FEDERATED LEARNING FOR ENHANCED SENSOR RELIABILITY OF AUTOMATED WIRELESS NETWORKS

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This thesis has been submitted to the University of Peradeniya as a partial fulfillment of the requirements for the degree of

Master of Science of Engineering

Declaration

The work presented in this thesis is submitted to the University of Peradeniya, Sri Lanka in partial fulfillment of the requirements for the degree of Master of the Science of Engineering (M.Sc. Eng.) offered as a part of the double degree programme offered jointly by University of Peradeniya, Sri Lanka and University of Oulu, Finland.

It is a result of original work of my own unless otherwise mentioned through references, notes, or any other statements. It has not been submitted for a degree or professional qualification to any other institution than University of Oulu, Finland.

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B.M.V.C. Basnayake

Abstract

Autonomous mobile robots working in proximity to humans and objects are becoming frequent and thus, avoiding collisions becomes important to increase the safety of the working environment. This paper develops a mechanism to improve the reliability of sensor measurements in a mobile robot network taking into account of inter-robot communication and costs of faulty sensor replacements. In this view, first, we develop a sensor fault prediction method utilizing sensor characteristics. Then, network-wide cost-capturing sensor replacements and wireless communication is minimized subject to a sensor measurement reliability constraint. Tools from convex optimization are used to develop an algorithm that yields the optimal sensor selection and wireless information communication policy for the aforementioned problem. Under the absence of prior knowledge of sensor characteristics, we utilize observations of sensor failures to estimate their characteristics in a distributed manner using federated learning. Finally, extensive simulations are carried out to highlight the performance of the proposed mechanism compared to several state-of-the-art methods.

Keywords— sensor reliability, autonomous mobile robots, wireless information, network operating costs, federated learning

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Contents

List of Abbreviations and symbols

Acronyms:

AC	Average Cost
CC	Communication Cost
CDF	Cumulative Distribution Function
CCDF	Complementary Cumulative Distribution Function
CL	Centralized Learning
FL	Federated Learning
KKT	Karush–Kuhn–Tucker
LOS	Line of Sight
ML	Machine Learning
MLE	Maximum Likelihood Estimation
MSE	Mean Square Error
NC	No Cooperation
C	With Cooperation
PDF	Probability Density Function
RV	Random Variable
SGD	Stochastic Gradient Descent
SMRO	Sensor Measurement Reliability Outages
SMVE	Sensor Measurement Variance Error
SNR	Signal to Noise Ratio
SINR	Signal to Interference plus Noise Ratio
SRC	Sensor Replacement Cost
WSN	Wireless Sensor Network

Roman letter notations:

α	Sensor failure rate
a	Sensor age
B	Nearby object interfering the local robot
$d_{v,s}^{\text{act}}$	Actual sensor measurement by sensor, s, of local robot, v
$d_{v,s}^{\text{obs}}$	Observed sensor measurement by sensor, s of local robot, v
$\mathbf{h}_{vv'}$	Channel gain of the link between local robot, v and neighbor robot, v'
$h(a, \lambda, k)$	Sensor failure distribution model
k	Shape parameter of sensor failure distribution model, $h(a, \lambda, k)$
K	Number of sensor lifetime data samples
K_v	Number of active sensors in sensor array, $\mathcal{S}_v$
l	Transmitter receiver distance
L	Maximum possible measuring error of a sensor
$n_{v,s}$	Sensor measurement noise of sensor, s of the local robot, v
$\mathcal{N}_v$	Neighborhood region of a local robot, v
N	Number of sensors in sensor array
N_{th}	Amount of active sensors required in the sensor array to maintain the reliability of sensor measurements at the reliability thresh hold level defined.
N_0	Variance of additive white Gaussian noise
P_{m}	Maximum power allocated for a single local robot for communication
$r_{v'}$	Achievable rate for the neighbor links, v'
r_{th}	Thresh hold rate of the neighbor links
s	s^{th} sensor in sensor array, $\mathcal{S}_v$
$\mathcal{S}_v$	Sensor array in a local robot, v
S_0	Radius of the neighborhood region
T	Maximum lifetime of a sensor
u	Central server of the wireless network

v	Single local robot in a set of robots $\mathcal{V}$
v'	Other robots except v in the set of robots $\mathcal{V}$
$\mathcal{V}$	Set of robots of the wireless network
$V(\alpha, \beta)$	Sensor measurement reliability achievable by local robot, v
$\boldsymbol{x}_v(t)$	Decision vector for optimum faulty sensor replacement at time instant t
$\boldsymbol{y}_v(t)$	Decision vector for optimum communication links with neighbor robots at time instant t

Greek symbols:

ϕ_s	Cost vector for sensor replacements in $\mathcal{S}_v$
ϕ_c	Cost vector for communication with each neighbor robot
α_s	Vector of sensor failure percentage of each senor in sensor array
$\beta_{v'}$	Vector of active percentage of sensor array in each neighbor robot
λ	Scale parameter of sensor failure distribution model, $h(a, \lambda, k)$

Math operations and notations:

Pr$(\cdot)$	Probability of the event
$f(\cdot)$	PDF of the distribution
$F(\cdot)$	CDF of the distribution
$\nabla_d f$	Gradient of function f with respect to d
$\prod$	Product operation
$\sum$	Summation operation
$\frac{\partial y}{\partial x}$	Partial differentiation of y w.r.t x
$\mathbb{R}$	Set of real numbers
$(.)^*$	Solution of an optimization problem
$Tr(\cdot)$	Trace of a matrix
$Var(\cdot)$	Variance function

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CHAPTER 1

Introduction

In the past decade, applications of wireless services have evolved from traditional voice and message communications to advanced applications, such as wireless communications in industrial automation, weather predictions, intelligent transportation, and remote health monitoring [4–7]. When industrial automation is considered, industries focus on automating industrial processes, such as navigation, transportation, and environment monitoring efficiently, where automated mobile robot wireless networks are getting important in industry [8]. In addition, in the manufacturing sites, with the increased density of robots in the working environment, there is a tendency for collisions among robots and humans and other nearby objects to increase. Unexpected collisions between robots and nearby humans or objects result in damage to resources, poor worker satisfaction, and medical costs. Thus, the reliability of the robots and their decisions in the working environment is a major concern. In this regard, the need for improved reliability in proper decision-making by mobile robots in an industrial environment has become a key role. Hence, in order to improve the safety of the environment, the sensory inputs which are used in decision-making must be closely evaluated to improve reliability in the decision-making of the robots [9]. Nevertheless, maintenance of improved reliability constitutes a large portion of costs in many industries and the costs are likely to increase due to rising competition in today's global economy, customers are compelled to explore new high reliable yet low-cost strategies for their automated mobile robot network. [10]. In order to reduce the possibility of system failures which will increase system operating costs and reduce system reliability, failures must be effectively diagnosed beforehand using state-of-the-art prediction, optimization, data-driven model learning, and strategies. Hence, the key motivation of this paper is to address the challenge of enhancing sensor reliability, while maintaining network operating costs at a minimum using data-driven learning strategies.

Contributions from this thesis are

- Propose a novel reliability metric for sensor measurements using statistical analysis of noise effect on sensor measurements.
- Optimizing the trade-off between sensor reliability and operating cost for a wireless network of automated devices using prediction and optimization principles.
- Enhancing local device sensor reliability by information exchange among neighbor devices in the wireless network
- Incorporating Federated Learning (FL) approach to build an automated sensor failure prediction system for autonomous wireless device networks.

Further, information exchange among neighbor robots using wireless communication is used to enhance sensor reliability, that is local sensor reliability can be enhanced additionally with communication with external robots or devices. Further, it was shown that sensor failure prediction can be done using the FL approach, using data available at the robots which is useful when previous knowledge about the system sensor failures are not available

CHAPTER 2

Literature Review

In designing a resource management solution for an automated robot wireless network, one must factor in a variety of constraints pertaining to the sensors of mobile robots and wireless networks such as sensor reliability, effective communication and communication resource allocation [11]. Few research works have studied how sensor reliability is enhanced while optimizing the network operating costs. Most automated robot wireless networks assume perfect, reliable sensor functioning and perfect reliability of sensory data. Thus, enhancing sensor reliability while maintaining optimal network operating costs, is a novel research approach for autonomous wireless networks. In particular, FL plays a major role in designing self-organizing mobile devices, that rely on local information, with a small variance from the Centralized Learning (CL) information [12]. In this section, work done so far on enhancing sensor reliability, while optimizing network operating costs and usage of the FL approach to predict sensor failures are discussed.

2.1 Automated robot wireless network

An automated wireless network is a network that uses wireless technology to connect devices and enables the automation of certain tasks or processes. In an automated wireless network, devices such as computers, smartphones, and sensors can communicate with each other and exchange data wirelessly. The network may be used to automate tasks such as data collection, monitoring, and control. Automated wireless networks can be used in a variety of settings, including industrial and manufacturing environments, transportation systems, and smart homes. They can help improve efficiency, reduce costs, and enhance the accuracy and reliability of tasks and processes [13].

There are various technologies and protocols that can be used to build an automated wireless network, such as WiFi, Bluetooth, Zigbee, and Z-Wave. The choice of technology will depend on the specific requirements of the application and the devices that need to be connected [10]. Industrial automation is a continuously progressing field. Industries focus on improving their efficiency, worker conditions and reducing energy consumed, by utilizing automation and effective communication. Mobile robots are utilized for various tasks, in the industry such as quality assurance, delivery of goods, production, delay handling. Therein, automated wireless networks are becoming highly effective in industries. Wireless techniques, enable device mobility, reduce costs for wired communication, and reach remote and dangerous areas. In order to increase the adaptability of mobile robot usage, wireless solutions and distributed machine-learning strategies are incorporated for effective communication among other mobile devices and the central or parent server.

2.1.1 Information exchange among robots

The main motivation for connecting the robots are to achieve a a single goal by connecting robots in a distributed and parallel way. In many practical applications this approach is more efficient and economical than the approach with a single intelligent robot. Recently, many researchers have focused on the importance of utilizing group behaviors that use local interactions for effective coordination and progress at achieving specific tasks. Real-time wireless communication can help dynamic resource management and self-organization for a team of cooperative devices. The multiple devices communicate with each other, sharing the same mission. Hence, for cooperative behavior in an intelligent robot system effective communication is essential [14].

2.1.2 Constraints for effective communication among mobile robots

Machine-to-machine wireless communications will become more important than the current trend that focuses on machine-to-human or human-to-human information exchange. It will open new research challenges for wireless system designers. Data can distort as a result of path loss which in turn creates problems for devices that attempt to retrieve data from other remote locations. Path loss reduces the efficiency of communication between the transmitter and the receivers, thus in order to diminish or reduce the effect of path loss it is modelled and links having sufficient rates for communication are selected optimally. Free space path loss of links can be modelled as $\log_2(\frac{4l}{\lambda})$, where l, λ represent the transmitter-receiver distance and wavelength of the wireless signal [15].

Water filling algorithm is considered the capacity achieving optimal power allocation strategy for wireless networks [16] (See Algorithm 1). Under water filling algorithm, the total amount of water filled (power allocated) is proportional to the SNR of the channel. Generally, the water-filling algorithm allocates more power to the user with the best channel and lower power to weak channels. The water-filling algorithm is given as follows, where Z_k, H, K, N_0, P_k are the variance of noise plus interference per user k, channel matrix, the variance of white Gaussian noise, power allocated per user k [17].

Algorithm 1: Iterative water filling algorithm

Initialize : Input co-variance per user k, $K_{x_k} = 0$
repeat
  for $k = 1, 2, 3, ..., K$ **do**
    $Z_k = N_0 I_{n_r} + \sum_{i \neq k} H_i K_{x_i} H_i^H$
    $K_{x_k} = \underset{Tr(K_{x_k} \leq P_k)}{\operatorname{argmax}} \log | Z_k + H_i K_{x_i} H_i^H |$
  end
until *sum rate converges*;

2.2 Sensor measurement reliability

Sensors are very crucial feedback elements in critical systems for timely assessment of system health and to take appropriate measures to prevent any catastrophic failure [18]. Sensor performance decreases due to deterioration resulting from age or usage. This deterioration is affected by several factors, including environment, operating conditions and maintenance.

2.2.1 Truncated Weibull distribution to generate a sensor failure model

In the past decades, many authors have shown interest in obtaining new probability distributions with higher flexibility in applications [19]. Weibull models are widely used for failure modelling of components and phenomena. They are one of the best-known and widely used distributions for the reliability or survival analysis [20]. In addition to the traditional two or three-parameter Weibull distributions, many other Weibull-related distributions are used to model failures. The two-parameter Weibull distribution with parameters scale, λ, shape, k, and maximum lifetime T has the probability density function,

$$f(a) = \frac{k}{\lambda}\left(\frac{a-T}{\lambda}\right)e^{(\frac{a-T}{\lambda})^k}. \tag{2.1}$$

Truncated Weibull distribution basically has three forms, namely left truncated, right truncated and doubly truncated. Some properties of right truncated Weibull include, having lower failure rate initially and higher failure rates at the maximum lifetime of a product. The right truncated two-parameter Weibull distribution is modelled as follows.

$$f_r(a) = \frac{\frac{\lambda}{k}(\frac{\lambda}{k})^{(\lambda-1)}e^{-(\frac{a}{k})^\lambda}}{1-e^{-(\frac{T}{k})^\lambda}}. \tag{2.2}$$

.

