Master's Degree in Wireless Communications Engineering

Thesis Presentation

FEDERATED LEARNING FOR ENHANCED SENSOR RELIABILITY OF AUTOMATED WIRELESS NETWORKS

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How to ensure that devices in automated wireless networks continue to function reliably if their sensors fail?

How can we predict sensor failure?

Key issues in existing automated wireless networks

Lack of sensor failure prediction strategies

Lack of reliable network connectivity

Lack of intelligent learning at device level

Overview

Motivation

Lack of **Sensor Failure Prediction Mechanisms** in Automated Wireless Networks

Objective

Enhance the **Sensor Failure Prediction** in Automated Wireless Networks using **Federated Learning**

Deliverables

A **novel binary optimization problem** is proposed to **predict sensor failures** and **select optimal sensors** to enhance measurement reliability.

Comparison of the **proposed Federated Learning** scheme with **baseline** approaches in terms of measurement error, measurement reliability outage, average cost, sensor replacement cost, and communication cost

Comparison of the **training** and **testing** phase **accuracy** in **proposed Federated Learning** scheme

Related Works

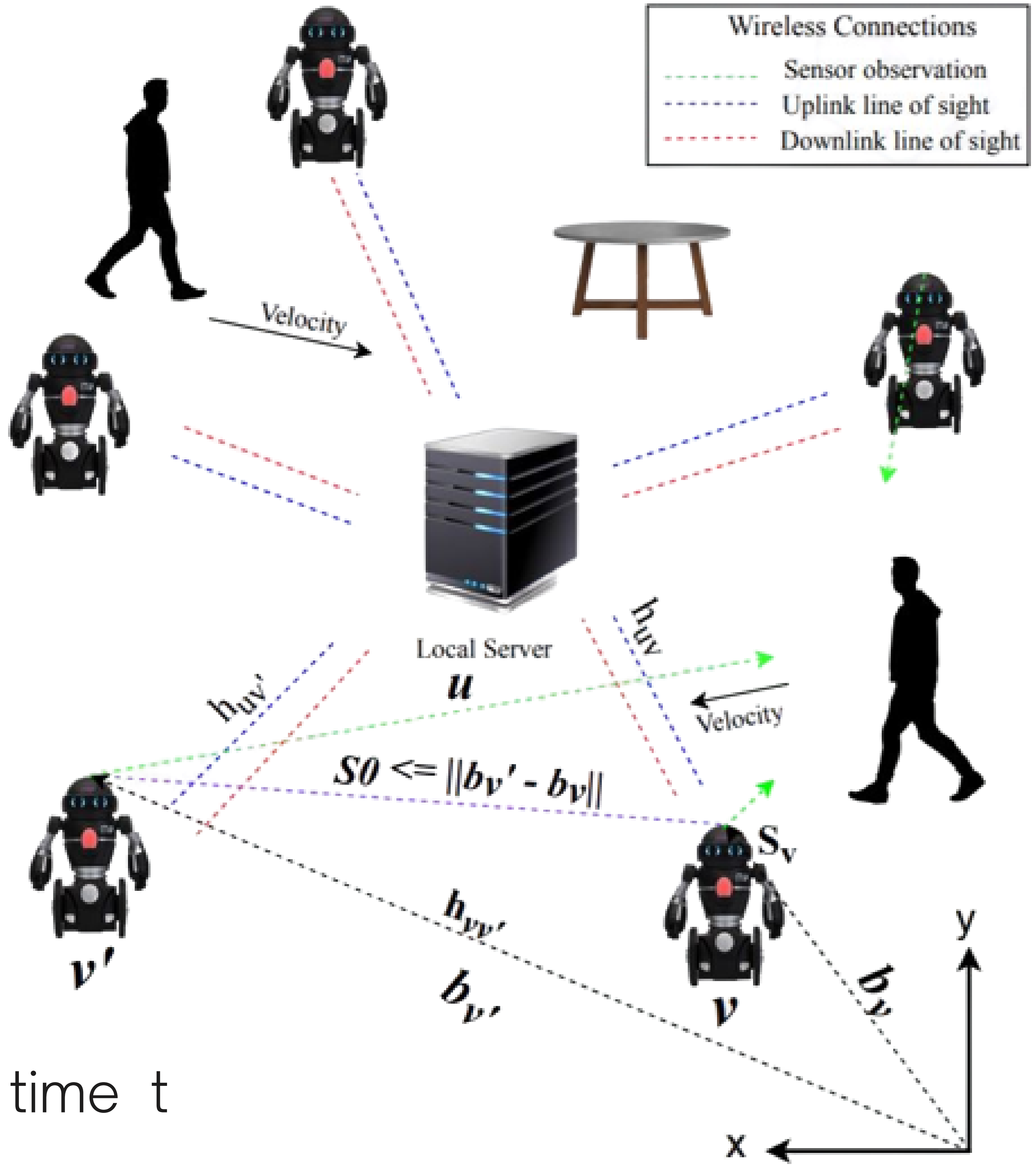
Related Work	Contributions	Sensor Measurement Reliability?
A Kalman Filter Based Link Quality Estimation Scheme for Wireless Sensor Networks doi: 10.1109/GLOCOM.2007.169 [1]	Sensor Measurement Error Minimization	Not Done
Data fusion with desired reliability in wireless sensor networks doi: 10.1109/TPDS.2010.93 [2]	Minimum Energy Reliable Information Gathering (MERIG), scheme: deliver packets with more information with higher reliability by using redundant transmission on fusion routes without acknowledgments.	Not done
A new approach for Weibull modeling for reliability life data analysis doi: 10.1016/j.amc.2014.10.036 [3]	A Novel approach for modeling the life data for system components that have failure modes following different Weibull models.	Not done
Federated learning through model gossiping in wireless sensor networks doi: 10.1109/BlackSeaCom52164.2021.9527886 [4]	Federated learning for network and energy cost minimization	Not done

Works on using Federated learning to enhance sensor measurement reliability while minimizing network operating costs ?

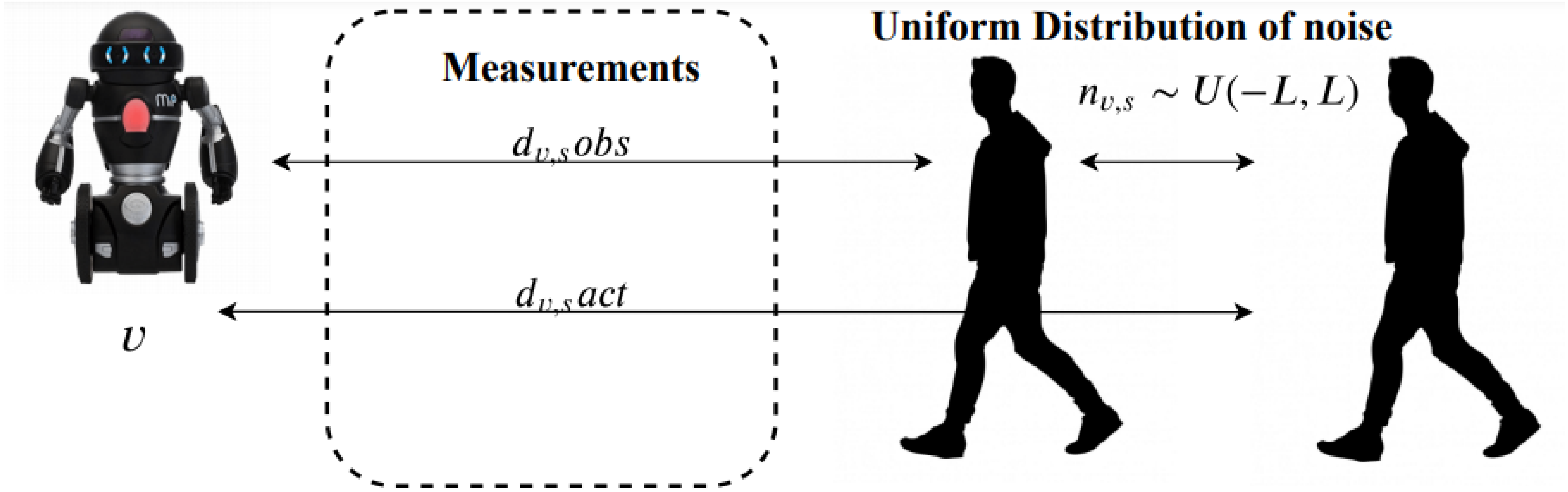
System Overview

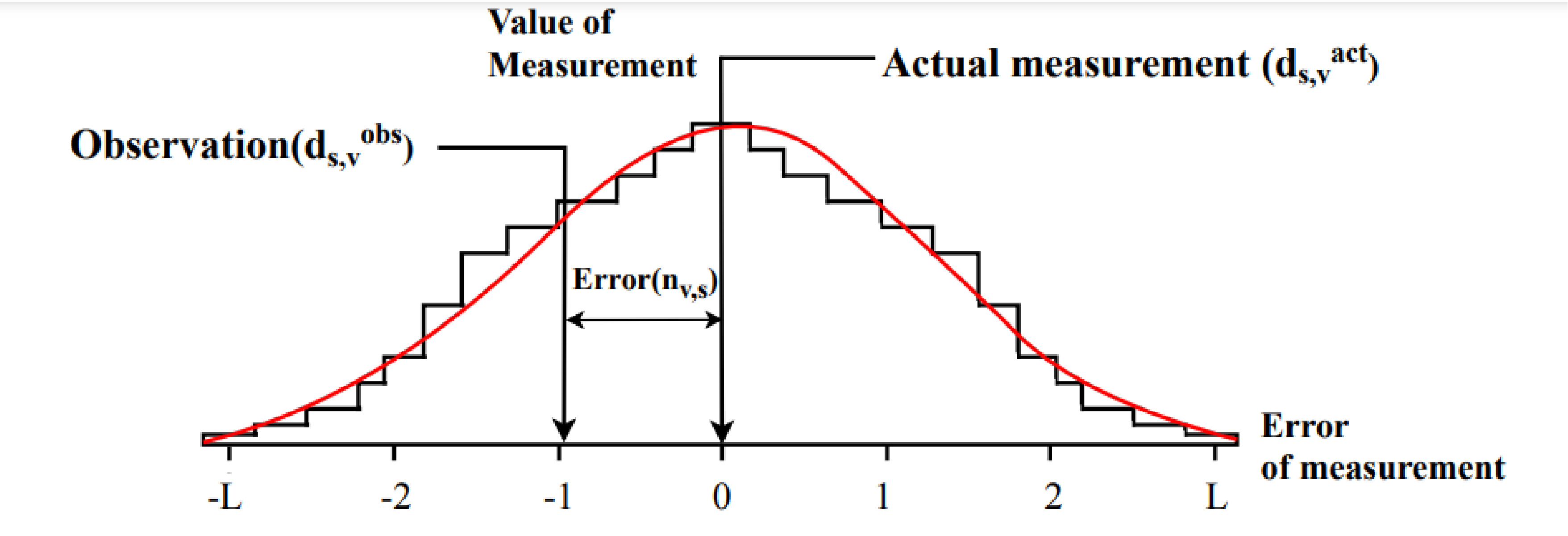
Local communication network with automated robots

- $v \leq V$ number of robots
- u Local central server
- LOS wireless links
- $h_{vv'}$ Channel coefficient
- $\mathcal{N}_v = \left\{ v' \middle| \left\| \vec{b_v} - \vec{b_{v'}} \right\| \leq S_0 \right\}$ Neighborhood region
- $\mathcal{K}_v \leq \mathcal{S}_v$ number of active sensors in each robot at time t



System Overview





Gaussian distribution of measurement error

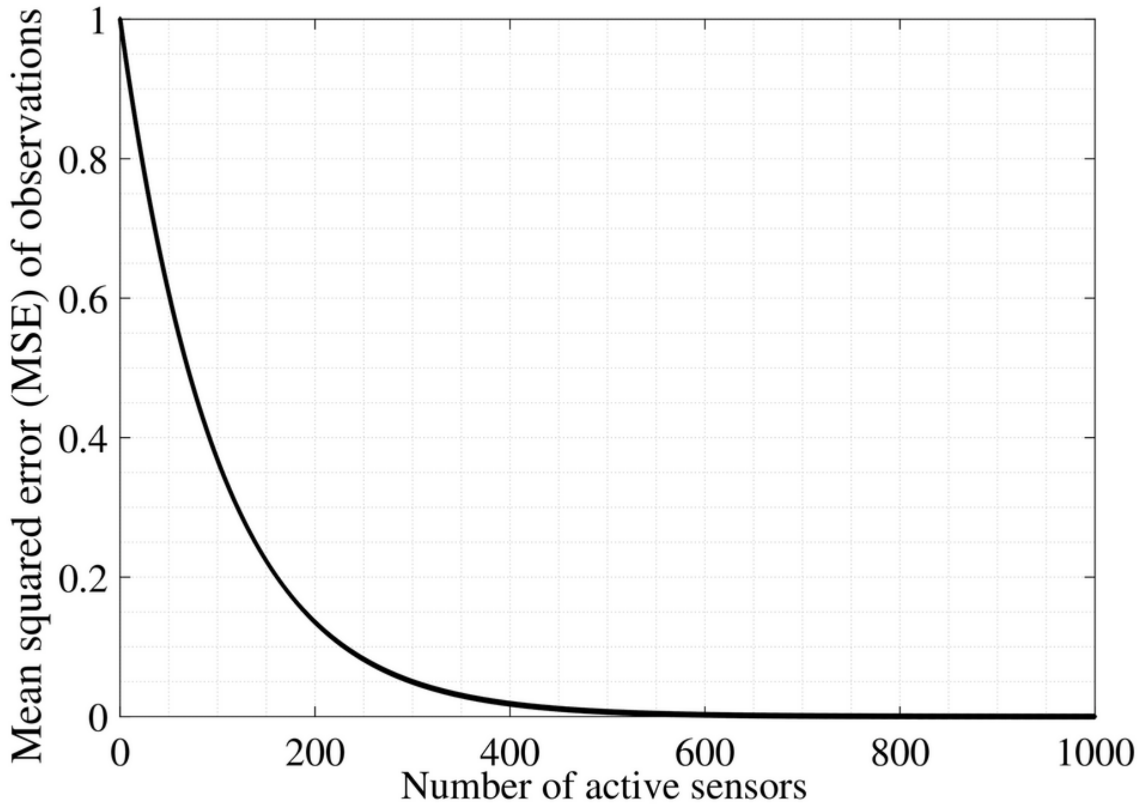
When robots work with humans/objects nearby, robots obtain measurements of the nearby human/object using sensory data.

$$\overline{d_{v,s}^{obs}} = d_{v,s}^{act} + n_{v,s}$$

Variance of observations estimate and error are same, thus

$$\mathrm{Var}(\overline{d_{v,s}^{obs}}) = \mathrm{Var}(n_{v,s})$$

System Overview



As $K \to \infty$

$$\overline{d_{v,s}^{obs}} = \frac{1}{K}\sum_{k=1}^{K} d_{v,s}^{obs\,(k)} = d_{v,s}^{act} + \frac{1}{K}\sum_{k=1}^{K} n = d_{v,s}^{act}$$

$$\mathrm{Var}(n_{v,s}) = \alpha\frac{L^2}{3}$$

As the number of active sensors increaase, the average measurement error decreases

$$\text{Reliability of } d_{v,s}^{\text{obs}} = ((1-\alpha)+\beta)\frac{L^2}{3}$$

System Overview

Weibull assisted Sensor failure prediction model

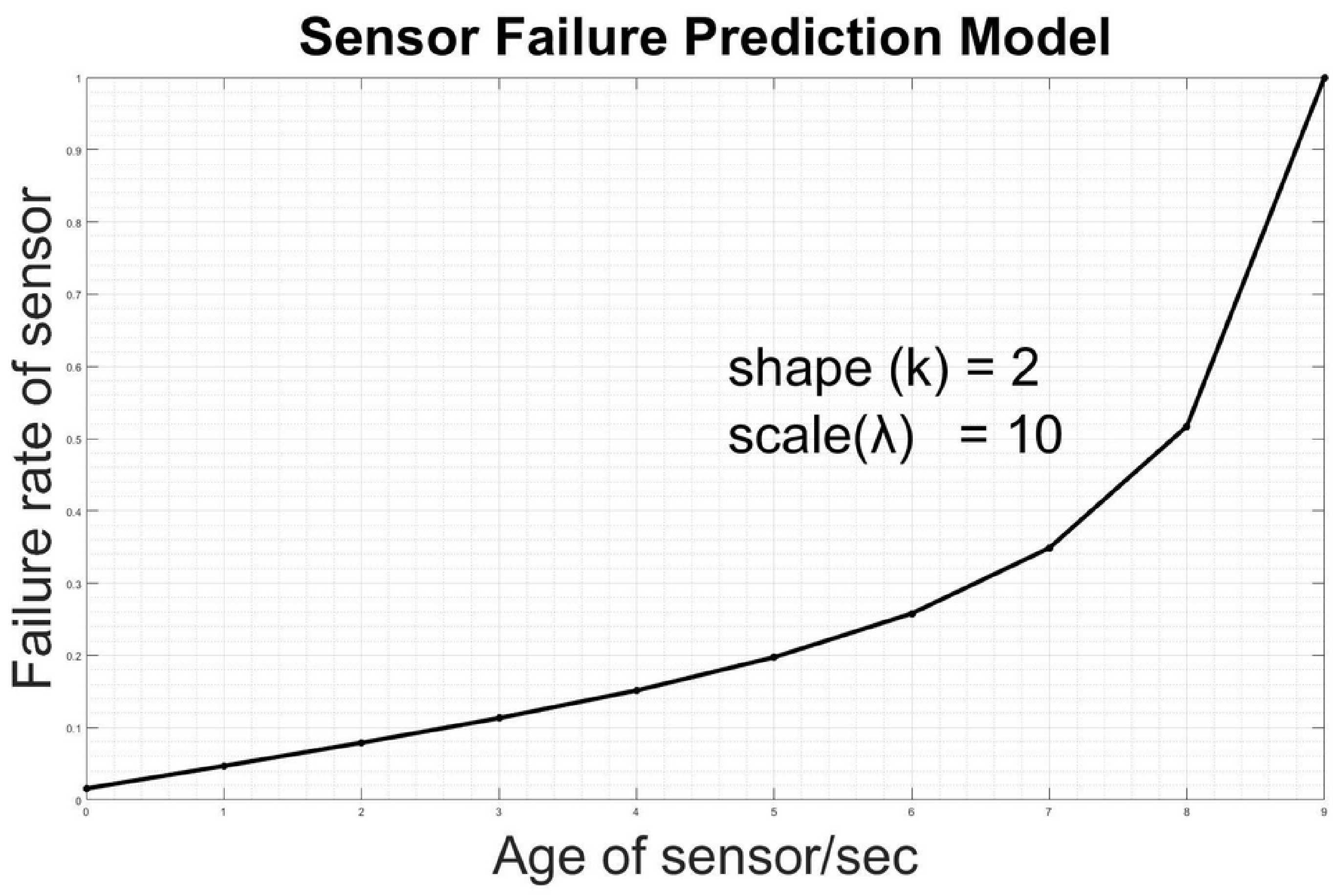
$$h(t,\lambda,k) = \begin{cases} \frac{1}{2}\left(\frac{f(T-t)}{F(T)}\right) & t \in [0,T] \\ 0 \text{ otherwise} \end{cases}$$

k: shape parameter

$$\frac{f(T-t)}{F(T)} = \frac{\frac{k}{\lambda}\left(\frac{T-t}{\lambda}\right)^{k-1} e^{-\left(\frac{T-t}{\lambda}\right)^k}}{1-e^{-\left(\frac{T}{\lambda}\right)^k}}$$

λ: scale parameter

T: maximum lifetime of sensor



Left truncated Weibull function

System Overview

Sensor failure model parameters

Maximum Likelihood Estimation

$$\begin{aligned} \underset{\lambda, k}{\text{maximize}} \quad & \prod_{K} \left\{ h(a, \lambda, k) \right\} \\ \text{subject to} \quad & \lambda \in (0, \mathbb{Z}^{+}), \\ & k \in (0, 1] \end{aligned}$$

