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MASTER'S THESIS

FEDERATED LEARNING FOR ENHANCED SENSOR RELIABILITY OF AUTOMATED WIRELESS NETWORKS

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ABSTRACT

Autonomous mobile robots working in-proximity humans and objects is becoming frequent and thus, avoiding collisions becomes important to increase the safety of the working environment. This thesis develops a mechanism to improve the reliability of sensor measurements in a mobile robot network taking into the 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 aforementioned problem. Under the absence of prior knowledge on 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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TIIVISTELMÄ

Autonomiset liikkuvat robotit, jotka työskentelevät läheisillä ihmisillä ja esineitä on tulossa yleiseksi ja siten törmäysten välttäminen on tärkeää työympäristön turvallisuuden lisäämiseksi. Opinnäytetyössä kehitetään mekanismi, jolla parannetaan anturimittausten luotettavuutta matkaviestinverkossa ottaen huomioon robottien välisen viestinnän ja virheellisten anturivaihtoehtojen kustannukset. Tässä mielessä kehitämme ensin anturin vian ennustamismenetelmän, jossa käytetään anturin ominaisuuksia. Sitten verkon laajuiset kustannusten kaappausanturien vaihto ja langaton viestintä minimoidaan anturin mittausturvallisuusrajoituksen alaisena. Kupera optimoinnin työkaluja käytetään sellaisen algoritmin kehittämiseen, joka tuottaa optimaalisen anturin valinnan ja langattoman tietoliikennepolitiikan edellä mainittuun ongelmaan. Jos anturien ominaisuuksista ei ole aikaisempaa tietoa, käytämme havaintoja anturihäiriöistä niiden ominaisuuksien arvioimiseksi hajautetusti käyttämällä federated learning. Lopuksi tehdään laajoja simulaatioita ehdotetun mekanismin suorituskyvyn korostamiseksi verrattuna useisiin uusimpiin menetelmiin. Avainsanat: anturin luotettavuus, autonomiset mobiilirobotit,

langatonta tietoa, verkon käyttökustannukset, yhdistetty oppiminen.

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FOREWORD

I would like to extend my sincere gratitude to my technical supervisor and mentor, Dr. Sumudu Samarakoon, for his continuous supervision, productive discussions, valuable suggestions and enormous patience throughout the period of the research, without which this thesis would not have been possible. Further, I would like to extend my gratitude to my main supervisor, Prof. Mehdi Bennis, for his insightful guidance and feedback to improve my thesis. In addition, I would extend my acknowledgements to my second examiner, Dr. Lilantha Samaranayake, from University of Peradeniya, for his valuable suggestions provided regarding my thesis. I greatly appreciate their vast knowledge and inspiring ideas, which cover a multitude of areas as well as their continual encouragement throughout my master's research and studies. I would like to extend my gratitude to Prof. Matti Latva-aho, and Prof. Nandana Rajatheva, for their support, guidance and encouragement towards research. Life in Oulu was wonderful thanks to the beloved Sri Lankan community, in and outside Oulu, for making me feel at home. My special thanks also goes to my fellow double degree students, for providing me numerous feedback, suggestions and motivation for my research and keeping me high spirited at all times. Finally, I would like to express my humble gratitude to my loving family: my mother Kusum, my father, Parakrama my younger brother Uditha, and elder brother Pulathisi for their love and caring, and for being the ultimate courage and strength of my life.

Oulu, 30th July, 2019

Vishaka Basnayake

LIST OF ABBREVIATIONS AND SYMBOLS

Acronyms:

CDF	Cumulative Distribution Function
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
SNR	Signal to Noise Ratio
SINR	Signal to Interference plus Noise Ratio

Roman letter notations:

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

1 INTRODUCTION

1.1 Background and Motivation

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, remote health monitoring [1, 2, 3, 4]. When industrial automation is considered, industries focus on automating industrial processes, such as navigation, transportation, environment monitoring efficiently, where automated mobile robot wireless networks are getting important in industry [5]. In addition, in the manufacturing sites, with the increased density of robots in the working environment, there is a tendency for the 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, medical costs. Thus, 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 have 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 decision making of the robots [6]. Nevertheless, maintenance of improved reliability constitute a large portion of costs in many industries, and that 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 [7]. 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, strategies. Hence, the motivation of this thesis is to address the challenge in enhancing sensor reliability, while maintaining network operating costs at a minimum using various strategies.

1.2 Scope of the thesis

Main objectives of this thesis are,

1. Proposing strategies of increasing reliability of sensor measurements.

   Sensors fail or wear-out with time and thus, their performance deteriorate from expected performance. Sensor failures affect sensor measurement reliability. Strategies on enhancing sensor measurement reliability using mathematical modelling of sensor failure prediction and sensor reliability optimization are discussed.

2. Sensor failure prediction and optimization of resource allocation in a wireless network.

   Sensor failure prediction and enhancing sensor reliability results in replacement of failed sensors, which results in increasing network operating costs. Thus, optimization of network resources while maintaining sensor reliability under satisfactory limits is one of the primary objectives.

3. Usage of wireless communication strategies to achieve sensor reliability.

   Effective communication is a necessity in an automated mobile wireless network. The possibility of utilizing wireless network strategies for sensor reliability enhancement and sharing data of sensor failures during real time operation of the system is a key objective of the thesis. Retrieving sensor failure data from neighbor mobile robots using wireless communication aspects of the network and using that data to enhance future sensor measurement reliability are discussed.

4. Usage of sensor failure model learning approaches to achieve sensor reliability

   Using learning approaches to estimate sensor failure model, predict sensor failures and enhance sensor reliability. Proposing the utilization of federated learning approach, when previous knowledge on sensor failure of the system is not available, to make sensor failure predictions in a distributed manner. Evaluating its performance over the existing strategies of enhancing sensor reliability.

2 RELATED WORK

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 network such as the sensor reliability, effective communication and communication resource allocation [8]. Little research work seems to 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 the autonomous wireless networks. In particular, federated learning plays a major role in designing a self organizing mobile devices, that rely on local information, with small variance from the centralized information [9]. In this section, work done so far on enhancing sensor reliability, while optimizing network operating costs and usage of federated learning approach to predict sensor failures are discussed.

2.1 Automated robot wireless network

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. [10]. This increased the need for new ways of communication inside the industrial environment, apart from wired communication [7]. Mobile robots are utilized for various tasks, in 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 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.

2.2 Information exchange among robots

The main motivation for connecting the robots is to achieve 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 single intelligent robot. Recently, many researches have focused on the importance of utilizing group behaviours 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 [11].

2.2.1 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 to wireless system designers. Data can distort as a result of path loss which in turn creates problems for devices who attempt to retrieve data from other remote locations. Path loss reduce the efficiency communication between the transmitter and the receivers, thus in order to diminish or reduce 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 [12].

Water filling algorithm is considered the capacity achieving optimal power allocation strategy for wireless networks [13]. 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 variance of noise plus interference per user k, channel matrix, variance of white Gaussian noise, power allocated per user k [14].

Algorithm 1 Iterative waterfilling algorithm

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

2.3 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 [15]. Sensor performance decreases due to deterioration resulting from age or usage. This deterioration is affected by several factors, including environment, operating conditions and maintenance.

2.3.1 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 [16]. Weibull models are widely used for failure modelling of components and phenomena. They are one of the best known and widely used distributions for reliability or survival analysis [17]. 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, and shape, k, has the probability density function,

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

Truncated Weibull distribution basically has three forms, namely left truncated, right truncated and doubly truncated. The right truncated two parameter Weibull distribution is modelled as follows.

$$f_r(a) = \frac{\frac{\lambda}{k}(\frac{\lambda}{k})^{(\lambda-1)}e^{-(\frac{a}{k})^{\lambda}}}{1-e^{-(\frac{T}{k})^{\lambda}}} \tag{2}$$

.

Some properties of right truncated Weibull include, having lower failure rate initially and higher failure rates at the maximum lifetime of a product.

2.3.2 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, [18] given as follows, where t and $F(\cdot)$, represent the lifetime of sensor and CDF of $h(a,k,\lambda)$ respectively.

$$\begin{aligned}\Pr\Big(t \le a+t_0 | t \ge a\Big) &= \frac{\Pr\Big(a \le t \le a+t_0\Big)}{\Pr\Big(t \ge a\Big)} \\ &= \frac{F(a+t_0)-F(a)}{F(T)-F(a)}.\end{aligned} \tag{3}$$

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

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

2.4 Estimation of model parameters using 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, the statistical methods are used when the 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 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, adaptive method used for MLE [19]. In general MLE algorithm formulation for a general problem is as follows [20]. 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 parameter, θ. Since the observations are independent, the joint density is the product of individual densities. given as

$$f(y_1, y_2, ..., y_N|\boldsymbol{\theta}) = \prod_{n=1}^{N} \left\{ f(y|\boldsymbol{\theta}) \right\} \tag{4}$$

In order to find observations that have 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,

$$L(\boldsymbol{\theta}|y_1, y_2, ..., y_N) = f(y_1, y_2, ..., y_N|\boldsymbol{\theta}) \tag{5}$$

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 $\boldsymbol{\theta}$.