2.2.2 Prediction of sensor failures

Prediction of sensor failures in the next time instant is related to the probability that lifetime comes to an end within the next small time increment of length t_0 given that the lifetime has exceeded a so far, given as follows where, t and $F(\cdot)$, represent the current lifetime of sensor and CDF of $h(a, k, \lambda)$ respectively [21].

$$\begin{aligned}\Pr\big(t \leq a + t_0 | t \geq a\big) &= \frac{\Pr\big(a \leq t \leq a + t_0\big)}{\Pr\big(t \geq a\big)} \\ &= \frac{F(a+t_0) - F(a)}{F(T) - F(a)}.\end{aligned} \tag{2.3}$$

where CDF $F(\cdot)$ characterizes the the cumulative distribution function of $h(a, \lambda, k)$ defined as,

$$F(a) = \frac{(1 - e^{-(\frac{T-a}{\lambda})^k)})}{(1 - e^{-(\frac{T}{\lambda})^k})}.$$

The sensor failure prediction model that is given by (2.3) can be utilized to predict sensor failures occurring prior to a predefined time interval (t_j). t_j is named as the prediction horizon. Let us define t_i ($t_i \leq t_j$) as the practical time taken to replace a failed sensor. Then predicting ahead of t_i will eventually enhance the performance of the system.

2.2.3 Estimation of model parameters using Maximum Likelihood Estimation (MLE)

Estimation of model para maters using graphical and statistical methods are presented in the literature. When the data size is small, graphical estimation methods are suitable, however, statistical methods are used when large data sets are used. The possible statistical estimation methods include MLE, method of moment, method of percentile and the Bayesian method. When the location parameter, T, is known, the Weibull distribution model becomes a two-parameter Weibull distribution. MLE can be used to estimate the two parameters. There are many ways to estimate model parameters and stochastic gradient descent is the most used, the adaptive method used for MLE [22]. In general MLE algorithm formulation for a general problem is as follows [23]. Suppose there exist N independent observations which follow a certain model, let us assume it is a continuous model. Assume that the model is characterized by a parameter, θ. Since the observations are independent, the joint density is the product of individual densities given as

$$f(y_1, y_2, ..., y_N|\boldsymbol{\theta}) = \prod_{n=1}^{N} \Big\{ f(y|\boldsymbol{\theta}) \Big\}. \tag{2.4}$$

In order to find observations that have the maximum likelihood to the function considered, it is appropriate to use joint density of the observations, given the observations, $y_1, y_2, y_3, ..., y_n$:, where $L(\boldsymbol{\theta}|y_1, y_2, ..., y_N)$ is called the likelihood function,

$$L(\boldsymbol{\theta}|y_1, y_2, ..., y_N) = f(y_1, y_2, ..., y_N|\boldsymbol{\theta}). \tag{2.5}$$

Since, θ is unknown the most likely value is approximated. This is done by maximizing the function $L(\boldsymbol{\theta}|y_1, y_2, ..., y_N)$ with respect to $\boldsymbol{\theta}$ given as,

$$\max_{\boldsymbol{\theta} \in \times} L(\boldsymbol{\theta}|y_1, y_2, ..., y_N),$$

where the search is limited to the parameter space, Θ and it is assumed that the initial θ used for MLE belongs to Θ. In practice, due to numerical stability issues, it is more convenient to use the log-likelihood function, named the log-likelihood function and maximize it. The log-likelihood function can be modelled as,

$$\ln L(y, \boldsymbol{\theta}) = \sum_{m \in \mathcal{M}} f(y, \boldsymbol{\theta}). \tag{2.6}$$

Finally, maximum likelihood estimator can be defined using the log-likelihood function as, the estimator $\boldsymbol{\theta}$ which maximizes the log-likelihood function,

$$\hat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta} \in \times}{\operatorname{argmax}}\, LL(y, \boldsymbol{\theta}). \tag{2.7}$$

2.3 Basics of convex optimization

Casting a problem into a convex optimization the form offers the mean of finding the optimal solution by applying Lagrangian multipliers/Karush-Kuhn-Tucker (KKT) conditions. A convex optimization problem [24] is of the form,

$$\text{minimize} \quad f_0(x) \tag{2.8a}$$

$$\text{subject to} \quad f_i(x) \leq 0, i = 1, 2, ..., m, \tag{2.8b}$$

where functions $f_0, ...f_m : \mathbb{R}^n \to \mathbb{R}$ are convex, i.e., satisfy

$$f_i(\alpha x + \beta y) \leq \alpha f_i(x) + \beta f_i(y),$$

with

$$\alpha + \beta = 1, \;\; \alpha \geq 0, \;\; \beta \geq 0 \;\; \text{where} \;\; \alpha, \beta \in \mathbb{R} \;\; \text{and}\; x, y \in \mathbb{R}^n.$$

2.4 Data driven learning approaches for system failure prediction

Statistical and learning techniques are widely used for deducing data-driven models. With the growing number of sensors in a real-world system, the possibility for environmental and current state monitoring increases. Therefore, most approaches in recent literature conduct predictive maintenance, failure prediction using data-driven models [25]. Furthermore, there are three different learning techniques, namely supervised, unsupervised and reinforcement learning [26]. In supervised learning, data collected previously from observing actual behaviors are used. In the area of failure type detection and predictive maintenance, supervised learning is the most commonly used learning type, when the real-world system is monitored and the historic data is available. This improves the accuracy prior to the decisions taken by the system. Reinforcement learning has explored and exploited phases. It creates a result, depending on the actual data in the real world. This implies that the accuracy of the estimate regarding the state of a real-world system effects the the output of the learning [27].

2.4.1 CL and FL approaches

CL and FL are two different approaches for learning data-driven models. CL learning approach is a traditional machine learning approach where data in the central server are utilized to find data-driven models (See Algorithm 2). FL is an approach where a global model is learned by averaging models that have been trained locally on client devices that generate data. [28] (See Algorithm 3). When the isolated data occupied by each client fails to produce an ideal model, the mechanism of FL makes it possible for clients to share a united model without data exchange. [29] Algorithms for CL and FL are generalized as follows [30]. The advantages and disadvantages of centralized and FL are summarized in in Table. 2.1 and 2.2 [31].

2.4.2 Trade-off between reliability and operating cost

A reliability metric for heterogeneous wireless sensor network (WSN) is addressed in [32] where the failure probabilities of the components of WSN is taken into consideration. Here, reliability is defined as the the probability that the wireless sensor network remains functional, in terms of coverage and con-

Algorithm 2: MLE using CL

input data : local data $\mathcal{M}_{u\in U}$, step size δ
estimate: k,λ;
select: μ, j
for $T_f = 1, 2, 3, ...,$ **do**
  Model $f(\mathcal{M})$
  Compute $\nabla_d\, f^d(\mathcal{M})$
  $\nabla_d\, f^d(i)$ = $\nabla_d\, f^d(\mathcal{M})$
  Update global estimations $d(T_f)$
  $d(i)$ = $d(T_f)$
  for $i = 1, 2, 3, ...,$ **do**
  Compute $d(i)$ =$d(i)$ - $\delta\ \nabla_d\, f^d(i)$
  end
  Download model to all clients $\mathcal{U}$
  for $k = 1, 2, 3, ..., K_u$ **do**
  Collect $\mathcal{M}_u$
  end
  Upload $\mathcal{M}_u$ to C
end

Algorithm 3: MLE using FL

input data : Gradients $\nabla_d\{f_u^d(0)\}_{u\in U}$, local estimations $\{d_u(0)\}_{u\in U}$ and step size δ
for $T_f = 1, 2, 3, ...,$ **do**
  Update local estimations $\{d_u(T_f)\}_{u\in U}$
  Compute $\nabla_d\{f_u^d(T_f)\}_{u\in U}$
  Download model to all clients $\mathcal{U}$
  for $k = 1, 2, 3, ..., K_u$ **do**
  $d_u(i)$ = $d_u(T_f)$
  $\nabla_d\, f_u^d(i)$ = $\nabla_d\, f_u^d(T_f)$
  for $i = 1, 2, 3, ...,$ **do**
  Compute $d_u(i)$ =$d_u(i)$ - $\delta\ \nabla_d\, f_u^d(i)$
  end
  end
  Upload $\nabla_d\{f_u^d(T_f)\}_{u\in U}$, local estimations $\{d_u(T_f)\}_{u\in U}$, K_u to C
end

nectivity, which is prone to component failures during its intended operating time. Further, in wireless sensor networks, the power of energy-constrained sensor nodes is largely drained by data communication tasks. Designing energy-efficient data communication mechanisms are, therefore, a major key to maximizing the lifetime of wireless sensor networks [33]. Here, the authors propose an algorithm that

Table 2.1: Advantages and disadvantages of CL approach [3]

Advantages	Disadvantages
Reduces data processing at the client	Complex data processing at the parent/central server
A large amount of data samples increase the accuracy of global parameter estimation	Increases data traffic due to large chunks of data transmitted by the client to server
Easier to manage small networks	The scalability is low
Sufficient networking and processing resources at the central server and system are relatively expensive	
Frequent sharing of model gradients with the clients	System performance for each client decreases when many try to connect simultaneously

Table 2.2: Advantages and disadvantages of FL approach

Advantages	Disadvantages
Less expensive than a centralized system	Clients require higher data processing resources or complex software
The scalability of the system is high	Need scheduling for sharing of gradients
When one client breaks down, the system goes on operating	Accuracy of the global model averaging depends on the size of shared model gradients
Privacy of data	Large-size data samples collected at the client
Share gradients with predetermined time intervals	Takes time to update sufficient gradients to the central server

selects a multi-path wireless signal transmission scheme with minimal end-to-end energy consumption for a given lower bound on reliability.

CHAPTER 3

Problem Formulation

3.1 Problem definition

Optimization of resources in an automated wireless network is a major concern under current research developments. Automated devices use many sensor measurements which need to be highly reliable for the successful completion of tasks without considerable human supervision. Hence, in this research, a major design goal is to achieve the balance between maximum reliability and minimum cost which will lead to a cost-effective sustainable reliable network. Further, maximizing the lifetime of automated wireless networks is a major concern, and thus designing an energy-efficient and cost-effective reliable algorithm is needed. In addition, the possibility of incorporating new technologies like FL for a group of automated devices connected via a wireless network have not been investigated earlier. Thus, the performances and challenges of incorporating such domains into wireless networks is a concerning matter since they can bring a less complex solution than the existing methods.

3.2 Method

A novel approach to modeling sensor measurement reliability considering sensor failure rate into account by incorporating emerging branches on artificial intelligence are unfolded in this thesis. FL, a new dimension of artificial intelligence, is applied in a distributed manner on a set of robots(insert symbol) The federated algorithm is designed to predict sensor failures using a prediction model based on Weibull distribution which is usually utilized to model sensor failures. Each robot creates a data log of sensors and their failure time. The data set collected thus is used to form the prediction model incorporating a flexible model parameter estimation method namely maximum likelihood estimation. Moreover, higher levels of measurement reliability incur higher maintenance costs. Hence, the trade-off between reliability and cost must be optimized as required. Thus, with the knowledge of the sensor predictions and the the possible information communication within the robots in the neighborhood, the optimal solution is provided by a convex optimization problem formed. The modeled optimization algorithm reduces the the average cost for communication and sensor replacement and enhances the reliability of the sensor measurements. The aforementioned process is unfolded elaborately with details in the following sections.

3.3 System model

Consider a local communication network consisting of a set V of robots, that can communicate with one another and a central server, u, over wireless links. The system model of the automated mobile robot wireless network is illustrated in Figure. 3.1. One robot, v, communicate with the neighbor robots, v', that is located within the neighborhood region of the radius, defined for the network. It is assumed that robots are located at random locations and the wireless link between v and v' is assumed to be a line of sight (LOS) channel with interference, with the channel gain parameter, $h_{vv'}$, The neighborhood region of robot v is $\mathcal{N}_v = \{v' || \vec{b}_v| - \vec{b}_{v'}\| \leq S_0\}$ where S_0, $\vec{b}_v$, and $\vec{b}_{v'}$ are the neighborhood range and location coordinates of v and v', respectively. It is assumed that the wireless signals are attenuated by free space path loss of, $\log_2(\frac{4S_0}{\lambda})$, within the region of radius, S_0.