Total number of sensor lifetime data samples

Reformulated to Maximize the Log Likelihood Estimation

$$\begin{aligned} \underset{\lambda, k}{\text{maximize}} \quad & \sum_{K} \ln \left\{ h(a, \lambda, k) \right\} \\ \text{subject to} \quad & \lambda \in (0, \mathbb{Z}^{+}), \\ & k \in (0, 1] \end{aligned}$$

Stochastic Gradient Descent for Optimal Shape and Scale parameters

System Overview

Gradients wrt to shape and scale parameters

$$\nabla_k h = \frac{\partial h(a)}{\partial k}$$

$$\frac{\partial \ln h(a)}{\partial k} = \frac{1}{k} + \ln(t) - \ln(\lambda) - e^{k\frac{a}{\lambda}} \ln \frac{a}{\lambda} - \frac{e^{-\frac{T}{\lambda}^k} e^{k \ln \frac{T}{\lambda}} \ln \frac{T}{\lambda}}{1 - e^{-\frac{T}{\lambda}^k}}$$

$$\nabla_\lambda h = \frac{\partial h(a)}{\partial \lambda}$$

$$\frac{\partial \ln h(a)}{\partial \lambda} = -\frac{k}{\lambda} + \boldsymbol{k} \frac{a}{\lambda}^{(k-1)} \frac{a}{\lambda^2} + \frac{k e^{-(\frac{T}{\lambda})^k} \frac{T}{\lambda}^{(k-1)} \frac{T}{\lambda^2}}{1 - e^{-(\frac{T}{\lambda})^k}}$$

Stochastic Gradient Descent Algorithm

For randomly selected point in K

Until converge

Update shape and scale

$$k(j+1) = k(j) - \mu \nabla_k h$$

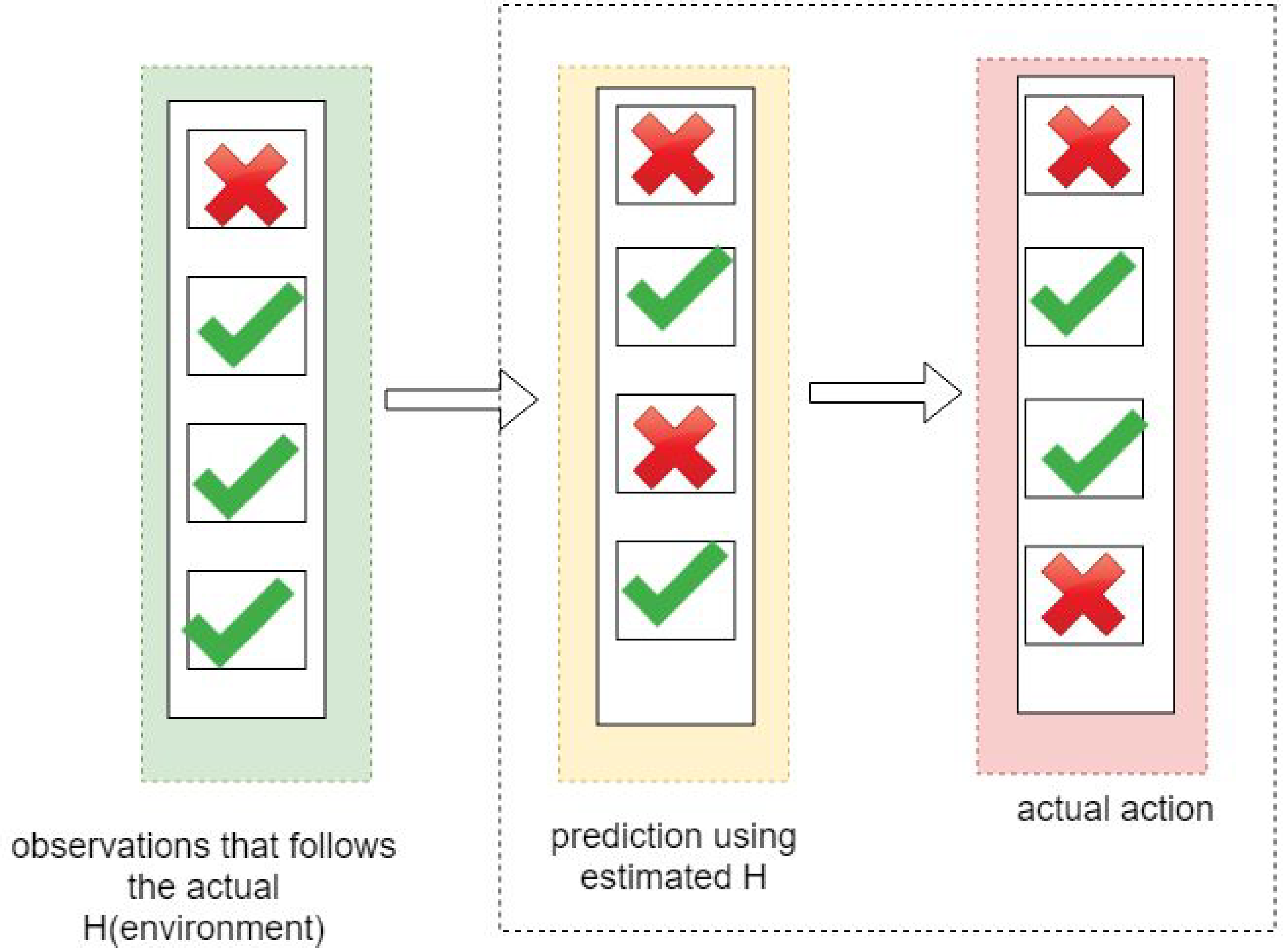
$$\lambda(j+1) = \lambda k(j) - \mu \nabla_\lambda h$$

end

end

System Overview

Probability of sensor failure at time (t+1)



$$\Pr\left(t \le a + t_0 | t \ge a\right) = \frac{\Pr\left(a \le t \le a + t_0\right)}{\Pr\left(t \ge a\right)}$$
$$= \frac{\int_0^{a+t_0} h(a,\lambda,k)dt - \int_0^{a} h(a,\lambda,k)dt}{1 - \int_0^{a} h(a,\lambda,k)dt}$$
$$= \frac{F(a+t_0) - F(a)}{F(T) - F(a)}$$

Problem Formulation

Minimize the sensor replacement and network cost

$$\begin{aligned} \underset{\boldsymbol{x}_v(t), \boldsymbol{y}_v(t)}{\text{minimize}} \quad & \phi_s \mathbf{1}^\dagger \boldsymbol{x}_v(t) + \phi_c \mathbf{1}^\dagger \boldsymbol{y}_v(t) \\ \text{subject to} \quad & V_0(\alpha, \beta) - N_{\text{th}} \geq 0, \\ & P_{vv'} \leq \boldsymbol{y}_v(t) P_{\text{m}}, \\ & \boldsymbol{y}_v(t)(r_{v'} - r_{\text{th})} \geq 0 \end{aligned}$$

Binary variables

Sensor measurement error variance constraint for measurement reliability

Transmit power constraint each device

SINR constraint for reliable communication

$$r_{th} = log_2(4S_0/\lambda)$$

where

$$V_0(\alpha, \beta) = \left(\sum_{s=1}^{N} (1 + \alpha_s(\boldsymbol{x}_v(t) - 1)) + \sum_{i=1}^{v'} (\boldsymbol{y}_v(t)\beta_s) \right)$$

$$r_{v'} = \frac{P_i h_{vj'}^2}{\sum_{l \in \mathcal{P}, v' \in \mathcal{V}', l \neq i, v' \neq j'} P_l h_{vv'}^2 + N_0}$$

Depend on weibull assisted sensor failure prediction

failure rate of next instance

number of neighbor robots

SINR at v robot

Problem Formulation

Binary variables

$$x_v(t) = \begin{cases} 1, & \text{if replaced} \\ 0, & \text{otherwise} \end{cases}$$

$$y_v(t) = \begin{cases} 1, & \text{if communicate with a neighbor robot,v'} \\ 0, & \text{otherwise} \end{cases}$$

ϕ_s Cost of replacement

ϕ_c: Cost of communication

$V_0(\alpha, \beta) - N_{\text{th}} \geq 0$, Realibility constraint

$P_{vv'} \leq y_v(t) P_{\text{m}}$ Transmit power constraint

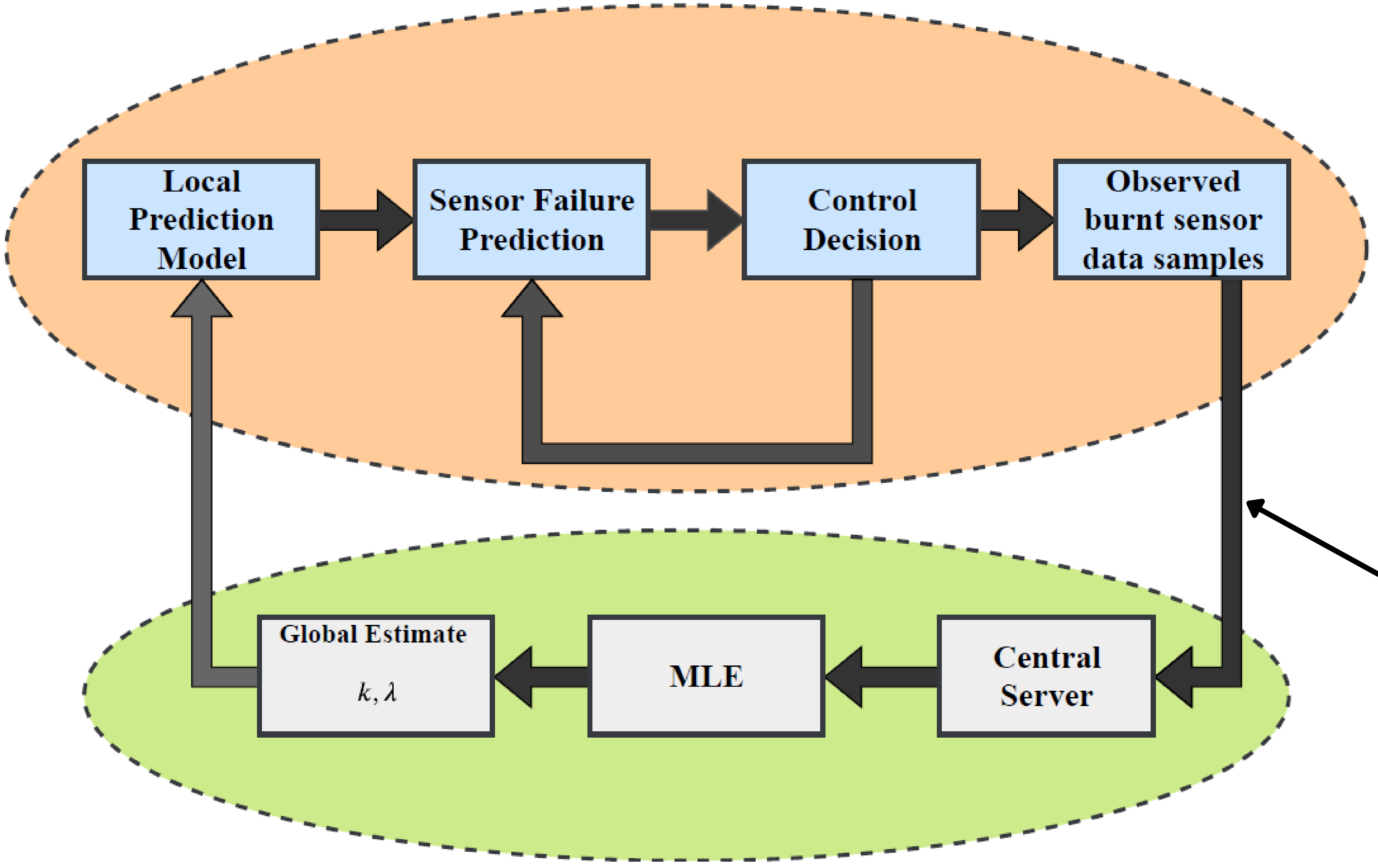
$y_v(t)(r_{v'} - r_{\text{th}}) \geq 0$ Communication constraint