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

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. Log likelihood function can be modelled as

$$\ln L(y, \boldsymbol{\theta}) = \sum_{m \in \mathcal{M}} f(y, \boldsymbol{\theta}) \tag{6}$$

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

$$\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta} \in \times} LL(y, \boldsymbol{\theta}) \tag{7}$$

2.5 Convex optimization

Casting a problem into convex optimization form offers the mean of finding the optimal solution by applying Lagrangian multipliers/ KKT conditions. A convex optimization problem is of the form [21].

$$\text{minimize} \quad f_0(x) \tag{8a}$$

$$\text{subject to} \quad f_i(x) \leq 0, i = 1, 2, ..., m \tag{8b}$$

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

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

with

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

2.6 Data driven learning approaches for system failure prediction

Statistical and learning techniques are widely used for deducing data-driven model. 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 [22]. Furthermore, there are three different learning techniques, namely supervised, unsupervised and reinforcement learning [23]. In supervised learning, data collected previously from observing actual behaviors is used. In the area of failure type detection and predictive maintenance, the 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. The reinforcement learning has explore and exploit phases. It creates a result, depending on the actual data in the real world. This implies that the accuracy in the estimate regarding the state of a real-world system effects the output of the learning [24].

2.6.1 Centralized and federated learning approaches

Centralized and federated learning are two different approaches for learning data driven models. Centralized learning approach is a traditional machine learning approach where data is in the central server are utilized to find data driven models. Federated learning is an approach where a global model is learned by averaging models that have been trained locally on client devices that generate data. [25]. When the isolated data occupied by each client fails to produce an ideal model, the mechanism of federated learning makes it possible for clients to share a united model without data exchange.[26] Algorithms for centralized and federated learning are generalized as follows [27].

Algorithm 2 MLE using centralized learning

```
input data : local data M_{u∈U}, step size δ
for T_f = 1, 2, 3, ....., do
    Model f(M)
    Compute∇_d f^d(M)
    ∇_d f^d(i) = ∇_d f^d(M)
    Update global estimations d(T_f)
    d(i) = d(T_f)
    for i = 1, 2, 3, ....., do
    Compute d(i) =d(i) - δ ∇_d f^d(i)
    end
    Download model to all clients U
    for k = 1, 2, 3, .....,K_u do
    Collect M_u
    end
    Upload M_u to C
end
```

Algorithm 3 MLE using federated learning

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

The advantages and disadvantages of centralized and federated learning are summarized in in Table. 1 and 2 [28].

Table 1. Advantages and disadvantages of centralized learning approach [29]

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

Table 2. Advantages and disadvantages of federated learning approach

Advantages	**Disadvantages**
Less expensive than centralized system	Clients require higher data processing resources or complex software
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 depend 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

3 ENHANCING SENSOR MEASUREMENT RELIABILITY

The design of a mechanism for enhancing sensor measurement reliability of an automated wireless network of mobile robots while maintaining operating costs of the network at minimum is one of main challenges in emerging mobile wireless networks at present.

3.1 System model and problem definition

Consider a local communication network consisting a set $\mathcal{V}$ of robots, that can communicate with one another and a central server, u, over wireless links. One robot, $\mathcal{V}$, communicate with the neighbor robots, v', that are located within the neighborhood region of radius S_0, 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, $log_2(4S_0/\lambda)$, within the region of radius, S_0.

Next, it is assumed that the information sharing from v to neighbouring robot v', is possible only when the rate exceeds a threshhold rate, r_{th} achievable under the effect of path loss at the radius S_0. The up-link rate of the communication links vary on the signal to interference 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 rate between v and v' is given as, considering the interference from other neighbor robot links and Gaussian noise, N_0 is given in (9) [30].

$$r_{v'} = \frac{P_i h_{vj'}^2}{\sum\limits_{l \in \mathcal{P}, v' \in \mathcal{V}', l \neq i, v' \neq j'} P_l h_{vv'}^2 + N_0} \tag{9}$$

The system model of the automated mobile robot wireless network is illustrated in Figure. 1

Further, each robot $v \in \mathcal{V}$ is equipped with an array $\mathcal{S}_v$ sensors to obtain proximity measurements for the purpose of collision avoidance. It is assumed that all sensors are manufactured under similar conditions and thus, having identical failure rates, i.e. likelihood of failure at a given age. Hence, the lifetimes of sensors (a) can be considered as random variables (RVs) drawn from independent and identical distributions. In this view, the sensor lifetime is modeled by a truncated Weibull distribution $h(a, \lambda, k)$ with scale parameter of λ, shape parameter of k, and maximum lifetime of T [31] that is given by,

$$h(a, \lambda, k) = \begin{cases} \frac{f(a)}{F(T)} & \text{if } a \in [0, T] \\ 0 & \text{otherwise,} \end{cases} \tag{10}$$

where $f(a)$ and $F(a)$ are the probability density function (PDF) and cumulative density function (CDF) of the truncated Weibull distribution respectively, defined as follows:

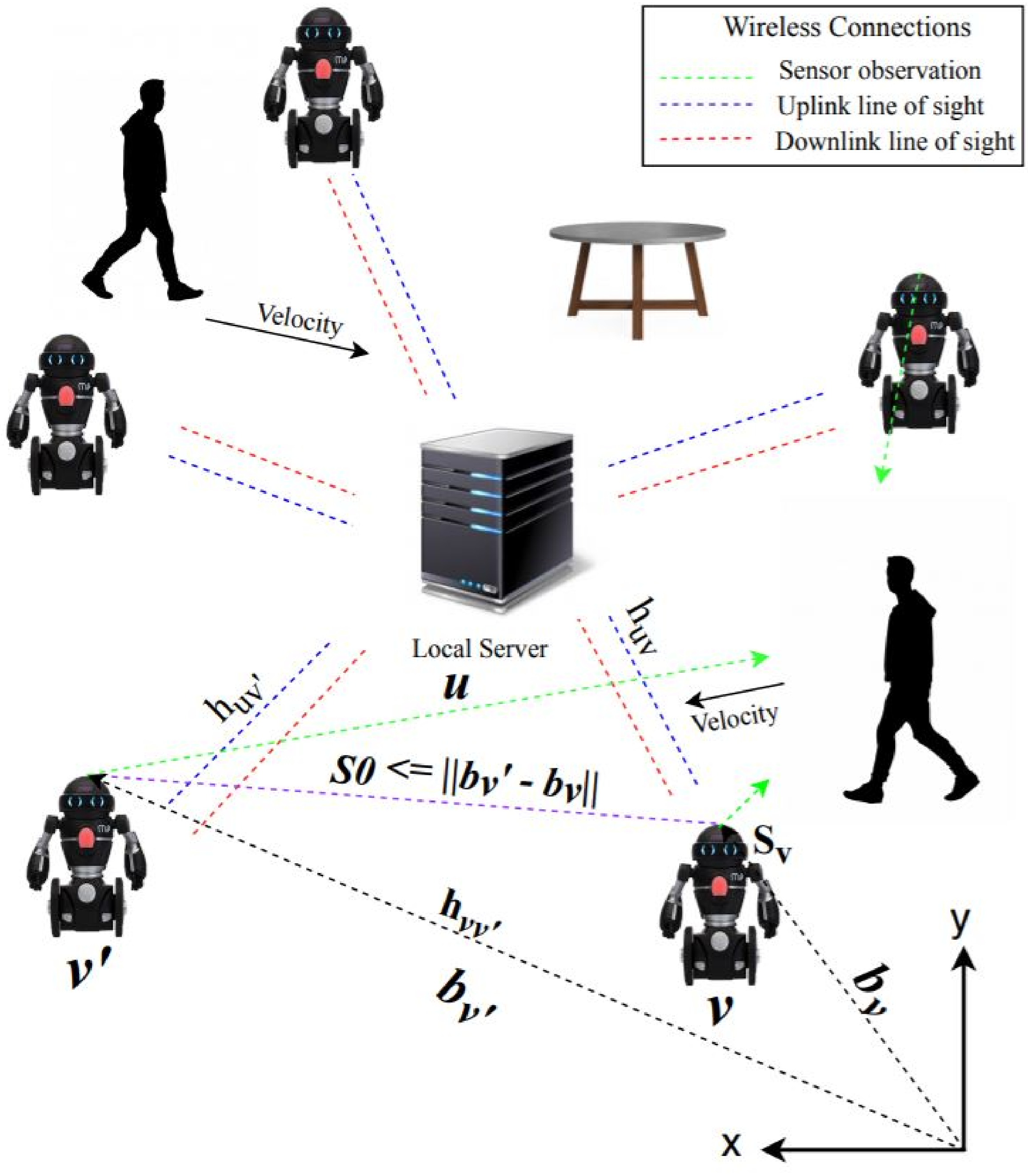

Figure 1. Simplified illustration of the system model containing the location of the local, neighbor robots and nearby objects within the radius S_0

$$f(a) = \frac{k}{\lambda}\Big(\frac{a}{\lambda}\Big)^{k-1} \exp\Big(-\Big(\frac{a}{\lambda}\Big)^{k}\Big) \tag{11}$$

$$F(a) = 1 - \exp\Big(-\Big(\frac{a}{\lambda}\Big)^{k}\Big) \tag{12}$$

Hence,

$$\frac{f(a)}{F(T)} = \frac{\frac{k}{\lambda}\Big(\frac{a}{\lambda}\Big)^{k-1} \exp\Big(-\Big(\frac{a}{\lambda}\Big)^{k}\Big)}{1 - \exp\Big(-\Big(\frac{T}{\lambda}\Big)^{k}\Big)} \tag{13}$$

Then, using (10), the probability that the sensor will be failed by $(a + t_0)$ can be calculated as follows, where a, $F(\cdot)$ represent the lifetime of sensor and CDF of the $h(a, \lambda, k)$ respectively.

$$\begin{aligned}\Pr\Big(t \leq a + t_0 | t \geq a\Big) &= \frac{\Pr\Big(a \leq t \leq a + t_0\Big)}{\Pr\Big(t \geq a\Big)} \\ &= \frac{\int_0^{a+t_0} h(a, \lambda, k)dt - \int_0^{a} h(a, \lambda, k)dt}{1 - \int_0^{a} h(a, \lambda, k)dt} \\ &= \frac{F(a + t_0) - F(a)}{F(T) - F(a)}.\end{aligned} \tag{14}$$

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 $d^{\text{act}}_{v,s}$ from robot v to an object using sensor s is modeled as,

$$\overline{d^{\text{obs}}_{v,s}} = d^{\text{act}}_{v,s} + n_{v,s}, \tag{15}$$

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

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 $d^{\text{obs}}_{v,s}$ from all the active sensors in $\mathcal{K}_v$ to obtain an estimate of $d^{\text{act}}_{v,s}$, i.e. $\hat{d}_v = \frac{1}{K_v}\sum_{s\in\mathcal{K}_v} d^{\text{obs}}_{v,s}$.

