Federated learning for enhanced sensor reliability in automated wireless networks

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 paper 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 FL. Finally, extensive simulations are carried out to highlight the performance of the proposed mechanism compared to several state-of-the-art methods.**

Index Terms—**sensor reliability, autonomous mobile robots, wireless information, network operating costs, federated learning**

I. 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, remote health monitoring [1]–[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 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 key motivation of this paper is to address the challenge in enhancing sensor reliability, while maintaining network operating costs at a minimum using data driven learning strategies.

Our Contribution on this paper 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 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 FL approach, using data available at the robots which is useful when previous knowledge about the system sensor failures are not available

II. 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, FL plays a major role in designing a self organizing mobile devices, that rely on local information, with small variance from the CL information [9]. In this section, work done so far on enhancing sensor reliability, while optimizing network operating costs and usage of FL approach to predict sensor failures are discussed.

A. 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.

B. 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].

C. 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 water filling algorithm

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

D. 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.

E. 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.

F. 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,

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

G. Estimation of model parameters using MLE

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, 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

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

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,

$$\hat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta} \in \times}{\operatorname{argmax}}\, LL(y, \boldsymbol{\theta}) \tag{7}$$

H. Basics of 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].

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

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

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

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

with

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

I. 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].

J. Centralized learning (CL) and federated learning (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 is in the central server are utilized to find data driven models. FL 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 FL makes it possible for clients to share a united model without data exchange. [26] Algorithms for CL and FL are generalized as follows [27].

Algorithm 2: MLE using CL learning

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 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

K. Trade-off between reliability and operating cost

A reliability metric for heterogeneous wireless sensor network (WSN) is addressed in [28] where the failure probabilities of the components of WSN is taken into consideration. Here, reliability is defined as the probability that the wireless sensor network remains functional, in terms of coverage and connectivity, 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 is, therefore, a major key to maximizing the life-time of wireless sensor networks [29]. Here, authors propose an algorithm that selects a multi-path wireless signal transmission scheme with a minimal end-to-end energy consumption for a given lower bound on reliability.

III. 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 needs to be high reliable for the successful completion of the tasks without considerable human supervision. Hence, in this research a major design goal is to achieve the balance between maximum reliability and minimum cost of which will lead to a cost effective sustainable reliable network. Further, maximizing the lifetime automated wireless networks is a major concern and thus designing a energy efficient 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.

IV. METHOD

A novel approach of modelling sensor measurement reliability considering sensor failure rate into account by incorporating emerging branches on artificial intelligence is unfolded in this paper. 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 weibul distribution which is usually utilized to model sensor failures. Each robots create 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 modelled optimization algorithm reduces 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.

V. System model

In order to formulate the optimization for an automated robot network, a suitable system model scenario is picked and defined. Starting from the derivation of the sensor measurement reliability parameter using statistical principles, the FL algorithm, maximum likelihood estimation based on stochastic gradient descent, sensor failure prediction, optimization models are designed to suit the system model defined. Under the assumption that the sensor failure rate follows a left truncated weibull distribution, when sensor failure data samples are present, the parameters for the model are estimated. Finally, the FL algorithm is trained using several data sets and then it is tested using other data sets. In this research, FL aims to learn a sensor failure prediction initially and aid in the optimal decision making.

Consider a local communication network consisting a set V of robots, that can communicate with one another and a central server, u, over wireless links. One robot, v, communicate with the neighbor robots, v', that are located within the neighborhood region of 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 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 (9), considering the interference from other neighbor robot links and Gaussian noise, N_0. [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 $v \in V$ 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

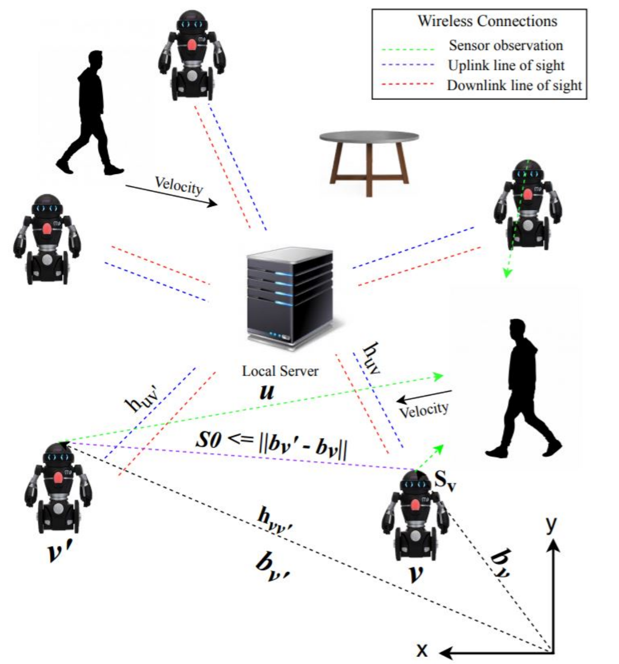

Fig. 1. Simplified illustration of the system model containing a group of automated robots connected to a a local wireless network operated by a central server, along with obstacles such as humans and solid objects nearby.

