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# Computational Intelligent Sensor-rank Consolidation Approach for Industrial Internet of Things (IIoT)

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**Abstract**—Continues field monitoring and searching sensor data remains an imminent element emphasizes the influence of the Internet of Things (IoT). Most of the existing systems are concede spatial coordinates or semantic keywords to retrieve the entail data, which are not comprehensive constraints because of sensor cohesion, unique localization haphazardness. To address this issue, we propose deep learning inspired sensor-rank consolidation ( $DL_i$ -SRC) system that enables 3-set of algorithms. First, sensor cohesion algorithm based on Lyapunov approach to accelerate sensor stability. Second, sensor unique localization algorithm based on rank-inferior measurement index to avoid redundancy data and data loss. Third, a heuristic directive algorithm to improve entail data search efficiency, which returns appropriate ranked sensor results as per searching specifications. We examined thorough simulations to describe the  $DL_i$ -SRC effectiveness. The outcomes reveal that our approach has significant performance gain, such as search efficiency, service quality, sensor existence rate enhancement by 91%, and sensor energy gain by 49% than benchmark standard approaches.

**Index Terms**—Cloud computing, Big data analytics, rank-inferior measurement index, Lyapunov approach, Optimal measurement analysis.

## I. INTRODUCTION

WITH the progressive aspect of IoT technologies, the scope of physical work is curtailed with a replacement of an intelligent decision-making system. Most IoT frameworks enable battery-powered devices to preserve energy usage, which is a behoove source to perpetuate the device operations and network lifespan. The battery will be exhausted if there is a technical glitch, which leads to an erratic way of overall application performance. As the IoT devices produce more surplus data to process, that require more computing resources, and it causes multiple issues. Therefore, curtailing surplus data generation sources with an intelligent fog system is a significant task that preserves data processing time and resources cost [1], [2]. A massive active devices network shows accurate results with increased network energy consumption and resource cost, vice versa. Hence, a prudent method is essential to incorporate a precise set of necessary devices based on sensor stability with an appropriate device location to ensure data quality and service reliability.

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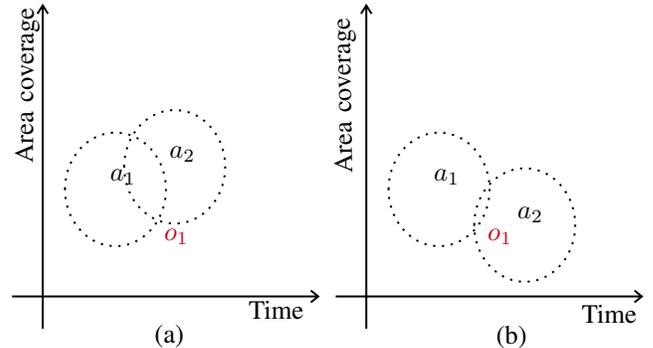


Fig. 1: Sensing area coverage problem

### A. Stability Analysis Framework

Network stability is a significant factor in intelligent IoT frameworks to optimize the system's control and monitor consequences. For instance, an unstable aircraft may crash due to a lack of technical control and monitor. Subsequently, if the sensors and controllers are wireless, the data sharing among sensors and base-stations may lead to packet loss due to device impairments, and the packet arrival status remains depicted by linear matrix inequality (LMI) iteration [3]. In [4], Energy-Harvesting and Cognitive Radio (EH-CR) IoT framework has been designed to optimize energy usage, data loss, collision probability. The sensing time, transmission time, and detection error probabilities are being analyzed to maintain network stability. In [5], a resource management model has been designed to enhance the network throughput for CR-IoT frameworks by scheduling a proper channel to ensure each device QoS. Significantly, the base-station QoS has been devised to manage all deployed sensors. In [6], a time switching model considers mutual coordination between sensors to transmit the data. The author analyzed the trade-off between energy and spectrum efficiency to optimize the base station's energy usage and throughput.

### B. Sensor Network Localization

Initially, the coverage area is divided into a fixed size of parts and makes a sensor subset to deploy on it, which ensures to monitor all divided area parts effectively. The main objective of every installed sensor is to fulfill its function in the deployed area. Sensor localization accomplishes in two ways (direct and indirect ranging mechanism). The direct-ranging-mechanism enables strength indication of the received signal, time difference of arrival (TDOA), time of arrival (TOA), angle of arrival (AOA) [7]. The indirect-ranging-mechanism enables DV-Hop [8], perfect point in triangulation test (APIT) [9], centroid

algorithm [10]. Most of the researchers have concentrated on nearby node measurements (direction of angle, data arrival rate, energy rate) to assess the sensor localization.