The illustration of $d^{\text{obs}}_{v,s}$ deviated from $d^{\text{act}}_{v,s}$ by $n_{v,s}$ is given in Figure. 3.

Figure. 4, depicts how Mean Square Error(MSE) of $d^{\text{obs}}_{v,s}$ collected by sensors in local robot, 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 follows [34].

$$Var(n_{v,s}) = \alpha\frac{L^2}{3} \tag{16}$$

Then, to reduce the variance, K_v, should be increased. where the maximum possible measuring error is L, and the failed percentage of the sensor is α.

$$\text{Reliability of } d^{\text{obs}}_{v,s} = (1 - \alpha)\frac{L^2}{3} \tag{17}$$

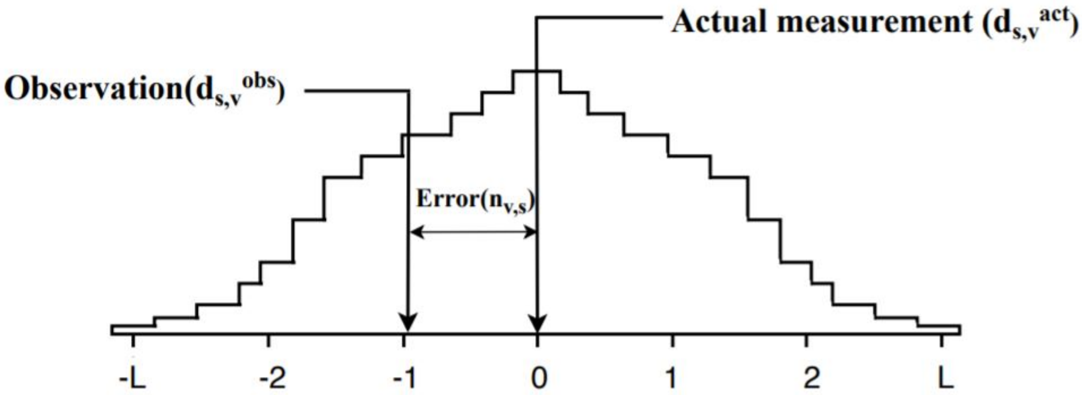

Figure 2. Degradation of actual sensor measurement,best estimate, due to measurement error [32]

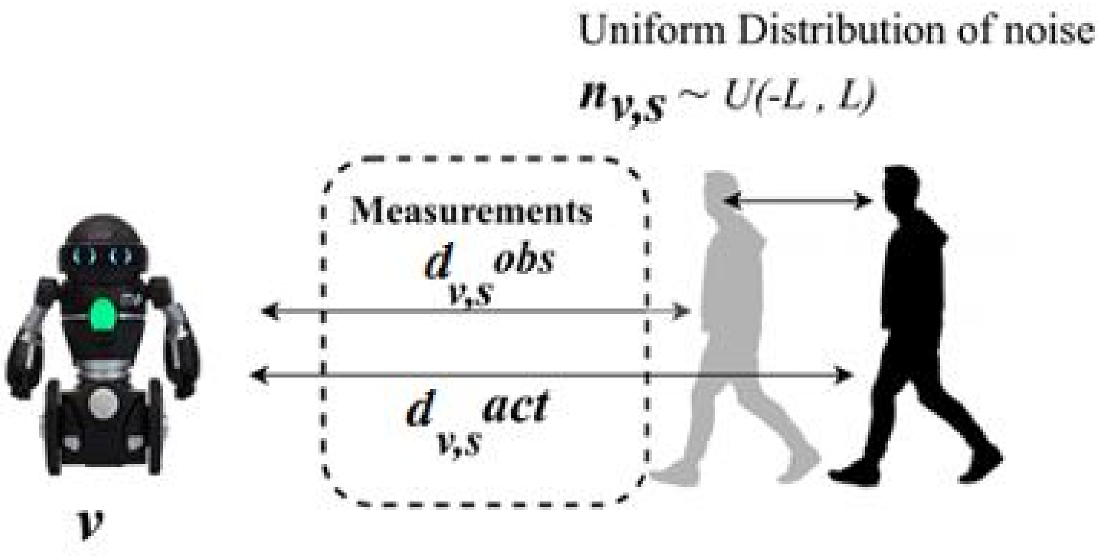

Figure 3. Degradation of actual sensor measurement due to measurement errors

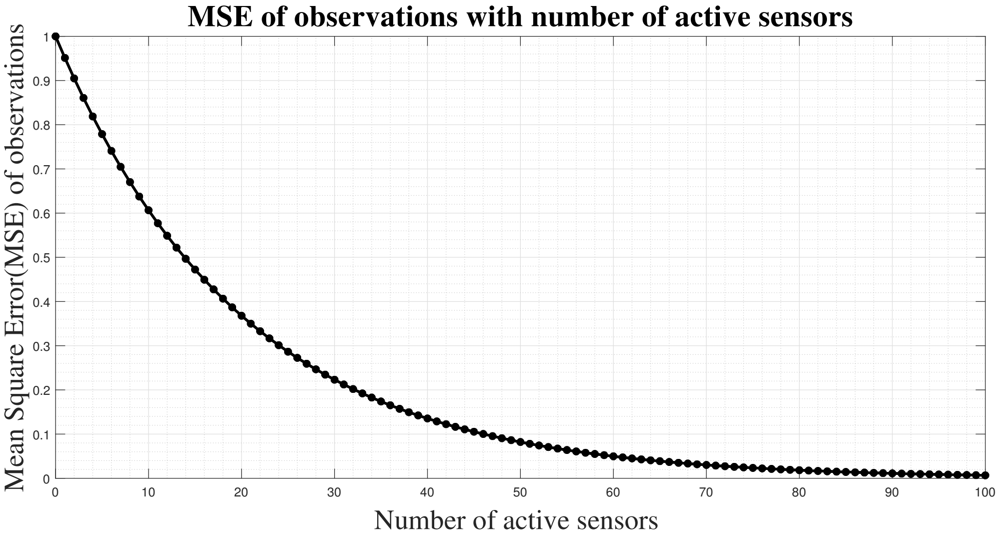

Figure 4. Mean Square Error (MSE) of measurement noise, $n_{v,s}$, against active number of sensors [33]

3.2 Optimal network resource allocation using convex optimization

The optimization problem of minimizing the network operating costs while maintaining reliability of sensor measurements above a threshhold, is categorized to two parts as with and without communication and the effect of communication on the optimization is observed. The basic flow of the optimization algorithms with and without communication is illustrated in Figure. 5.

Further, 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 vector 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 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 threshhold 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.

$$\text{where } \boldsymbol{x}_v(t) = \begin{cases} 1, & \text{if sensors replaced} \\ 0, & \text{otherwise} \end{cases} \tag{18}$$

$$\text{and } \boldsymbol{y}_{v'}(t) = \begin{cases} 1, & \text{if communicate with v'} \\ 0, & \text{otherwise} \end{cases} \tag{19}$$