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, $h(a, \lambda, k)$ are defined as follows respectively:

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

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

Hence,

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

Then, using (10), the probability that the sensor will be failed by $(a + t_0)$ can be calculated as follows, where a, $F(\cdot)$

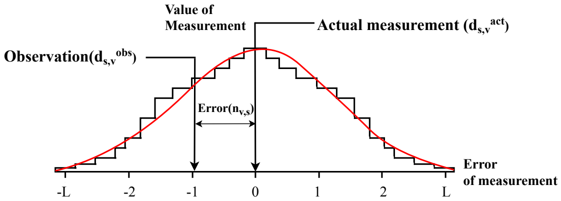

Fig. 2. Actual sensor measurement $d_{s,v}^{\text{act}}$ gets degraded by a random measurement error of $n_{v,s}$ which can take a value between [-L,L] and result in $d_{s,v}^{\text{obs}}$ [32]

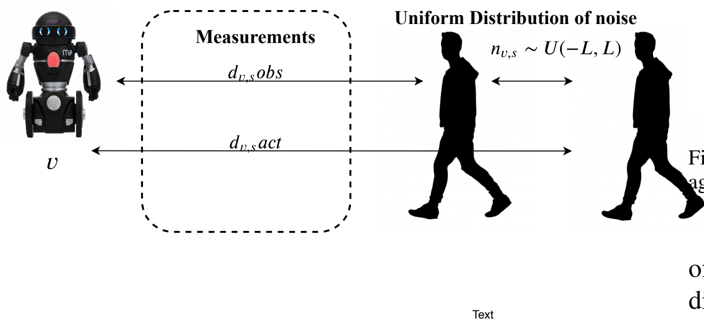

Fig. 3. Mean Square Error (MSE) of measurement noise, $n_{v,s}$, against active number of sensors [33]

represent the lifetime of sensor and CDF of the $h(a, \lambda, k)$ respectively.

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

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,

$$\overline{d_{v,s}^{\text{obs}}} = d_{v,s}^{\text{act}} + n_{v,s}, \qquad (15)$$

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

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 $\mathcal{K}_v$ 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.

Figure. 4, depicts how Mean Square Error(MSE) of $d_{v,s}^{\text{obs}}$ 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

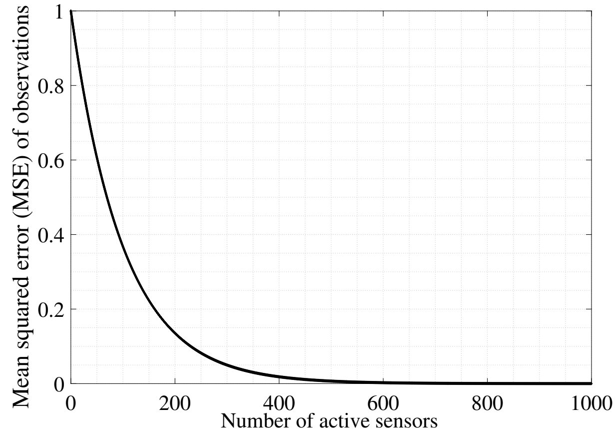

Fig. 4. Variation of mean squared error (MSE) of measurement noise, $n_{v,s}$, against active number of sensors available in the system [33]

of sensor measurement noise/error, which follows a uniform distribution is calculated as follows [34].

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

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

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

VI. 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 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.

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

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

$V(\alpha, \beta)$ 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.

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

$$\begin{aligned} \underset{\boldsymbol{x}_v(t), \boldsymbol{y}_v(t)}{\text{minimize}} \quad & \phi_s \mathbf{1}_N^T \boldsymbol{x}_v(t)^T + \phi_c \mathbf{1}_N^T \boldsymbol{y}_{v'}(t)^T && \text{(20a)} \\ \text{subject to} \quad & V(\alpha, \beta) - N_{\text{th}} \geq 0, && \text{(20b)} \\ & P_{vv'} \leq \boldsymbol{y}_{v'}(t) P_{\text{m}}, && \text{(20c)} \\ & \boldsymbol{y}_{v'}(t)(r_{v'} - r_{\text{th})} \geq 0 && \text{(20d)} \end{aligned}$$

Here, objective function given in (**??**) 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 (**??**), the transmit power constraint of allocation of power considering the water filling algorithm to each neighbor robot is given in (8b) 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 (**??**).

Water filling algorithm is considered the capacity achieving optimal power allocation strategy for wireless networks [35]. 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 4: Iterative water filling algorithm

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

Further, in the results section the behavior of the aforementioned proposed solution with and without communication is observed.

VII. 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 likelihood 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.

A. 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, 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 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, adaptive method used for MLE [19]. In general MLE algorithm formulation for this problem is as follows [20]. Suppose there exist N independent lifetime of sensors which follow a sensor failure rate 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

$$f(y_1, y_2, ..., y_N | \boldsymbol{\theta}) = \prod_{n=1}^{N} \left\{ f(y|\boldsymbol{\theta}) \right\} \tag{21}$$

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,

$$L(\boldsymbol{\theta}|y_1, y_2, ..., y_N) = f(y_1, y_2, ..., y_N | \boldsymbol{\theta}) \tag{22}$$

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

$$\ln L(y, \boldsymbol{\theta}) = \sum_{m \in \mathcal{M}} f(y, \boldsymbol{\theta}) \tag{23}$$

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

$$\hat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta} \in \times}{\operatorname{argmax}} \, LL(y, \boldsymbol{\theta}) \tag{24}$$

(MLE) Here, lifetime data of sensors are known and 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.

$$\underset{\lambda, k}{\text{maximize}} \quad \prod_{K} \Big\{ h(a, \lambda, k) \Big\} \tag{25a}$$

$$\text{subject to} \quad \lambda \in (0, \mathbb{Z}^{+}), \tag{25b}$$

$$k \in (0, 1] \tag{25c}$$

It can be reformulated as,

$$\underset{\lambda, k}{\text{maximize}} \quad \sum_{K} \ln \Big\{ h(a, \lambda, k) \Big\} \tag{26a}$$

$$\text{subject to} \quad \lambda \in (0, \mathbb{Z}^{+}), \tag{26b}$$

$$k \in (0, 1] \tag{26c}$$

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 [36].