Each sensor has limited battery capacity; therefore, it measures the data in the specified radio range. Fig. 1 speak about the sensing area coverage problem. Where  $o_1$  is a deployed objective device, and  $a_1, a_2$  refers divided area with certain radius. In the first sub-figure, the device is not placed in a divided area, so the devices cause to create ambiguous data. In the second sub-figure, the device is deployed at the edge of the region; even that causes data loss, energy consumption, delay response. Therefore, leveraging the sensor and area characteristics at the earliest before initial deployment and after the first or second round may cause sensor re-locations to meet the objective, which are challenging tasks.

Our proposed sensor unique localization approach solves the issue based on the rank-inferior measurement index, where the base-station and their respective sensor positions are leverage before deployment over the network. Most of the existing systems have resolved the issue based on structural computation, leading to data redundancy through distributed and centralized mechanisms. The centralized system works based on the distance measurement model for sensor installation [11].

### C. Sensor Data Search

Searching queries might not resemble a respective outcome because the IoT frameworks do not allow the installation of mobile gadgets at most prior. Sometimes, unable to provide reliable and accurate sensing service, even the device installation is well in adaptive place because of sensing capability constraint [12], [13], [14]. For instance, to estimate a specific city air quality index (AQI), the data have been collected from installed sensors at various places, which has to use to conclude the AQI outcome. Here, all sensor data has mixed, which might lead to making a wrong decision because of a prognosticating method (which assesses sensor subset for each divided area and influences data classification as per fixed area with respective sensors and a set of features) absence. In [15], a novel Genetic Algorithm (GA) has been designed based on two objective functions to maximize area coverage with few sensors. The underlying objective is to optimize the area overlapping but do not have adequate performance in a complex heterogeneous system.

Therefore, our system resolves this issue by consolidating a feasible sensor position and sensor selection, active in the network and its inference mechanism with sensor ranking and data association. In this regard, we divide the problem into two sub-problems. First, the sensor ranks not be assessed based on query response rate and its matching rate. For instance, two cameras have been installed at an identical focused area. However, there is a deviation in sensing the data because of sensor properties constraints such as resolution, distance, battery impact. Second, to assess the sensor reliability index, combining all data would impact data computation and analysis cost.

Our main contributions can be summarized as follows.

- 1) We design a deep learning-inspired sensor-rank consolidation (DL<sub>i</sub>-SRC) system, enabling a 3-set of algorithms to streamline three individual objectives such as searching efficiency, data accuracy, and sensor stability rate improvement.
- 2) We design sensor unique localization algorithm based on rank-inferior measurement index to formulate sensor unique localization issue and avoid redundancy data and data loss towards enhancing data accuracy.
- 3) Develop a heuristic directive algorithm to improve data search efficiency, which returns from appropriate ranked sensors as per searching specifications.
- 4) Develop a sensor cohesion algorithm based on Lyapunov approach to accelerate sensor stability by equilibrium usage of the resource. As usual, resource consolidation is also an essential task, which we considered for finite adaptability.

The rest of this article is organized as follows. The related work focused on rank-search-quality, sensor localization, quality-aware data search, sensor data fusion according to multi-objective optimization in Section II. The proposed DL<sub>i</sub>-SRC system and its functional methods are described in Section III. The proposed algorithm's performance is described based on its outcome in Section IV and finally, we conclude this article in Section V.

## II. RELATED WORK

Recent approaches are surveyed for the sensor data search mechanisms, sensor stability, and sensor localization in the estimated area. The related work is classified as follows.

### A. Quality-Aware Feedback Search

Billions of interconnected IoT devices continuously generate a massive volume of data with high dimensionality because of dynamic complex frameworks. Getting access to efficient specific data is crucial; so, there is a scope to design an imminent novel approach for IIoT. In [16], a coverage control algorithm has been designed based on Practical Spam Optimization (PSO) approach to optimize the energy usage and area coverage issue in Wireless Sensor Networks (WSNs) by the consideration of random deployment. The PSO model regulates the sensor radius range in an inadequate area.

In [17], [18], [19], sensor deployment and re-location systems have been designed based on node die/active status due to overload or battery/energy level. A novel approach has been designed to deploy different sensors in unique places to resume network functionality. It is a common perspective of the deployment problem in IoTs; however, it is not fabricated and measured in state-of-art systems.