x_v Replacement decision

y_v Communication decision

Proposed Scheme

Centralized learning assisted sensor failure prediction



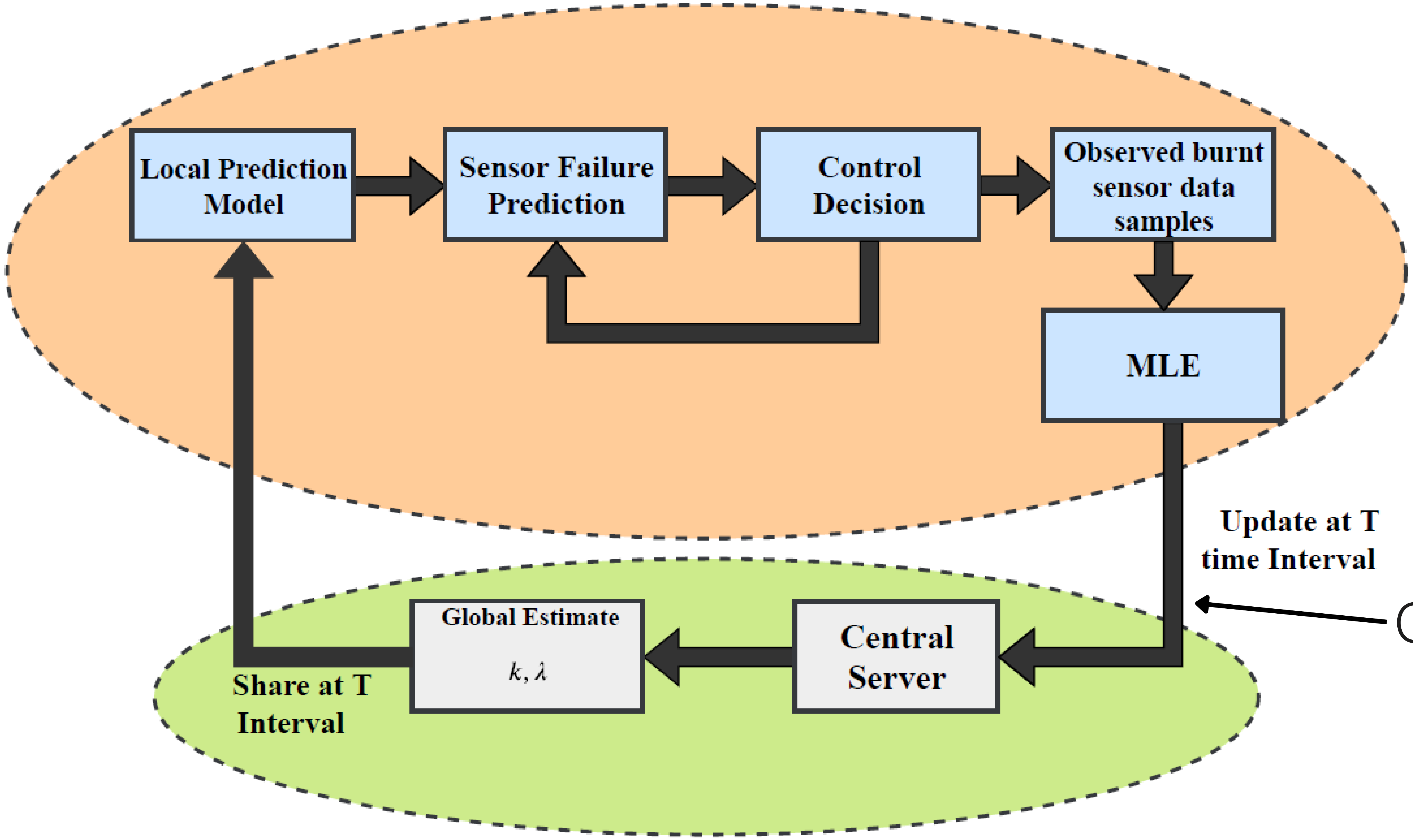
Raw data are sent to the server

Centralized learning

MLE at the server

Proposed Scheme

Fedeated learning assisted sensor failure prediction

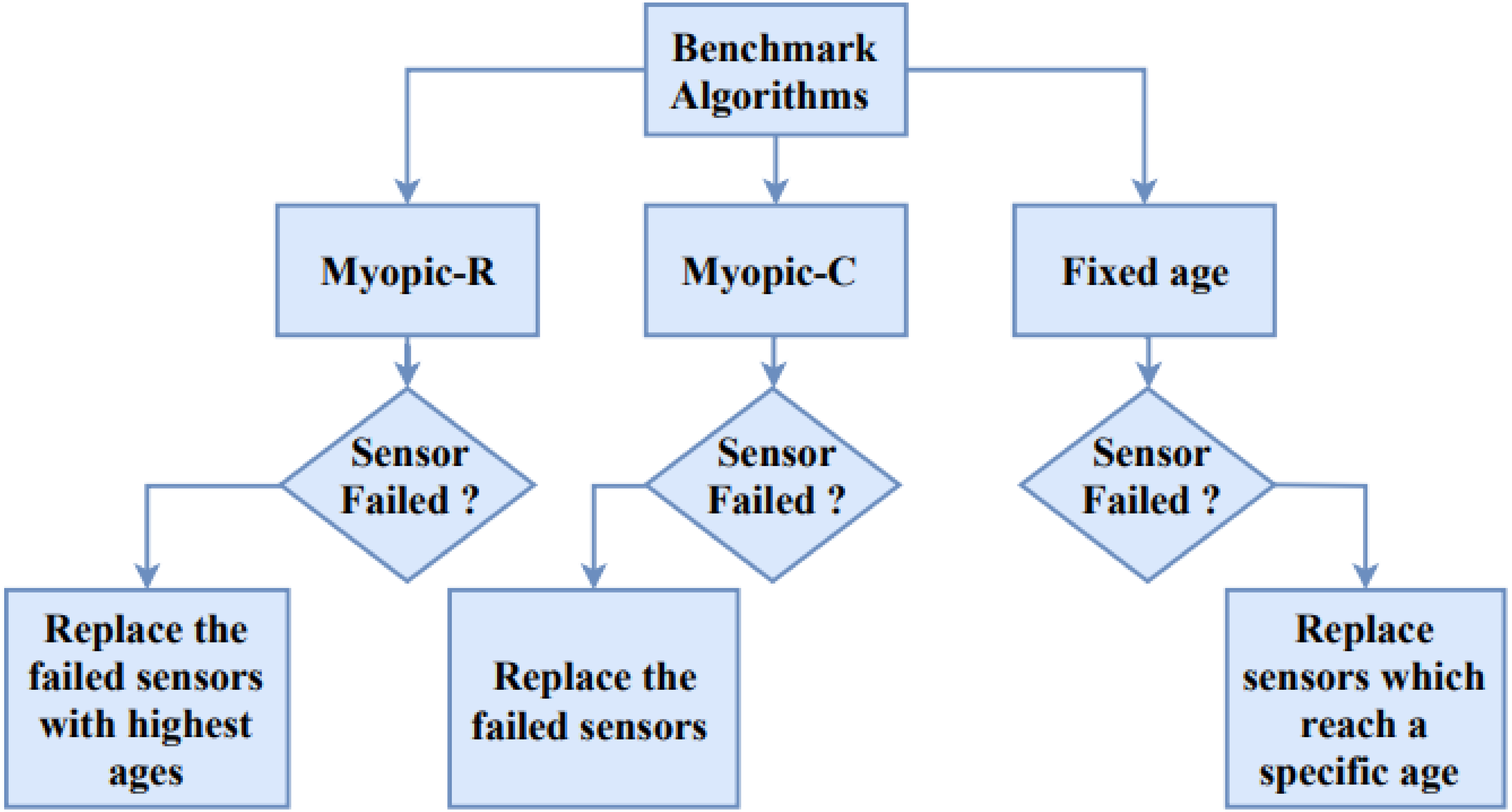


Federated learning

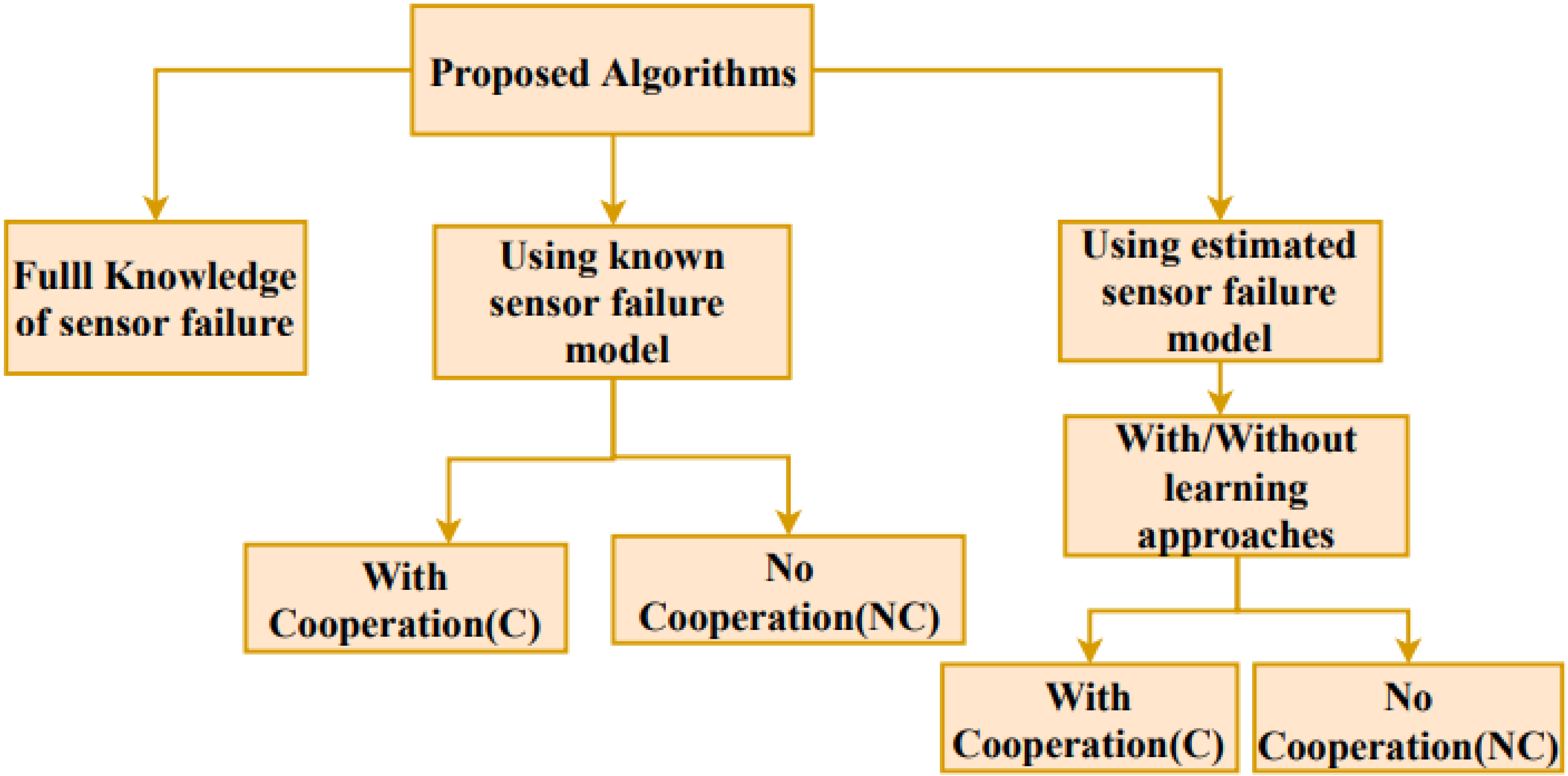
Only model parameters are sent to the server

MLE at the device

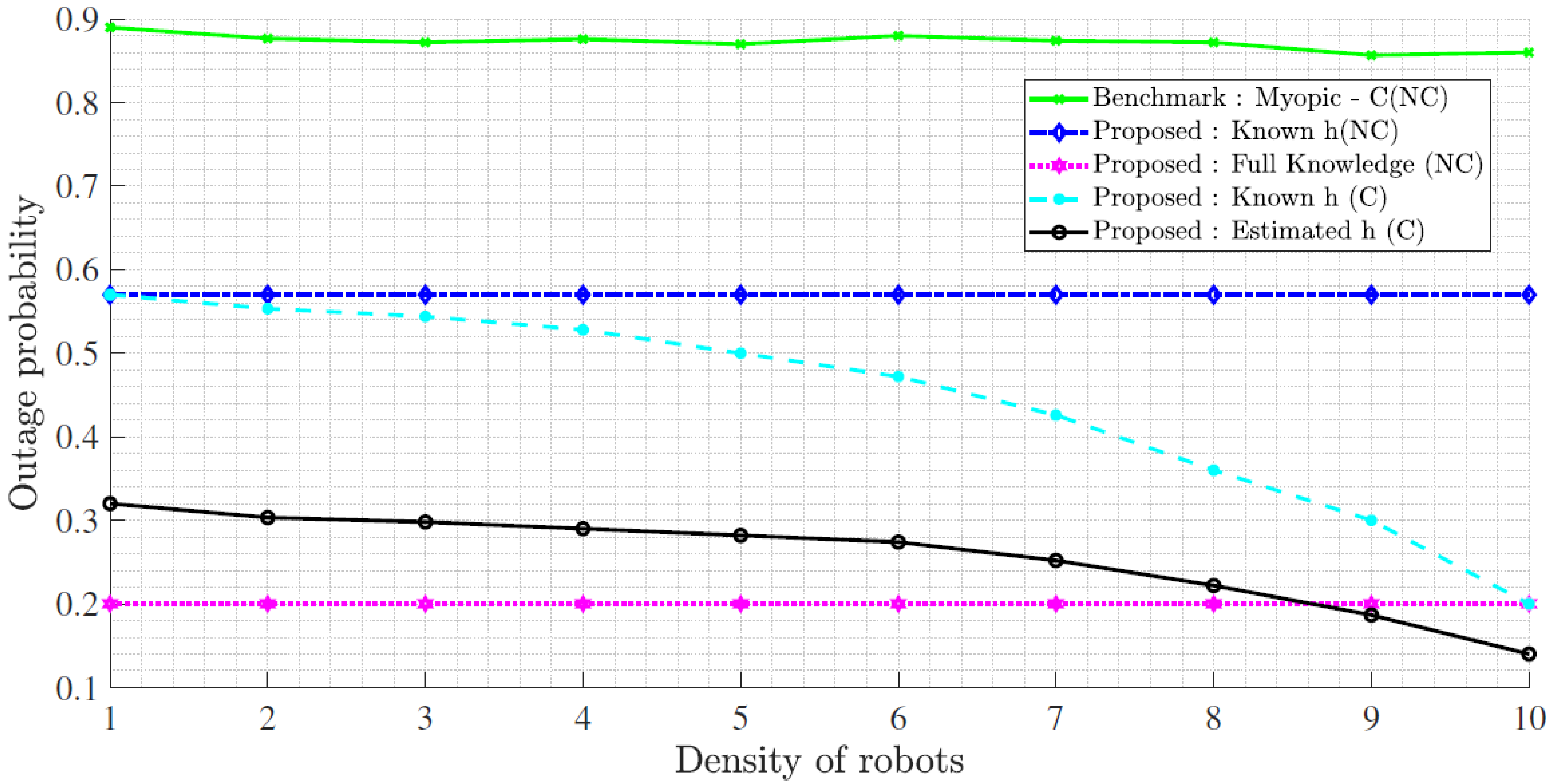
Baseline and Proposed Schemes



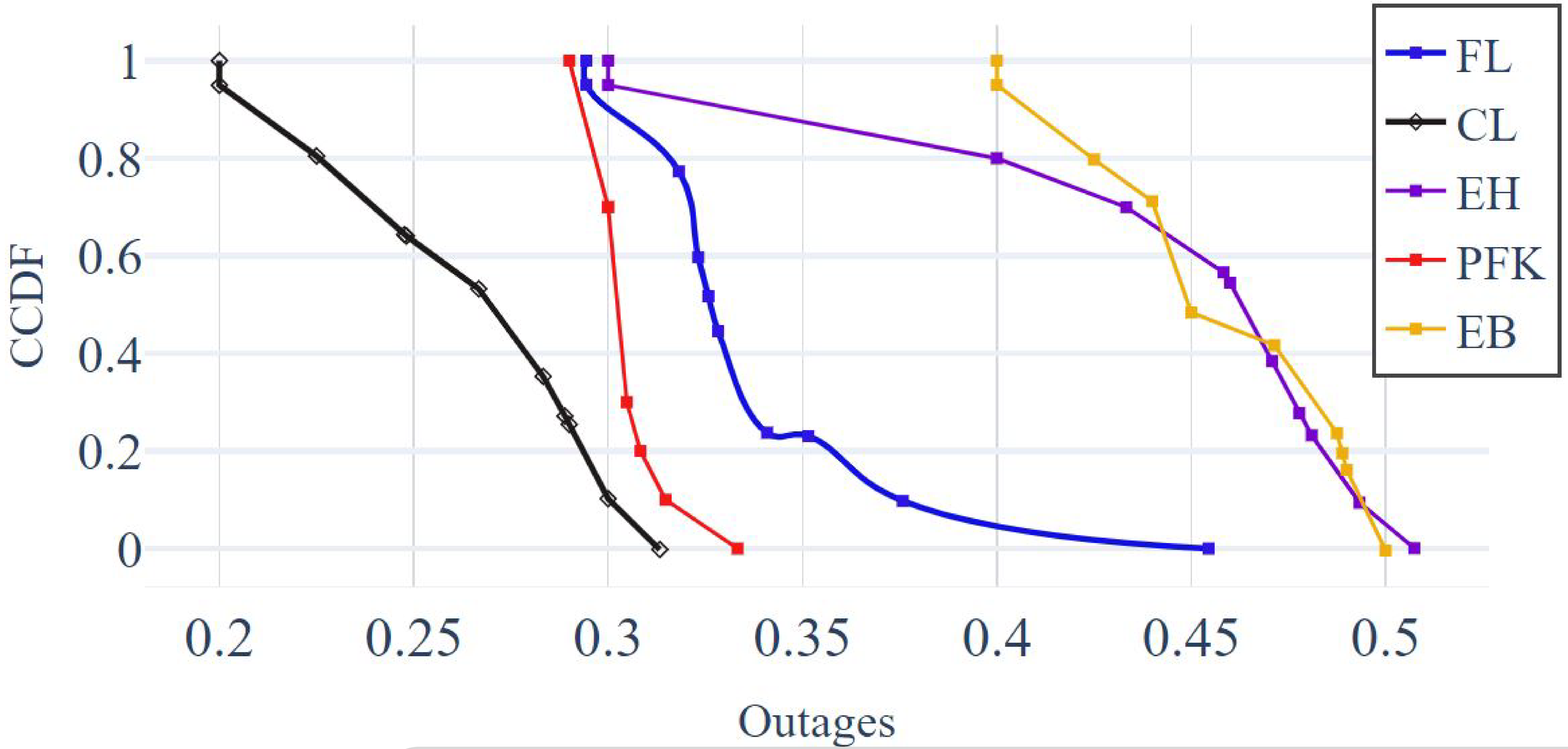
Baseline and Proposed Schemes



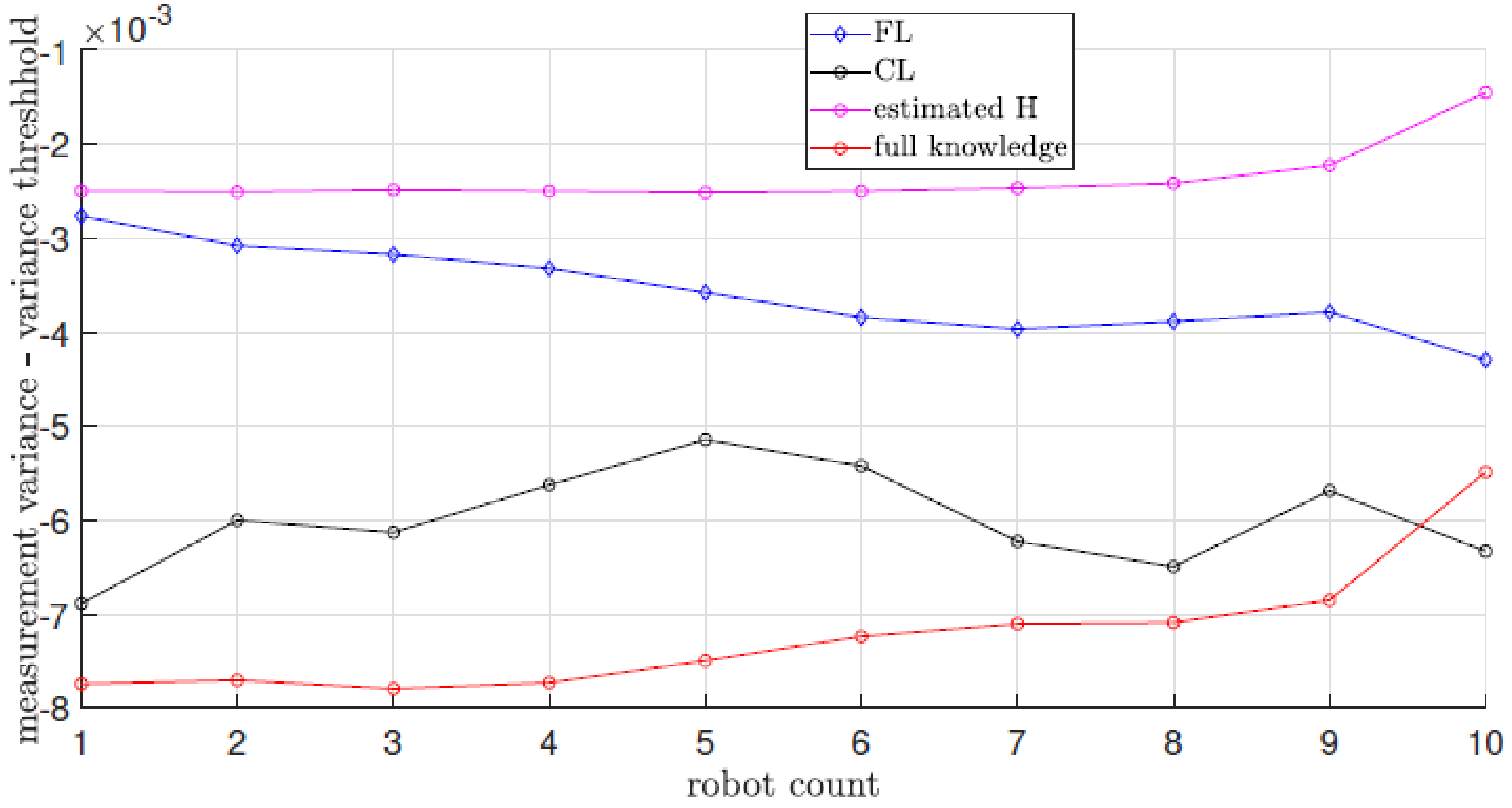
Simulation Results



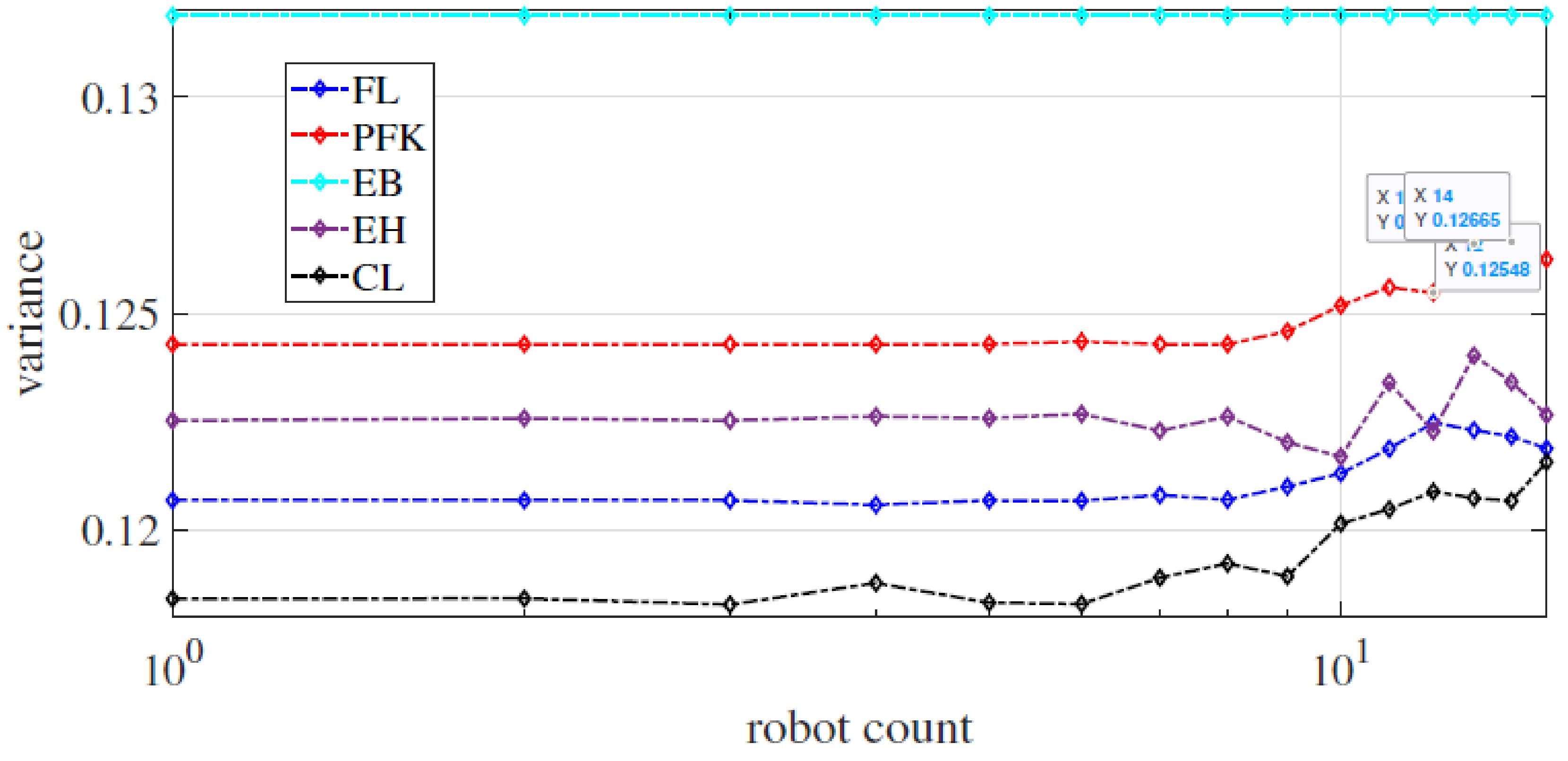
Reliability Outage Probability vs density of robots