1) Gradient of $h(t, \lambda, k)$ with respect to model parameters: Gradient with respect to k is formulated as,

$$\nabla_k h = \frac{\partial h(a)}{\partial k} \tag{27}$$

$$\frac{\partial \ln h(a)}{\partial k} = \frac{1}{k} + \ln(t) - \ln(\lambda) - e^{k \frac{a}{\lambda}} \ln \frac{a}{\lambda} - \frac{e^{-\frac{T}{\lambda}^{k}} e^{k \ln \frac{T}{\lambda}} \ln \frac{T}{\lambda}}{1 - e^{-\frac{T}{\lambda}^{k}}} \tag{28}$$

Gradient with respect to λ is formulated as,

$$\nabla_\lambda h = \frac{\partial h(a)}{\partial \lambda} \tag{29}$$

$$\frac{\partial \ln h(a)}{\partial \lambda} = -\frac{k}{\lambda} + k \frac{a}{\lambda}^{(k-1)} \frac{a}{\lambda^2} + \frac{k e^{-(\frac{T}{\lambda})^{k}} \frac{T}{\lambda}^{(k-1)} \frac{T}{\lambda^2}}{1 - e^{-(\frac{T}{\lambda})^{k}}} \tag{30}$$

Algorithm 5: 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) - $\mu \, \nabla_k \, h_k$
    λ(j+1) = λ(j) - $\mu \, \nabla_\lambda \, h_\lambda$
    end
    end
end

B. 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 (CL)
2) Federated learning (FL)

1) 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 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, 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.. 5.

2) Federated learning approach: 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 [27]. The flow chart depicting the federated approach is given in Fig.. 6

3) 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.