In [20], the service node selection problem has been formulated based on QoS factors concerning the resource constraint. A multi-objective optimization model (MOOM) has been designed to estimate the sensor's impact based on metric measurements and its conflicts among sensors. MOOM concentrated on sensor Spatio-temporal mobility impact on data transmission and data collection.

In [22], a uniform representation model has been designed for adequate sensor data storage with an efficient search policy based on structured query style. The grid R-tree structure has been proposed for searching historical and real-time Spatio-temporal data to maximize efficiency and reduce cost.

### B. PageRank Algorithm

The PageRank evaluates the sensor's quality, and connections count to decides the significance of a specific page. The page's significance generally depends on the number of connections [21]. In other words, a low significant page gets less number of connections because it has less worth than a page that gets more number of connections, and not all connections are similarly significant. The sensor significance weight is estimated based on a count of outlines. Let page count is  $n$  and the PageRank  $P_i = 1, 2, \dots, n$  is formulated as

$$P_i = \sum_{k=1 \in ol_k}^n \frac{P_k}{OL_k} \quad (1)$$

Where  $ol_k$  is a outline count from page  $p_k$ , and  $ol_k$  are the pages that legitimately associated with page  $p_k$ . Eq. 9 repeat till 2-successive PageRank vectors have formed, which are to be identical. The recursive formula for PageRank is described as

$$P_i = \frac{1 - \rho}{n} + \rho \times \sum_{k=1 \in ol_k}^n \frac{P_k}{|OL_k|} \quad (2)$$

### C. Sensor Data Evaluation

The sensor's feedback has to estimate based on the utilization of various assets since the research on sensor data search is not up to the mark. In [22], the coverage rate is fundamental in assess the sensor sensing quality and the area divided into a grid cell; each cell deployed with a sensor that causes to a finalize area coverage sensors based on historical analysis. The Maximum Lifetime Coverage Scheduling (MLCS) issue is formulated in [23] by developing a polynomial-time constant-factor approximation algorithm based on the rate of target coverage and the frequency of data collection. The k-coverage issue in [24] has formulated using the distribution methods based on the Coverage Contribution Field (CCA).

A greedy algorithm has formulated a scheduling issue in [25], [26], the Maximum Coverage Sets find possible sensors scheduling by integer linear program to optimize the network lifetime. In [27], [28], divided the sensing area into clusters to gain high energy efficiency and enhance the network's lifetime and cluster head consumes more energy because it collects data from its member nodes, data aggregation, and finally sending it to the base station. Proficient bee colony-clustering protocol (PBC-CP) has been designed based on artificial bee colony (ABC) algorithm by considering node's energy, degree, and distance to access point. In [29], energy and bandwidth management factors play an important role in collaborative relay networks. An opportunity-aware adaptive relay (OAR)

TABLE I: Notations

Notation	Description
$v_{i..m}$	Number of Sensors
$R_{v_i}$	Sensor sensing radius
A	Feasible sensing area
$C_a(V, A, \tau)$	a set of sensors to collect information at time $\tau$
$\phi_{i,i+1}$	Edge quality among sensors and access point
$\aleph_i(\tau)$	Amount of sensed data at time $\tau$
$\vartheta_{v_i}$	Sensor data transmission rate
$p$	Positive integer
$\lambda_i$	Non-negative weighting factor
$d_{i,i+1}$	Distance between $i^{th}$ sensor and $i + 1^{th}$ sensor
$R_{v_i}^{thr}$	Radius coverage threshold rate based on area
$\xi_{v_i}^{thr}$	Residual energy threshold rate of sensor
$\gamma_{thr}$	Threshold area coverage rate