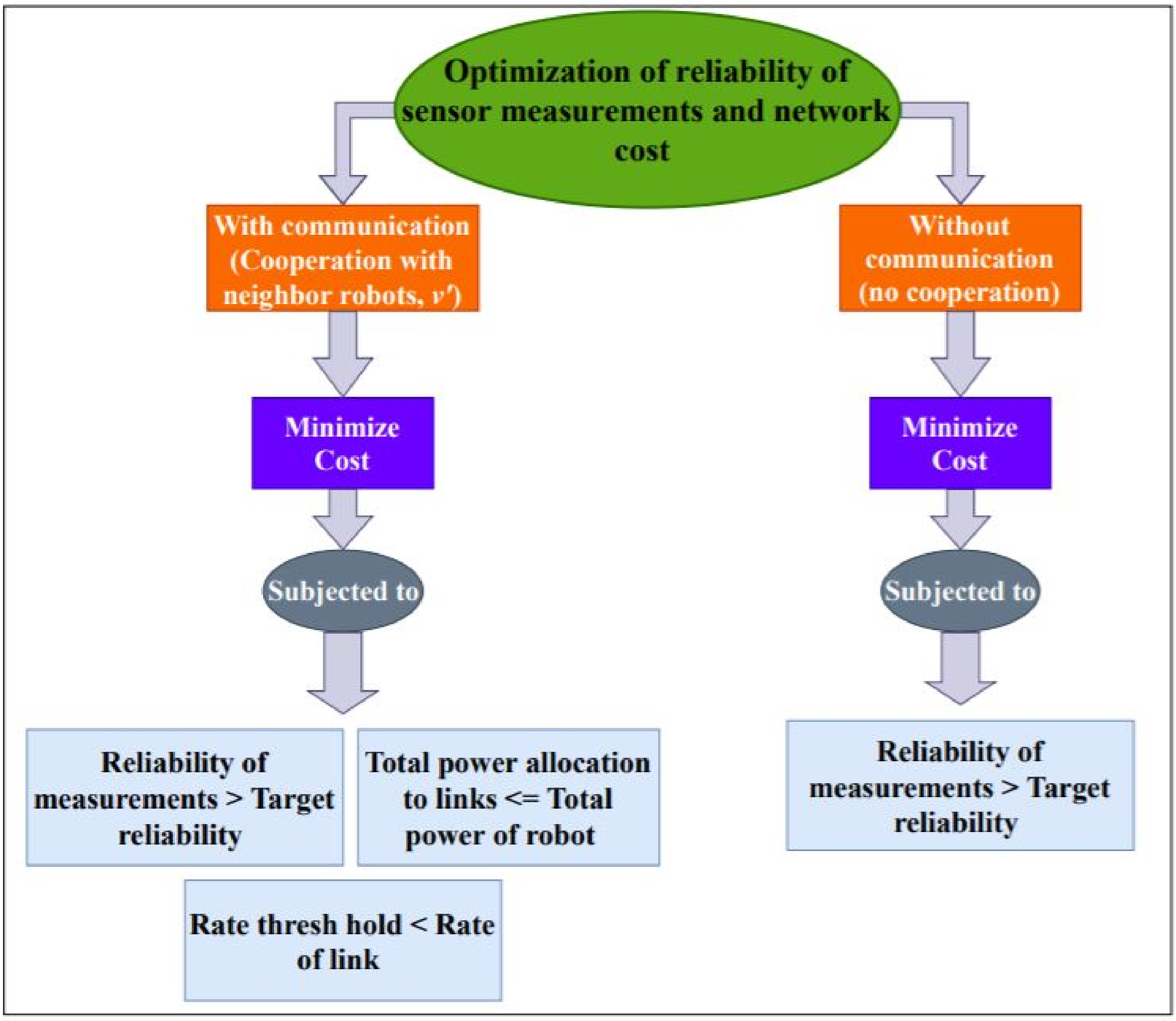

Figure 5. Implementation of optimization algorithm

$V(\alpha, \beta)$ 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.

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

$$\underset{\boldsymbol{x}_v(t), \boldsymbol{y}_v(t)}{\text{minimize}} \quad \phi_s \boldsymbol{x}_v(t) + \phi_c \boldsymbol{y}_{v'}(t) \tag{20a}$$

$$\text{subject to} \quad V(\alpha, \beta) - N_{\text{th}} \geq 0, \tag{20b}$$

$$P_{vv'} \leq \boldsymbol{y}_{v'}(t) P_{\text{m}}, \tag{20c}$$

$$\boldsymbol{y}_{v'}(t)(r_{v'} - r_{\text{th})} \geq 0 \tag{20d}$$

Here, objective function given in (20a) 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 active percentage threshold of N_{th} required to maintain the reliability threshhold, given in (20b), the transmit power constraint of allocation of power considering the water filling algorithm to each neighbor robot is given in (20c) and communication constraint of communicating only when rate of the channel exceeds a threshhold rate determined by the rate achievable at the radius S_0 under the effect of path loss, given in (20d).

3.3 Learning of sensor failure model

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

3.3.1 Sensor failure model parameter estimation using MLE algorithm

Maximum Likelihood Estimation (MLE) is used to find the best estimation of the sensor failure prediction model, $h(a, \lambda, k)$. Here, lifetime data of sensors are known and model parameters The model parameters, scale k and shape λ which best fits the data is found. Using maximum likelihood estimation, the product of samples which follow the PDF of prediction model is maximized. Thus, MLE is formulated as follows, where K is the total number of sensor lifetime data samples.

$$\begin{aligned} \underset{\lambda, k}{\text{maximize}} \quad & \prod_{K} \left\{ h(a, \lambda, k) \right\} && \text{(21a)} \\ \text{subject to} \quad & \lambda \in (0, \mathbb{Z}^{+}), && \text{(21b)} \\ & k \in (0, 1] && \text{(21c)} \end{aligned}$$

It can be reformulated as,

$$\begin{aligned} \underset{\lambda, k}{\text{maximize}} \quad & \sum_{K} \ln \left\{ h(a, \lambda, k) \right\} && \text{(22a)} \\ \text{subject to} \quad & \lambda \in (0, \mathbb{Z}^{+}), && \text{(22b)} \\ & k \in (0, 1] && \text{(22c)} \end{aligned}$$

SGD is used to maximize the log likelihood function of the sensor failure model, parameterized by a model parameters scale and shape. SGD is an iterative method. We start with some set 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. Here the shape, k, and scale parameters, λ, are updated simultaneously [35].

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

Gradient with respect to k is formulated as,

$$\nabla_k h = \frac{\partial h(a)}{\partial k} \tag{23}$$

$$\frac{\partial \ln h(a)}{\partial k} \quad = \quad \frac{1}{k} \quad + \quad \ln(t) \quad - \quad \ln(\lambda) \quad - \quad e^{k\frac{a}{\lambda}} \ln\frac{a}{\lambda} \quad - \quad \frac{e^{-\frac{T}{\lambda}^{k}} e^{k \ln \frac{T}{\lambda}} \ln \frac{T}{\lambda}}{1 - e^{-\frac{T}{\lambda}^{k}}} \tag{24}$$

Gradient with respect to λ is formulated as,

$$\nabla_\lambda h = \frac{\partial h(a)}{\partial \lambda} \tag{25}$$

$$\frac{\partial \ln h(a)}{\partial \lambda} \quad = \quad -\frac{k}{\lambda} \quad + \quad k\frac{a}{\lambda}^{(k-1)} \frac{a}{\lambda^2} \quad + \quad \frac{k e^{-(\frac{T}{\lambda})^k} \frac{T}{\lambda}^{(k-1)} \frac{T}{\lambda^2}}{1 - e^{-(\frac{T}{\lambda})^k}} \tag{26}$$

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 $\in$ shuffle(1,2,3,.......,n))do
  for j $\in$ 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

3.3.2 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, two methods of learning approaches are proposed for this system

1. Centralized learning

2. Federated learning

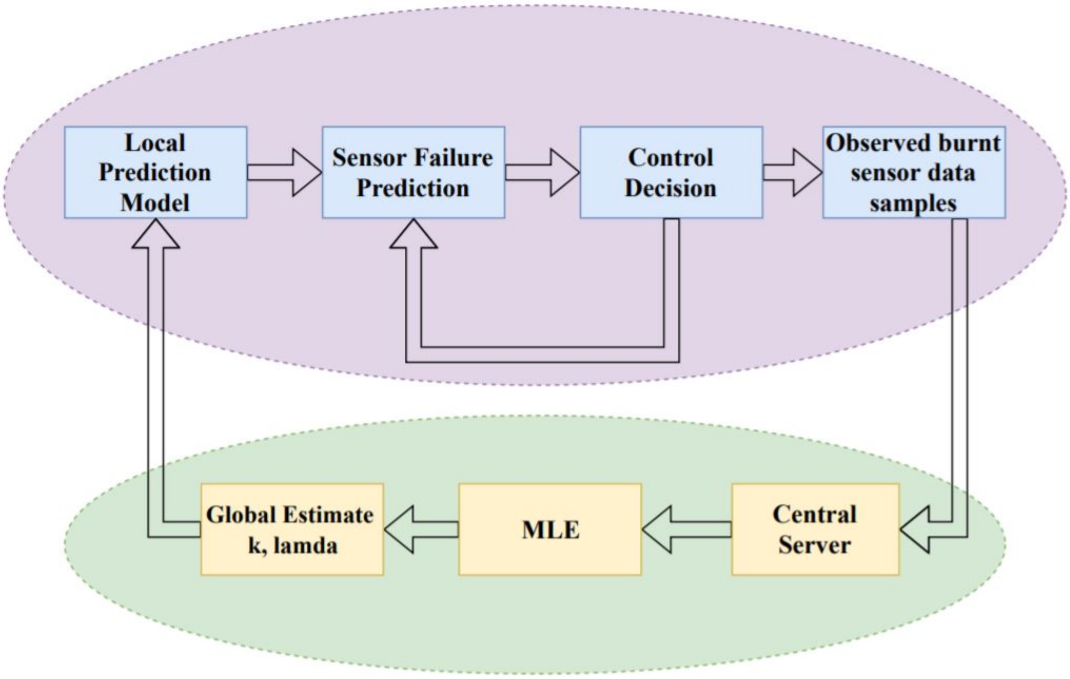

Figure 6. Centralized learning process

Centralized learning approach

Centralized approach is used when the processing power at the local robots in the network is insufficient to conduct complex data processing. When centralized 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, global estimate of the model parameters, are shared with the local robots at each time instant. The flow chart depicting the centralized approach is given in Figure. 6.