Algorithm 6: 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
```

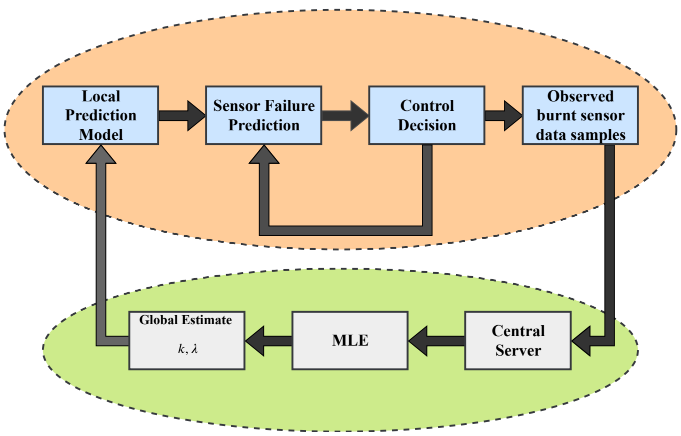

Fig. 5. Operation of the centralized learning process for an autonomous local wireless network

Algorithm 7: MLE using federated learning

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

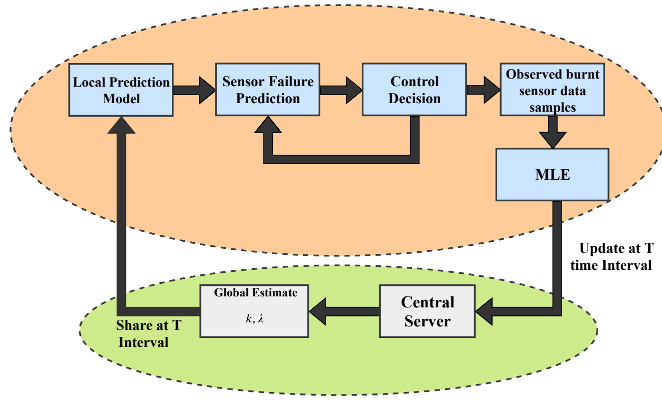

Fig. 6. Operation of the federated learning process for an autonomous local wireless network

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 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 is smaller in size
2) Data processing at the central server is higher under 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 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

C. 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,

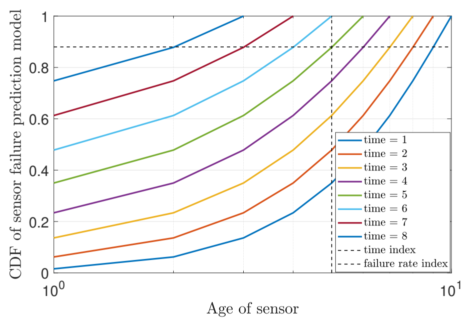

Fig. 7. Variation of failure rate of sensors at each time instant against the age of sensor

VIII. Experiments

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.

A. Numerical results

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. 7.

B. Data sheets

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.

C. Experimental setup

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 $100\mathrm{m}^2$ 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.

D. Evaluation

1) Proposed algorithms: 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 $(N - N_{\text{th}})$ 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 Fig.. **??**.
  1) **Full knowledge (PFK)**:
     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 (KH)**:

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 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(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 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 learnt by collecting data of sensor lifetimes by observing real time sensor failures of the sensor array, S_v, of the robot.

E. Simulation

For several different scenarios, performance indicators such as sensor measurement reliability outages (SMRO), sensor measurement variance error (SMVE), average cost (AC),sensor replacement cost (SRC), communication cost (CC), were evaluated. The robot density, communication range, transmit power were varied creating different scenarios and the performance indicators were evaluated.

Simulation parameters utilized are given in table.II.

TABLE I
SIMULATION 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

Simulation scenarios considering robot density, communication range and transmit power are labeled as A,B,C respectively and the simulation specific parameters are given in the following table.

TABLE II
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]

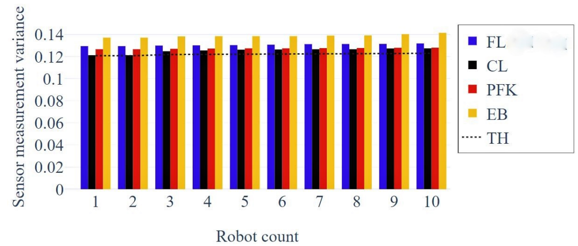