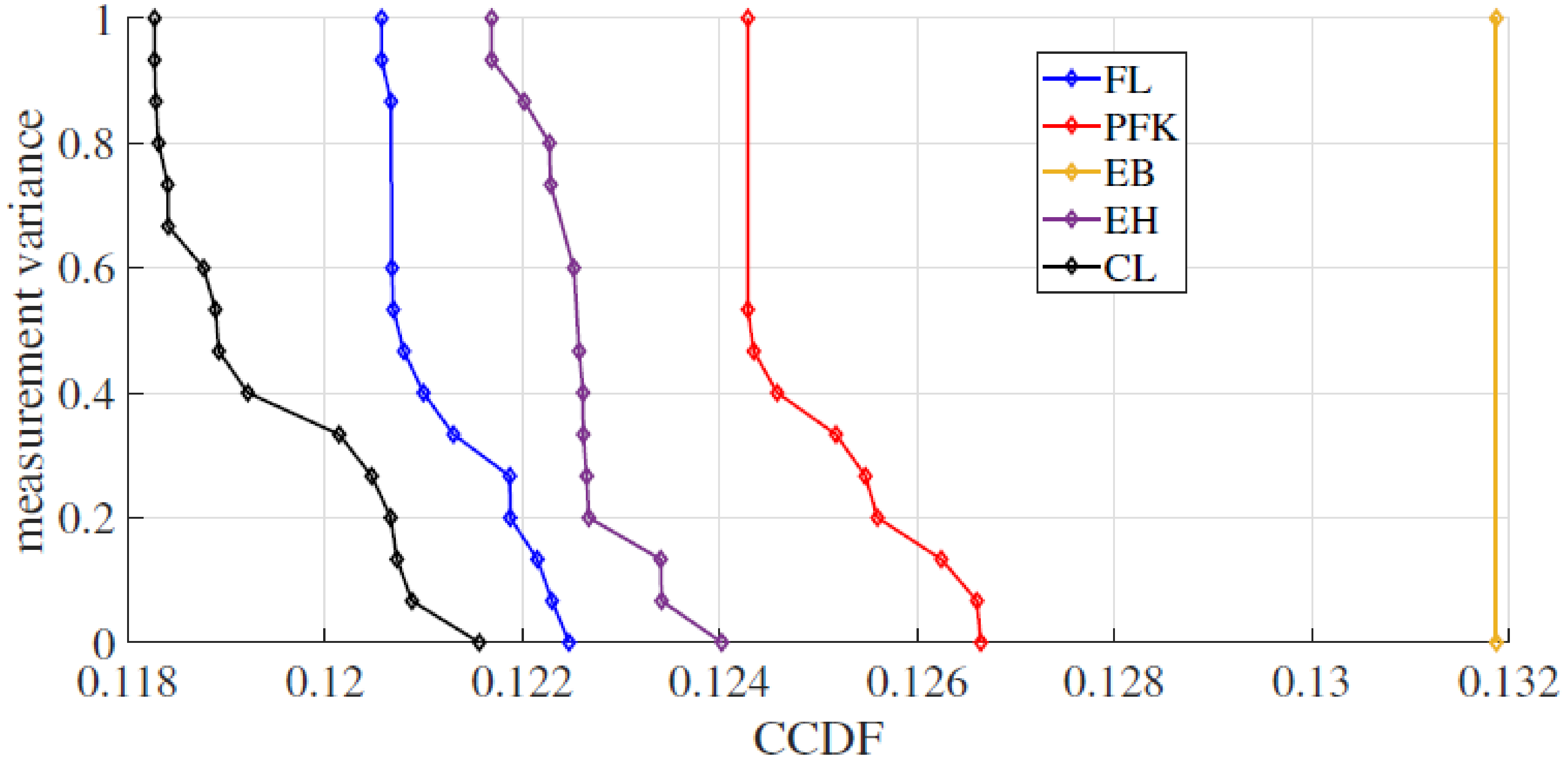
CL anf FL has lesser outages than EH and EB



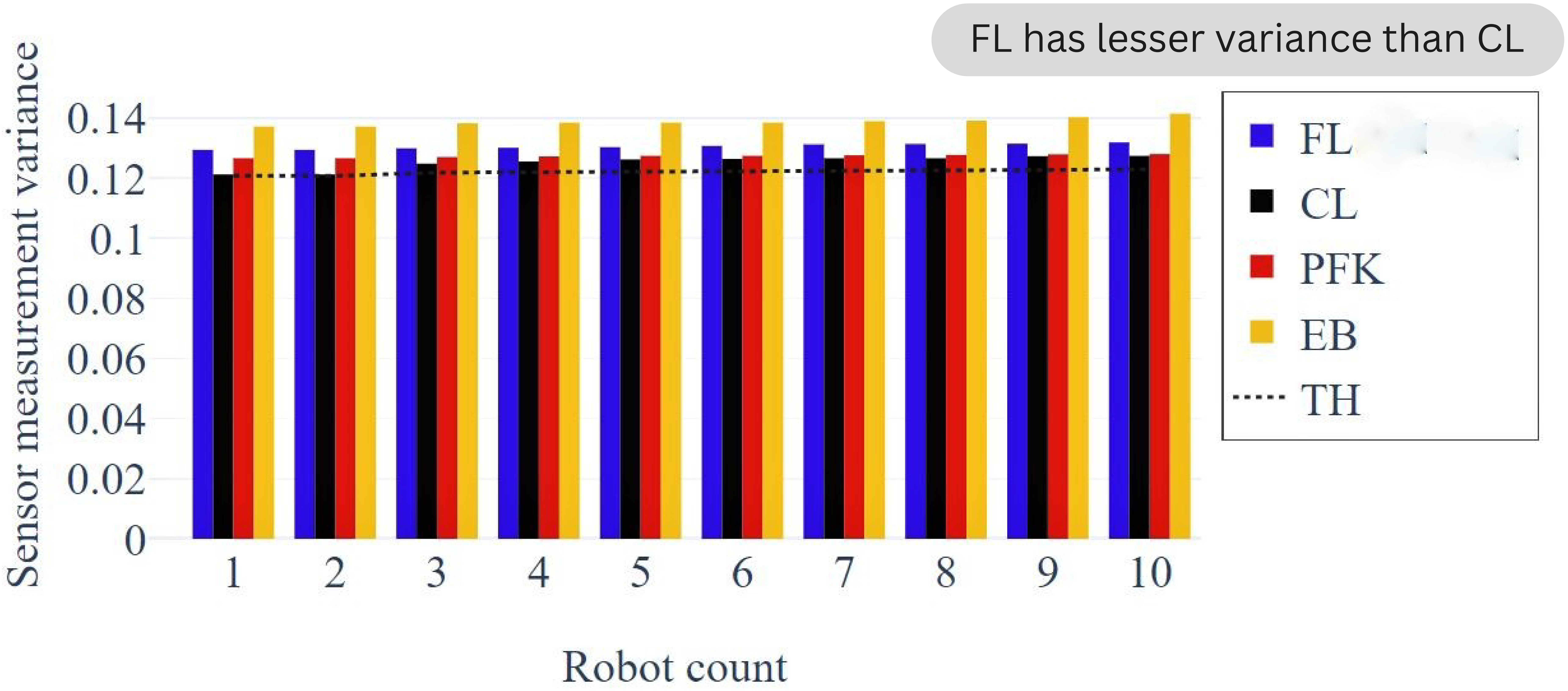
$\times 10^{-3}$
FL
CL
estimated H
full knowledge
measurement variance - variance threshhold
robot count



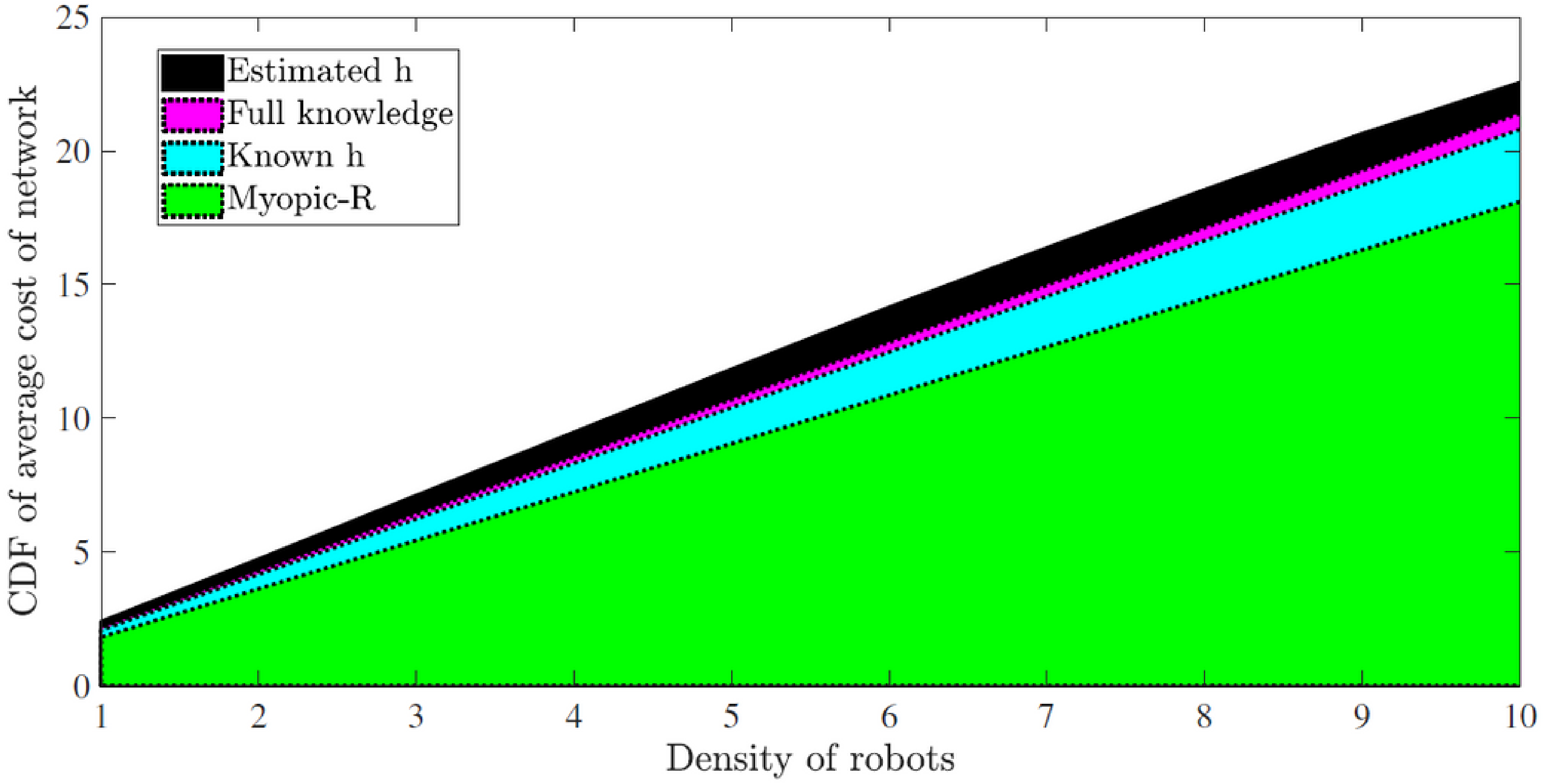
FL
PFK
EB
EH
CL
X 14
Y 0.12665
Y 0.12548
variance
robot count



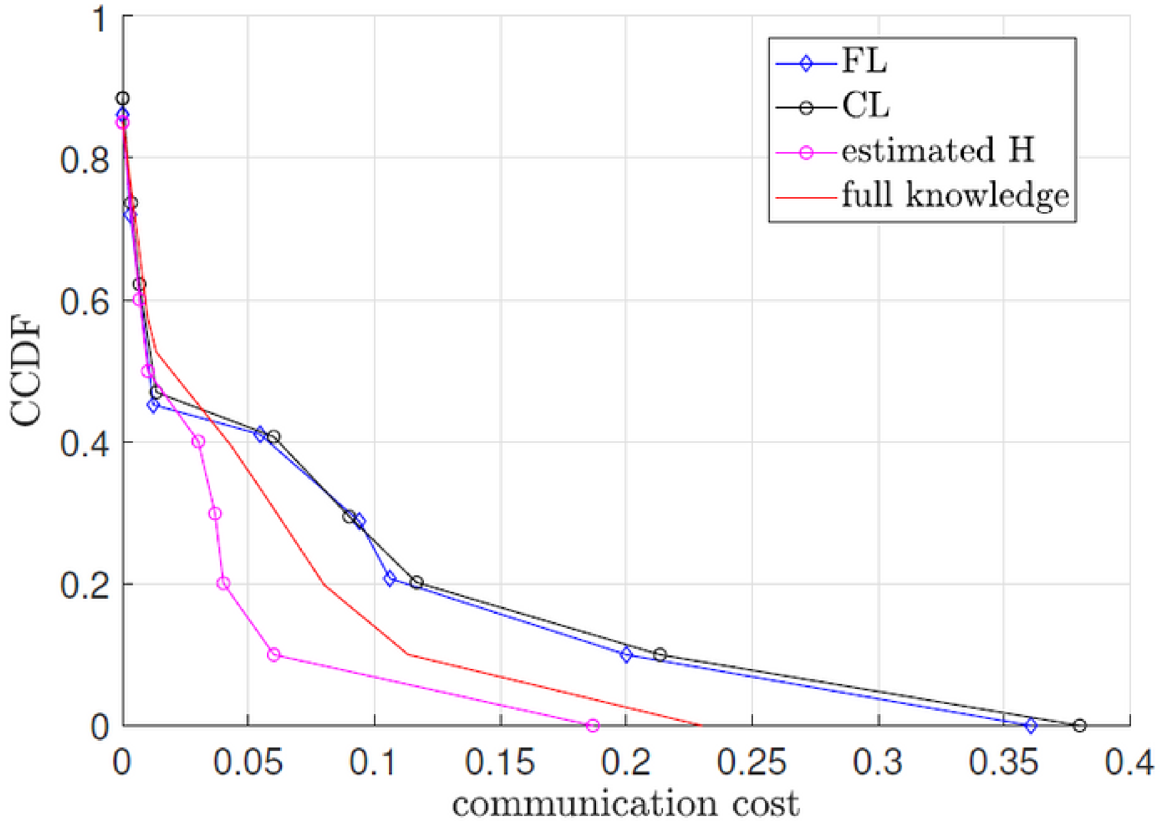
FL
PFK
EB
EH
CL
measurement variance
CCDF



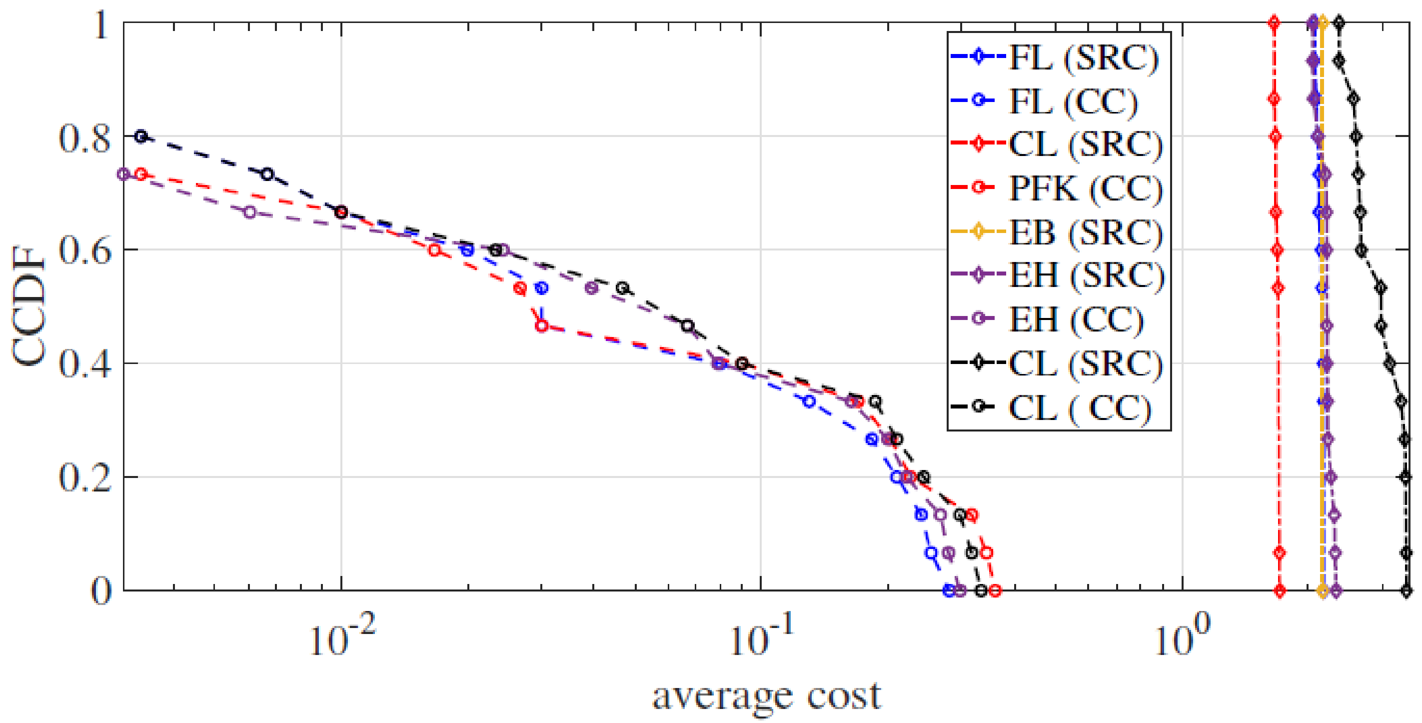
Variation of sensor measurement variance against robot count



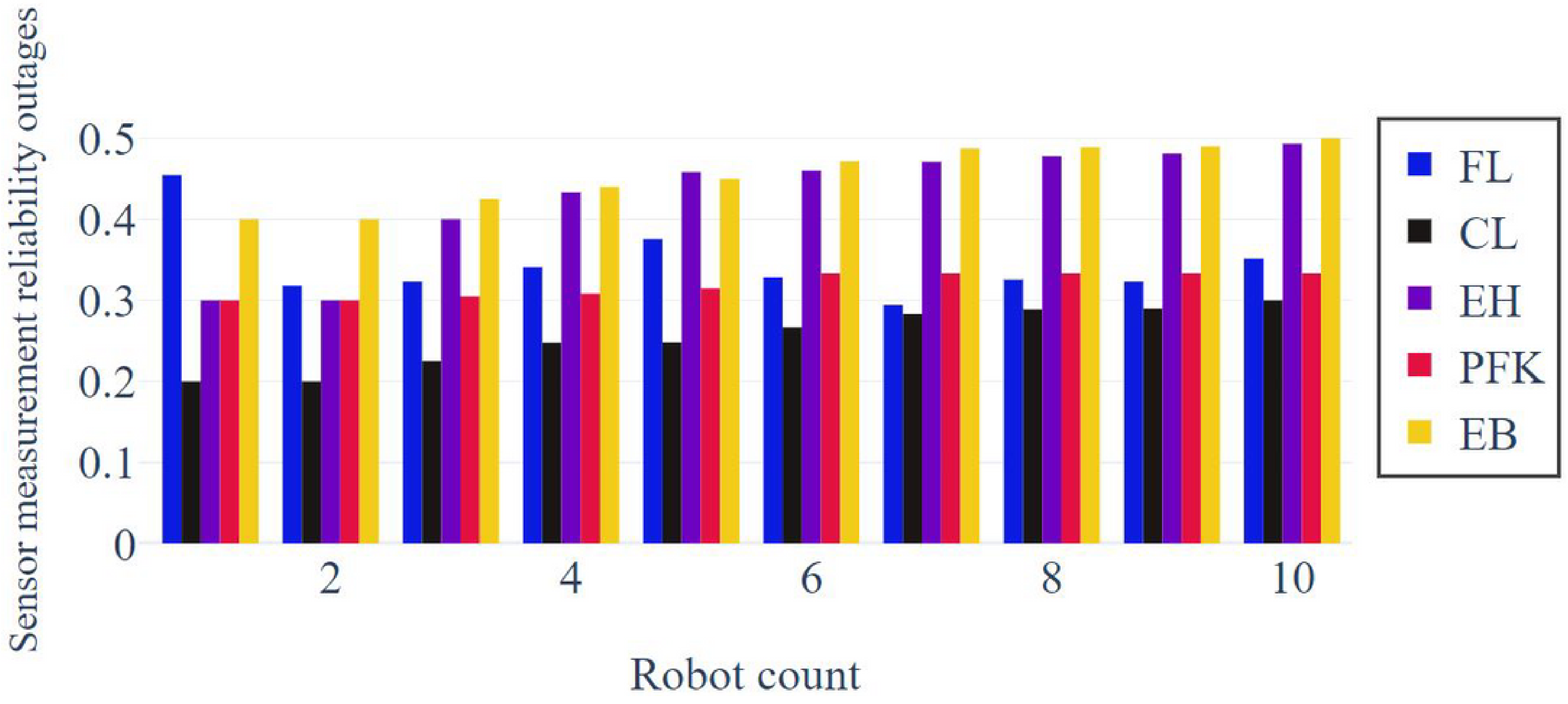
CDF of network cost vs density of robots