Next, it is assumed that the information sharing from v to neighboring robot v', is possible only when the rate exceeds a threshold rate, $r_{\text{th}} = \log_2(\frac{4S_0}{\lambda})$, achievable under the effect of path loss at the radius S_0. The up-link rate of the communication links varies on the signal to interference plus noise ratio, (SINR) of the link. SINR is deduced using power allocated to the robots, P_v, the channel gain of the link, $h_{vv'}$, and interference added by neighboring links. The achievable SINR between v and v' is given as (3.1), considering the interference from other neighbor robot links and Gaussian noise, N_0 [17].

$$r_{v'} = \frac{P_i h_{vj'}^2}{\sum\limits_{l \in \mathcal{P}, v' \in \mathcal{V}', l \neq i, v' \neq j'} P_l h_{vv'}^2 + N_0}. \tag{3.1}$$

Further, each robot $v \in V$ is equipped with an array $\mathcal{S}_v$ sensors to obtain proximity measurements

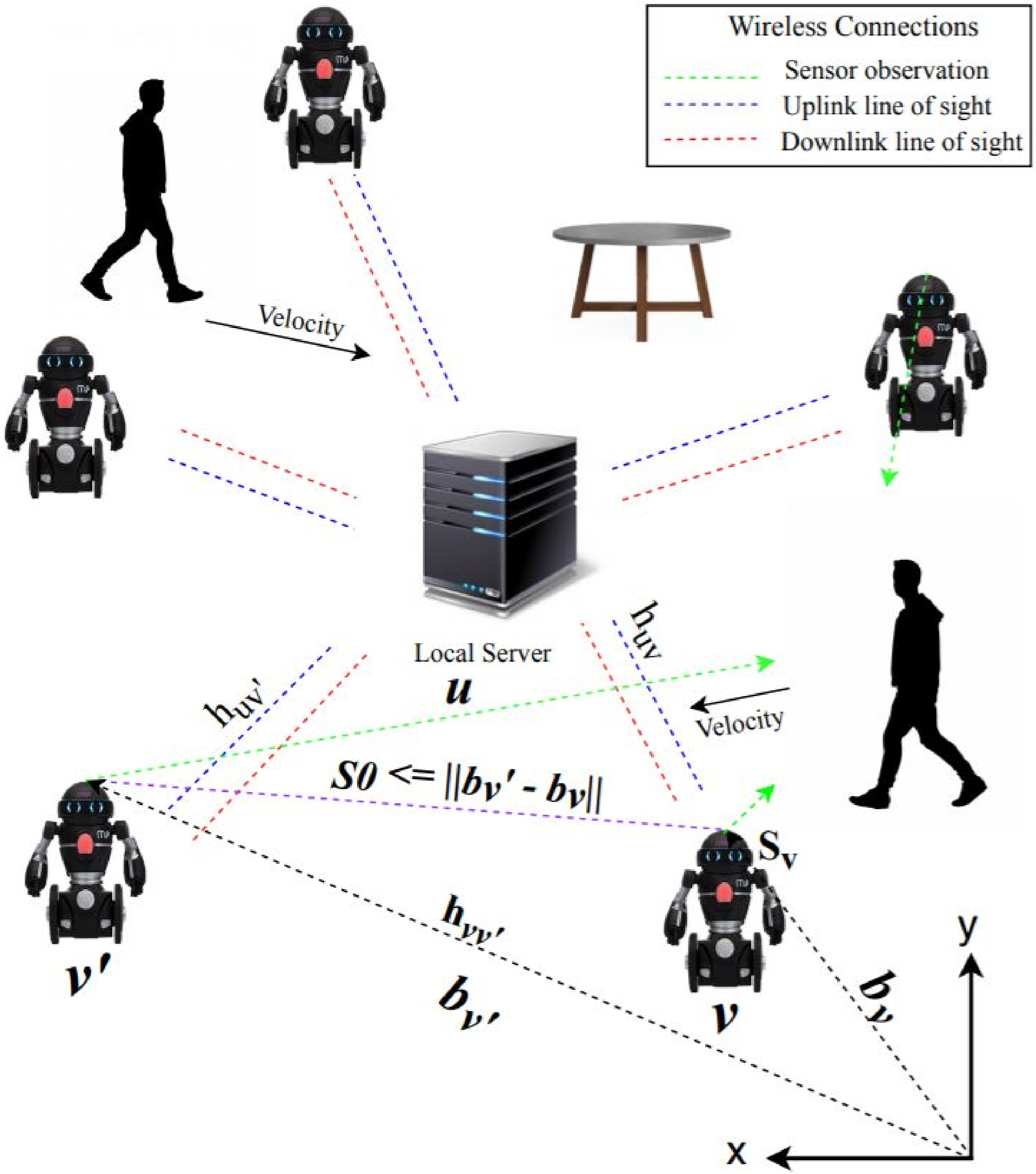


Fig. 3.1: Simplified illustration of the system model containing a group of automated robots connected to a a local wireless network operated by a central server, along with obstacles such as humans and solid objects nearby.

for the purpose of collision avoidance. It is assumed that all sensors are manufactured under similar conditions and thus, have identical failure rates, i.e. likelihood of failure at a given age. Hence, the life-times of sensors (a) can be considered as random variables (RVs) drawn from independent and identical distributions.

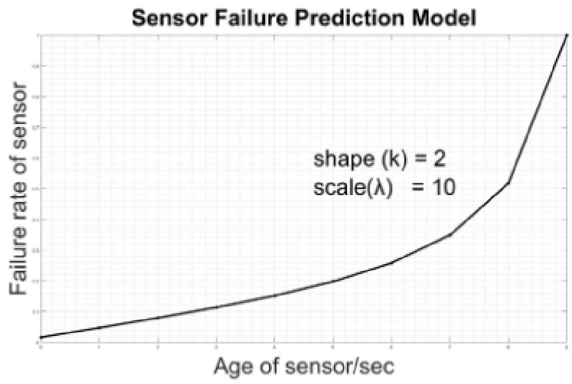


Fig. 3.2: Left truncated Weibull distribution, $h(a, \lambda, k)$

In this view, the sensor lifetime is modeled by a truncated Weibull distribution $h(a, \lambda, k)$ (See Fig. 3.2), with scale parameter of λ, shape parameter of k, and maximum lifetime of T [34] that is given by,

$$h(a, \lambda, k) = \begin{cases} \frac{f(a)}{F(T)} & \text{if } a \in [0, T], \\ 0 & \text{otherwise,} \end{cases} \tag{3.2}$$

where $f(a)$ and $F(a)$ are the probability density function (PDF) and cumulative density function (CDF) of the truncated Weibull distribution, $h(a, \lambda, k)$ are defined as follows respectively in (3.3) and (3.4). The value of T is determined by the manufacturing process of a particular sensor type and remains constant.

$$f(a) = \frac{\frac{k}{\lambda}\left(\frac{a}{\lambda}\right)^{k-1} \exp\left(-\left(\frac{a}{\lambda}\right)\right)^{k}}{(1 - \exp^{-(\frac{T}{\lambda})^k})}, \tag{3.3}$$

$$F(a) = \frac{(1 - \exp^{-(\frac{a}{\lambda})^k})}{(1 - \exp^{-(\frac{T}{\lambda})^k})}. \tag{3.4}$$

Hence,

$$\frac{f(a)}{F(T)} = \frac{\frac{k}{\lambda}\left(\frac{a}{\lambda}\right)^{k-1} \exp\left(-\left(\frac{a}{\lambda}\right)^{k}\right)}{1 - \exp\left(-\left(\frac{T}{\lambda}\right)^{k}\right)}. \tag{3.5}$$

Then, using (3.2), the probability that the sensor will be failed by $(a + t_0)$ can be calculated as in (3.6), where a, $F(\cdot)$ and α represent the lifetime of sensor and CDF of the $h(a, \lambda, k)$ and sensor failure rate respectively.

$$\begin{aligned}
\Pr\big(t \leq a + t_0 | t \geq a\big) &= \frac{\Pr\big(a \leq t \leq a + t_0\big)}{\Pr\big(t \geq a\big)}, \\
&= \frac{\int_0^{a+t_0} h(a,\lambda,k)dt - \int_0^{a} h(a,\lambda,k)dt}{1 - \int_0^{a} h(a,\lambda,k)dt}, \\
\alpha &= \frac{F(a+t_0) - F(a)}{F(T) - F(a)}.
\end{aligned} \tag{3.6}$$

The above result is utilized for sensor failure predictions in the rest of the discussion. It is assumed that each sensor measurement is degraded by a random measurement noise that is modeled by a random variable with independent and identical uniform distribution over $[-L, L]$. In this view, the measured distance $d_{v,s}^{\text{act}}$ from robot v to an object using sensor s is modeled as,

$$\overline{d_{v,s}^{\text{obs}}} = d_{v,s}^{\text{act}} + n_{v,s}, \tag{3.7}$$

where $n_{v,s}$ is the measurement noise, and $\overline{d_{v,s}^{\text{obs}}}$ is the estimate of $d_{v,s}^{\text{act}}$ aggregated by a local robot regarding B

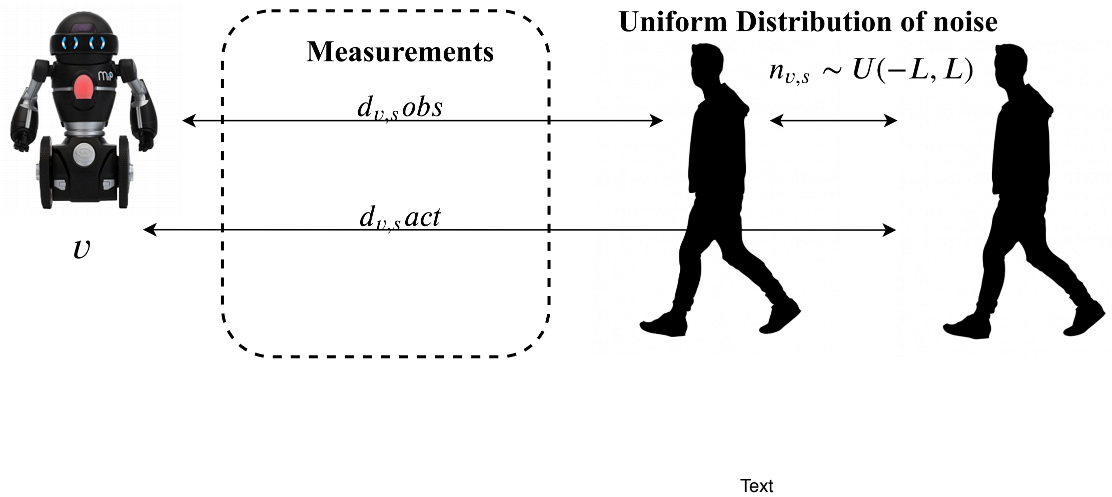


Fig. 3.3: Actual sensor measurement $d_{s,v}^{\text{act}}$ gets degraded by a random measurement error of $n_{v,s}$ which can take a value between [-L,L] and result in $d_{s,v}^{\text{obs}}$ [1].

Suppose the robot v utilizes a portion $\mathcal{K}_v \subset \mathcal{S}_v$ of its sensors as active sensors for a particular measurement. Hence, after a sensor reading, the robot v averages $d_{v,s}^{\text{obs}}$ from all the active sensors in $\mathcal{K}_v$

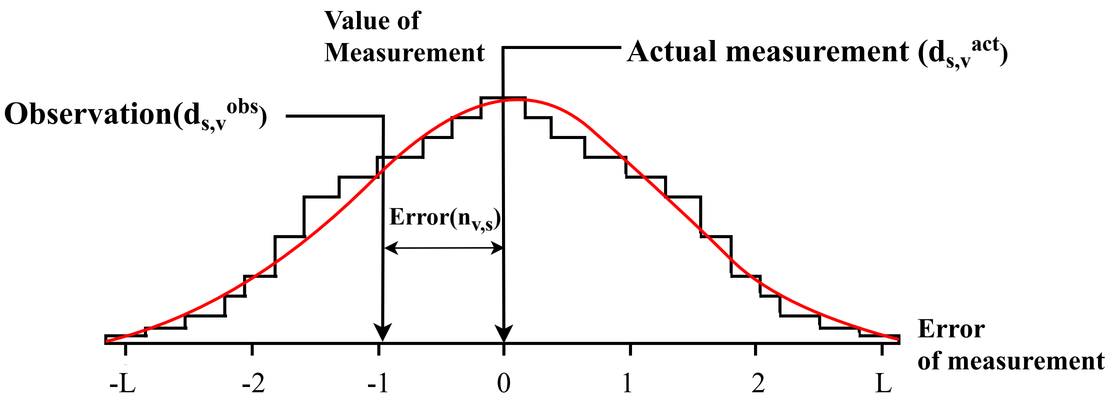


Fig. 3.4: Distribution of Estimated sensor measurement $d_{s,v}^{\text{obs}}$ with respect to the measurement error of $n_{v,s}$ which can take a value between [-L,L].

to obtain an estimate of $d_{v,s}^{\text{act}}$, i.e. $\hat{d}_v = \frac{1}{K_v}\sum_{s\in\mathcal{K}_v} d_{v,s}^{\text{obs}}$. The illustration of $d_{v,s}^{\text{obs}}$ deviated from $d_{v,s}^{\text{act}}$ by $n_{v,s}$ is given in Fig. 3.3.

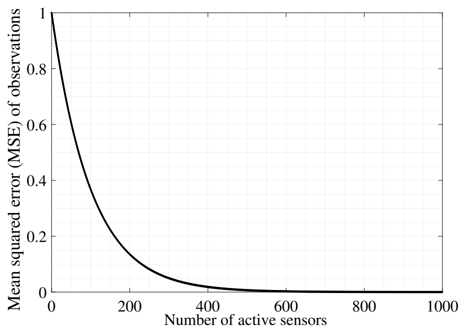


Fig. 3.5: Variation of mean squared error (MSE) of measurement noise, $n_{v,s}$, against the active number of sensors available in the system [2].