Fig. 8. Variation of sensor measurement variance against robot count under FL, CL, EH, PFK, EB against robot count under FL when robot count is varied from 1 - 10m and per robot communication range is 10m in the network

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. 8, 9, 10, 11, 12, 13, 14, 15, 16, 17. 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. In addition, the performance of CL and EH approaches perform better than the existing baseline (EB) methods. When the FL 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. 9, 10.

Average optimal cost The average costs for sensor replacements and communication were evaluated and the Fig. 11 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

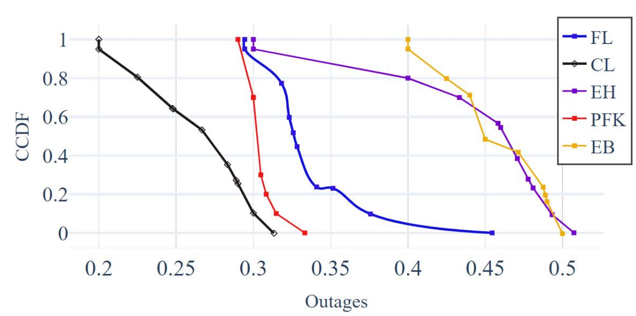

Fig. 9. Variation of CCDF of sensor measurement reliability outages under FL, CL, EH, PFK, EB against robot count under FL when robot count is varied from 1 - 10m and per robot communication range is 10m in the network

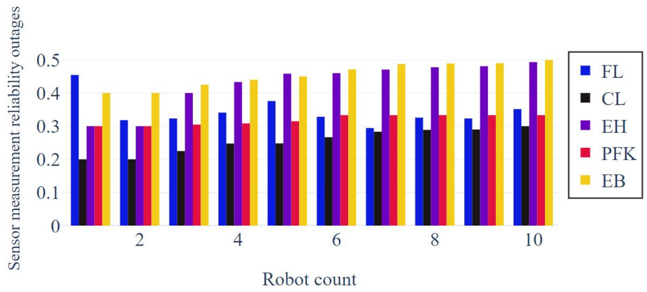

Fig. 10. Variation of sensor measurement reliability outages against robot count under FL, CL, EH, PFK, EB against robot count under FL when robot count is varied from 1 - 10m and per robot communication range is 10m in the network

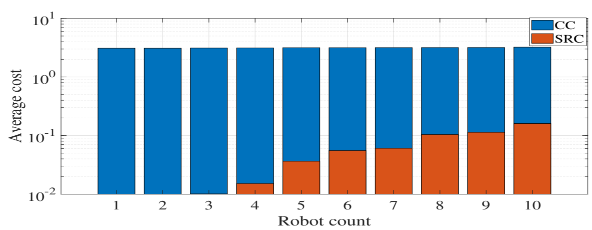

Fig. 11. Variation of communication cost (CC) and sensor replacement cost (SRC) against robot count under FL when robot count is varied from 1 - 10m and per robot communication range is 10m in the network

nearly the same with 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. 12. Therefore, FL approach shows flexibility in achieving both reliability and minimizing operating costs. Further, variation of only communication cost against robot count is illustrated in Fig. 13, where the average communication cost for FL approach is almost as same as EH and PFK algorithms and lower than CL.

Further, it can be observed from Fig. 14, 15, 16, 17, that performance of the FL approach improves with the amount of data samples collected for implementing the FL algorithm.

The sensor measurement variance error (SMVE), sensor measurement reliability outages (SMRO), average cost (AC), sensor replacement cost (SRC), communication cost (CC) given in Fig. 14, 15, 16 17 continues decrease slowly when the amount of data collected increases under the FL approach.

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 CL approach performs better than the FL approach.

B: Communication range Next, the performance of the FL approach when the communication range of the robots varied was evaluated and is shown in the Fig. 18, 19, 20, 21, 22, 23,

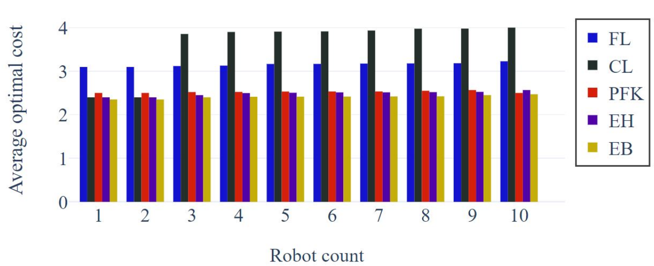

Fig. 12. Variation of average optimal cost (CC) against robot count under FL, CL, PFK, EH, EB when robot count is varied from 1 - 10m and per robot communication range is 10m in the network

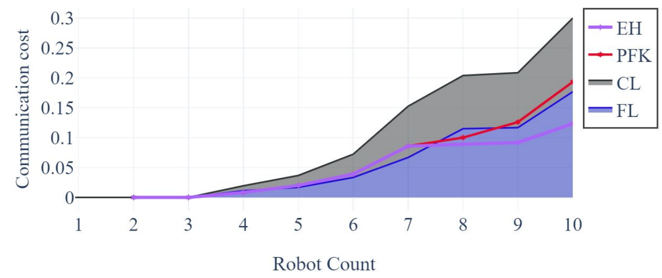