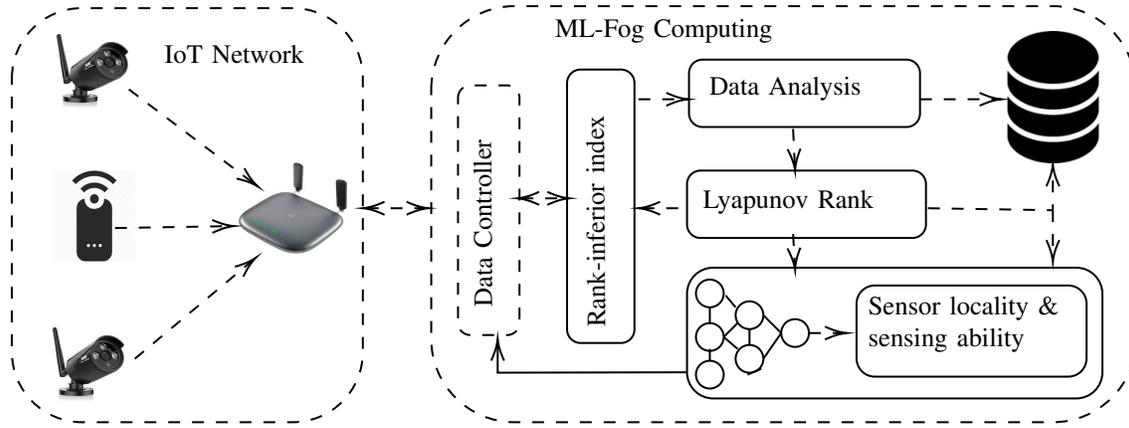
node selection algorithm has been designed based on bit error rate (BER) estimation for effective data sensing. Node residual energy estimation extends the network life cycle. However, in the above two methods, the sensor selection has been formulated, but the coverage area rate has not been discussed for maintaining sensor data quality. Therefore, there is a scope to design an optimal solution that simultaneously accelerates the coverage rate—the performance accuracy shown through hypothetical simulation investigations. We have considered the coverage rate to assess the sensor rank for quality data search. All notations of the equations have listed in Table I.

## III. PROPOSED MODEL

Fig. 2 illustrates the complete functionality of the proposed deep learning-inspired sensor-rank consolidation (DL<sub>i</sub>-SRC) system with soft computing models. Initially, the sensed data controlled and stored by a data controller manager. After that, the rank measurement index function assesses the data by converting unstructured data into structured data. The heuristic directive algorithm improves data search efficiency, which returns relevant ranked sensor results per searching specifications from top-rank sensors. It accomplishes through the remaining two steps. Sensor cohesion algorithm based on the Lyapunov method accelerates the sensor stability once the respective sensor is labeled with a high-rank value; otherwise, the sensor location must be re-positioned based on its sensing data error rate, data quality, and cost. If a sensor does not meet the requirement, then the unique sensor localization executes based on the rank-inferior measurement index. It accomplishes adequate sensing data quality and low cost by avoiding redundancy data and data loss during the data generation.

### A. Sensor Radio Converge Measurement

The proposed probabilistic sensing model works on distance coverage between target and source sensor node to provide a versatile and commonsense assessment. Let  $v_i$  implies a sensor; the detection error range  $e_i$  to estimate the sensor

Fig. 2: (DL<sub>i</sub>-SRC) system model

uncertainty. The point  $X(x, y)$  covered by the sensor, and it expresses as

$$C_a(v_i, X) = \begin{cases} 0, & d(v_i, X) > R_{v_i} + e_i \\ 1, & d(v_i, X) \leq R_{v_i} - e_i \\ e^{-\hbar\sqrt{\gamma}}, & R_{v_i} - e_i \leq d(v_i, X) \leq R_{v_i} + e_i \end{cases} \quad (3)$$

where  $d(v_i, X) = \log((x - x_i)^2 + (y - y_i)^2)$  is the distance between  $v_i(x_i, y_i)$  and point  $X$ ;  $\gamma = d(v_i, X) - d(R_{v_i} - e_i)$ ,  $\hbar$  refer decay factor that uses to measure sensing speed w.r.t distance. Therefore, history information or numerical analysis remain consider to define a target area called coverage of area (COA) denotes  $a$ , and it assessed with eq. 4

$$C_a(v_i, a) = 1/a_c \times \sum_{i=1}^n \sum_{a \in A} C_a(v_i, a) \quad (4)$$

Where  $a_c$  remains subset of  $A$ . Specifically, (3) and (4) denotes collecting data of the coverage area at specific time  $\tau$ , it defined as  $C_a(v_i, A, \Gamma)$ . The area coverage at time interval  $\Gamma = [\tau_1, \tau_2)$  and it assess with

$$C_a(v_i, A, \Gamma) = \frac{1}{\tau_t} \int_{\tau_i}^{\tau_{i+1}} \sum_{i=1}^m \sum_{a \in A} C_a(v_i, a, \tau) dt \quad (5)$$

where  $\tau_t = \tau_2 - \tau_1$  is length of  $\Gamma$ . The sensors typically collect data regularly at various time allotment, and the mobile hubs can not have programmed moving direction.