Figure. 3.5, depicts how Mean Square Error(MSE) of $d_{v,s}^{\text{obs}}$ collected by sensors in the local robots, varies with K_v. It can be seen that MSE reduces with the increment in K_v The variance of sensor measurement noise/error, which follows a uniform distribution is calculated as in (3.8) [35]. Furthermore, when a specific sensor is considered, its sensor measurement variance is directly proportional to the α as the noise variance increments as the sensor impairments increase. Hence, the noise variance is formulated as,

$$Var(n_{v,s}) = \alpha\frac{L^2}{3}. \tag{3.8}$$

Then, to reduce the variance, K_v, should be increased. where the maximum possible measuring error is L. Thereby, the reliability of the $d_{v,s}^{\text{obs}}$ is formulated as,

$$\text{Reliability of } d_{v,s}^{\text{obs}} = (1-\alpha)\frac{L^2}{3}. \tag{3.9}$$

3.4 Optimization problem formulation

This section describes the the optimization problem formulation and its reformulation as a convex optimization problem to make is solvable. First, it is formed into a convex optimization problem which is solved using Lagrangian multipliers/Karush–Kuhn–Tucker (KKT) conditions. The optimization algorithm implemented is given as follows, where ϕ_s, ϕ_c, α_s, $\beta_{v'}$, P_m are cost vectors for faulty sensor replacements in the sensor array, cost vector for communication established with neighbor robots, vector of sensor failure percentage of each senor in the sensor array, vector of sensor active percentage of sensor array in each neighbor robot, v' and the maximum power allocated for a single local robot for communication. N_{th} is the amount of active sensors required in the sensor array to maintain the reliability of sensor measurements at the reliability threshold defined for the system.

Here, $\boldsymbol{x}_v(t) = [x_{sv}(t)]_{s\in\mathcal{S}_v}$ and $y_{v'}(t) = [y_{v'}(t)]_{v\in\mathcal{V}'}$ are the control decision vector of optimal sensor replacements and optimal communication required with neighbor robots, derived from the optimization problem. $x_{sv}(t) = 1$ if the sensor $s \in \mathcal{S}_v$ is replaced at time t and $y_{v'}(t) = 1$ if the sensor local robot retrieve data from v'$\in \mathcal{V}$ at time t.

$$\text{where } \boldsymbol{x}_v(t) = \begin{cases} 1 & \text{if sensors replaced,} \\ 0 & \text{otherwise,} \end{cases} \tag{3.10}$$

$$\text{and } \boldsymbol{y}_{v'}(t) = \begin{cases} 1 & \text{if communicate with } v', \\ 0 & \text{otherwise.} \end{cases} \tag{3.11}$$

$V(\alpha,\beta) = \left(\sum_{s=1}^{N}(1+\alpha_s(\boldsymbol{x}_v(t)-1)) + \sum_{i=1}^{v'}(\boldsymbol{y}_{v'}(t)\beta_{v'})\right)$ is the reliability achievable using optimal sensor replacements, $(x_v(t))^*$, and optimal communication with neighbor robots, $(y_{v'}(t))^*$, derived using the optimization algorithm presented as follows.

$$
\begin{aligned}
\underset{\boldsymbol{x}_v(t), \boldsymbol{y}_v(t)}{\text{minimize}} \quad & \phi_s \mathbf{1}_N^T \boldsymbol{x}_v(t)^T + \phi_c \mathbf{1}_N^T \boldsymbol{y}_{v'}(t)^T, && (3.12a)\\
\text{subject to} \quad & V(\alpha, \beta) - N_{\text{th}} \geq 0, && (3.12b)\\
& P_{vv'} \leq \boldsymbol{y}_{v'}(t) P_{\text{m}}, && (3.12c)\\
& \boldsymbol{y}_{v'}(t)(r_{v'} - r_{\text{th})} \geq 0. && (3.12d)
\end{aligned}
$$

The objective function is given in (3.12a) which is the summation of cost for faulty replacements of sensors and communication, is minimized subjected to reliability constraint of maintaining the active percentage of sensors of the total sensor array of N sensors above the active percentage threshold of N_{th} required to maintain the reliability threshold, given in (3.12b), the transmit power constraint of allocation of power considering the water filling algorithm to each neighbor robot is given in (3.12c) and communication constraint of communicating only when the rate of the channel exceeds a threshold rate determined by the rate achievable at the radius S_0 under the effect of path loss, given in (3.12d).

Water filling algorithm, given in Algorithm 1, is considered the capacity achieving optimal power allocation strategy for wireless networks [17]. Under the water-filling algorithm, the total amount of water filled (power allocated) is proportional to the SNR of the channel. Generally, the water-filling algorithm allocates more power to the user with the best channel and lower power to weak channels. The water-filling algorithm is given as follows, where Z_k, H, K, N_0, P_k are the variance of noise plus interference per user k, channel matrix, variance of white Gaussian noise, power allocated per user k [17]. Further, in the results section, the behavior of the aforementioned proposed solution with and without communication is observed.

3.5 Learning of sensor failure model

In order to predict sensor failure, knowledge of the sensor failure model is required. Once the data on the lifetime of sensors are available, the model parameters are estimated using the MLE algorithm. MLE is considered the most suitable state of the art method to estimate model parameters. Thus, MLE is used for the estimation of model parameters in this study.

3.5.1 Sensor failure model parameter estimation using MLE algorithm

Estimation of model parameters using graphical and statistical methods are presented in the literature. When the data size is small, graphical estimation methods are suitable, however, statistical methods are used when large data sets are used. The possible statistical estimation methods include Maximum Likelihood Estimation(MLE), method of moment, method of percentile and the Bayesian method. When the maximum lifetime parameter, T, is known, the Weibull distribution model becomes a two-parameter Weibull distribution. MLE can be used to estimate the two parameters. There are many ways to estimate model parameters and stochastic gradient descent is the most used, an adaptive method used for MLE [22]. In general MLE algorithm formulation for this problem is as follows [23].

With available lifetime data of sensors, the model parameters, scale k and shape λ which best fits the data are found using MLE. Using maximum likelihood estimation, the product of samples that follow the PDF of the prediction model is maximized. Thus, MLE is formulated as follows, where K is the total number of sensor lifetime data samples.

$$\underset{\lambda,\,k}{\text{maximize}} \quad \prod_{K} \Big\{ h(a, \lambda, k) \Big\}, \tag{3.13a}$$

$$\text{subject to} \quad \lambda \in (0, \mathbb{Z}^{+}), \tag{3.13b}$$

$$k \in (0, 1]. \tag{3.13c}$$

It can be reformulated as,

$$\underset{\lambda,\,k}{\text{maximize}} \quad \sum_{K} \ln \Big\{ h(a, \lambda, k) \Big\}, \tag{3.14a}$$

$$\text{subject to} \quad \lambda \in (0, \mathbb{Z}^{+}), \tag{3.14b}$$

$$k \in (0, 1]. \tag{3.14c}$$

SGD is an iterative method used to maximize the log-likelihood function of the sensor failure model, parameterized by a model parameters scale and shape (See Algorithm 4). We start with some sets of values for our model parameters and improve them slowly. To improve a given set of parameters, we try to get a sense of the value of the likelihood function by calculating the gradient. Then we move in the direction which maximizes the likelihood function. By repeating this step many times, we'll continually maximize the log-likelihood function. The shape, k, and scale parameters, λ, are updated simultaneously [36].

Algorithm 4: MLE using SGD.

```
input data : Failure rates of sensors(t), cutoff time(T)
estimate: shape, k, scale, λ;
select: learning rate, μ, number of iterations, j
while not converged do
    for i ∈ shuffle(1,2,3,.......,n))do
    for j ∈ 1,2,3,.....,K
    update k and λ
    k(j+1) = k(j) - μ ∇_k h_k
    λ(j+1) = λ(j) - μ ∇_λ h_λ
    end
    end
end
```

3.5.1.1 Gradient of $h(t, \lambda, k)$ with respect to model parameters

Gradient with respect to k is formulated as,

$$\nabla_k h = \frac{\partial h(a)}{\partial k}. \tag{3.15}$$

$$\frac{\partial \ln h(a)}{\partial k} = \frac{1}{k} + \ln(t) - \ln(\lambda) - e^{k\frac{a}{\lambda}} \ln\frac{a}{\lambda} - \frac{e^{-\frac{T}{\lambda}^k} e^{k\ln\frac{T}{\lambda}} \ln\frac{T}{\lambda}}{1 - e^{-\frac{T}{\lambda}^k}}. \tag{3.16}$$

Gradient with respect to λ is formulated as,

$$\nabla_\lambda h = \frac{\partial h(a)}{\partial \lambda}. \tag{3.17}$$

$$\frac{\partial \ln h(a)}{\partial \lambda} = -\frac{k}{\lambda} + k\frac{a}{\lambda}^{(k-1)}\frac{a}{\lambda^2} + \frac{ke^{-(\frac{T}{\lambda})^k}\frac{T}{\lambda}^{(k-1)}\frac{T}{\lambda^2}}{1 - e^{-(\frac{T}{\lambda})^k}}. \tag{3.18}$$

3.5.2 Learning approaches

Learning approaches are useful when past data of sensor failures of the system are not available and thus it is unable to find an estimate of the prediction model due to lack of data. The data needed can be acquired by observing the sensor failures happening actually in the system with time. However, when compared with the system with data availability, this method takes time to collect sufficient amount of data and obtain the estimate of model parameters which is possible with large amount of data. In this research, CL and FL learning approaches are proposed for this system

3.5.2.1 CL approach

Algorithm 5: MLE using CL.

input data : local data $\mathcal{M}_{u\in U}$, step size δ
for $T_f = 1, 2, 3, ...,$ **do**
  Model $f(\mathcal{M})$
  Compute $\nabla_d\, f^d(\mathcal{M})$
  $\nabla_d\, f^d(i)$ = $\nabla_d\, f^d(\mathcal{M})$
  Update global estimations $d(T_f)$
  $d(i)$ = $d(T_f)$
  for $i = 1, 2, 3, ...,$ **do**
  Compute $d(i)$ =$d(i)$ - δ $\nabla_d\, f^d(i)$
  end
  Download model to all clients $\mathcal{U}$
  for $k = 1, 2, 3, ..., K_u$ **do**
  Collect $\mathcal{M}_u$
  end
  Upload $\mathcal{M}_u$ to C
end

Centralized approach is used when the processing power of the local robots in the network is insufficient to conduct complex data processing. When the CL approach is used, the sensor failure data collected at the robots are shared with the central server at each time instant. The central server collects data from all the robots and the collected data are processed at the central server and the model parameters are estimated using MLE. The model parameters estimated, the global estimate of the model parameters, are shared with the local robots at each time instant. The flow chart depicting the CL approach is given in Fig. 3.6. Furthermore, the CL procedure using MLE is detailed in Algorithm 5.

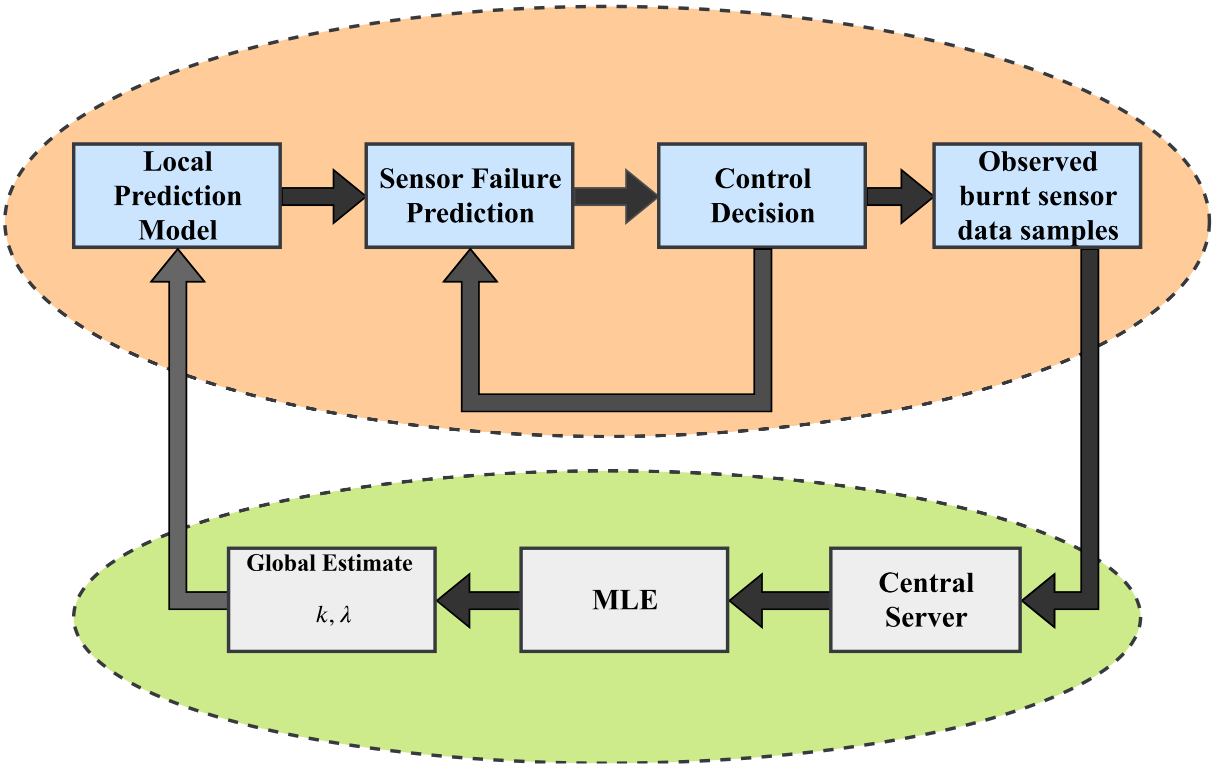


Fig. 3.6: Operation of the CL process for an autonomous local wireless network.