Federated learning approach

The main idea to use FL is that sharing training samples in a centralized 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 [27]. The flow chart depicting the federated approach is given in Figure. 7

Comparison between centralized and federated approaches

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

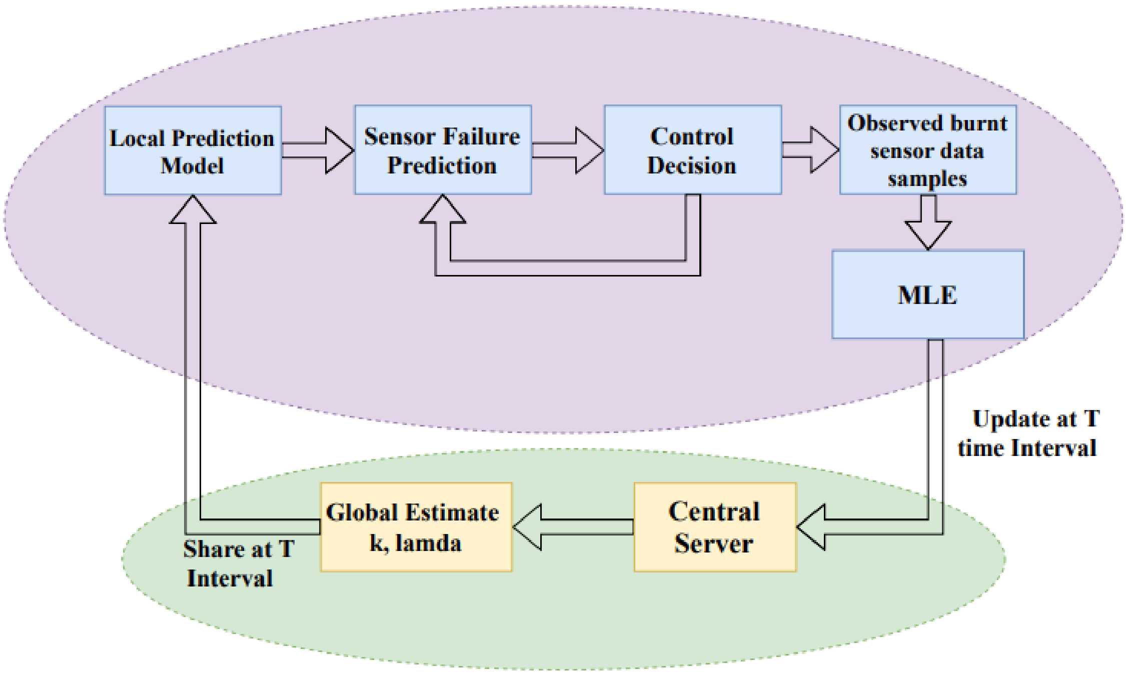

Figure 7. Federated learning process

1. Centralized approach shares chunks of data samples of sensor failure data at each time instant with the central server, while federated approach shares only local estimates of the model parameters at specific time intervals. Thus, the data traffic anticipated from centralized approach is higher than the federated learning approach since sensor failure data collected at the robot can be large in size while the locally estimated model parameters by each robot is smaller in size

2. Data processing at the central server is higher under centralized approach since large chunks of data need to be processed in order to find the estimate of the model parameters using MLE, while in 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

4 RESULTS

4.1 Introduction

In this chapter the simulation of the scenario discussed in system model, simulation configurations and comparison of results to compare the performance of the proposed solution over the state of the art methods is presented. The steps followed to implement the simulation results are given in the following sections.

4.2 Numerical results

First the numerical results obtained to initiate the system model is presented and explained. A suitable sensor lifetime data distribution which models the actual sensor lifetimes for the system is determined. Further, when lifetime data are available the model parameters are estimated using MLE algorithm. Thus, using MLE to estimate the model parameters in the simulation is explained in the proceeding sections.

4.3 Initiating the system model

4.3.1 Lifetimes and ages of sensors

Lifetimes of the sensors used in the system were generated choosing random lifetime samples which follow the cdf of actual sensor failure model, described in (12) in the system model. The ages of sensors were designed assuming that the starting age of a sensor in the system is a random and has not reached its lifetime. It is assumed that all $s \in S_v$ which are failed at the beginning are replaced with new sensors. Thus, when the system model is initiated, all $s \in S_v$ are active. The simulation parameters of the system model are defined as given in Table 3.

Table 3. 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	$100\,\mathrm{m}^2$

4.3.2 Choosing suitable sensor failure model parameters

First, numerical results were obtained for suitable sensor failure model parameters which can be used for sensor failure prediction.The validity of the model parameters for sensor failure prediction in the system we considered is evaluated as follows. The Figure. 8 represents how the failure rate of sensors sensors vary with the age of sensors. Since there is a specific gap between the failure rate curves of the sensor with the increment in of the age of a sensor, it is possible to clearly determine whether active or inactive status of the sensor with each age of sensor. Thus, the actual sensor failure model parameters chosen, given in Table. 3 are suitable to implement the system scenario and predict the sensor failures accurately with time.

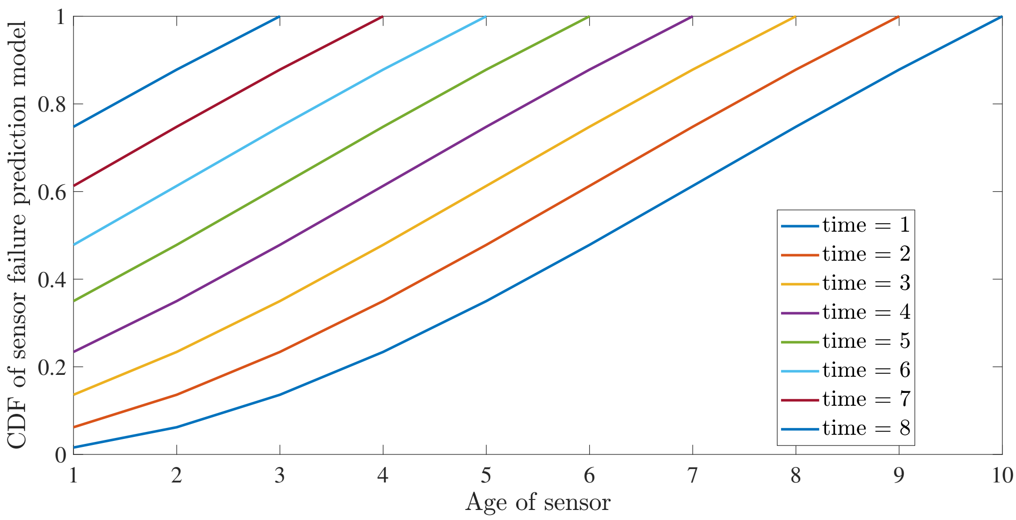

Figure 8. Variation of failure rate of sensor with the increment in the age of sensor

The curves of Figure. 8 has the a low slope at the beginning and and a high slope near the maximum lifetime of sensors, which means that the sensors have lesser failure probability when their age is low and higher failure rate when the age of sensor reach the maximum lifetime of sensors.

4.3.3 Actual and estimated model parameters

Next MLE algorithm was used to estimate the actual model parameters and obtain numerical results for estimated model parameters. The MLE algorithm uses the sensor failure data to estimate the actual model parameters. Since the total number of data samples effects in the final estimated model parameters, variation of model parameters with the total number of data samples is given in Table. 4.

and the comparison of actual model with the estimated sensor failure model which varies with the number of data samples is given in Figure. 9

Since there exists an estimation error between actual and estimated model parameters, the prediction based on the estimated model has been deviated from the actual model. Therefore, the optimal decisions taken using the actual and estimated models vary. It can be observed that the highest deviation between the estimated and actual model occurs

Table 4. Simulation parameters of the system model

Number of data samples	Estimated shape	Estimated scale
1	1.0433e+10	2.2053
10	1.9999	5.5630
1000	1.0804	8.1973
100000	1.3433	1.5433

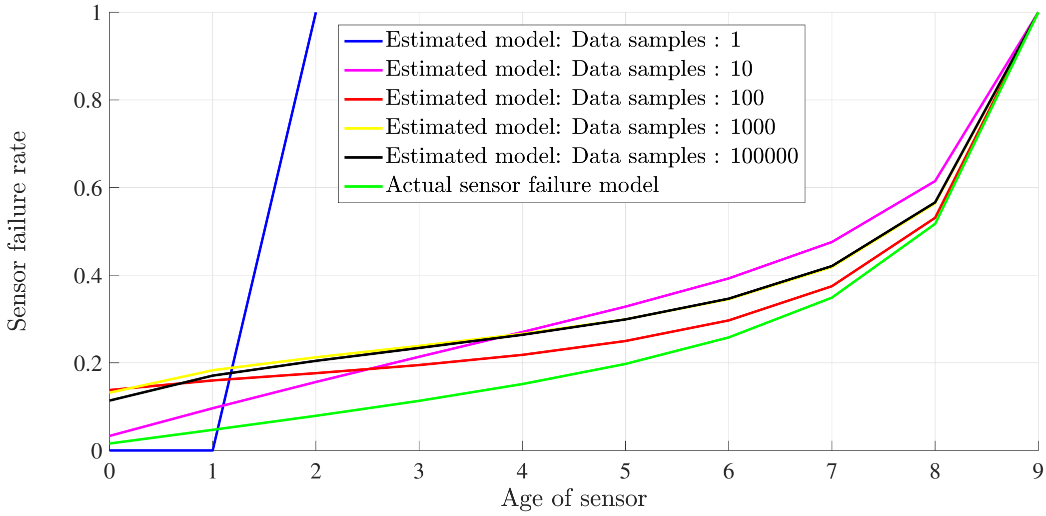

Figure 9. Variation of estimated sensor failure prediction model with number of data samples

when the number of data samples equals 1. However, when the data samples increase the shape of the estimated model start following the actual model.

When a prior knowledge on sensor life time distribution is unavailable, it has to be estimated using MLE, by collecting data of sensor failures in real time. This strategy is used when implementing centralized and federated approaches and learn the sensor failure model parameters.

4.3.4 Robot deployment

The network area of the system is assumed as $100\,\mathrm{m}^2$ and robots are assumed to be at random locations throughout a single simulation. Thus, the amount of neighbor robots of each local robot varies, since the amount of robots in the neighborhood region of a local robot is random.

