \longrightarrow u_2(t) \longrightarrow \text{Inner state variables} \longrightarrow y_1(t) \\ \vdots \\ u_r(t) \longrightarrow x_1, x_2, \cdots x_n \longrightarrow y_p(t)$$

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -5 & -26 & -5 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u$$
$$y = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

Period Adaptation - Flowchart

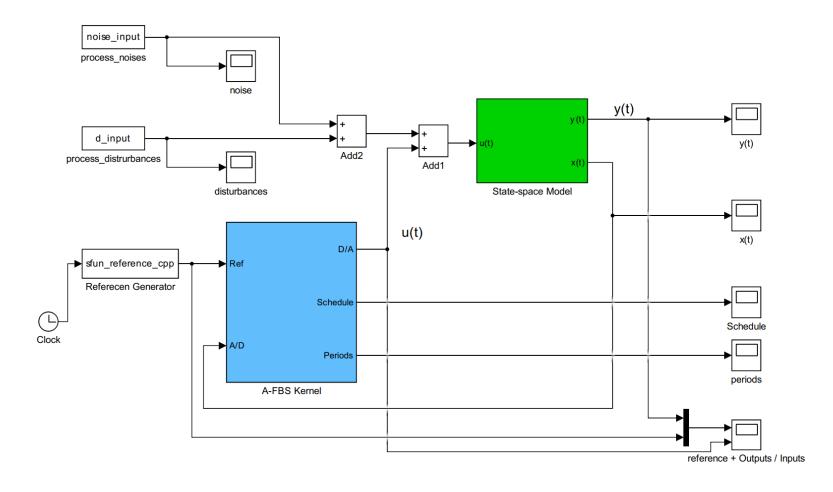


Evaluation

- 1. Experiment Setup
- 2. Demonstration
- 3. Utilization v.s. Control Quality
- 4. Robustness
- 5. Multiple tasks
- 6. Overhead analysis

Evaluation – Environment

- MATLAB / Simulink: dynamic systems simulation
- Task scheduler: s-function



Evaluation – Environment

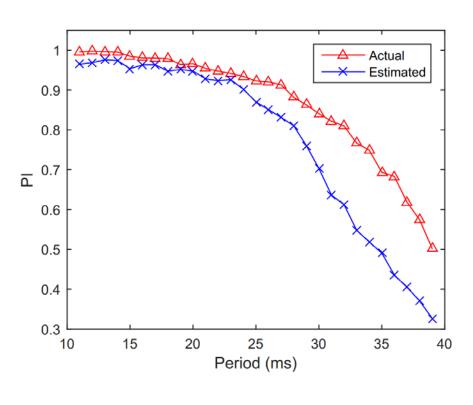
System dynamics:

$$\begin{bmatrix} \dot{x_1} \\ \dot{x_2} \end{bmatrix} = \begin{bmatrix} 10 & 25 \\ -25 & 10 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1.6 \end{bmatrix} u$$
$$y = \begin{bmatrix} 2.5 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

• Taskset:

Task	$C_i \text{ (ms)}$	T_i (ms)	Control Task
$ au_0$	0.42	1.57	
$ au_1$	0.10	2.15	
$ au_2$	0.53	4.99	
$ au_3$	0.87	7.77	
$ au_4$	0.48	8.01	
$ au_5$	1.00	10.00	(x)

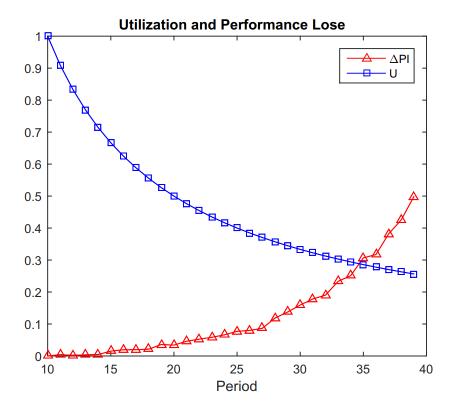
Evaluation



- 1. Minimal PI = 0.3, step size = 1 ms
- 2. In each step:5,000 samples + 3,000 predictions
- 3. Prediction is one step ahead
- 4. Terminated at $T_i = 39 \text{ ms}$
- Prediction error increases but is conservative