3.5.2.2 FL approach

Algorithm 6: MLE using FL.

input data : Gradients $\nabla_d\{f_u^d(0)\}_{u\in U}$, local estimations $\{d_u(0)\}_{u\in U}$ and step size δ
for $T_f = 1, 2, 3, \ldots.., $ **do**
    Update local estimations $\{d_u(T_f)\}_{u\in U}$
    Compute $\nabla_d\{f_u^d(T_f)\}_{u\in U}$
    Download model to all clients $\mathcal{U}$
    for $k = 1, 2, 3, \ldots.., K_u$ **do**
        $d_u(i)$ = $d_u(T_f)$
        $\nabla_d\ f_u^d(i)$ = $\nabla_d\ f_u^d(T_f)$
        for $i = 1, 2, 3, \ldots..,$ **do**
            Compute $d_u(i)$ =$d_u(i)$ - $\delta\ \nabla_d\ f_u^d(i)$
        end
    end
    Upload $\nabla_d\{f_u^d(T_f)\}_{u\in U}$, local estimations $\{d_u(T_f)\}_{u\in U}$, K_u to C
end

The main idea to use FL is that sharing training samples in a CL approach require more communication resources and imposes higher latency. In this approach, model parameters are updated to the central server in fixed time intervals and the model parameters are collected from all the robots. The collected model parameters are averaged which results in the global estimate of the model parameters. The global parameters are shared with the robots at each fixed time instance, specified for the system [30]. The flow chart depicting the federated approach is given in Fig. 3.7. Moreover, the MLE-assisted FL procedure is detailed in Algorithm 6.

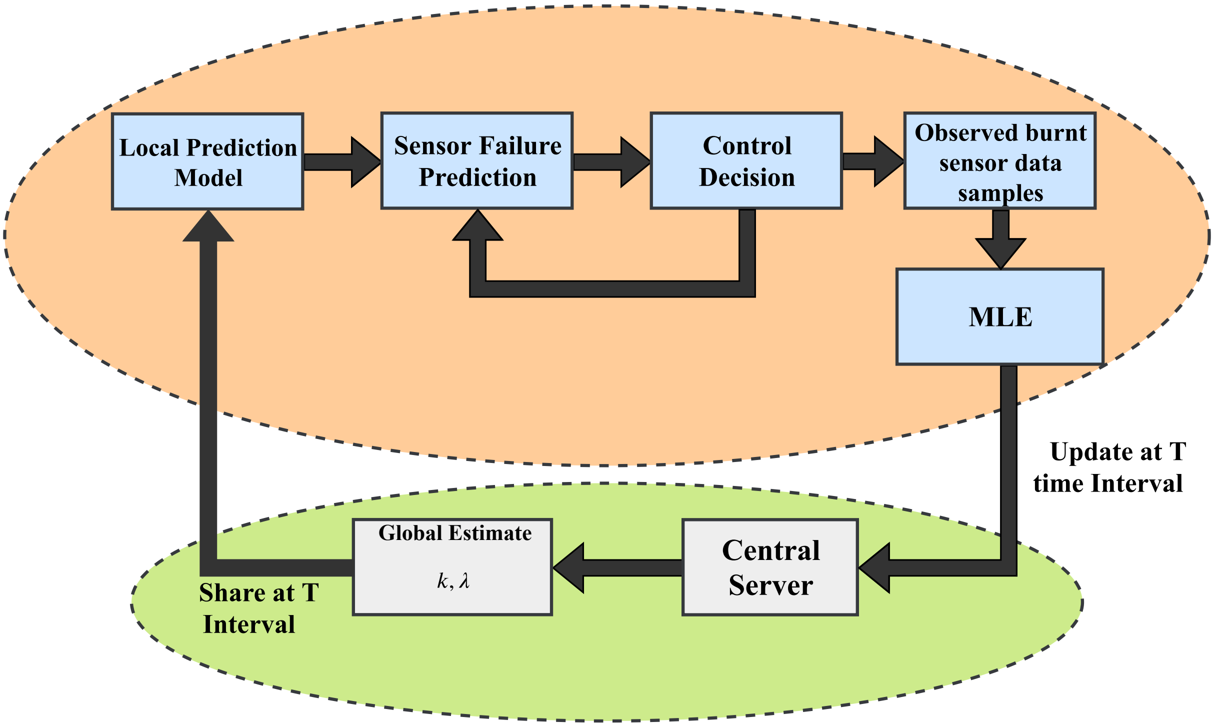


Fig. 3.7: Operation of the FL process for an autonomous local wireless network.

3.5.2.3 Comparison between CL and FL approaches

In both approaches, the global estimates of the model parameters are shared with the local robots by the central server. However, there are differences between the two approaches.

1. Centralized approach shares chunks of data samples of sensor failure data at each time instant with the central server, while the federated approach shares only local estimates of the model parameters at specific time intervals. Thus, the data traffic anticipated from the CL approach is

higher than the FL approach since sensor failure data collected at the robot can be large in size while the locally estimated model parameters by each robot are smaller in size

2. Data processing at the central server is higher under the CL approach since large chunks of data need to be processed in order to find the estimate of the model parameters using MLE, while in the federated approach only the local data collected are used to derive the estimate of the model parameters and only the model parameters need to be transferred via the communication link at fixed intervals

3.5.3 Training and testing

The parameters λ, k of the proposed sensor failure model, $h(t, \lambda, k)$, are trained using sufficient number of sensor lifetime data generated form the system. Next, the performance of the learning algorithm developed for specific set of training data is verified using test data. The performance of the system under the test data compared to training data is evaluated using the statistic named as inference accuracy. Inference accuracy gives an idea on how much successful the performance of the system under practical scenarios with actual, random, realistic data. Thus, the inference accuracy calculated under test data that will cover all possible data the system will encounter. Therefore, the test data to test the learning approaches are generated from a

1. Portion of data distribution following the same sensor failure model, h(a,λ,k), defined for this network

2. Random distribution of lifetime data

obtained both from distributions following the sensor failure model.

CHAPTER 4

Results and Discussion

The performance of the proposed solutions were analyzed by building the system model used for this research in a Matlab simulation environment. First, the environmental setup of the system model was built by defining the simulation parameters and numerically calculating suitable sensor failure prediction model parameters that follows the practical nature of sensor failure according to weibul distribution. Next, after constructing the environment of the system, random ages were used as the initial ages of sensors in the sensor arrays of the robots and the parameters related to sensor measurement reliability and average costs of the network were collected and analyzed. Furthermore, the simulation parameters used in this work are given in Table. 4.1.

Table 4.1: Simulation parameters of the system model

Parameter	**Value**
Scale, λ	10
Shape, k	2
Maximum lifetime,T	10 sec
Variance of measurement error	1
Threshhold of variance of $d_{v,s}^{\text{obs}}$	0.125
Maximum power for communication per v	10 W
Channel type	Rayleigh fading
Gaussian Noise variance,N_0	1
Network area	$100\,\text{m}^2$

4.1 Experimental setup

Modelling environmental sensor failure A left truncated weibul function was used to mathematically model the actual sensor failures occurring in sensors used in automobile robot systems in an industrial environment. The Weibull function is a survival function used to model the sensor failure in the mathematical domain and the behaviour of the function determine the failure rate at different stages of the life of a sensor. The model parameters define behavior and the shape of the function should bring the sensor failure pattern very close to the ground truth. Thus, weibul parameters were selected such that the possibility for initial sensor failure is low and failures occurring close to maximum lifetime is high. In order for prediction to occur accurately, the gap between the sensor failure models at each time instant for a single sensor must be sufficient enough so that probability of failing in the next time instant can be calculated without an error. Therefore, plots of sensor failure rate against age of sensor were used to verify the failure rate distribution with the increment of the age of the sensor (a) which is given in Fig. 4.1.

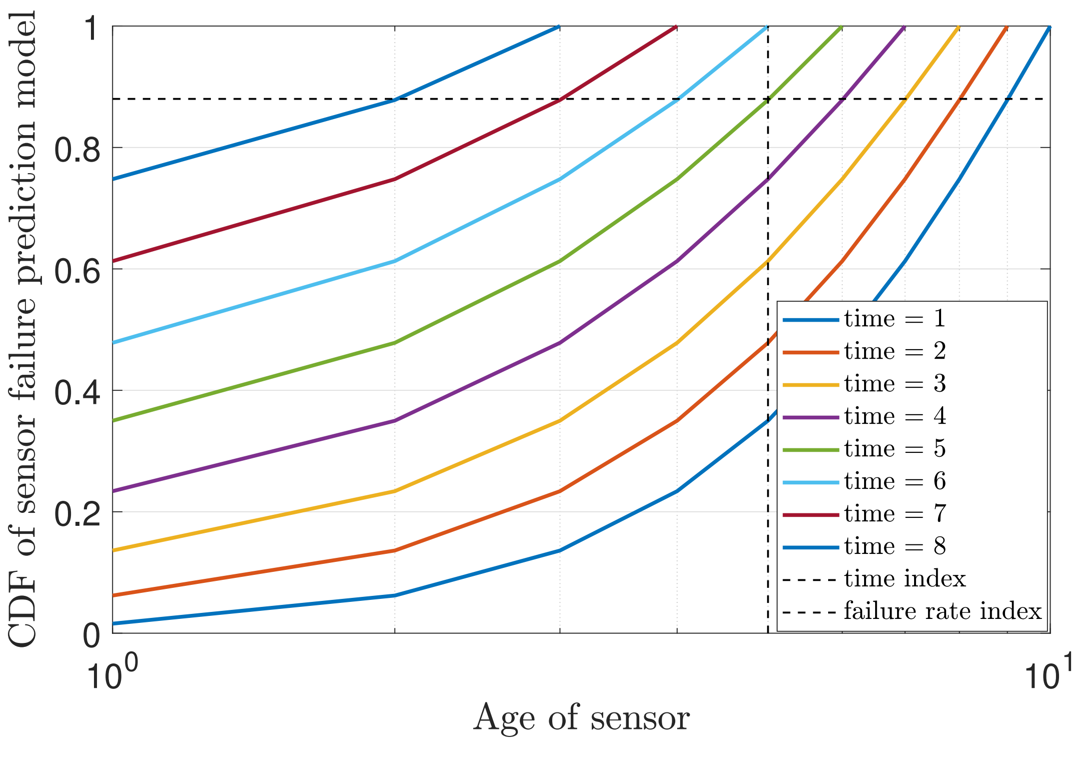


Fig. 4.1: Variation of failure rate of sensors at each time instant against the age of sensor.

Environmental sensor lifetime data samples were generated using the model parameters decided in the previous section. These data samples are utilized to build the environmental sensor failures of the system model. Next, the proposed solutions are used to predict the environmental failures. The error between the actual and predicted sensor failures and its effect on the performance is evaluated.

Many algorithms are used to evaluate the performance of the FL based approached which is our major concern. The performance of the FL approach is analyzed using several variables of the robot network such as robot density, communication range, transmit power. The proposed method which utilizes the federated learning approach was validated using the sample robot network whose robots are randomly located in a medium scale industry with an area of 100m^2 with each robot having a sensor array consisting 10 motion detecting sensors. Enhancement of sensor measurement reliability was conducted by predicting the sensor failures using a sensor failure prediction model. A left truncated weibul was used as the sensor failure prediction model.

4.2 Simulation

4.2.1 Evaluation

We evaluated and compared our proposed state-of-the-art approaches against benchmarks detailed as follows.

- *Benchmark algorithms*: The sensor replacement decisions in the benchmark algorithms depends on the predefined rules and they do not use failure predictions techniques.

  1. **Myopic-C**:

     Replace failed sensors until the reliability target is met. In this view, after every measurement, all robots observe their malfunctioning sensors. If the number of failed sensors, N_f, exceeds N_{th}, then $(N - N_{\text{th}})$ the number of failed sensors are replaced by new sensors.

  2. **Myopic-R**:

     Replacing failed sensors until the reliability target is met.The difference between Myopic - C and Myopic - R is that in Myopic - R, failed sensors are replaced with new sensors, according to the descending order of the ages of sensors

  3. **Fixed age**:

     Replace sensors that reach a predefined age. Additionally, **Fixed age** enforces robots to replace even functioning sensors that exceed a certain age limit, e.g. 50% of T as they are likely to fail in the near future.

- *Proposed algorithms*: The proposed algorithms utilized both sensor failure prediction and optimization algorithms. The proposed algorithms are detailed as follows and simply illustrated in Fig. 4.2.

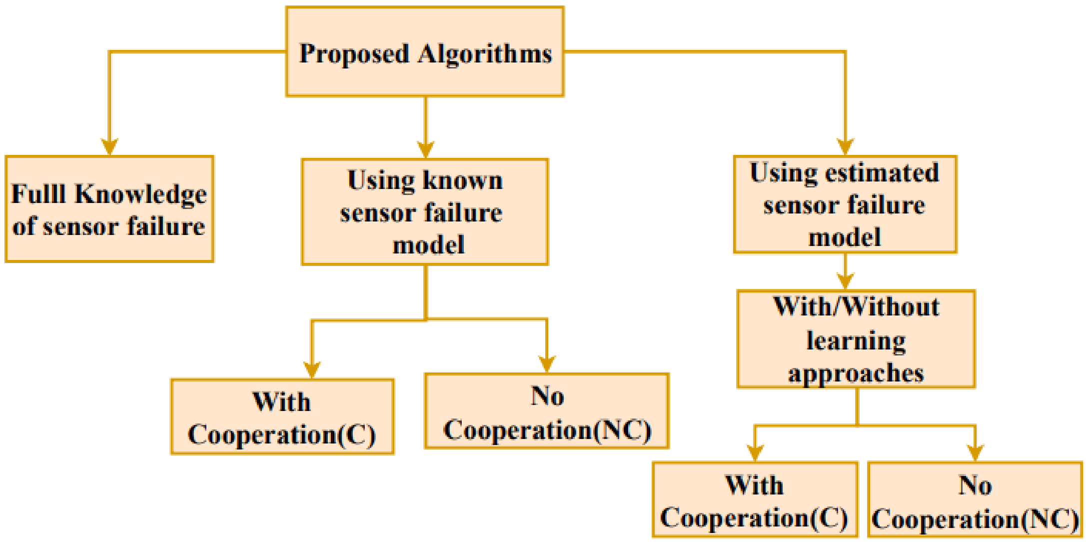


Fig. 4.2: Algorithms proposed for the autonomous robot network to optimize the reliability and the network costs.