4.3.5 Effect of communication

First, the system model was simulated without using communication aspects to inspect he functioning of the proposed solution. Next, effect of communication on the performance of the proposed solution is evaluated. Next, communication is utilized to implement the system under centralized and federated learning approaches, where the robots share data with the central server and the central server shares global estimate of the sensor failure prediction model parameters.

4.4 Simulation scenarios

To validate the performance of the proposed solution, different scenarios of proposed algorithms are designed to compare the proposed solution with benchmark algorithms.

- *Benchmark algorithms*: The sensor replacement decisions in the benchmark algorithms depends on the predefined rules and they do not use failure predictions techniques.The benchmark algorithms detailed as follows and simply illustrated in Figure. 10.

  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 $(N - N_{\text{th}})$ number of failed sensors are replaced by new sensors.

  2. **Myopic-R**:

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

- *Proposed algorithms*: The proposed algorithms utilize both the sensor failure prediction and optimization algorithm.The proposed algorithms detailed as follows and simply illustrated in Figure. 11.

  1. **Full knowledge**:

     Full knowledge means the system posses the knowledge of the lifetime of sensors, Thus, the system is able to predict sensor failures accurately. Thus, here 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

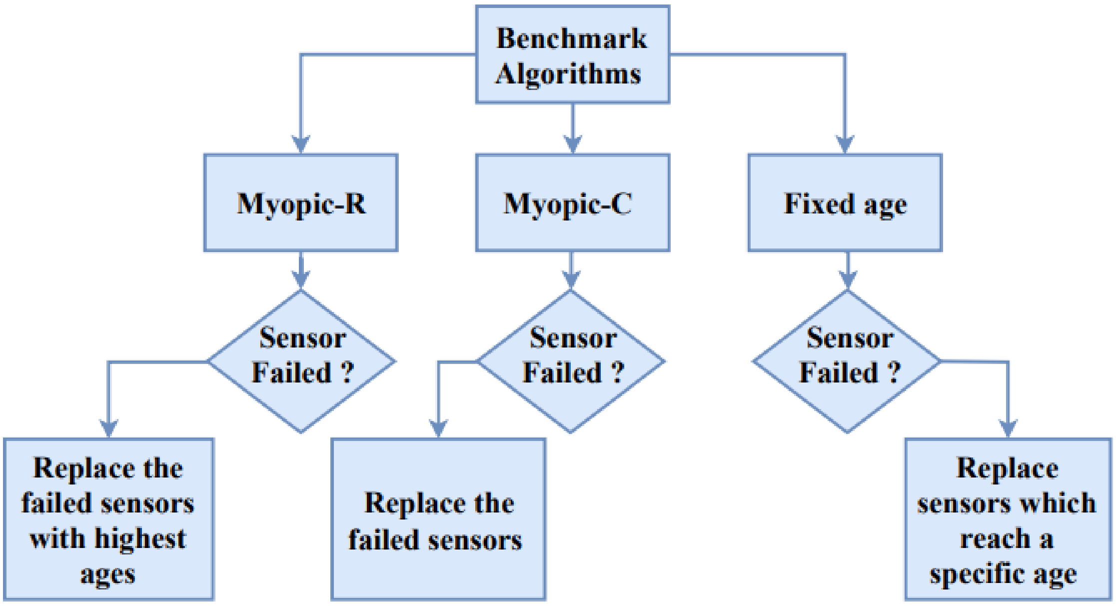

Figure 10. Implementation of benchmark algorithms

knowledge and this algorithm is that this scenario predicts sensor failures using a known model, which is modelled using limited number of known lifetime data of sensors. Thus, it does not posses 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 full knowledge scenario and this scenario , is evaluated using simulations. Hence, the effect of prediction using a known sensor failure model and 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)**: 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 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 centralized and federated learning approaches, where sensor failure model parameters are learnt by collecting data of sensor lifetimes by observing real time sensor failures of the sensor array, S_v, of the robot.

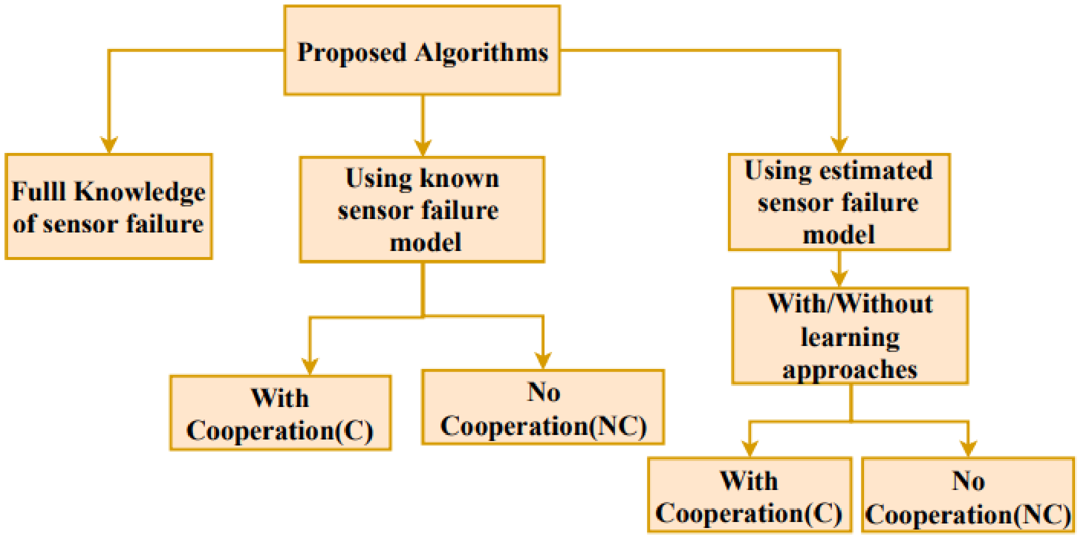

Figure 11. Implementation of proposed algorithms

4.5 Simulation Results

4.5.1 Outage probability

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, variance of sensor measurements is inversely proportional to reliability of sensor measurements. For simulations, the incident of sensor measurement variance exceeding threshhold variance is named as 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 information rate is less than the required threshold information rate.

4.5.2 Variation of reliability outage probability against cost ratio, $\frac{\phi_c}{\phi_s}$.

First, the impact of costs of sensor replacements and communication with neighbor robots on the reliability outages of the system is analyzed in Figure 12. Therein, it can be seen that the reliability fluctuations/outages increases 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 replacements decision taken by the optimization algorithm. The prediction of sensor failures are done using the sensor failure prediction model. Thus, the accuracy of prediction effect the final sensor replacement decision taken and cost incurred for sensor replacements.

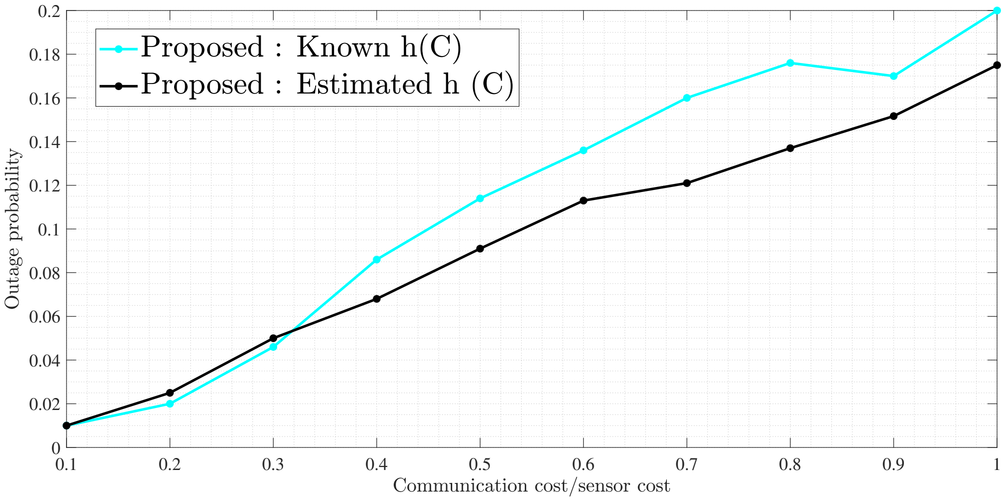

Figure 12. Outages/Reliability fluctuations against sensor replacement and communication cost ratio

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 local robot achieve from the neighbor robots increase, which increases reliability of the sensor measurement and reduce reliability outages. Thus, from the trends in Figure.12, it can be concluded that more communication among neighbor robots and lesser sensor replacements, reduces reliability outages.

4.5.3 Variation of reliability outage probability against density of robots

The Figure. 13 illustrates the reliability outages/fluctuations against density of robots in the robot 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 are same.