In our framework, a set of sensors are hooked to collect information as per their objective; such as  $V = \{v_1, v_2, \dots, v_m\}$ , the sensing of area at time  $\tau$  described as

$$C_a(V, A, \tau) = 1 - \prod_{v_i \in V} (1 - C_a(v_i, A, \tau)) \quad (6)$$

Algorithm 1 enhance the response frequency of the system with accurate data from top-ranked sensors. Line-1 defines the threshold area coverage rate, Line 2-3 estimates the sensor rank and sensor position in the network. Line 4-18 finalize the potential sensor list to be active in the network to collect the data. In between, line-6,9,13 consolidate each sensor based on sensing range rate, rank less than 10, threshold coverage area, and residual energy parameters, respectively.

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### Algorithm 1: Heuristic Directive algorithm

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**input** : Graph  $g$ ,  $V$  sensor set,  $v_i$ ,  $p$ ,  $n$ ,  $\xi_{v_i}^{thr}$ ,  $R_{v_i}^{thr}$   
**output**: Optimal search frequency with accurate data from top rank sensor

```

1 Define  $\gamma_{thr}$ ;
2 Let estimate the sensor rank with Algorithm 2;
3 Update Sensor Location accuracy :  $H_i^o$  with Algorithm 3;
4 for each  $v_i = 1$  to  $m$  do
5   Update Vertices of  $v_i$ ;
6   if  $R_{v_i} \leq R_{v_i}^{thr} \parallel \varphi(v_i) \leq 10 \parallel \xi_{v_i} \leq \xi_{v_i}^{thr}$  then
7     Estimate  $C_a(v_i, X)$ ;
8     Update Cost esteem;
9     if  $d(v_i, X) \leq \gamma_{thr}$  then
10      Remove the  $v_i$ ;
11      Update  $V[t] = V[t] - v_i$ ;
12    end
13    else if  $R_{v_i}$  fulfil  $\gamma_{thr}$  then
14      Update  $Q_i^j \leftarrow (v_i)$ ;
15      Sensor localization amendment with Algorithm 3;
16    end
17  end
18 end
19 Return Feasible sensors

```

---

1) *Sensor Rank Measurement Model*: Sensor hub expands vitality while collecting data of its neighborhood. Therefore, vitality usage and computing data rate from sensors are proportional to each other, called sensing cost. In our proposed system, we adapted the energy measurement index to streamline our objective. The sensing process consumes vitality in multiple ways, such as sending, computing. Vitality usage for transmission remains to include some sub-process such as reporting, sensing and receiving. However, we focused on sensing error rate, coverage rate and moving vitality, which is pivotal for the information age. For estimating vitality utilization, we develop an adaptive square model as follows:

$$\xi_{v_i} = \xi_{ini} \times \phi_{i,i+1} \times R_{v_i} \times \aleph_i(\tau) \times \sum_{\tau=1 \in \Gamma}^{\Gamma} d(\tau) \quad (7)$$

In case the speed of sensing or arrival rate is not considered, then energy usage must be linear w.r.t distance between target-to-source node. The active sensor collects data at the allocated time  $\Gamma = \{\tau_1, \tau_2, \dots, \tau_m\}$ . During the estimation of weight factor, if node has below rank, but unable to cover the fixed area  $a$ , then it has streamlined as bellow.

$$\varpi = \sum_{i=1}^m \frac{1}{V} \times \ell_{v_i/\varphi(v_i)} \quad (8)$$

Where,  $\ell_{v_i}$  refers outer link count of the feasible sensor  $v_i$ . The sensor positions are progressively stimulated by including

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**Algorithm 2: Sensor Cohesion algorithm**


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**input :** Graph  $g$ ,  $V$  no of sensors,  $\xi_{ini}$ ,  $\phi_{i,i+1}$ ,  $\ell_{v_i}$

**output:** Optimal sensor rank

```

1 Let initialize  $\xi_{ini}$ ,  $\phi_{i,i+1}$ ,  $\ell_{v_i}$ ;
2  $\varphi(v_i) = 0$ ;
3 for each  $v_i = 1$  to  $m$  do
4   Estimate
      $\xi_{v_i} = \xi_{ini} \times \phi_{i,i+1} \times R_{v_i} \times \aleph_i(\tau) \times \sum_{\tau=1 \in \Gamma}^{\Gamma} d(\tau)$ ;
5   Update  $\xi_{v_i}$ ;
6   Estimate  $\varphi(v_i) \leftarrow (\xi_{v_i}/V) + C_a(v_i, A, \Gamma)$ ;
7   Update  $\varphi(v_i)$ ;
8 end
9 if  $\max(\varphi(v_i))$  not fulfil area 'a' then
10  for each  $v_i = 1$  to  $m$  do
11    Algorithm 1, cross check the coverage ratio;
12    for each  $v_{i+1} = 1$  to  $m$  do
13      Estimate  $\varpi = \sum_{i=1}^m \frac{1}{V} \times \ell_{v_i/\varphi(v_i)}$ ;
14      Update  $\varphi(v_i) \leftarrow \varpi + (1 - \varpi) \times \xi_{v_i}$ ;
15    end
16  end
17 end
18 Return Feasible rank of sensor