1. **Full knowledge (PFK)**:

   Full knowledge means the system possesses the knowledge of the lifetime of sensors, Thus, the system is able to predict sensor failures accurately. Thus, the performance of the optimization algorithm, without the effect of errors in sensor failure prediction, can be evaluated.

2. **Using a known sensor failure prediction model (Known h)**:

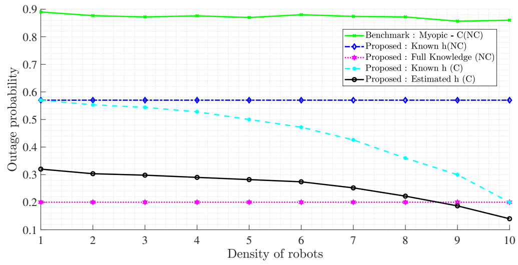
   Here, sensors are replaced to achieve the target reliability assuming, the exact sensor failure prediction model is known. The difference between full knowledge and this algorithm is that this scenario predicts sensor failures using a known model, which is modeled using the limited number of known lifetime data of sensors. Thus, it does not possess the full knowledge of failures of sensors. Thus, the sensor failure prediction is not as accurate as full knowledge. Thus, the effect of error between the full knowledge scenario and this scenario is evaluated using simulations. Hence, the effect of prediction using a known sensor failure model and the optimization algorithm is observed in this scenario. This scenario is further evaluated, under with and without communication. The effect of communication to improve the performance of this scenario is observed.

3. **Using an estimated sensor failure prediction model(Estimated h/EH)**:
   Since, the actual sensor failure prediction model is unknown, estimated sensor failure prediction is used for prediction, when previous knowledge of sensor failures in the system is known. Thus, the effect of prediction using an estimated sensor failure model and the optimization algorithm is observed in this scenario. This scenario is also further evaluated, under with and without communication. The effect of communication to improve the performance of this scenario is observed. When previous knowledge of sensor failures in the system is unknown, this scenario is implemented using CL and FL approaches, where sensor failure model parameters are learned by collecting data of sensor lifetimes by observing real-time sensor failures of the sensor array, S_v, of the robot.

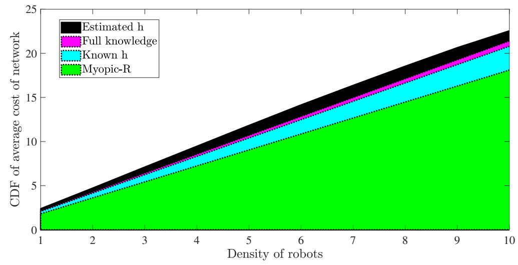
4.2.2 Result analysis

In this section, we analyze the results of the proposed schemes to determine the optimal methods for improving sensor reliability and minimizing network costs. The variance of sensor measurements must be kept below the threshold variance to keep the reliability of the sensor measurements above the threshold of the reliability of sensor measurements. Hence, the variance of sensor measurements is inversely proportional to the reliability of sensor measurements. For simulations, the incident with the sensor measurement variance exceeding threshhold variance is named a reliability outage. Thus, in order to maintain higher reliability in the system, the probability of reliability outage must be kept low. The probability that reliability outages occur is named as *outage probability* through all the simulation results. Thus, it should be noted that this is not the outage defined in communication, as the incident where the information rate is less than the required threshold information rate.

The Figure. 4.3a illustrates the reliability outages/fluctuations against density of robots in the robot



(a) Outages/Reliability fluctuations against the density of robots.



(b) Cumulative of the average cost of the network against the density of robots.

Fig. 4.3: Variation of sensor measurement reliability outages and average costs against robot count under proposed and baseline schemes.

network under the benchmark algorithms vs proposed algorithms. Here, it is assumed that the network operating costs of sensor replacements and communication with a neighbor robot is the same. In Figure.4.3a, the outages of the benchmark algorithm, increase with the density of robots in the network. The outage probability of the benchmark algorithm, Myopic - R, is high because it does not use any prediction or optimization strategies to prevent future reliability outages. It observes the real-time failures of sensors and replace after the amount of sensor failures exceeds the threshold amount of sensor failures required to maintain the reliability threshold of sensor measurements. The outages of the algorithms, without communication/no cooperation (NC) have fixed outage probability with the density of robots in the network. The reason is that since those algorithms are not communicating, the density of robots in the network does not affect the sensor replacement decision taken by those algorithms. Thus, the outages do not change with the increment of robots in the network. The full knowledge scenario, has the lowest outage probability, however it still has a certain outage probability, due to the existence of initial sensor failures, that may occur randomly. Thus, even though failures are predicted accurately, there is a chance that the new sensor which is replaced has already failed at that time instant. Here, it is clear that with the increment in the density of robots, the proposed algorithms which use the known and estimated sensor failure prediction model displays a reduction in the probability of reliability outages with the increase in the density of robots when compared with other algorithms.

In addition to reliability outage probability, the variation of cumulative average network operating cost against the density of robots of the network is evaluated in Figure. 4.3b. The average cost is higher when sensors are replaced using the predictions based on the estimated $h(a, \lambda, k)$. The optimization algorithm tends to replace more sensors in order to maintain its reliability constraint. From the figure, it is clear that the average cost of all the algorithms increases with the increment in the density of robots in the network. Here, it is assumed that the costs for faulty sensor replacements and communication are the same. Although, the proposed algorithm which uses the estimated sensor failure model, $h(a, \lambda, k)$, for prediction, has the highest cumulative costs, the gap between other algorithms is considerably less. Furthermore, since the proposed algorithm with estimated $h(a, \lambda, k)$ has the lowest outage probability variation against the density of robots, the costs incurred to attain such reliability are not as high as expected when compared with the higher outage probabilities of other algorithms. The algorithm, Myopic - R shows the lowest average network operating costs due to the fact of replacing faulty sensors only after faults occur in the sensors and not predicting sensor failures. The rest of the algorithms, which use prediction and optimization algorithms to predict sensor failures and optimize network operating costs, spend more due to the probability of replacing sensors even if they actually do not fail and communicate more with the neighbor robots seeking higher sensor measurement reliability.

When compared with Figure. 4.3a, the proposed algorithm with estimated $h(a, \lambda, k)$ shows a reduction in reliability outage probability with the density of robots. and here the average network operating cost incurred is nearly equal to the other algorithms. Hence, the proposed algorithm with estimated $h(a, \lambda, k)$, is the optimal strategy that the optimizes the network operating average cost and reduces reliability outages of the sensor measurements which is the objective of this research.

The impact of costs of sensor replacements and communication with neighbor robots on the reliability outages of the system is analyzed in Figure 4.4. Therein, it can be seen that the reliability fluctuations/outages increase with the increase in the cost ratio of $\frac{\phi_c}{\phi_s}$. The reason behind the increase in outages is that when the cost ratio increases, ϕ_c increases, and in order to minimize the total network operating cost, the local robot tends towards more sensor replacements compared to communication with neighbor robots. Here, prediction of sensor failures, effect the optimal sensor replacement decision taken by the optimization algorithm. The prediction of sensor failures is done using the sensor failure prediction model. Thus, the accuracy of prediction effect the final sensor replacement decision taken and the cost incurred for sensor replacements. When communication of sensor failure data from neighbor robots are taken into account, when the density of robots in the network increase, the amount of information that the

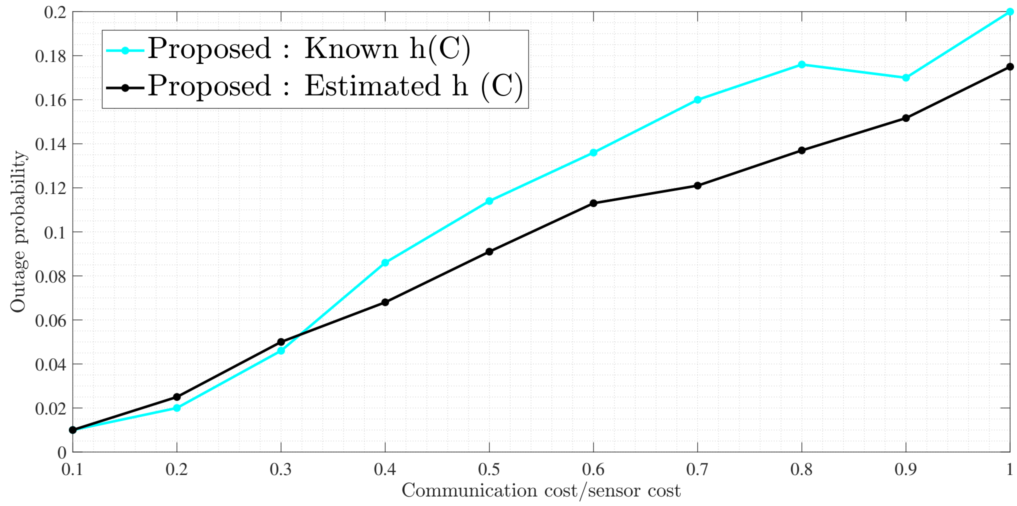


Fig. 4.4: Outages/Reliability fluctuations against sensor replacement and communication cost ratio.

local robot achieves from the neighbor robots increase, which increases the reliability of the sensor measurement and reduces reliability outages. Thus, from the trends in Figure.4.4, it can be concluded that more communication among neighbor robots and lesser sensor replacements, reduces reliability outages.

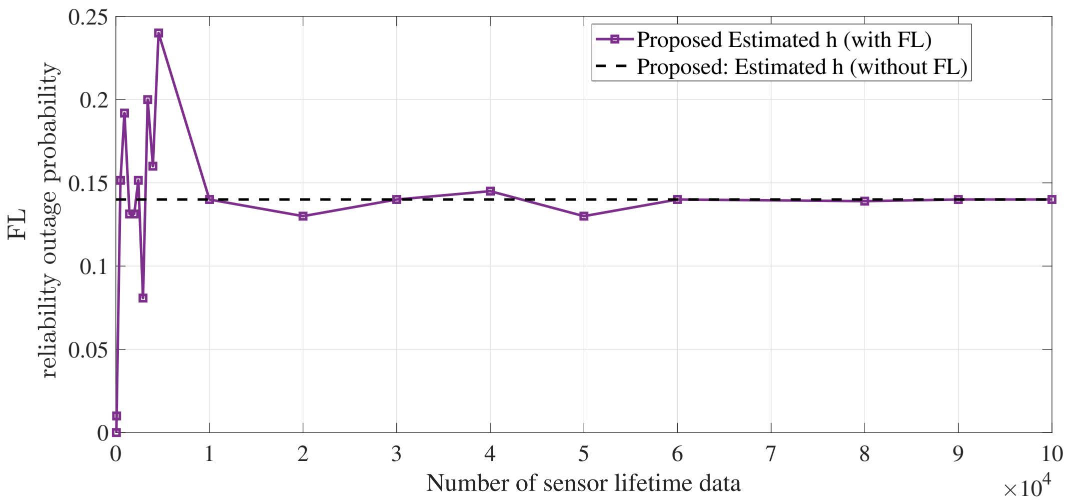


Fig. 4.5: Variation of reliability outage probability against the number of sensor lifetime data.

The effect of sensor lifetime data on the performance of the FL algorithm is discussed herewith where the system model was simulated for a robot network consisting of ten robots. From Figure. 4.5, it is observed that In the beginning when the number of sensor lifetime data is low, the reliability outage probability shows higher fluctuation. Furthermore, it is observed that with the increase in the number of sensor lifetime data, the reliability outage probability of the FL method converges perfectly to the reliability outage probability of the proposed algorithm with estimated $h(a, \lambda, k)$ implemented without FL, i.e. using the total sensor failure data already available.

Next, the robot density, communication range, and transmit power were varied creating different scenarios and the performance indicators were evaluated. Simulation parameters utilized are given in Table. 4.2. Simulation scenarios considering robot density, communication range and transmit power

Table 4.2: Scenario specific parameters

simulation	**area**	**total time**	**age step**	N	λ	k	L
A	100	100	1	10	10	2	1
B	100	100	1	10	10	2	1
C	100	100	1	100	10	2	1

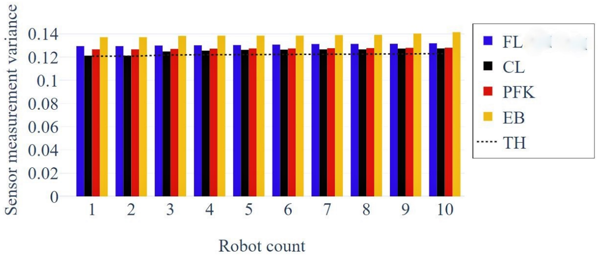
are labeled as A, B, and C respectively and the simulation-specific parameters are given in the following Table 4.3.