From Figure.13, 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 probabilitywith the density of robots in the network. The reason is that since those algorithms are not communicating, the density of robots in the network do 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 density of robots, the proposed

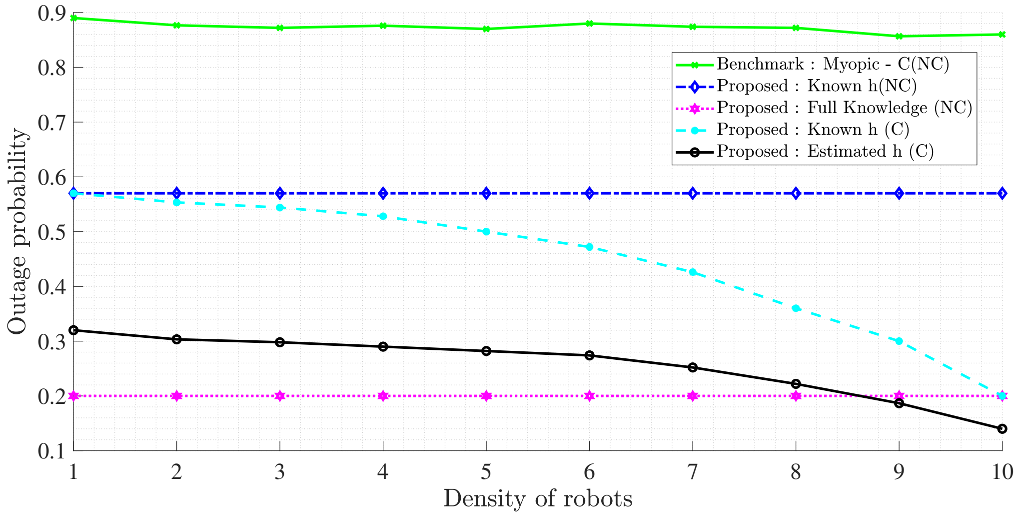

Figure 13. Outages/Reliability fluctuations against density of robots in robot network area for proposed algorithms without sensor failure learning approaches

algorithms which uses 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.

4.5.4 Variation of cumulative average network cost against density of robots

In addition to reliability outage probability, the variation of cumulative average network operating cost against density of robots of the network is evaluated in Figure. 14. From the figure, it is clear that the average cost of all the algorithms increase with the increment in the density of robots in the network. Here, it is assumed that the costs for faulty sensor replacements and communication is 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 is 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 fault occur in the sensors and not predicting sensor failures. The rest of 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 communicating more with the neighbor robots seeking higher sensor measurement reliability.

When compared with the Figure. 13 the proposed algorithm with estimated $h(a, \lambda, k)$ shows reduction in reliability outage probability with the density of robots. and here the average network operating cost incurred is nearly equal as the other algorithms. Hence, the proposed algorithm with estimated $h(a, \lambda, k)$, is the optimal strategy that the

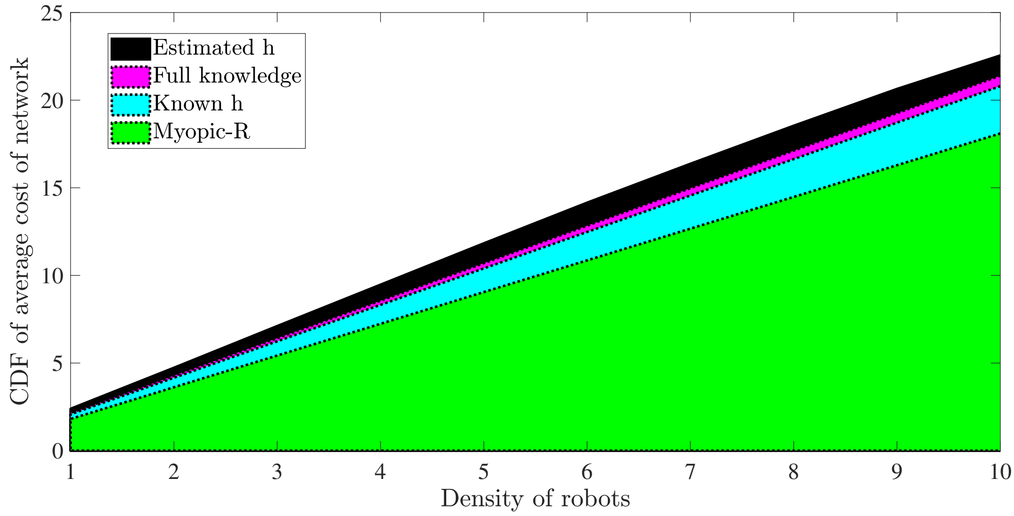

Figure 14. Outages/Reliability fluctuations against density of robots in robot network area for proposed algorithms without sensor failure learning approaches

optimizes the network operating average cost and reduces reliability outages of the sensor measurements which is the objective of this research.

4.5.5 Variation of reliability outage probability against density of robots using learning approaches

The effect of using sensor failure model parameters learning approaches on the reliability fluctuations in the network, when the density of robots increase, is evaluated in Figure. 15. These learning are useful when the previous knowledge of sensor failure data of the system is not available and the sensor failure model needs to be estimated.

It is observed that the count of reliability fluctuations increase with the increment in the density of robots, when learning approaches are used. Thus, the proposed algorithm works efficiently, when the density of robots in the network are high and when learning approaches are used. Both federated learning and centralized approaches show a similar trend. The amount of outages are high, when the number of robots are low, because the amount of data of either lifetime of sensors or of model parameters, collected at the central server are very low. Thus, the global estimate of the model parameters generated at the central server which is shared with the local robots, is not sufficient to give a good estimate of the sensor failure prediction model. Thus, at the initial instance , the estimated model from small amount of data, result in increasing reliability fluctuations. However, when the density of robots is high, more data are collected at each of the robot and shared with the central server. Here, the central server is able provide a better estimate of the model parameters, due to the availability of larger amount of data in the robots.

From, Figure .15, it was shown that the values of the estimated model parameters effect the estimated sensor failure prediction model, which impacts the reliability fluctuations in the the system. Figure.16 illustrates how the estimated model parameters effect the reliability fluctuations of the system.

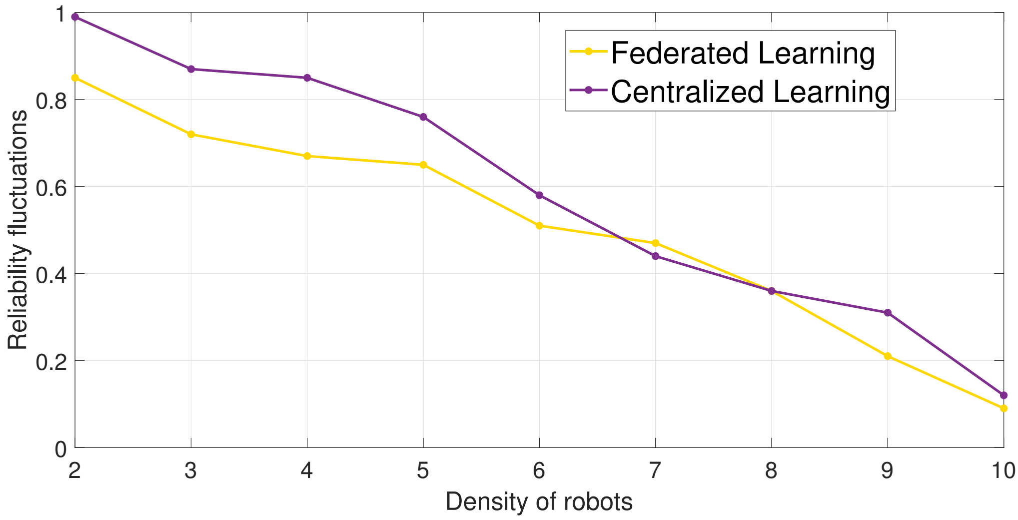

Figure 15. Outages/Reliability fluctuations against density of robots with sensor failure learning approaches

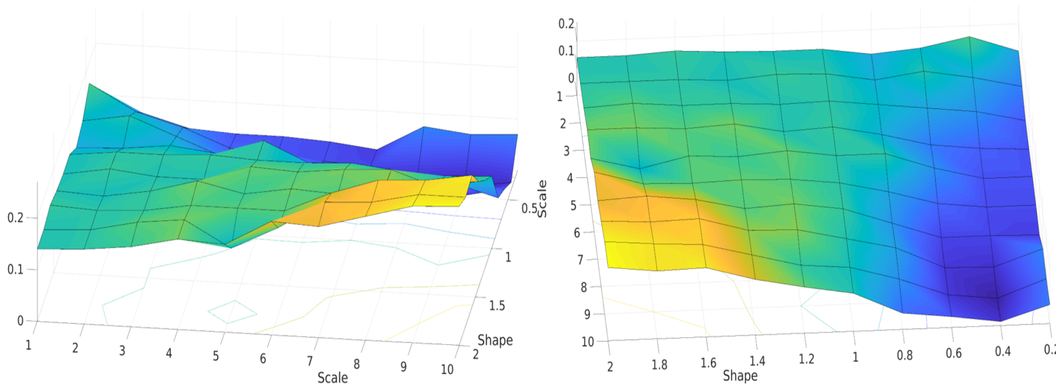

Figure 16. Variation of reliability fluctuations with estimated model parameters

4.5.6 Variation of reliability outage probability against communication range

The system model is designed for the local robot to communicate with neighbor robots within a communication radius defined. The effect of communication radius on the number of reliability fluctuations under the scenarios of proposed algorithms using actual and estimated sensor failure prediction models is shown in Figure. 17.

From the Figure.17, the reliability fluctuations of the proposed system declines with the increment of the communication radius/range of the local robot, implying that the reliability outage decrease with the increase in the number of neighbor robots providing information. The estimated model parameters effect the sensor failure prediction which effects the final optimal decisions for sensor replacement and communication with neighbor robots.