Fig. 13. Variation of communication cost (CC) against robot count under FL, CL, PFK, EH when robot count is varied from 1 - 10m and per robot communication range is 10m in the network

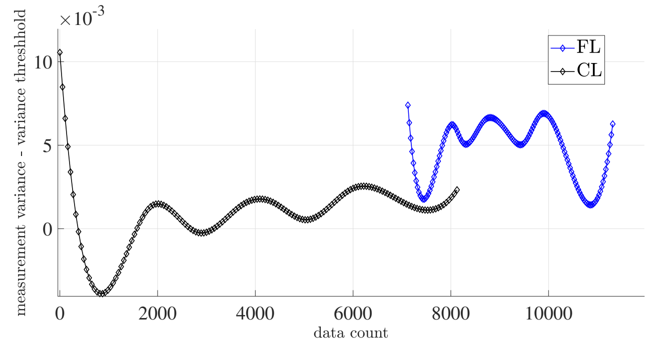

Fig. 14. Variation of error between sensor measurement variance and threshhold variance against data count under FL and CL when robot count is varied from 1 - 10m and per robot communication range is 10m in the network

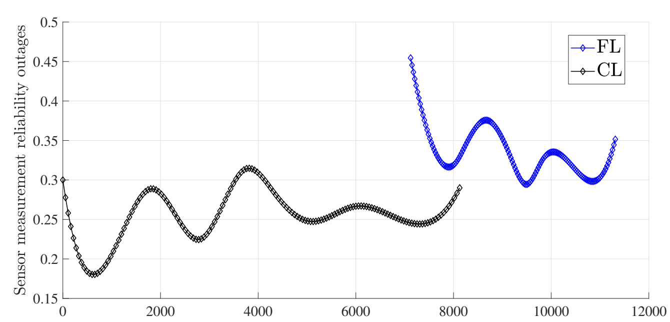

Fig. 15. Variation of sensor measurement reliability outages against data count under FL and CL when robot count is varied from 1 - 10m and per robot communication range is 10m in the network

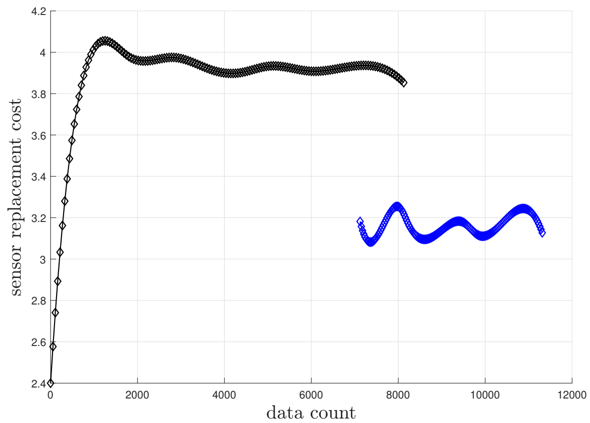

Fig. 16. Variation of sensor replacement cost (SRC) against data count under FL and CL when robot count is varied from 1 - 10m and per robot communication range is 10m in the network

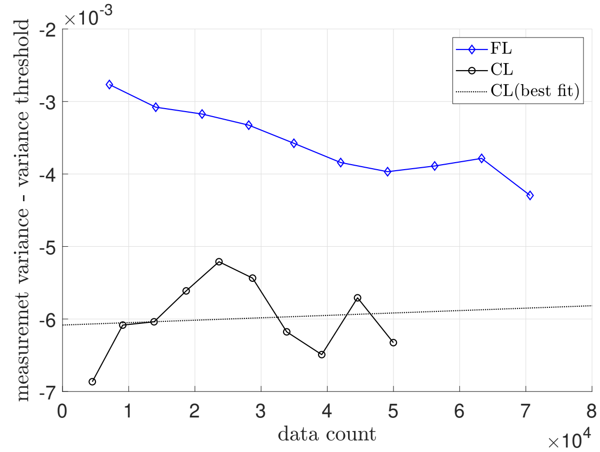

Fig. 18. Variation of error between sensor measurement variance and threshold variance against data count under FL and CL when communication radius is varied from 1 - 20m and total of 10 robots in the network

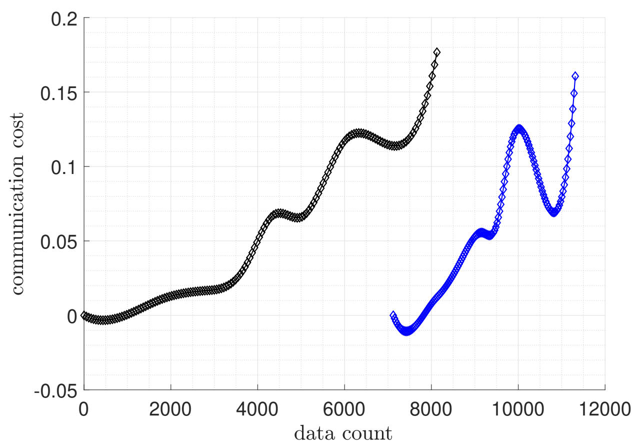

Fig. 17. Variation of communication cost (CC) against data count under FL and CL when robot count is varied from 1 - 10m and per robot communication range is 10m in the network

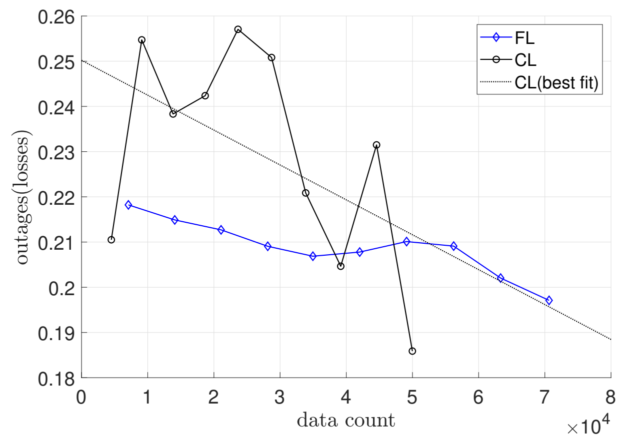

Fig. 19. Variation of sensor measurement reliability outages against data count under FL and CL when communication radius is varied from 1 - 20m and total of 10 robots in the network

24, 25.

Increment in the communication range of each robot has decreased the SMRO, SMVE, AC, SRC, CC. Further, the number of data samples available improves the expected performance of FL of decreasing SMRO, SMVE, AC, SRC. However, parameters SMVE and SMVO under CL approach performs better than the FL approach.

Further, FL approach shows the 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 figure.26 show the performance with the variation of transmit power. It is observed that during low transmit power, high reliability

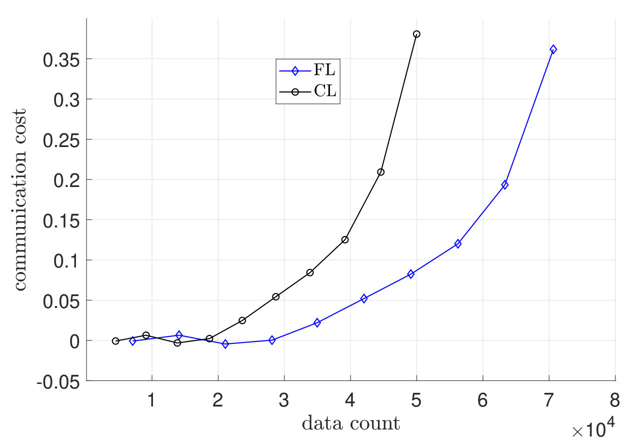

Fig. 20. Variation of communication cost against data count when communication radius is varied from 1 - 20m and total of 10 robots in the network

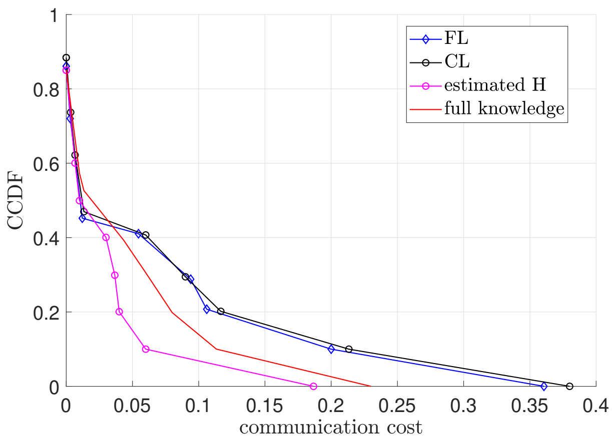

Fig. 21. CCDF of communication cost under FL, CL, EH and PFK when communication radius is varied from 1 - 20m and total of 10 robots in the network

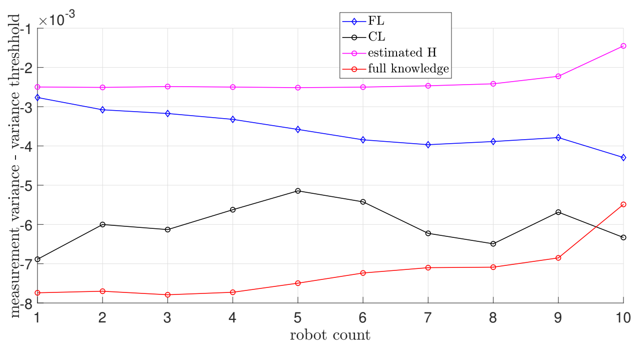

Fig. 22. Variation of error between of sensor measurement variance and threshhold variance under FL,CL,EH,PFK when communication radius is varied from 1 - 20m and total of 10 robots in the network

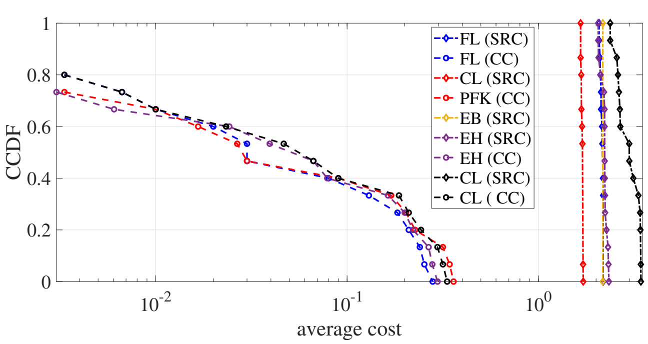