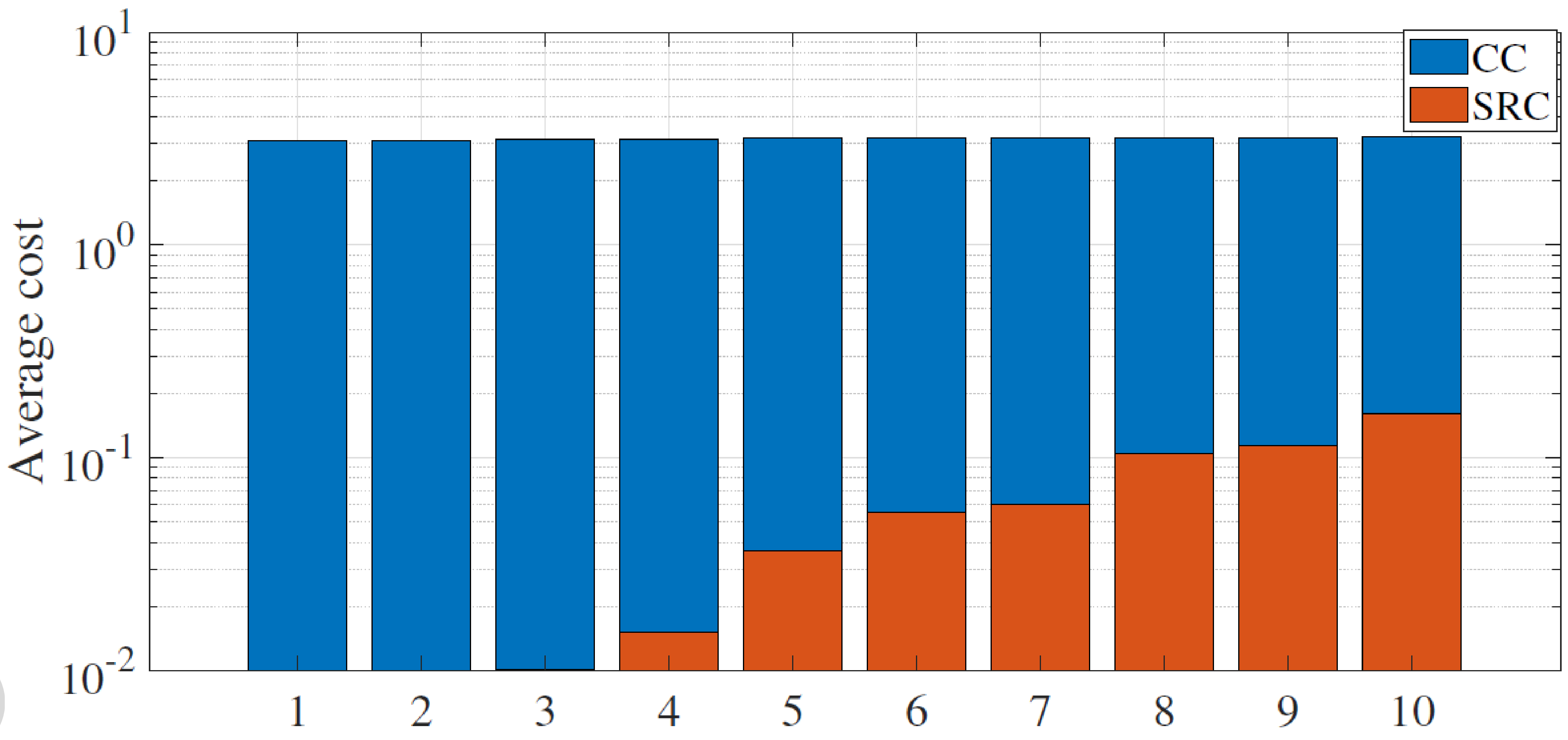


CCDF of network cost

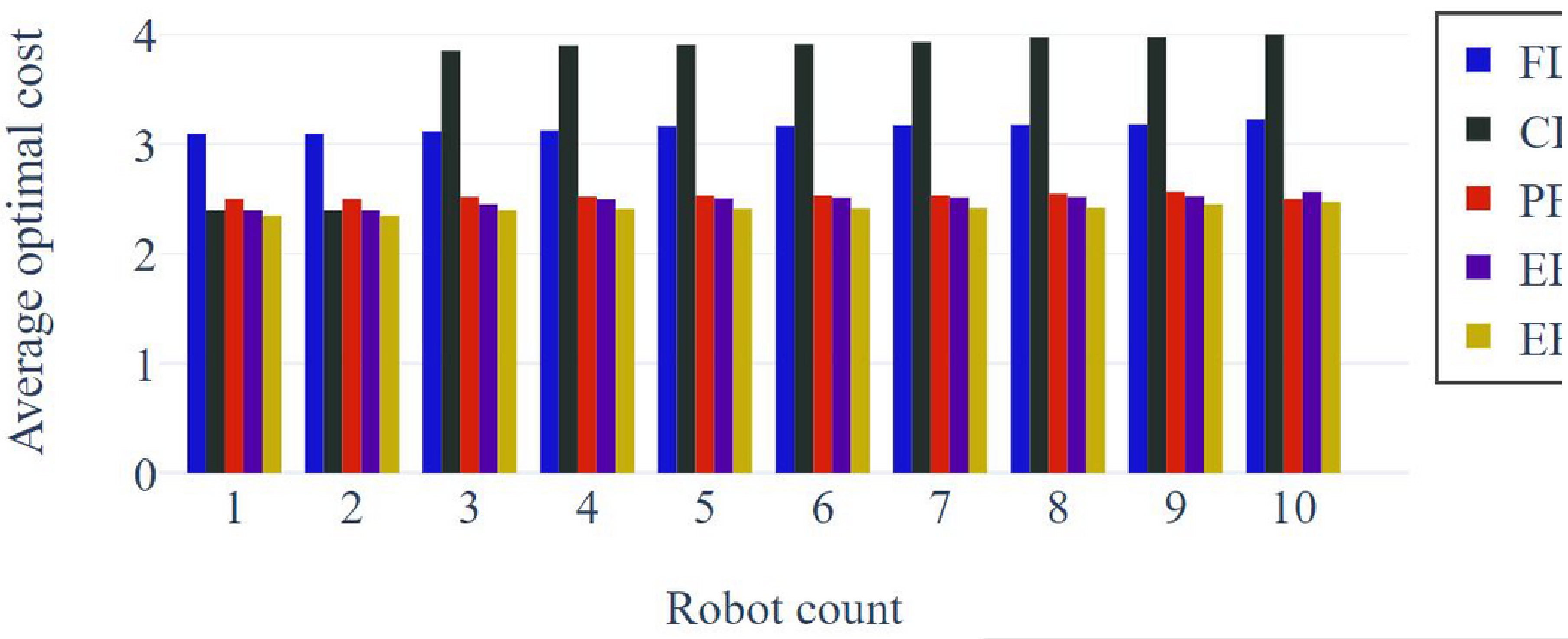


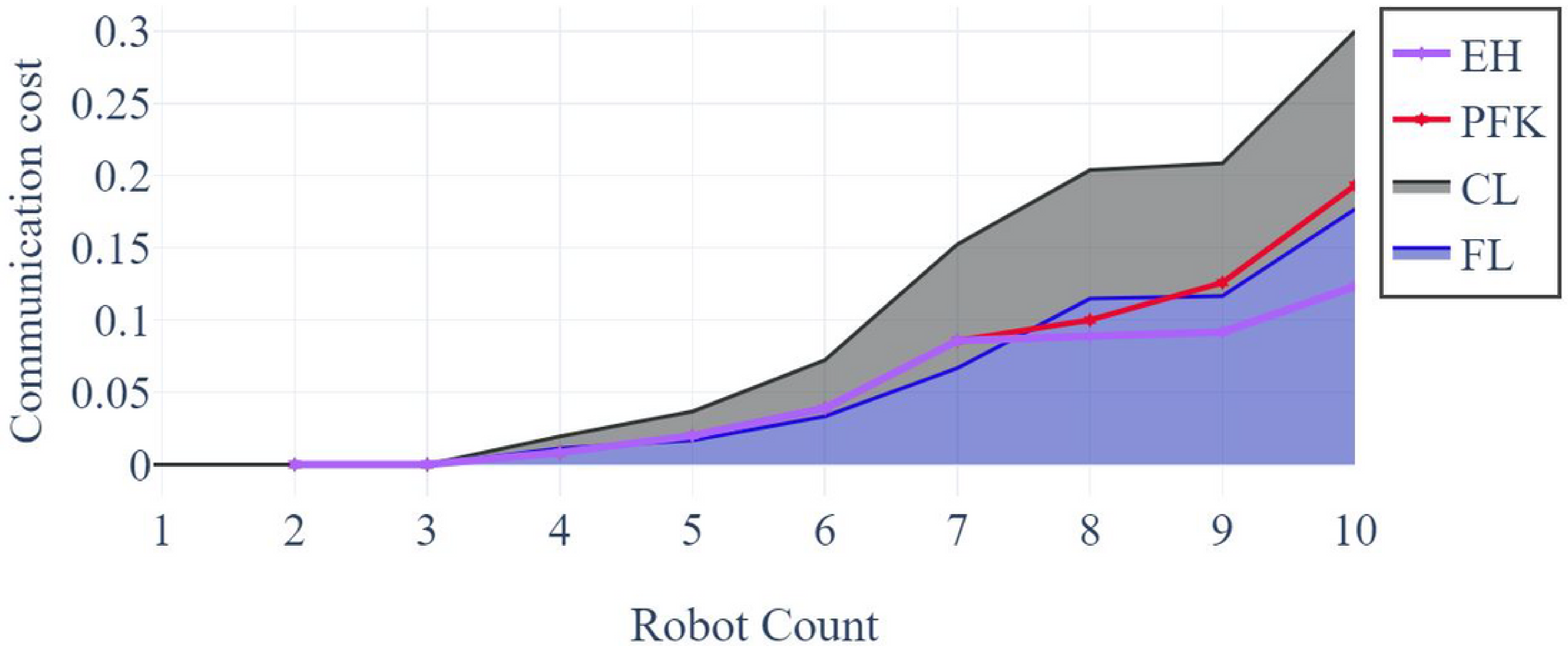
CL assisted estimated h based optimization : higher sensor replacement