```

---

the significance of each gadget system. The neighbor sensor connections are divided with objective outlines to coverage the segregated area and lost data at time  $t$ . This procedure remains rehashed continuously based on measurement values until it covers the objectives during Sensor Rank qualities  $\varphi(v_i)$  assessment. Thereby, this approach concedes the decay factor in assessing the last value of rank over the system. However, each sensor remains to quantify by enriching all aspects, but a potential set of sensors are permitted to stay dynamic to ration vitality and enhance battery life.

Algorithm 2 assesses the sensor rank based on its service satisfaction weight factor based on measured data error rate and phenomenal parameters. Line-1&2 define initial parameter values. Line 3-8 defines each sensor's rank based on area coverage cost, residual energy, sensing capacity range, edge capacity, edge degree, and re-transmission rate. Line 9-17

defines the area coverage efficiency since it has an impact on the decision-making system. In our simulation, at each round, the gathered information streams towards the storage point. Subsequently, each node gets enrolled into the network by satisfying all entails like residual energy rate, location, link quality, link characteristics. Our system framework keeps up this process until the completion of data fusion. In our functional procedure, the sensor rank estimation algorithm executes with significant metric  $\varphi(v_i)$ .

### B. Sensor Unique Localizability Index

Directed Acyclic Graph (DAG)  $(G, V)$  is a unique system to trace and maintain sensing speed or arrival vector rate linearly.

$$\begin{aligned} \vartheta_{v_i} &= \frac{dv}{dt} \\ &= \frac{|v_i - v_{i+1}|}{|dt|}, \quad \forall (i, i+1) \in edge \end{aligned} \quad (9)$$

The distance of contiguous hubs must be prominent than  $R_{v_i}$ . More unequivocally, the extant strategies not designed based on contiguous value  $\|v_i - v_{i+1}\| \geq R_{v_i}$ .

Each sensor, individual position assessment issue (9) remains hard because of nonconvex distance equality values. A obscure matrix  $V = \{v_1, v_2, \dots, v_m\} \in \mathbb{V}$  and  $U = V^T V$  has consider to modify sensor localization issue as a coverage achievability issue of discovering obscure matrix, communicated as follows:

$$\begin{aligned} U &= V^T V \\ (\varepsilon_i - \varepsilon_{i+1})^T U (\varepsilon_i - \varepsilon_{i+1}) &= \sqrt{d_{i,i+1}(\tau)} \\ \begin{bmatrix} v_i \\ -\varepsilon_i \end{bmatrix} \begin{pmatrix} I_v & V \\ V^T & U \end{pmatrix} \begin{bmatrix} v_i \\ -\varepsilon_i \end{bmatrix} &= \sqrt{d_{i,i+1}(\tau)} \\ U &= V^T V \end{aligned} \quad (10)$$

where  $\varepsilon_i \in \mathbb{E}$  refers unit vector, enables  $i^{th}$  index value which is exceptional and  $I_v \in \mathbb{E}$  remains identity matrix. The feasibility issue reformulated as adequate multi-objective issue through rank imperative on  $Q$ , which refers positive sensor position definite matrix.

$$\begin{aligned} Q &= \begin{pmatrix} I_v & V \\ V^T & U \end{pmatrix} \\ \text{Min}_Q & 0 \\ Q_{(1:v)} &= I_v \\ [0_{v \times 1} : \varepsilon_i - \varepsilon_{i+1}]^T Q [0_{v \times 1} : \varepsilon_i - \varepsilon_{i+1}] &= \sqrt{d_{i,i+1}(\tau)} \\ [v_k : -\varepsilon_i]^T Q [v_k : -\varepsilon_i] &= \sqrt{d_{i,i+1}(\tau)} \\ Q &\geq 0, \text{Rank}(Q) = k. \end{aligned} \quad (11)$$