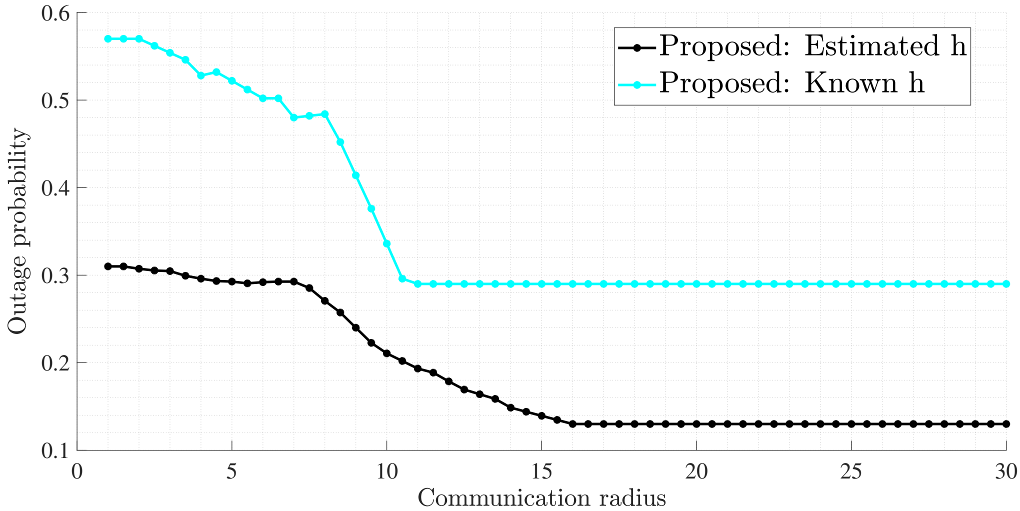

Figure 17. Outages/Reliability fluctuations against the communication range of the local robot

4.5.7 Variation of network operating costs with estimated model parameters, scale, λ and shape, k

The Figure.18 illustrates how the estimated model parameters effect the average sensor replacement cost of the system. The Figure.19 illustrates how the estimated model

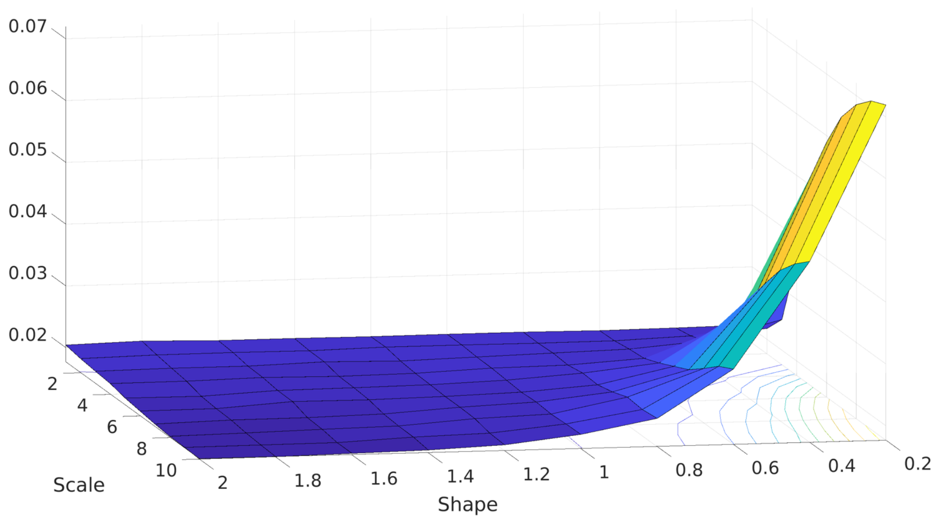

Figure 18. Variation of average sensor replacement cost of the model with estimated parameters

parameters effect the average neighbor communication cost of the system. If the model parameters are within the region which results in lower sensor replacement and communication costs, then the network operating costs can be maintained low as much as possible.

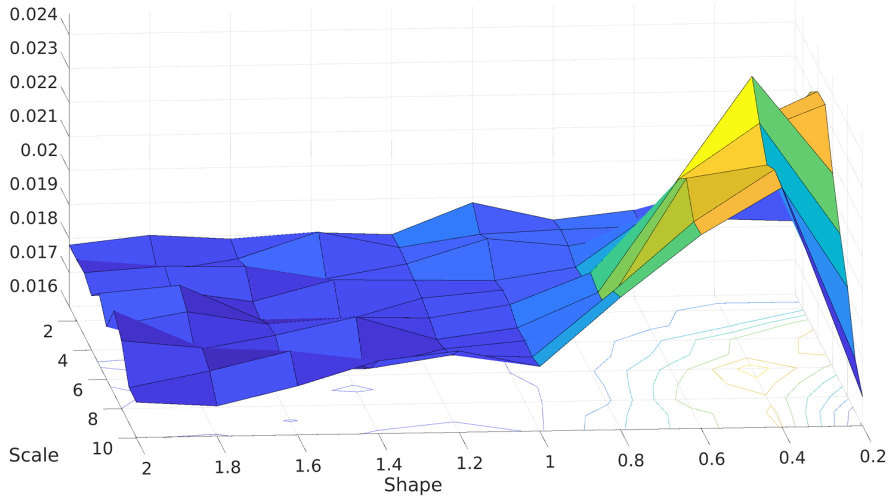

Figure 19. Variation of average communication cost of the model with estimated parameters

4.5.8 Variation of log likelihood estimation of (a, λ, k) *with estimated model parameters, scale,* λ *and shape,* k

The Figure.20 illustrates how the estimated model parameters effect the log likelihood estimation of the sensor failure prediction model. From these simulations, the range of model parameters that will increase the inference accuracy of the system model is determined.

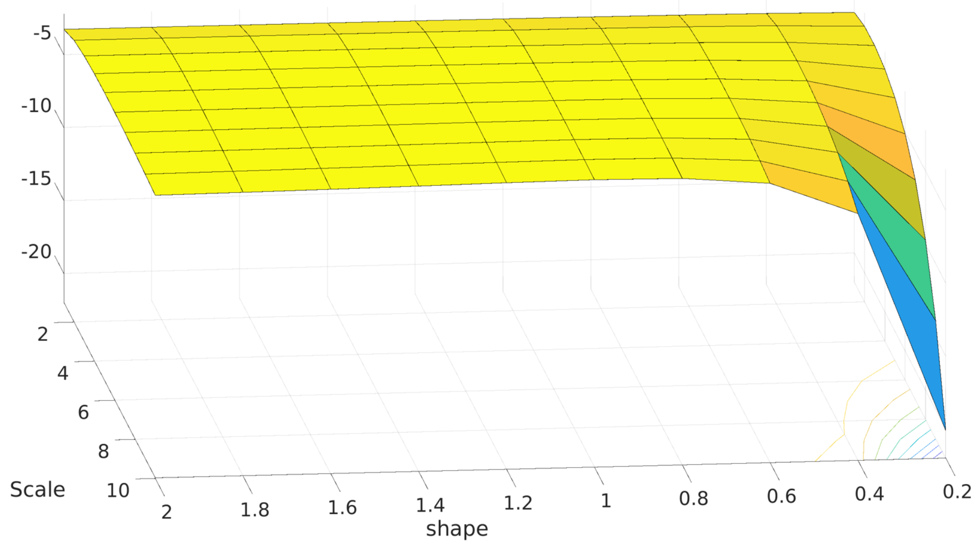

Figure 20. Variation of log likelihood estimation of $h(a, \lambda, k)$ with estimated parameters

4.5.9 Variation of reliability outage probability against sensor lifetime data samples in federated learning

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 ten robots. From Figure. 21 it is observed that at the beginning when the number of sensor lifetime data are low, the reliability outage probability shows higher fluctuation. Furthermore, it is observed that the 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.

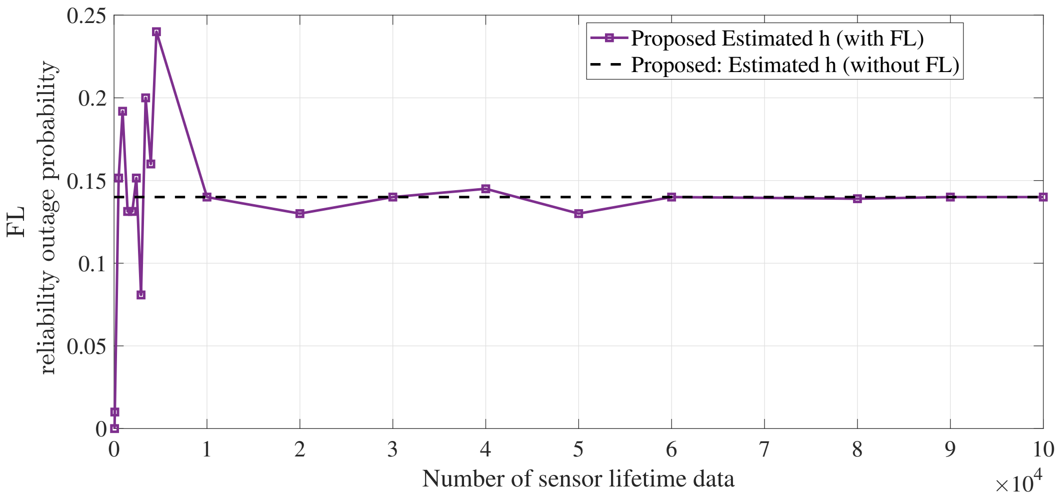

Figure 21. Variation of reliability outage probability with number of sensor lifetime data

5 CONCLUSION

With the increase in usage of mobile robots for automation in tasks such as manufacturing, navigation, environment monitoring, the interaction with humans and objects nearby is becoming frequent. Hence, the need to increase safety of the environment becomes important. This thesis develops a mechanism to improve the reliability of sensor measurements in a mobile robot network taking into the 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, 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 on sensor characteristics, we utilize observations of sensor failures to estimate their characteristics in a distributed manner using federated learning. 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 federated learning approach, using data available at the robots which is useful when previous knowledge about the system sensor failures are not available.

6 FUTURE WORK

The main focus of this thesis 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 thesis, 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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