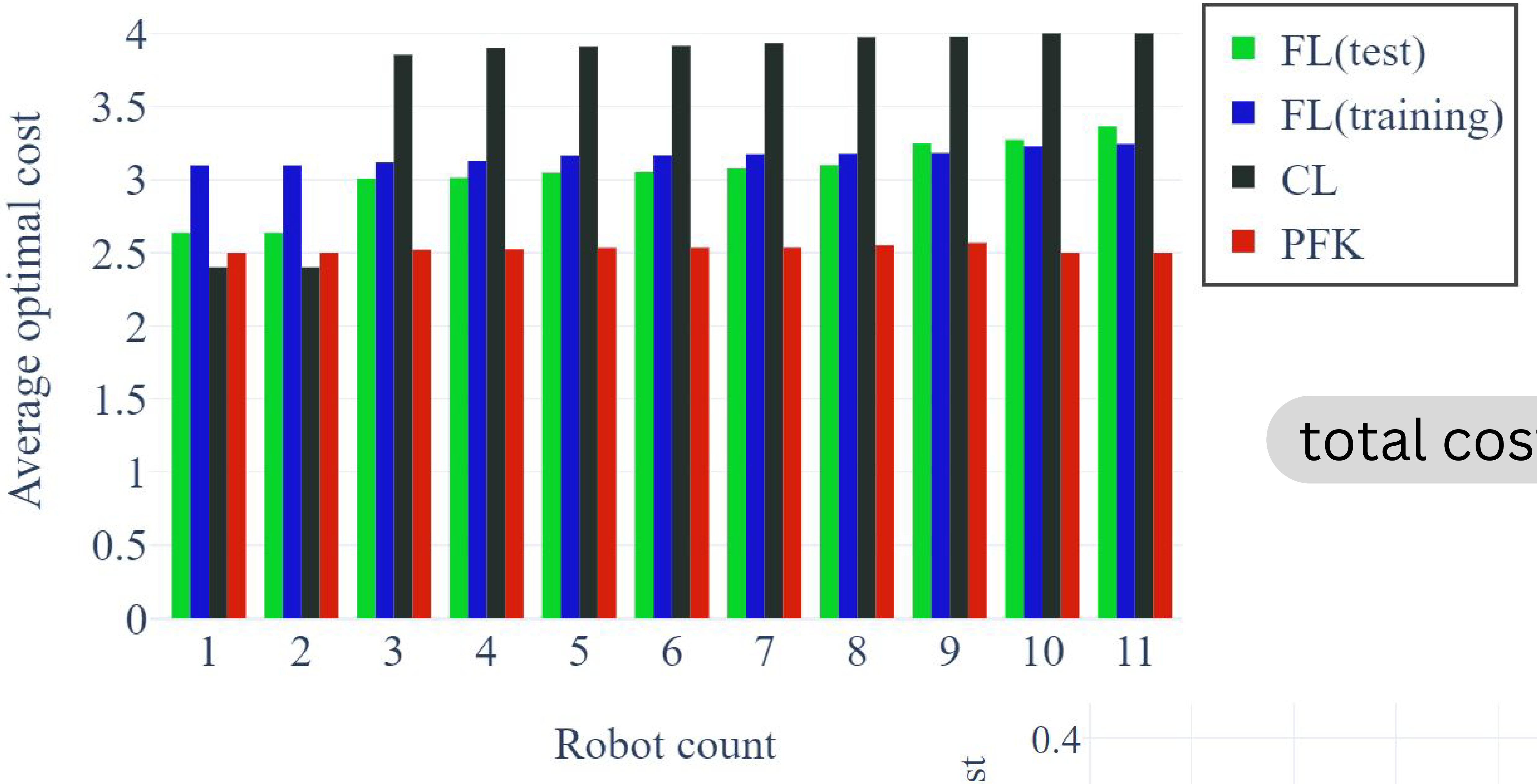


CL has lesser relibility outages than FL

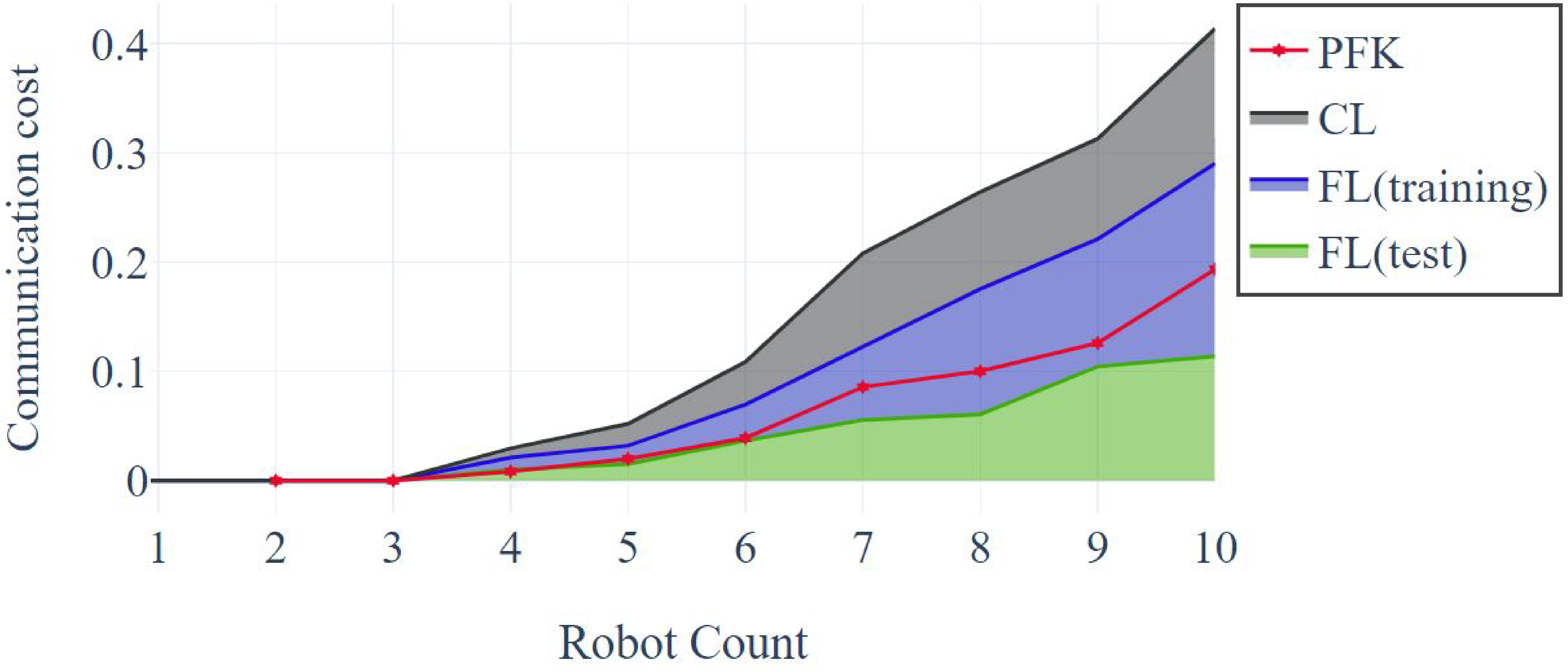


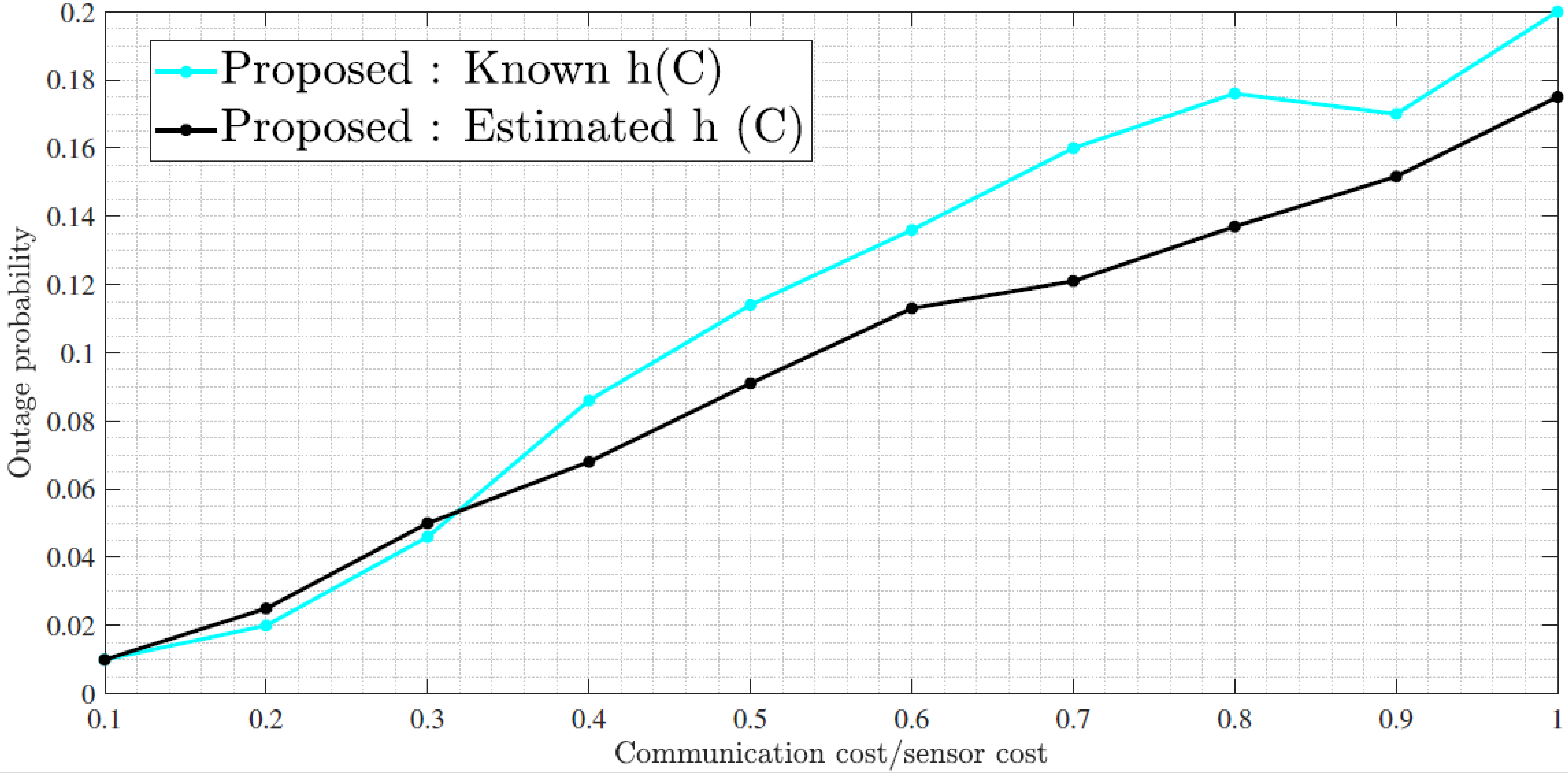


FL reduces average cost than CL



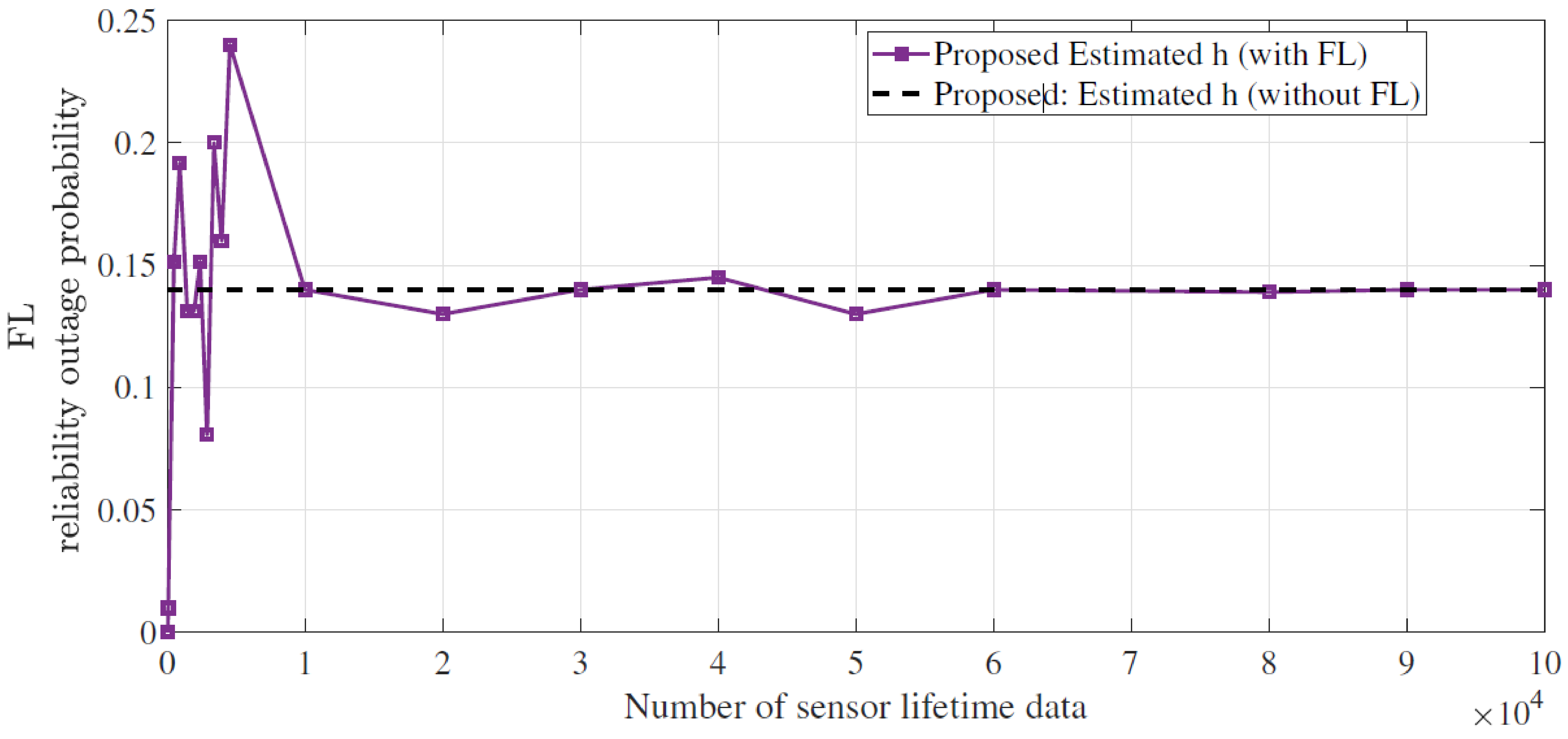
total cost vs robot count lower in FL





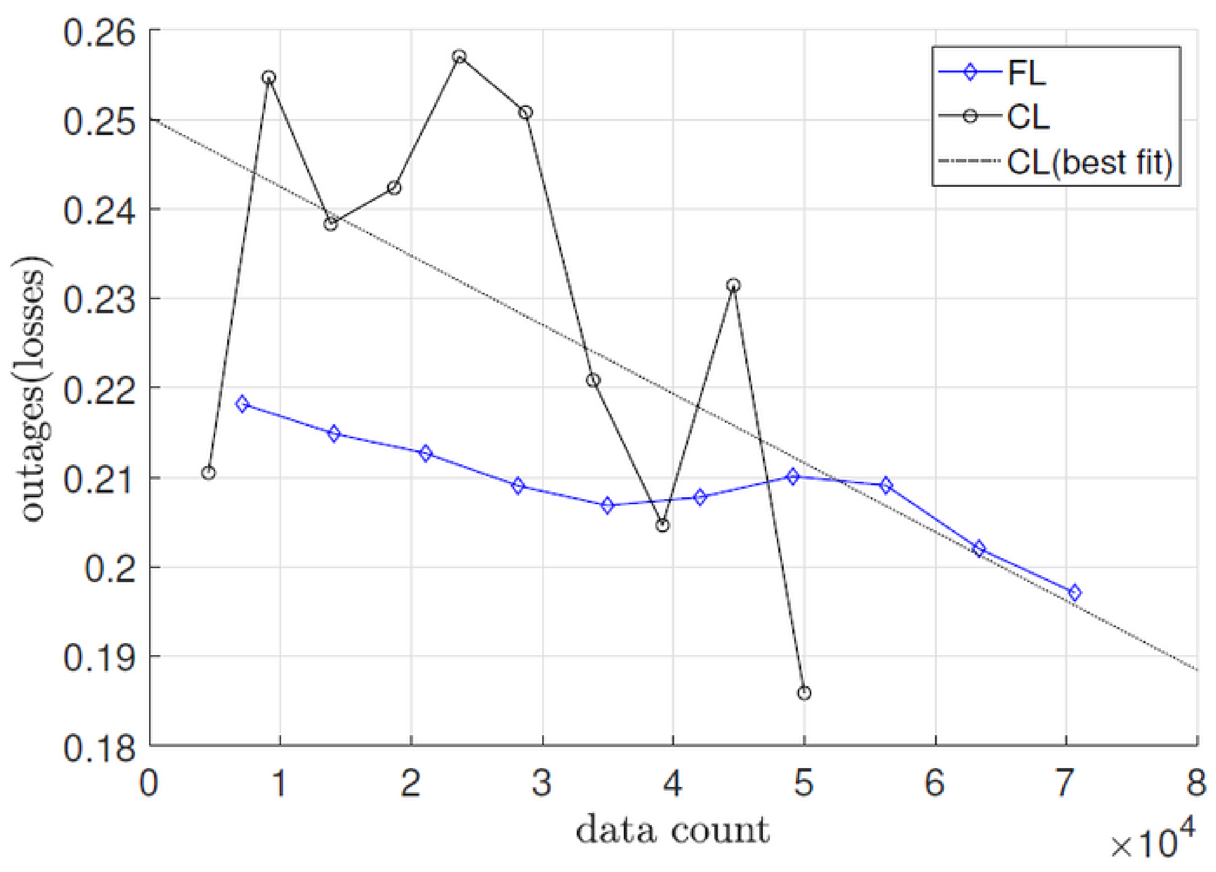
Reliability Outage Probability vs ratio of communication cost over sensor cost

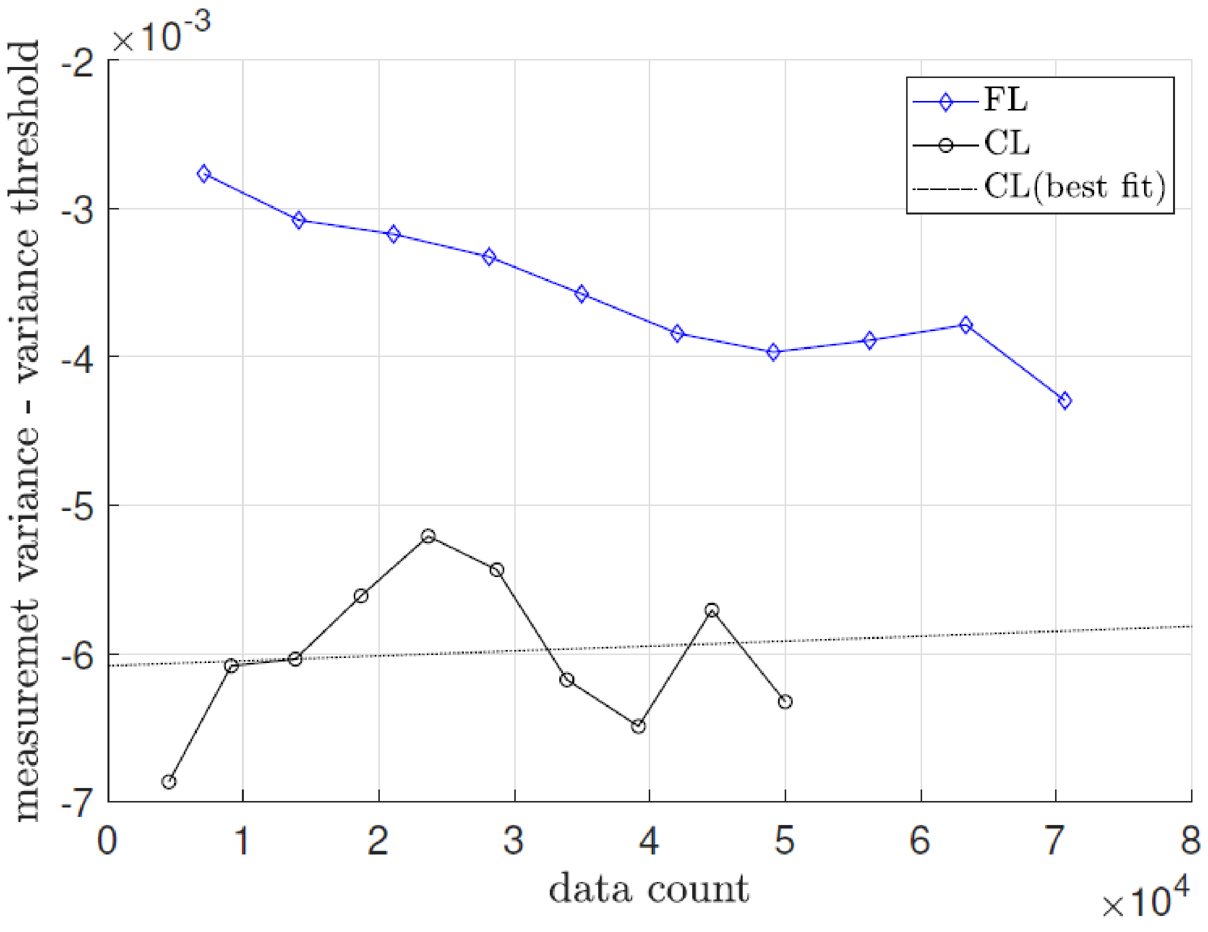
Optimization selects the best network links to communicate