1) *Rank Weight Analysis:* Consider a rank-constrained sensor instalment issue as below:

$$\begin{aligned} \text{Min}_v \langle Q_o, V \rangle \\ \text{Where } \langle Q_i, V \rangle &= a_i, \quad \forall i = 1, 2, \dots, n \\ \langle Q_i, V \rangle &\leq a_i, \quad \forall i = n+1, n+2, \dots, N \\ \text{rank}(v) &\leq p \end{aligned} \quad (12)$$

Where  $V \in \mathbb{V}$  refer sub-finite matrix and  $Q \in \mathbb{R}$  refers identical coefficient lattices remains not positive numbers,  $a_i \in \mathbb{R}$  alludes constant variable of a linear matrix, and  $p$  remains a positive number.

Rather than disregarding the rank requirement in (12), we supplant the rank requirement  $(v) \leq p$  by an elective set of limitations, communicated as below:

$$\begin{aligned} \langle H, I_n \rangle &= n - p, \quad H \in PN^+ \\ V \perp H \cdot V &\in PN^+ \\ I_n - H &\in PN^+ \end{aligned} \quad (13)$$

Where  $I_n \in \mathbb{R}^{v \times v}$  alludes an indentity matrix and  $PN^+$  refers k-dimension symmetric matrix.  $V \perp H$  demonstrates that  $W$  is a symmetrical supplement of  $V$ , such as,  $\langle V, H \rangle = 0$ . Reformulating limitations consider into integral conditions, as appeared in (13).

**Theorem 1:** The rank requirement  $rank(V) \leq p$  for  $V \in PN^+$  remains comparable with set of limitations expressed in (13).

**Proof:** Letting  $U = I - H$ , it suitable to see that the requirements in (13) are proportionate to

$$\begin{aligned} \langle V, U \rangle &= track(V) \\ \langle I, U \rangle &= p \\ 0 &\geq U \geq 1. \end{aligned} \quad (14)$$

In this context, we adopted a rotating technique to understand  $V$  and  $H$  independently by deteriorating them toward 2-curved sub-problems. Also, the network equity limitation  $\langle V, H \rangle = 0$  remain detached. In particular, expecting the  $k^{th}$  dimension, figured as

$$\begin{aligned} Min_v \langle Q_0, V \rangle + \lambda_i \langle V, H_{i-1} \rangle \\ Where \langle Q_o, V \rangle = a_i, \quad \forall i = 1, 2, \dots, n \\ \langle Q_o, V \rangle \leq a_i, \quad \forall i = n + 1, n + 2, \dots, N \\ V \geq 0 \end{aligned} \quad (15)$$

Where  $\lambda_i$  alludes a non-negative weighting factor, let  $v_i$  consider as ideal sensor which position dependent on (15). By giving an underlying worth  $v_0$ , (14) and (15) can continue until it fulfils the halting standard.

### C. Distributed Remote Control Analysis

In this segment, a hub-based sensor unique localization (SUL) model is designed, where the first issue deteriorated into sub-problems, and it comprehended autonomously by utilizing the proposed rank-inferior measurement (RIM) index. In SUL calculation, initially, every node uses local data to streamline the sensor positioning issue. It can just get the quantifiable distances of base-station and nodes situated inside its coverage range. For instance,  $i^{th}$  node position vector at the  $j^{th}$  emphasis as  $V \in \mathbb{R}$ , at that point the  $i^{th}$  sub-problem is defined as follows:

$$\begin{aligned} Min_{v_i} 0 \\ \|v_i - v_{i+1}\| = \sqrt{d_{i,i+1}(\tau)} \varepsilon_i \in \mathbb{R} \end{aligned} \quad (16)$$

where  $v_i^j \in \mathbb{R}$  alludes evaluated  $j^{th}$  nodes point of vector deployment at the  $(j-1)^{th}$  step.

$$Q_i^j = \begin{pmatrix} I_v & V_i^j \\ V_i^T & U \end{pmatrix} \in PN^+ \quad (17)$$

By supplanting the imperative rank through its comparability state, and the goal function, confessing a weighted discipline term issue remain resolved with RIM indexing mechanism.

$$\begin{aligned} Min_{Q_i^j, \hat{d}_{i,i+1}} \sum_{j \in J} \left| \hat{d}_{i,i+1} - d_{i,i+1} \right|^2 + \lambda_i \langle V, H_{i-1} \rangle \\ Q_{(1:v)} = I_v \\ [0_{v \times 1} : \varepsilon_i - \varepsilon_{i+1}]^T Q [0_{v \times 1} : \varepsilon_i - \varepsilon_{i+1}] = \sqrt{\hat{d}_{i,i+1}(\tau)} \\ [v_k : -\varepsilon_i]^T Q [v_k : -\varepsilon_i] = \sqrt{d_{i,i+1}(\tau)} \\ Q^j \geq 0 \end{aligned} \quad (18)$$