Fig. 23. Variation of CCDF of sensor replacement cost (SRC) and communication cost (CC) under FL,CL,EH,PFK,EB when communication radius is varied from 1 - 20m and total of 10 robots in the network

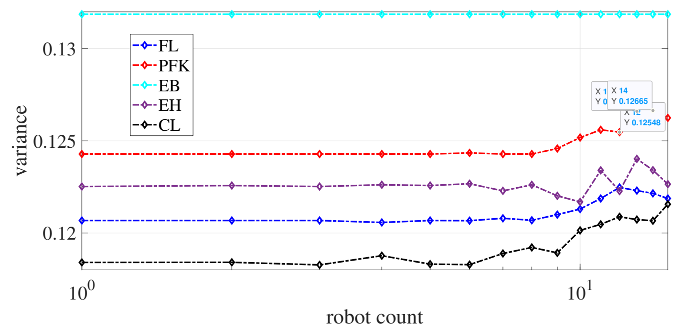

Fig. 24. Variation of sensor measurement variance against robot count under FL,CL,EH,PFK,EB when communication radius is varied from 1 - 20m and total of 10 robots in the network

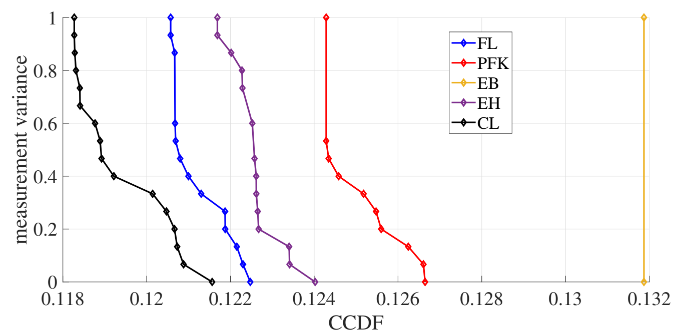

Fig. 25. CCDF of sensor measurement variance per robot when communication radius is varied from 1 - 20m and total of 10 robots in the network

losses were apparent, while there is a optimal transmit power above which the losses start decreasing.

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 a newly built wireless network related systems with unique sensor failures.

IX. 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. 27, 28, 29, 33, 31, 32, 36, 37, 30, 34,

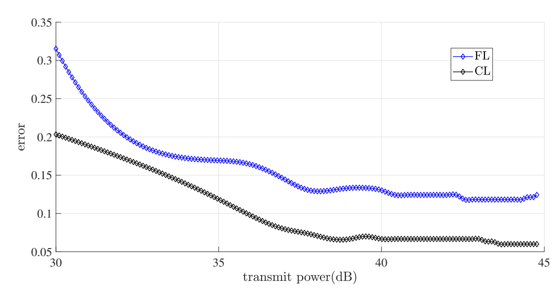

Fig. 26. Variation of sensor measurement reliability outages vs transmit power for a network of 10 robots and per robot communication range of 10m

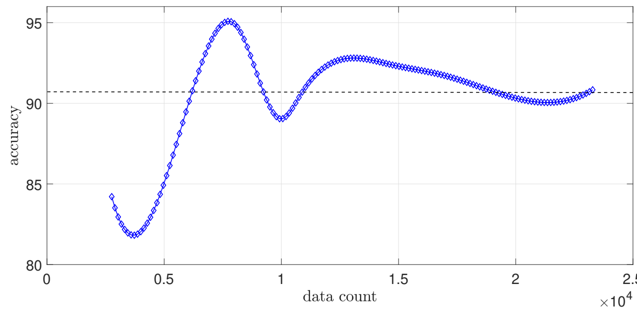

Fig. 27. Variation of accuracy between sensor measurement variance of trained and tested algorithms against number of data samples, when the test data follows the sensor failure model, $h(a, \lambda, k)$

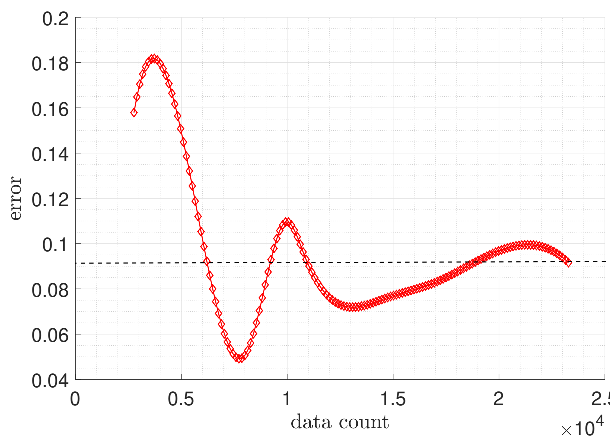

Fig. 28. Variation of error between sensor measurement variance of trained and tested algorithms against number of data samples, when the test data follows the sensor failure model, $h(a, \lambda, k)$

35. Here test data is categorized into several types such as data following sensor failure model, $h(a, \lambda, k)$ and and random distribution.

sensor measurement reliability under test data The results under Fig. 27 shows the accuracy achieved by test data following $h(a, \lambda, k)$ and random distribution under SMRO parameter using FL approach. Furthermore, 28 and 29 shows the error resulting under test data following $h(a, \lambda, k)$ and random distribution respectively. It is observed that the error decreases and converges to a percentage of 10% with the increment in the number of data samples.

The Fig. 30 shows the sensor measurement variance of test data following $h(a, \lambda, k)$ against data samples under FL. The test data has a better performance FL under training phase and CL in terms of sensor measurement variance.

The Fig. 31 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 training phase and CL in terms of SMVE. Similarly, SMRO of test data has a better performance than FL under training phase and CL in terms of SMVE as shown in 32.

average cost under test data The variation of average cost

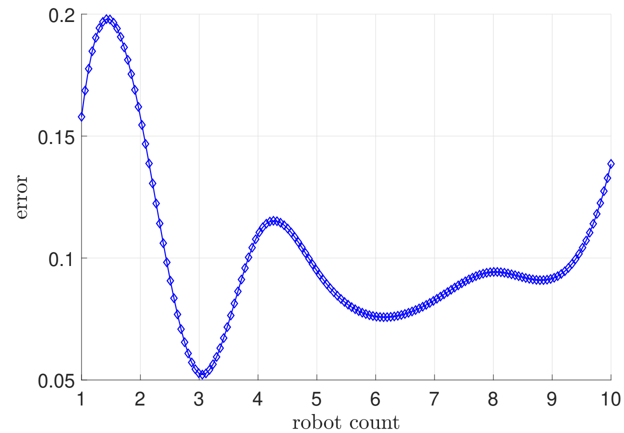

Fig. 29. Variation of error between sensor measurement variance of trained and tested algorithms against number of data samples, when the test data follows a random distribution