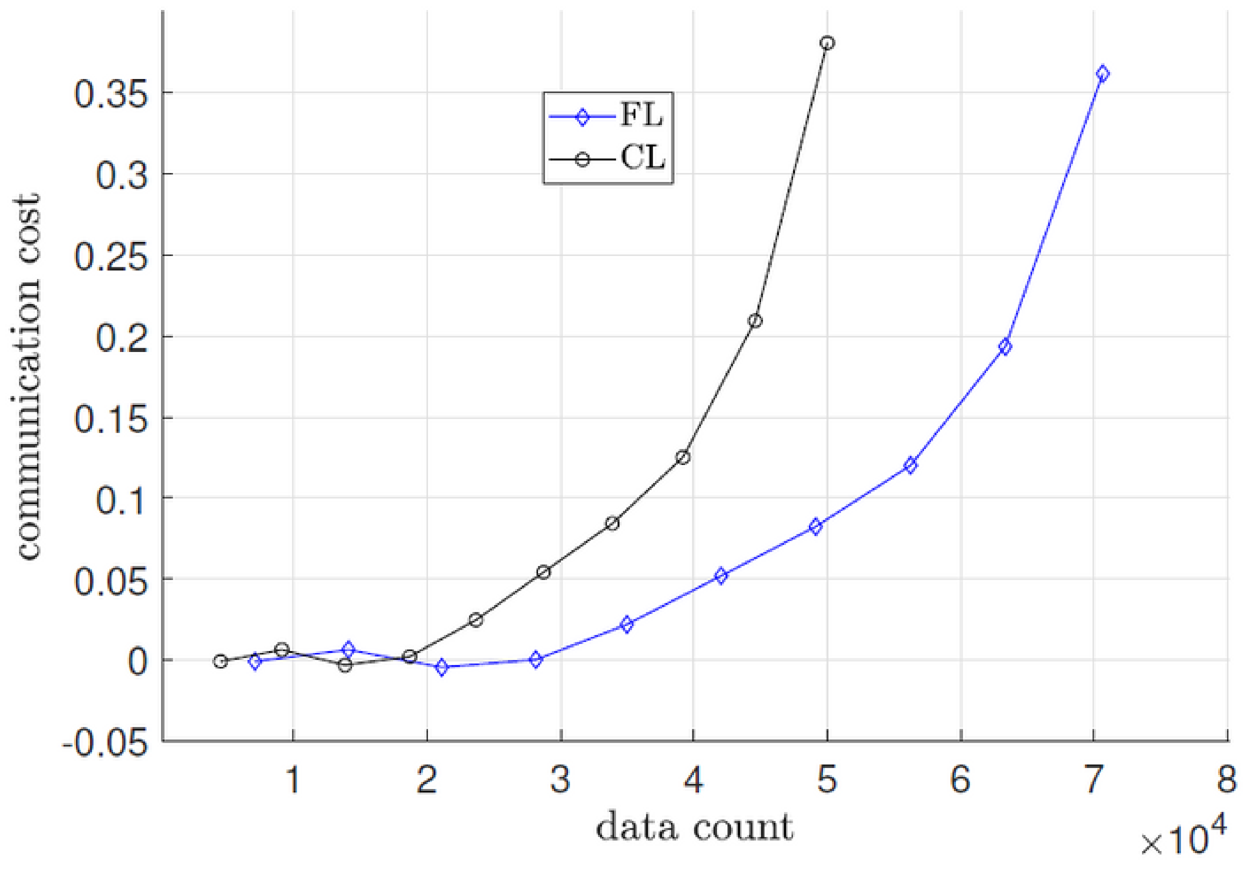


Reliability Outage Probability vs data size

As the data size increases the outages converge to known h based outages



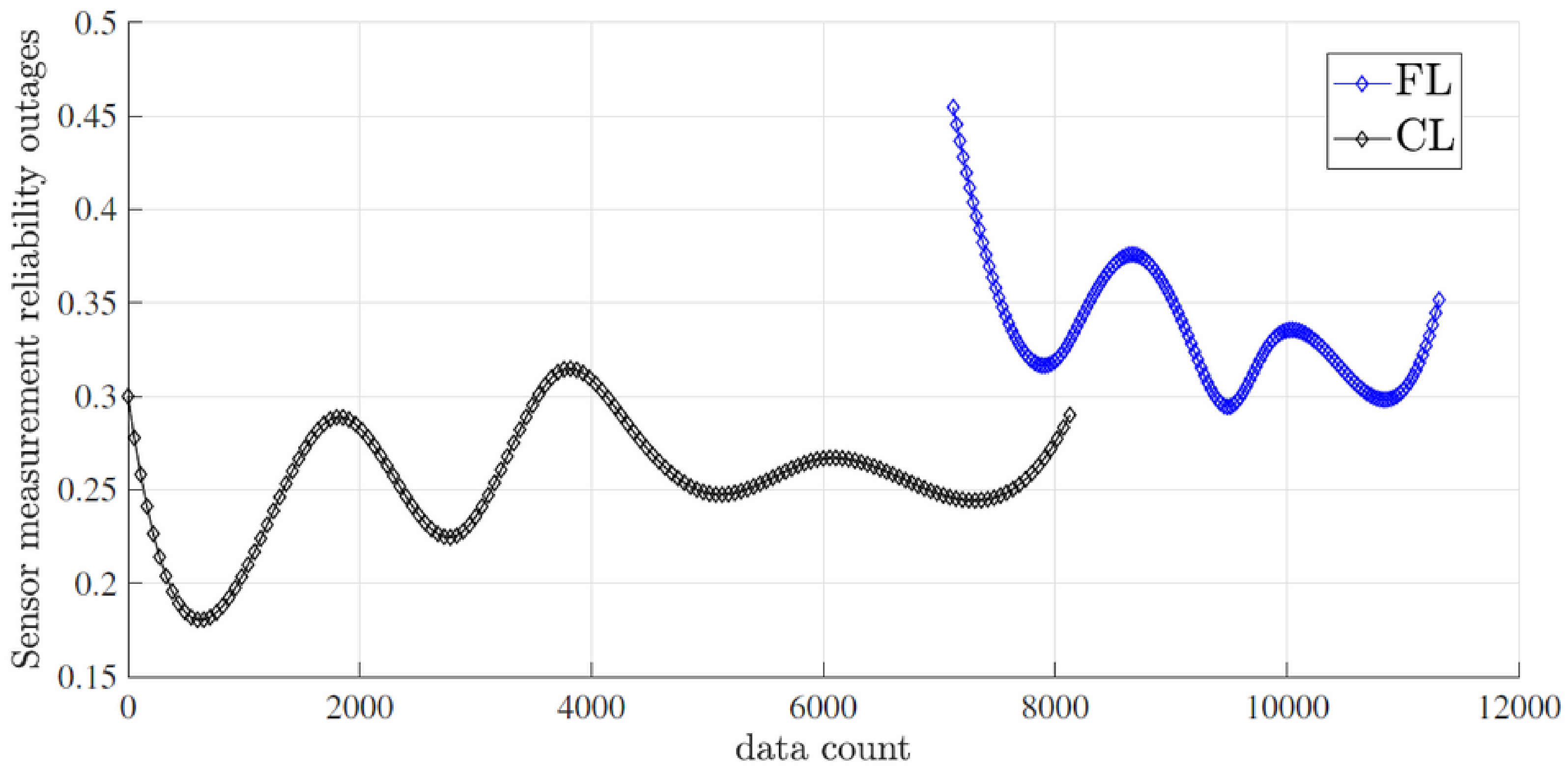




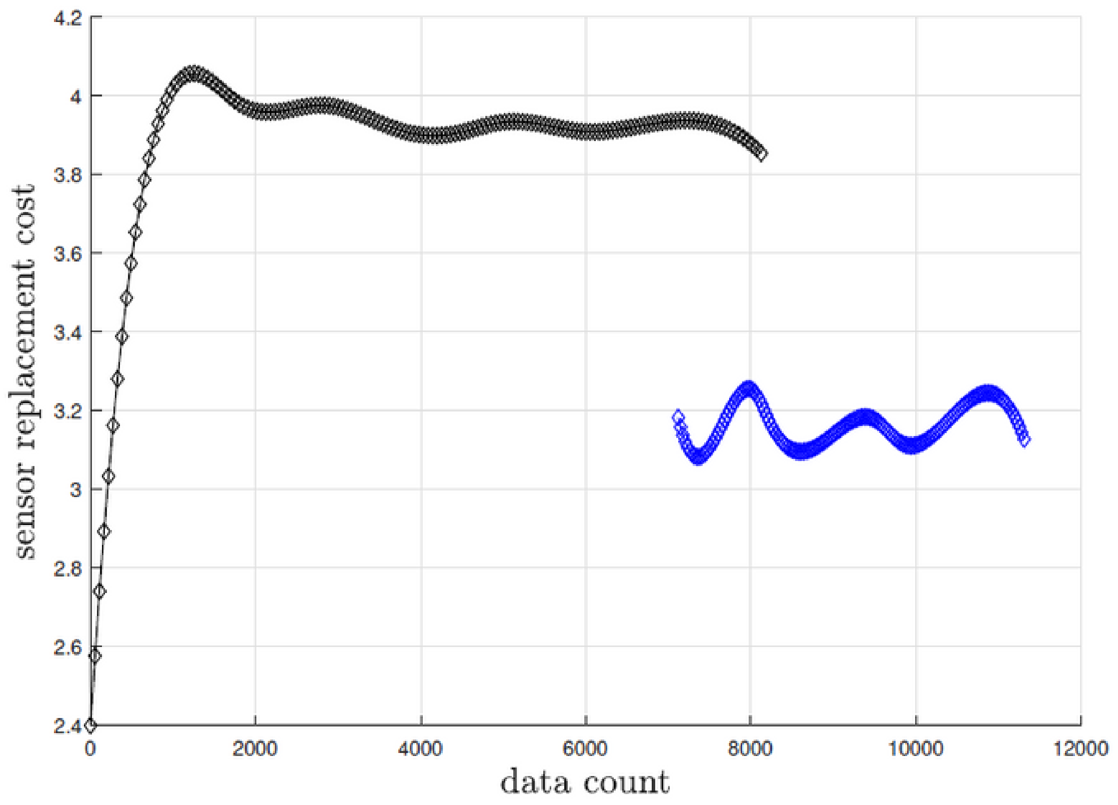
CL performs better than FL in terms of reliability outages

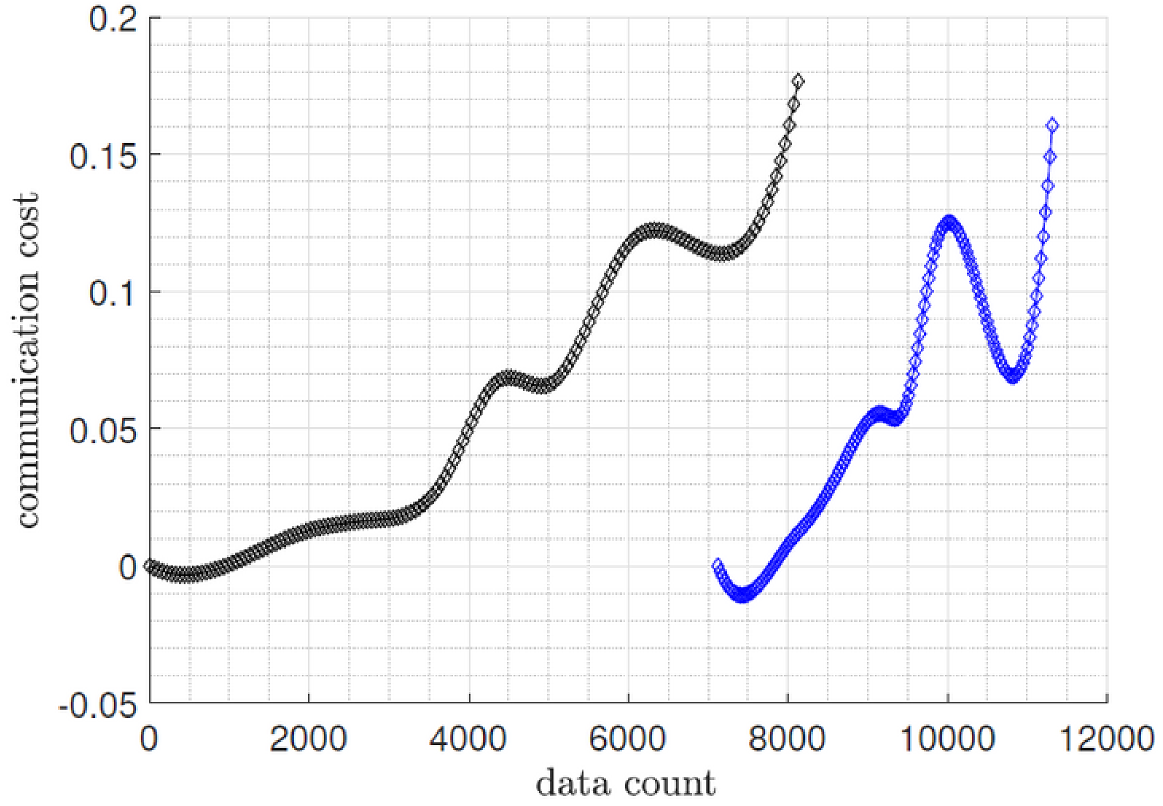
FL performs better than FL in terms of network cost

FL (training) start later because sufficient data needs to be collected to train FL at device level