Table 4.3: Simulation: Performance against robot density

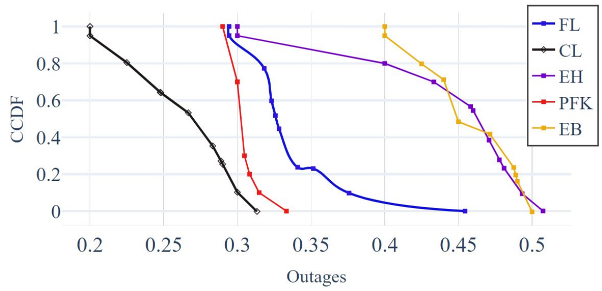
simulation	**R**	R_0	P_m
A	[1:10]	10	10
B	100	[1:10]	10
C	100	10	[1:20]

- **A. Robot density:** First, the performance of the FL approach when the robot density of the network is varied was evaluated and shown in Fig. 4.6a, 4.6b, 4.6c, 4.7a, 4.7b, 4.7c. The performance is compared with other proposed and baseline algorithms.

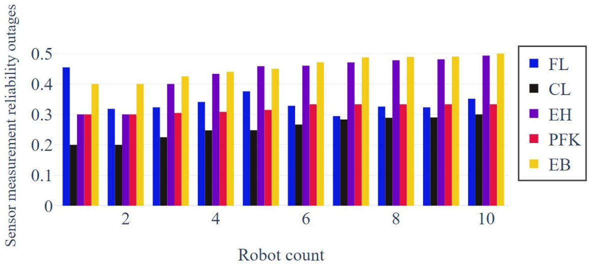
  Sensor measurement reliability It is apparent that the sensor measurement reliability outage probability of the proposed algorithms, FL, CL, EH, PFK, decreases with the increase in the robot density in this medium-scale robot network as shown in Fig. 4.6a. In addition, the performance of CL and EH approach perform better than the existing baseline (EB) methods. When the FL



(a) Variation of sensor measurement variance against robot count.



(b) Variation of Complementary Cumulative Distribution Function (CCDF) of sensor measurement reliability outages.



(c) Variation of sensor measurement reliability outages against robot count.

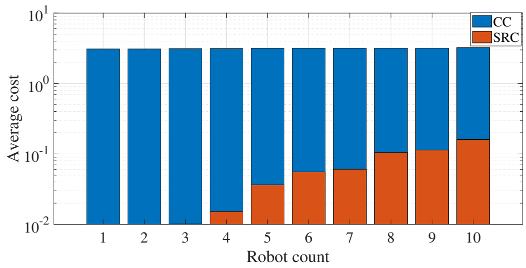
Fig. 4.6: Variation of sensor measurement reliability outages under under FL, CL, EH, PFK, EB against robot count under FL when robot count is varied from 1 - 10m and per robot communication range is 10m in the network.

approach is concerned it has lesser outage probabilities than the existing scenario (EB) and proposed algorithms such as EH, PFK. The outage probability when CL is implemented is lower than the FL approach. These results are illustrated in Fig. 4.6b, 4.6c. The CL approach predicts the sensor failures more accurately compared to FL, due to gaining all data from each robot device and predicting the k and λ values more accurately than FL.

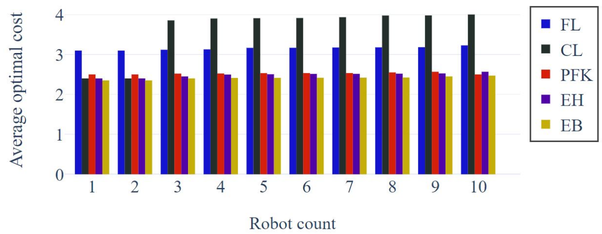
Average optimal cost The average costs for sensor replacements and communication were evaluated and Fig. 4.7a shows their behavior against the robot count. It can be seen that the communication cost increases when the number of robots is increased. However, the total average cost remains nearly the same as the number of robots.

Further, when the robot density is increased, the average cost incurred for CL is higher than the FL approach as shown in Fig. 4.7b. Therefore, the FL approach shows flexibility in achieving both reliability and minimizing operating costs.

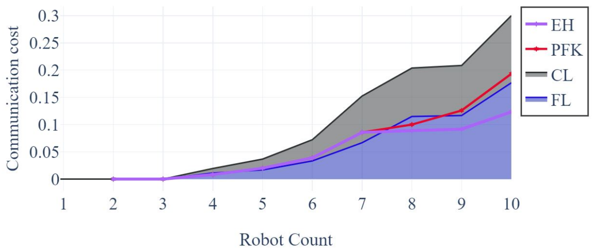
Further, the variation of only communication cost against robot count is illustrated in Fig. 4.7c, where the average communication cost for the FL approach is almost as same as EH and PFK algorithms and lower than CL. The cost of CL is higher due to predicting sensor failures higher than even the PFK scheme, in order to avoid sensor failures at all costs. However, the FL scheme showcases lesser costs due to utilizing device-level data to predict future sensor failure rates, which results in predictions suitable for the specific robot.



(a) Variation of communication cost (CC) and sensor replacement cost (SRC) against robot count.



(b) Variation of average optimal cost against robot count.



(c) Variation of communication cost (CC) against robot count.

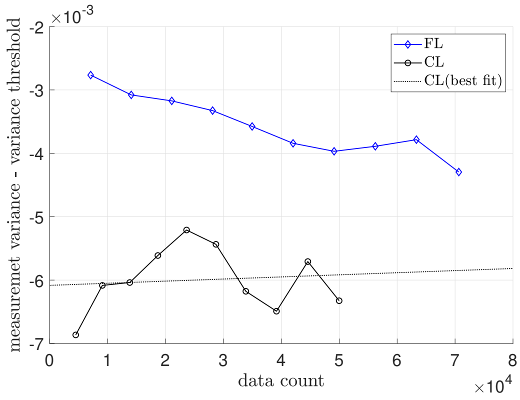
Fig. 4.7: Variation of average costs under FL, CL, EH, PFK, EB when robot count is varied from 1 - 10m and per robot communication range is 10m in the network.

Further, it can be observed from Fig. 4.8a, 4.8b, 4.8c that performance of the FL approach improves with the amount of data samples collected in the system in terms of reliability outages and communication costs. However, the CL approach is more significant than FL in terms of sensor measurement variance as seen in Fig. 4.8a. Moreover, during the testing phase, FL shows lesser reliability outages than CL as shown in Fig. 4.8b. Once a device is trained under FL, it performs with the known knowledge of previous sensor failure predictions. Thus, it can be deduced that the performance of the FL approach in enhancing sensor measurement reliability increases with the amount of data collected while optimizing the network operating costs. However, it should be noted that the parameters SMVE and SMVO under the CL approach performs better than the FL approach as shown in Fig. 4.8c. The reason for such behavior is due to CL has a higher sensor replacement frequency than FL. Moreover, once the number of robots in the network increase, the communication cost of the network increases as the communication between robots and the central server increase.

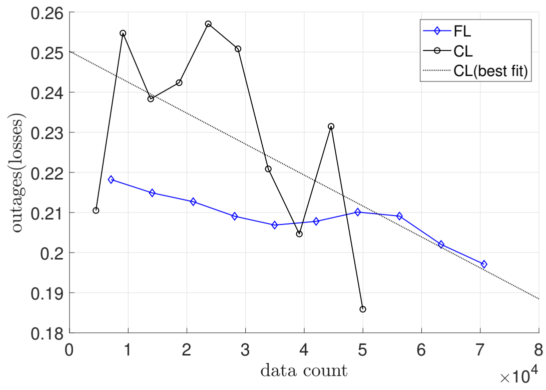
- **B. Communication range:** Next, the performance of the FL approach when the communication range of the robots varied was evaluated and is shown in Fig. 4.8a, 4.8b, 4.8c, 4.9a, 4.9b, 4.9c, 4.9d. Increment in the communication range of each robot has decreased the SMRO, SMVE, AC, SRC, and CC. Further, the number of data samples available improves the expected performance of FL by decreasing SMRO, SMVE, AC, and SRC. However, parameters SMVE and SMVO under The CL approach performs better than the FL approach. Further, the FL approach shows optimal performance as it enhances the optimal measurement reliability while minimizing the network operating costs when increasing the communication range.

- **C. Transmit power:** Furthermore, the effect on performance when the transmit power is varied is also a major concern as we want to minimize the energy consumption of the proposed scenario. Therefore, it was evaluated by varying the transmit power used by each robot. The following results in Fig. 4.10 show the performance with the variation of transmit power. It is observed that during low transmit power, high-reliability losses were apparent, while there is an optimal transmit power above which the losses start decreasing. The transmit power increment increases the received SNR at each device level, which improves the reliability of communication among the robots to make a sufficient amount of estimations for an accurate sensor failure prediction.

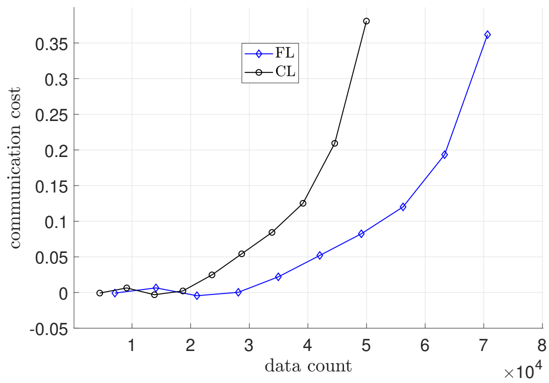
  The accuracy value of the system is improving with the FL approach with the data count and converges with the system with historical data available. Thus, it increases the reliability of the proposed FL approach and is a convenient scenario for practical implementation for newly built wireless network-related systems with unique sensor failures.



(a) Variation of error between sensor measurement variance against data count.



(b) Variation of sensor measurement reliability outages against data count.



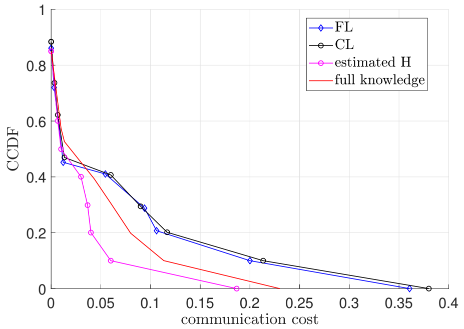
(c) Variation of communication cost against data count.

Fig. 4.8: Variation of sensor measurement reliability and communication cost against data count under CL and FL schemes.

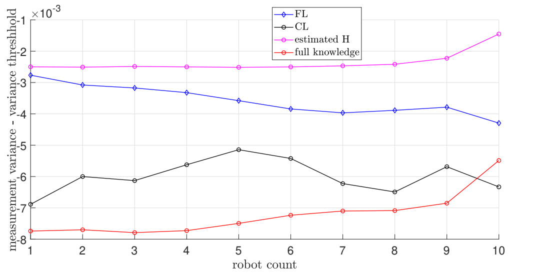
4.2.3 Training and testing

Furthermore, the behavior of the FL approach under training and test phases is very important.It is evaluated and results are depicted in Fig. 4.11a, 4.11b, 4.13b, 4.12a, 4.12b, 4.14a, 4.14b, 4.13a, 4.13c, 4.13d. Here test data is following the sensor failure model, $h(a, \lambda, k)$.

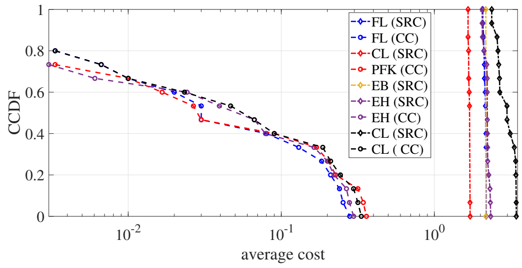
Sensor measurement reliability under test data The results under Fig. 4.11a shows the the accuracy achieved by test data following $h(a, \lambda, k)$ under SMRO parameter using FL approach. It was noted that the accuracy of sensor failure prediction converged to approximately $90\% \pm 2\%$. Furthermore, 4.11b shows the error resulting under test data following $h(a, \lambda, k)$. It is observed that the error decreases and converges to a percentage of $10\% \pm 1.8\%$ with the increment in the number of data samples. The Fig.



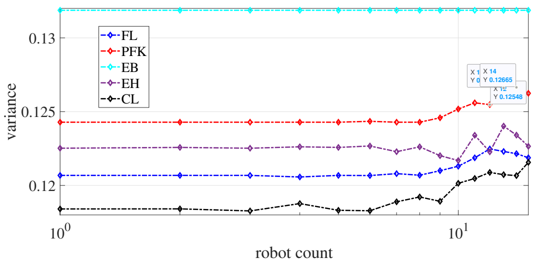
(a) CCDF of communication cost.



(b) Variation of error between of sensor measurement variance and threshold variance.



(c) Variation of CCDF of sensor replacement cost (SRC) and communication cost (CC).



(d) Variation of sensor measurement variance against robot count.

Fig. 4.9: Variation of communication cost, sensor measurement variance, average cost under FL, CL, EH, PFK, EB schemes when the communication radius is varied from 1 - 20m and a total of 10 robots in the network.