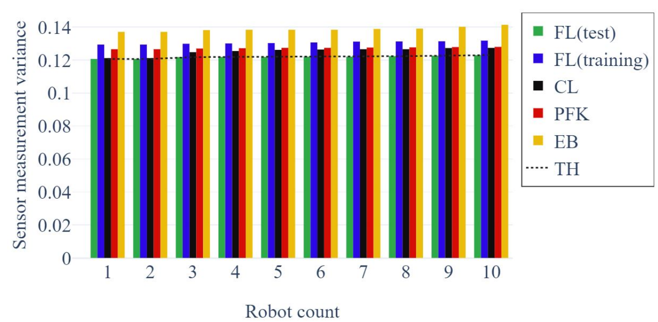

Fig. 30. Variation of sensor measurement variance against robot count of the robot network under training phase of FL, test phase of FL, CL, PFK and EB (Myopic - R) where TH is the variance threshold

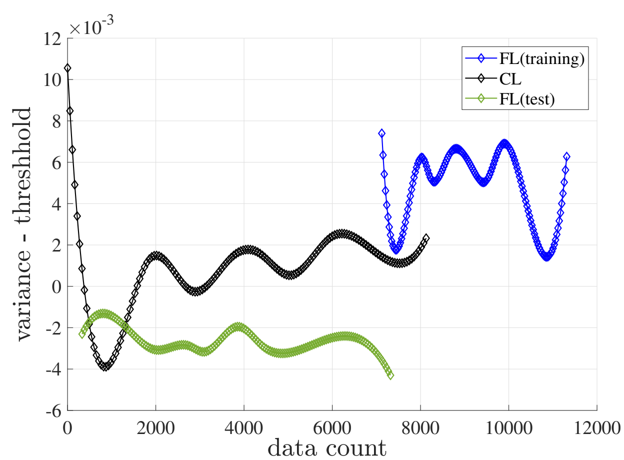

Fig. 31. Variation of error between actual sensor measurement and threshhold variance against total data samples collected by the robot network under training phase of FL, test phase of FL, CL

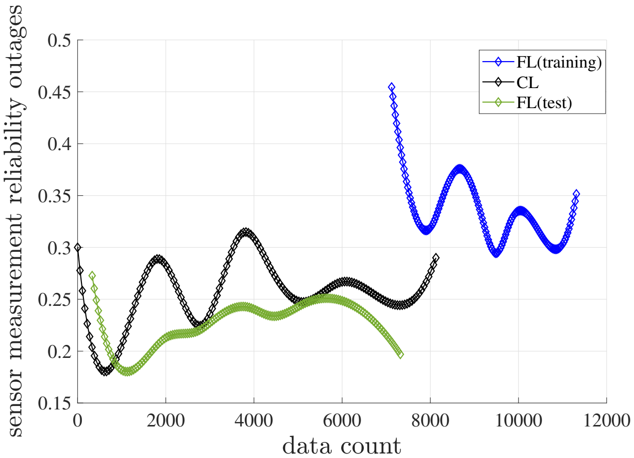

Fig. 32. Variation of total sensor measurement reliability outages against total data samples collected by the robot network under training phase of FL, test phase of FL, CL

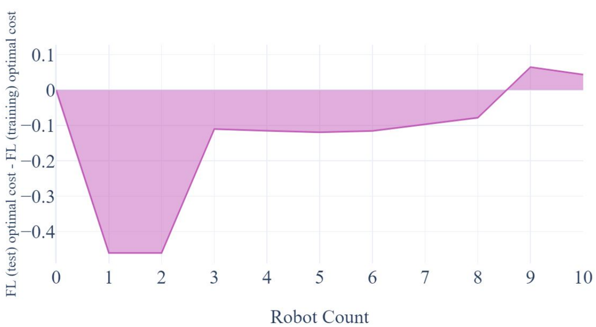

Fig. 33. Variation of difference between optimal cost under test and training phase against robot count of the robot network

under test data following the $h(a, \lambda, k)$ and training data are compared and results are illustrated in Figs. 33, 36, 37, 34, 35.

With the increment in the robot count the average optimal cost difference for FL under test and training data slowly which shown in 33. The average optimal costs for testing and training phases are separately depicted in 34 which also shows that the average cost under test data increases slightly compared to training data with the robot count.

Further, 36, 37 shows the variation of sensor replacement cost and communication cost against number of data samples. It is seen that the communication cost under test data has a higher increment than training phase with the number of data samples. The sensor replacement cost shows a different behavior which is shown in 36. There the sensor replacement cost under testing phase remains lower than the training phase

X. 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 paper develops a

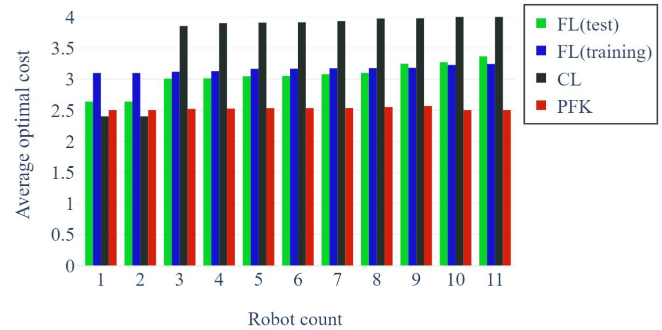

Fig. 34. Variation of average optimal cost against robot count of the robot network under training phase of FL, test phase of FL, CL and PFK

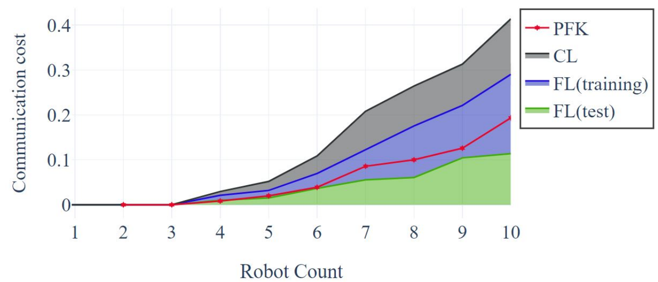

Fig. 35. Variation of communication cost against robot count of the robot network under training phase of FL, test phase of FL, CL and PFK

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

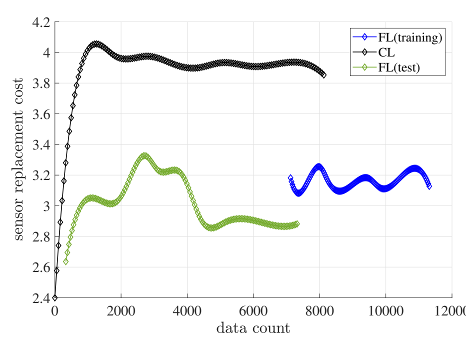

Fig. 36. Variation of total sensor replacement cost against total data samples collected by the robot network under training phase of FL, test phase of FL, CL

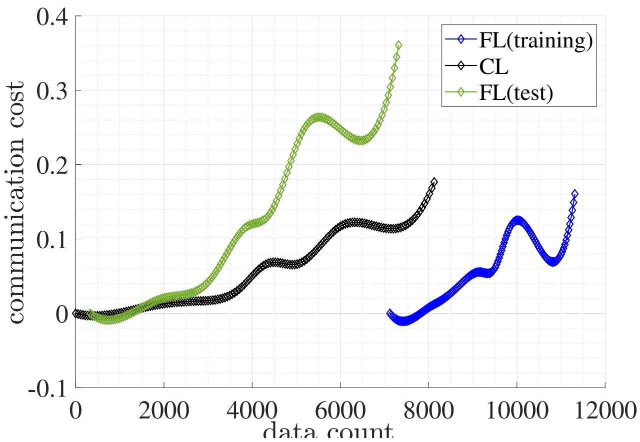

Fig. 37. Variation of average communication cost against total data samples collected by the robot network under training phase of FL, test phase of FL, CL

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.

XI. 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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