Evaluation

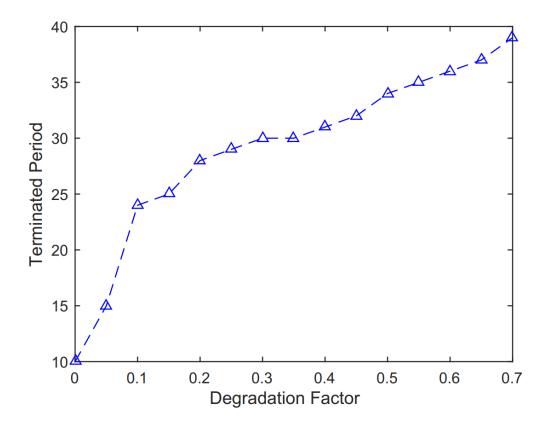
ΔPI and Utilization



Trade-off between control performance and CPU usage

Evaluation

• If varying the degradation factor (ΔPI):



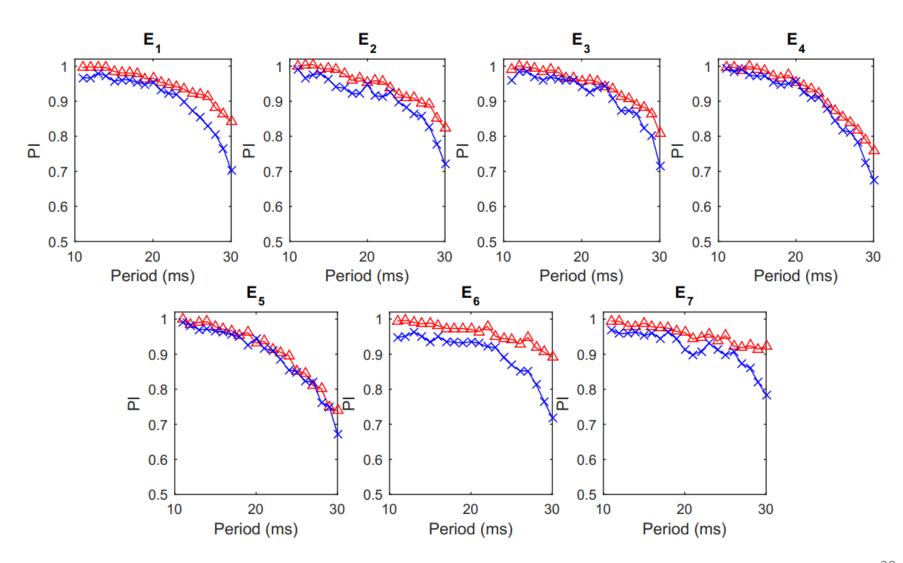
• In this example, 0.2 is a good trade-off point.

Evaluation - Robustness

• Experiment sets:

Experiment	System Dynamics	Task Model	
E_1	Ideal		
E_2	-5%	Normal	
E_3	+5%]	
E_4	Ideal	WCET	
E_5	+5% WCE1		
E_6	Ideal	BCET	
E_7	-5%		

Evaluation - Robustness



Multiple Control Tasks

- Highest Priority First (HPF) The highest priority task has the largest margin and the highest interferes with non-control tasks, and also changing higher priority task first can avoid the need for recalculating periods of lower priority task.
- Least Sensitivity First (LSF) The task is selected according to its sensitivity of performance index by changing its period. This is evaluated by a sensitivity function:

$$\Delta J = \frac{\partial J}{\partial h} \Delta h \Big|_{h = T_i(k-1)}$$

• Least Uncertainty First (LUF) Select the controller that behaves closest to its prediction model, i.e., minimal prediction bias and error.

Discussion on Overheads

Computation

- calculating performance statistics and run-time monitoring: only addition operations
- run as a low priority background service to create minimum interferences to other running tasks in the system.

Communication

- only packets contain statistical data are transferred to the cloud server
- the communication bandwidth and reliable requirement is low.

Memory

- buffer traces and statistical data
- a hundred bytes to a few kilobytes depending on the sampling rate

Conclusion

In this work, we have made the following contributions:

- 1. Adaptive task scheduling for CPCS
- 2. Monte Carlo to solve control scheduling co-design
- 3. Utilizing statistical information for performance prediction and error estimation
- 4. Proposed an adaptation method and evaluated its performance.

Future Work

- 1. Fixed adaptation step -> variable step
- 2. Uniprocessor -> multicores
- 3. Task dependencies: control <-> control, control <-> non-control

Thank You!