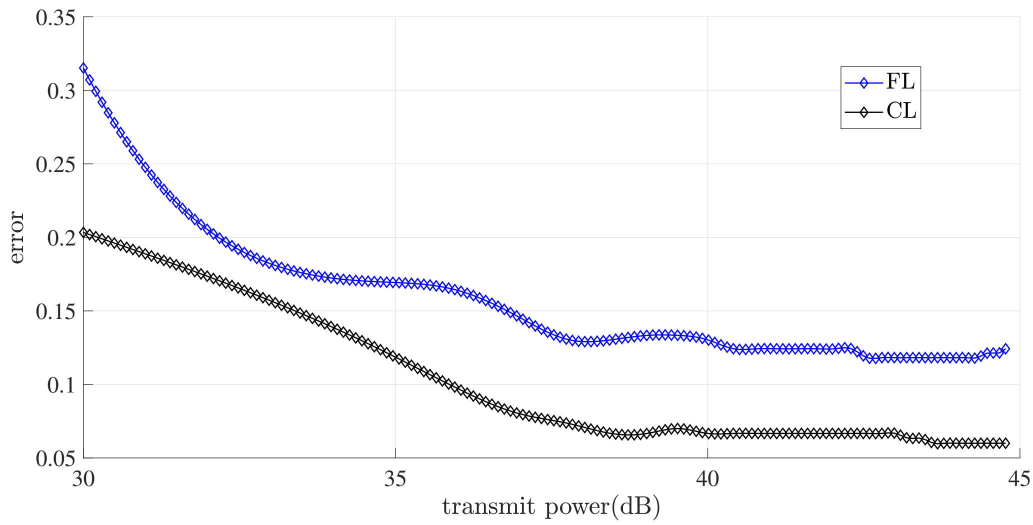
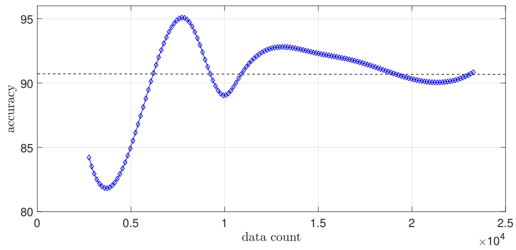
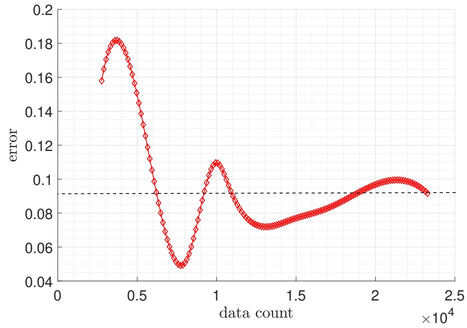


Fig. 4.10: Variation of sensor measurement reliability outages vs transmit power for a network of 10 robots and per robot communication range of 10m.





(a) Variation of accuracy between sensor measurement the variance of trained and tested algorithms against the number of data samples.

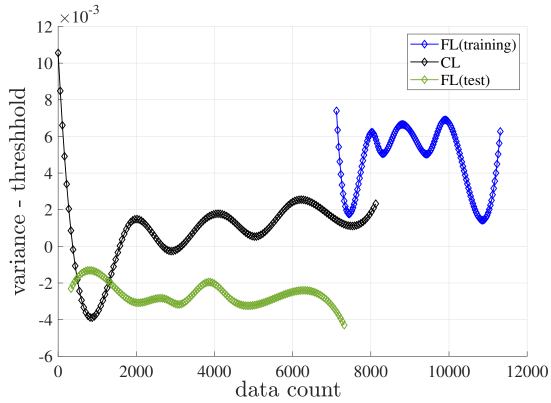
(b) Variation of error between sensor measurement the variance of trained and tested algorithms against the number of data samples.

Fig. 4.11: Variation of error and accuracy of FL when the test data follows the sensor failure model, $h(a, \lambda, k)$.

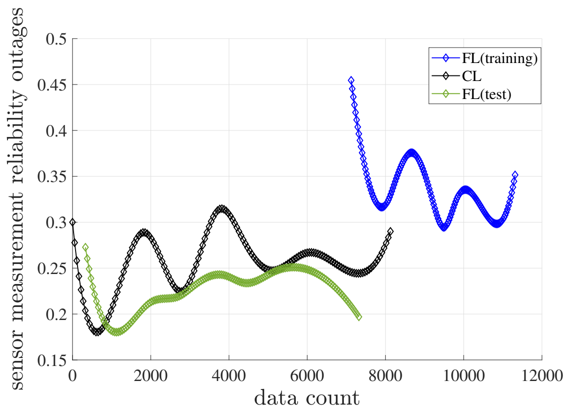
4.12a shows the SMVE of test data following $h(a, \lambda, k)$ against data samples under FL. The test data has a better performance FL under the training phase and CL in terms of SMVE. Moreover, the training phase of FL requires a sufficient amount of data at each robot level to start its prediction. Hence, the SMVE and SMRO are obtained at a later instance with a high data count. Similarly, SMRO of test data has a better performance than FL under the training phase and CL in terms of SMVE as shown in 4.12b. The Fig. 4.13a shows the sensor measurement variance of test data following $h(a, \lambda, k)$ against the robot count The total cost is lesser under FL than CL. The device-level sensor failure prediction is more accurate with the device-level data samples and the estimated λ, k parameters. Moreover, the test phase of FL has a better performance than the FL training phase and CL in terms of sensor measurement variance. The testing phase prior knowledge about sensor failure prediction enhances the accuracy of prediction.

Average cost under test data The variation of average cost under test data following the $h(a, \lambda, k)$ and training data are compared and results are illustrated in Figs. 4.13b, 4.14a, 4.14b, 4.13c, 4.13d. With the increment in the robot count the average optimal cost difference for FL under test and training data slowly increase which shown in 4.13b. The total communication cost increases with the number of robots as the number of transmissions between robots increase. The average optimal costs for testing and training phases are separately depicted in 4.13c which also shows that the average cost under test data increases slightly compared to training data with the robot count.

Further, 4.14a, 4.14b shows the variation of sensor replacement cost and communication cost against



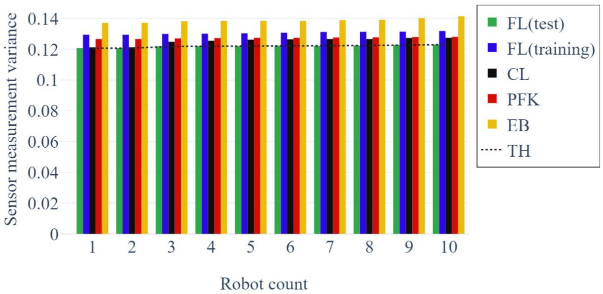
(a) Variation of error between actual sensor measurement and threshold variance against total data samples.



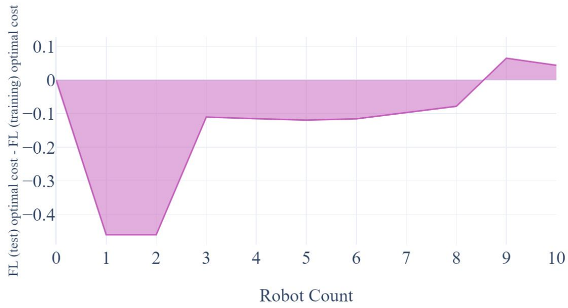
(b) Variation of total sensor measurement reliability outages against total data samples.

Fig. 4.12: Variation of sensor measurement variance and reliability outages against the data count under CL, training phase of FL, and testing phase of FL.

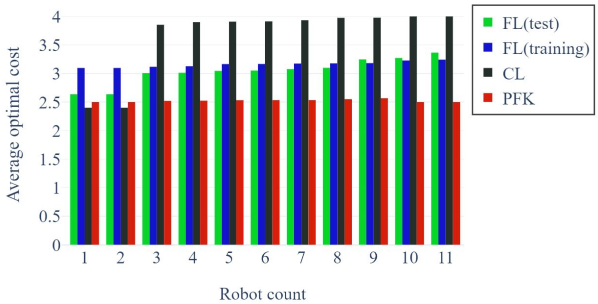
the number of data samples. It is seen that the communication cost under test data has a higher increment than the training phase with the number of data samples. The sensor replacement cost shows a different behavior which is shown in 4.14a. There the sensor replacement cost under the testing phase remains lower than in the training phase. As depicted in fig. 4.14b the communication cost under the test phase of FL remains low than the training phase of FL and CL. Hence, it is seen that robots that are trained under FL using sufficient data perform optimally under both the sensor failure prediction and sensor replacement costs compared to CL.



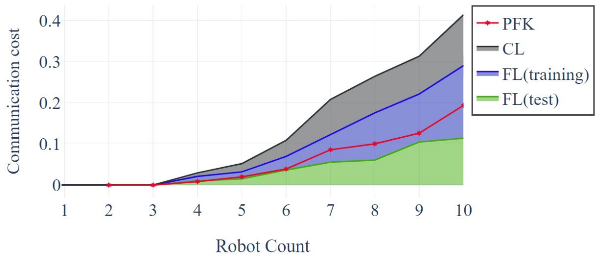
(a) Variation of sensor measurement variance against robot count of the robot network under the training phase of FL, test phase of FL, CL, PFK, and EB (Myopic - R) where TH is the variance threshold.



(b) Variation of difference between optimal cost under test and training phase against robot count of the robot network.

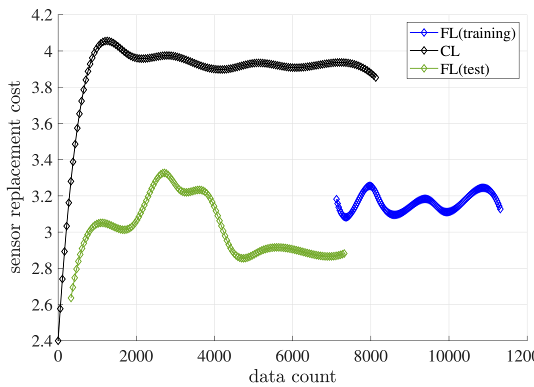


(c) Variation of average optimal cost against robot count.

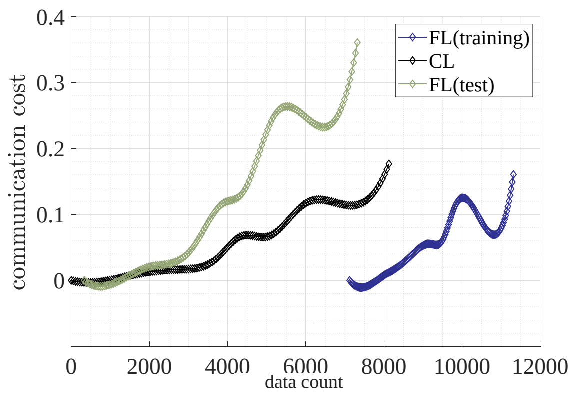


(d) Variation of communication cost against robot count.

Fig. 4.13: Variation of network costs against robot count under CL, FL (training), and FL (test) schemes.



(a) Variation of total sensor replacement cost against total data samples.



(b) Variation of average communication cost against total data samples.

Fig. 4.14: Variation of network costs against the data count under CL, FL (training), and FL (test) schemes.

CHAPTER 5

Conclusion and future work

With the increase in the usage of mobile robots for automation in tasks such as manufacturing, navigation, and environment monitoring, interaction with humans and objects nearby is becoming frequent. Hence, the need to increase the safety of the environment becomes important. This paper develops a mechanism to improve the reliability of sensor measurements in a mobile robot network taking into account of inter-robot communication and costs of faulty sensor replacements.

In order to provide a solution, first a sensor fault prediction method is developed utilizing sensor characteristics. Then, the network-wide cost of sensor replacements and wireless communication is minimized subject to a sensor measurement reliability constraint. Tools from convex optimization are used to develop an algorithm that derives the optimal sensor selection and wireless information communication decision for the problem. Under the absence of prior knowledge of sensor characteristics, we utilize observations of sensor failures to estimate their characteristics in a distributed manner using FL. Finally, extensive simulations were carried out to highlight the performance of the proposed mechanism compared to several state-of-the-art methods.

Novelty, of the research, can be seen where both the network operating costs and sensor reliability thresholds are optimally maintained for the mobile robot network considering the proposed algorithms which utilize prediction and optimization principles. Further, information exchange among neighbor robots using wireless communication is used to enhance sensor reliability, that is local sensor reliability can be enhanced additionally with communication with external robots or devices. Further, it was shown that sensor failure prediction can be done using FL approach, using data available at the robots which is useful when previous knowledge about the system sensor failures are not available.

5.1 Future Work

The main focus of this paper is to propose an algorithm for network resource cost minimization and sensor measurement reliability enhancement above a threshold reliability level assuming robots are located randomly. However, the possibility of connecting robots in specific network topologies and observing its effect needs to be evaluated. In addition, the proposed system worked under a low interference level system. Thus, the effect of higher levels of interference on the proposed algorithm needs to discussed. Furthermore, sensor failures of only the next time instant was predicted for sensor replacements. However since in practical scenarios, it is difficult to conduct instantaneous sensor replacements, sensor failures must be predicted well before the failure happens, which gives sufficient time for the system to prepare and update its sensors beforehand.

Hence, as future work for this paper, attention will be drawn to evaluating the performance of the proposed strategy when robots in the automated mobile network are connected in specified network topologies having different communication protocols. Further, strategies for interference management for robot networks with higher interference levels will be focused, which will be beneficial when implementing the proposed solution in a practical scenario. In addition, the possibility of improving the prediction horizon, the range ahead by which the prediction is done, for sensor failure prediction will be evaluated.

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