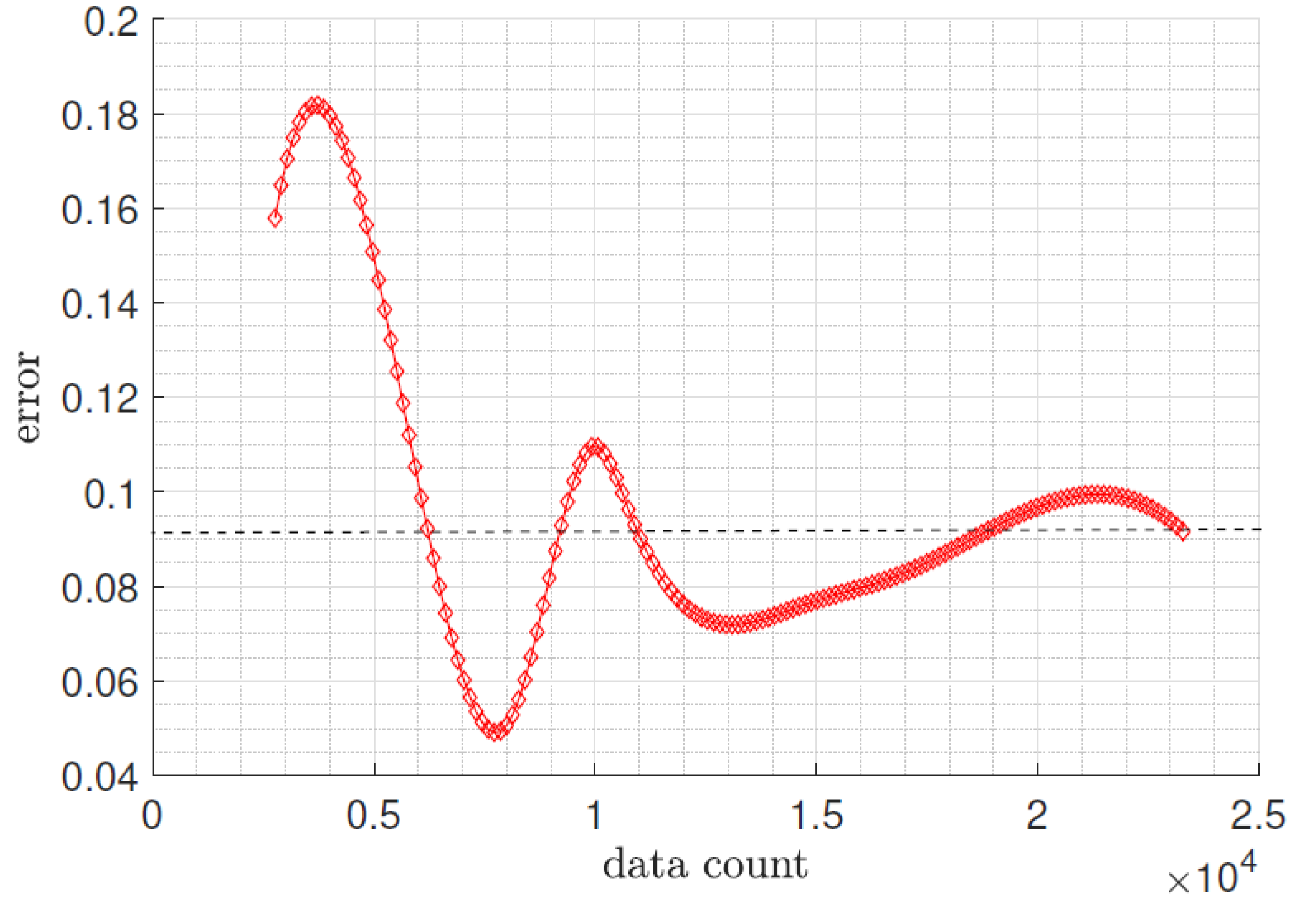


FL reliability outages > CL against training data

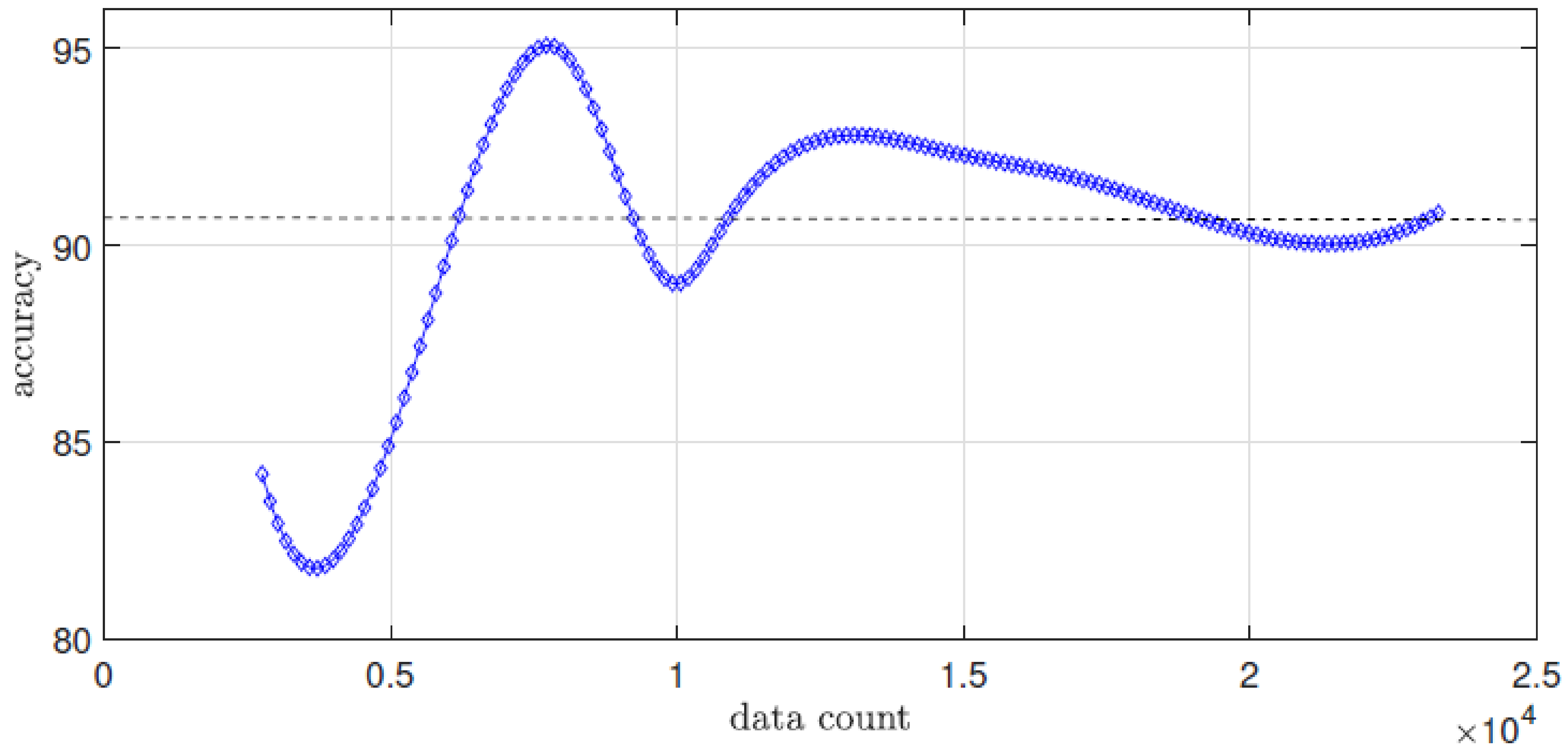




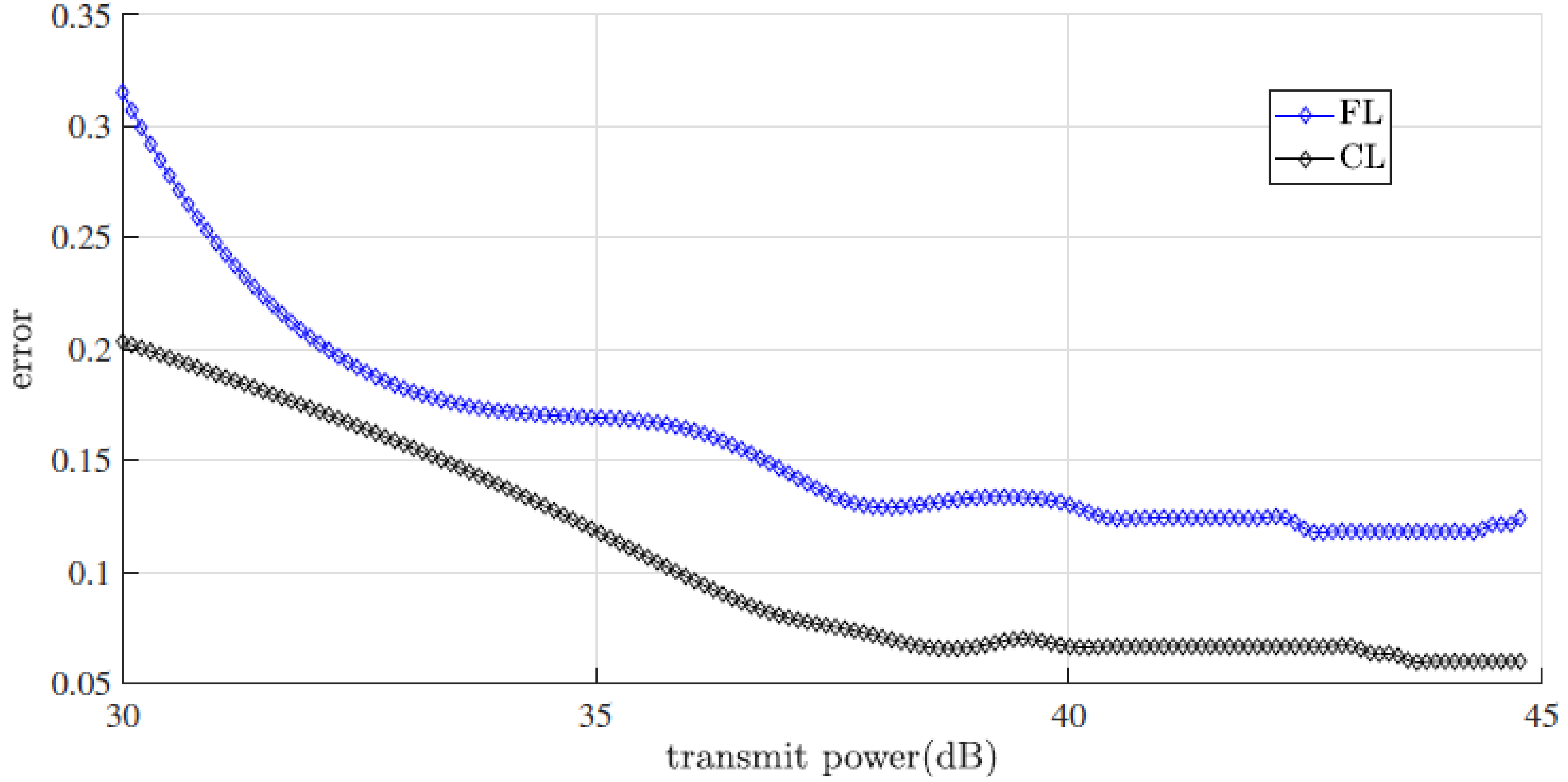
FL costs < CL against training data



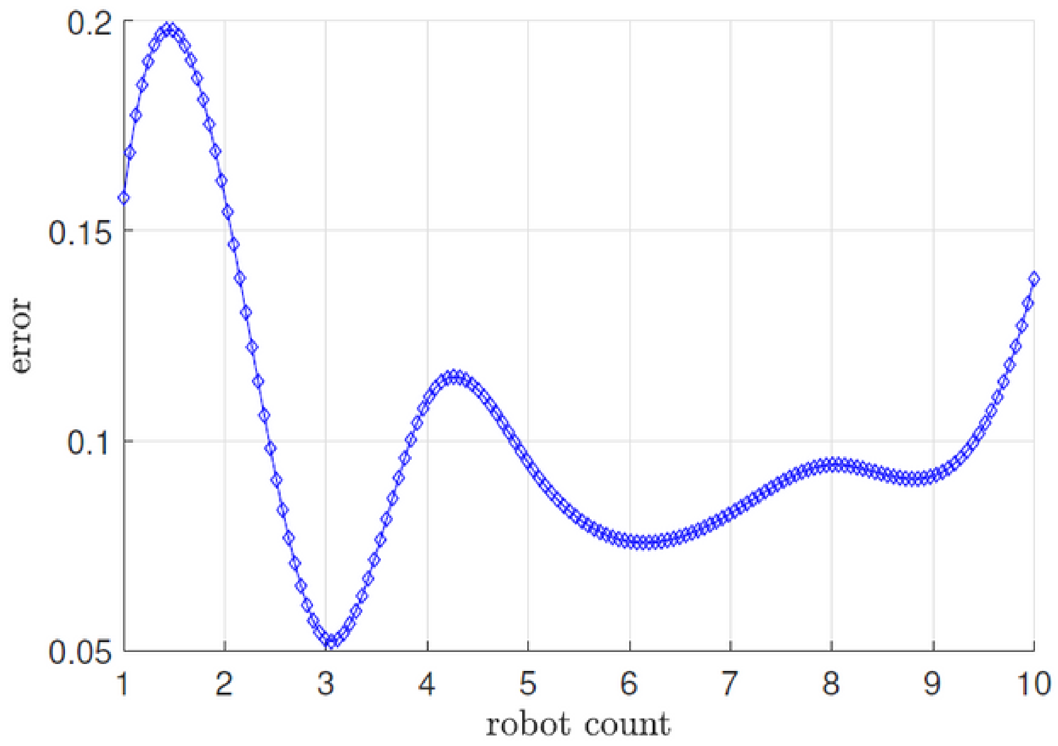
FL training: error



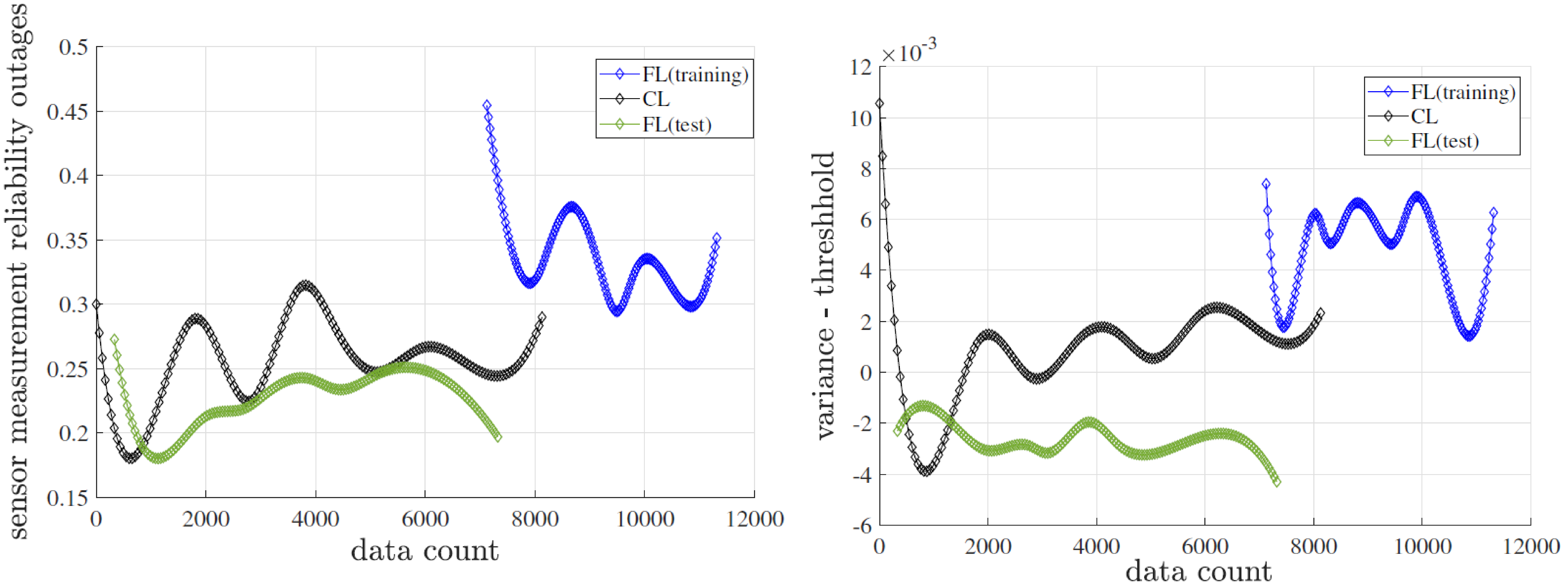
FL training: accuracy



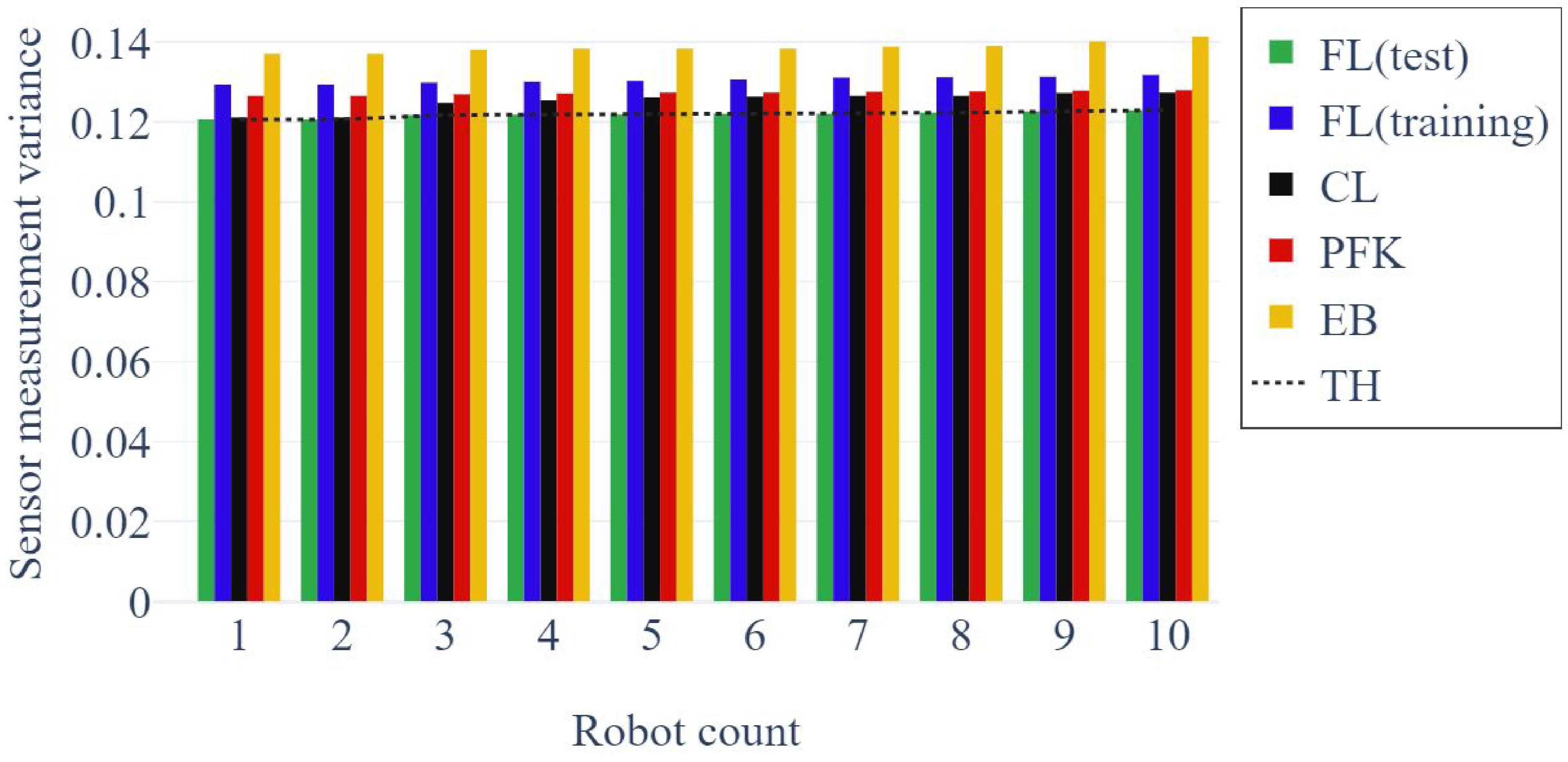
FL training: error vs transmit power



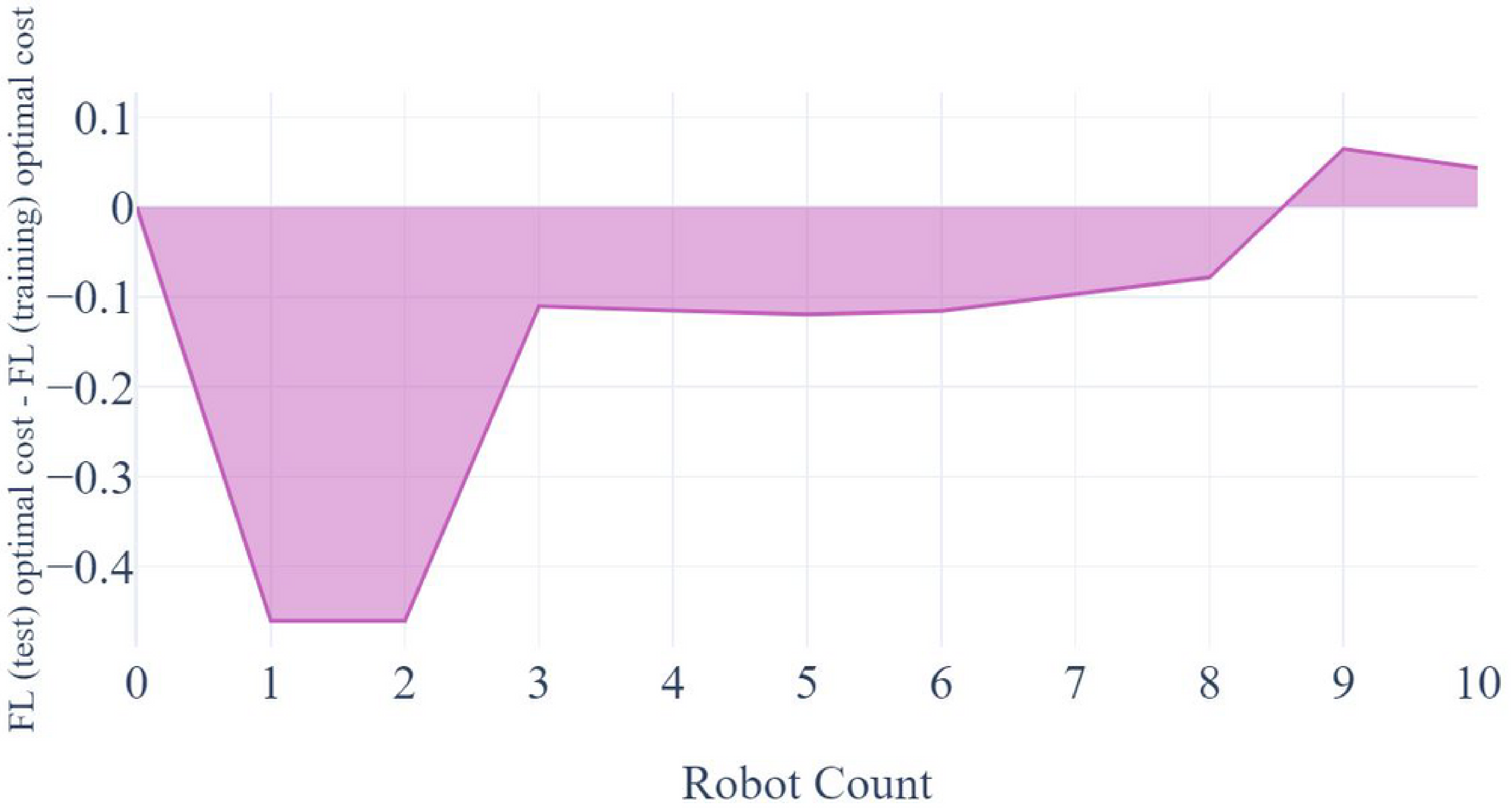
FL training: error vs number of robots



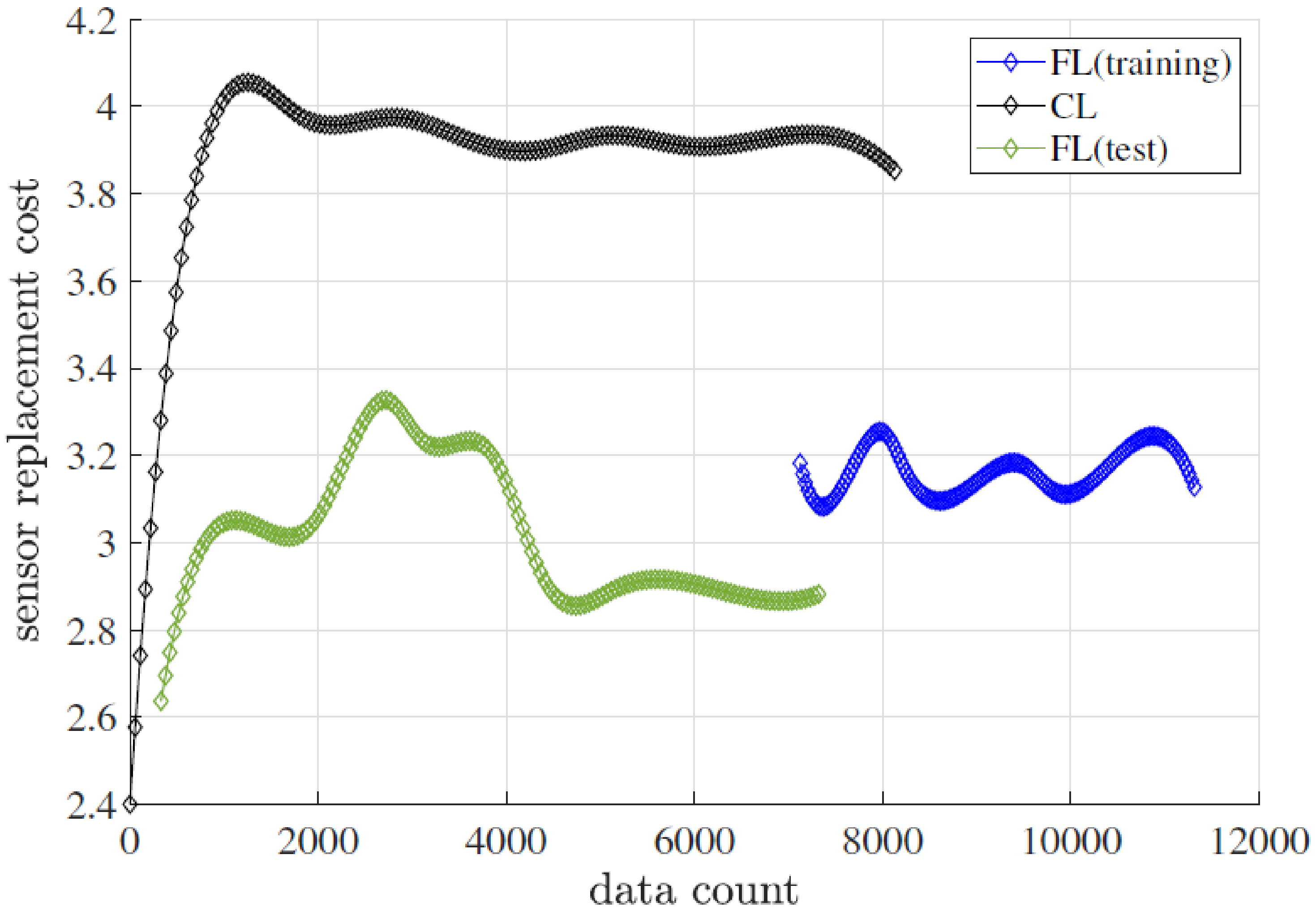
FL reliability outages higher in training phase than testing phase: but shows a decrement

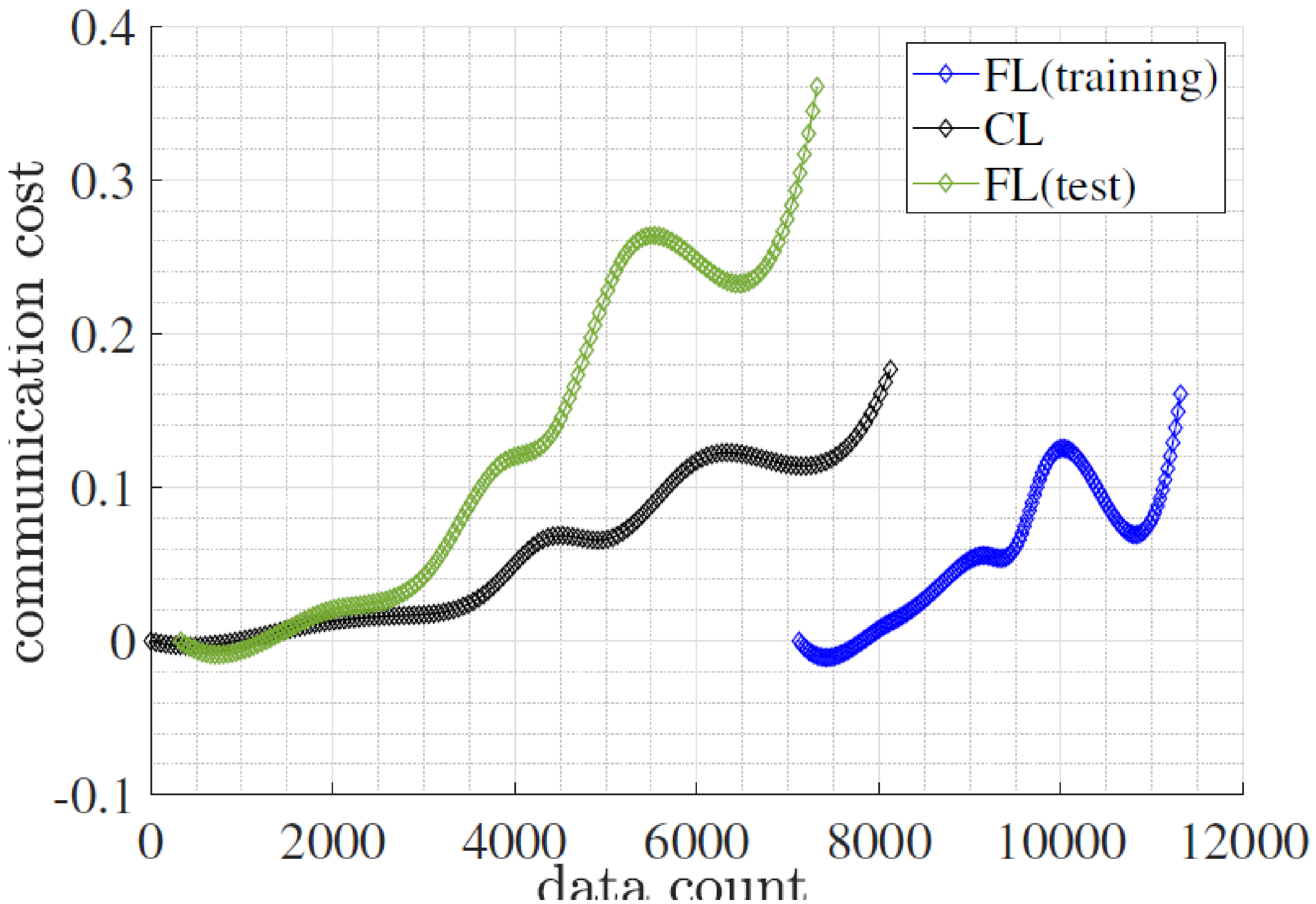


Sensor measurement variance lesser in FL (test)



FL (test) total cost increases when number of robot increase





Sensor replacement cost in FL (training) higher than FL (test) and CL

Communication cost in FL (test) higher than FL (training) and CL

Contribution

Novel Sensor failure prediction model using Federated Learning

Device level data utilization for prediction

Novel Binary Optimization problem for sensor measurement reliability

Information exchange among neighbor robots to enhance sensor measurement reliability

Federated Learning scheme has comparable performance compared to Centralized learning

Future Work

Improving the Sensor failure Prediction horizon

References

[1] M. Senel, K. Chintalapudi, D. Lal, A. Keshavarzian and E. J. Coyle, "A Kalman Filter Based Link Quality Estimation Scheme for Wireless Sensor Networks," IEEE GLOBECOM 2007 - IEEE Global Telecommunications Conference, 2007, pp. 875-880, doi: 10.1109/GLOCOM.2007.169.

[2] H. Luo, H. Tao, H. Ma and S. K. Das, "Data Fusion with Desired Reliability in Wireless Sensor Networks," in IEEE Transactions on Parallel and Distributed Systems, vol. 22, no. 3, pp. 501-513, March 2011, doi: 10.1109/TPDS.2010.93.

[3] Elmahdy, Emad E., 2015. "A new approach for Weibull modeling for reliability life data analysis," Applied Mathematics and Computation, Elsevier, vol. 250(C), pages 708-720.

[4] J. S. Mertens, L. Galluccio and G. Morabito, "Federated learning through model gossiping in wireless sensor networks," 2021 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom), 2021, pp. 1-6, doi: 10.1109/BlackSeaCom52164.2021.9527886.