Next, given  $Q^j$  is consider to determine  $H_i^j$  by solving

$$\begin{aligned} Min_{H_i^j} \sum_{j \in J} \left| \hat{d}_{i,i+1} - d_{i,i+1} \right| + \lambda_i \langle Q_i^j, H_{i-1} \rangle \\ Trace(H_i^j) \geq n - p \\ I - (H_i^j) \geq 0 \\ (H_i^j) \geq 0 \end{aligned} \quad (19)$$

Algorithm 3 evaluate each sensor position in the network since it has an adequate impact on the data fusion system. Where  $\kappa_1, \kappa_2, \kappa_3$  are constants,  $v$  is position weight factor. Line 1&2 define initial sensor-position and its feasible, not feasible sets. Line 3-25 assesses the sensor position based on a positive definite position matrix ( $Q$ ), positive feasible sensor matrix ( $H$ ). Where line 5-9 removes not feasible sensors from the feasible sensor set. Line 9-11 update the concerned matrices. Line 12-15 assesses the sensor and base-station positions. Line 17-23 assess final sensor position set.

## IV. SIMULATION

Our proposed system performance is estimated with all proposed models' cross-validation by considering noisy and noiseless data. The heuristic directive algorithm 1 improves data search efficiency by enhancing the effective utilization of gathered data, which returns relevant ranked sensor results as per searching specifications. Sensor cohesion algorithm 2 based on Lyapunov approach accelerates sensor stability by equilibrium the resource usage. As usual, resource consolidation is also an essential task, which we considered for the IIoT system's finite sustainability. The sensor-unique localization (SUL) algorithm 3 works based on rank-inferior measurement (RIM) index to enhance data accuracy by avoiding redundancy data, data loss. The three algorithms are actualized in MATLAB 2019a. The PC enables a 3.60 GHz Intel Core-i7 processor, RAM 16-GB, which has used for simulations. The simulation parameters are listed in Table II and where Transmission Power (TP), Channel Bandwidth (CB), Channel Model (CM) are simulation functions.

**Algorithm 3:** Sensor-Unique Localization (SUL) algorithm

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**input** :  $v_i, p, n, \kappa_1, \kappa_2, \kappa_3, v$   
**output**: Optimal sensor localization

- 1 Let *Random locations of sensor* :  $H_i^o$ ;
- 2 int T,  $FS[t_i] \neq 0, NFS[t_i] = 0$ ;
- 3 **for** each  $\eta_{v_i}^j = 1$  to  $J$  **do**
- 4     **for** each  $v_i = 1$  to  $m$  **do**
- 5         **if**  $\xi_{v_i} \not\leq \xi_{v_i}^{thr}$  **then**
- 6              $NFS[t_i] \leftarrow v_i$ ;
- 7             update set  $FS[t_i] \leftarrow FS[t_i] - NFS[t_i]$ ;
- 8         **end**
- 9         Update Vertex of  $v_i$ ;
- 10         Update  $Q_i^j$  by evaluating Eq. 18, with  $H_i^j$ ;
- 11         Update  $H_i^{j+1}$  by evaluating Eq. 19, with  $Q_i^{j+1}$ ;
- 12         **if**  $\sum_{j \in J} |\hat{d}_{i,i+1} - d_{i,i+1}| + \lambda_i \langle Q_i^j, H_{i-1} \rangle \leq \kappa_1$   
            **then**
- 13             Update  $\hat{v}_i^{j+1} \leftarrow v_i^j$ , confine as base-station;
- 14             **end**
- 15             Update  $v_{i+1}$  with  $Q_i^{j+1}$  by evaluating Eq. 17;
- 16         **end**
- 17         Update  $V^{j+1} = [\hat{v}_i^{j+1}, \dots, \hat{v}_m^{j+1}]^{Tranp}$ ;
- 18         **if**  $\sum_{i=1}^m \langle Q_i^{j+1}, H_{v_i}^{j+1} \rangle \leq \kappa_2$  &  $V^{j+1} - V^j \leq \kappa_3$  **then**
- 19             Halt the process;
- 20         **else**
- 21              $V^{j+1} \leftarrow V^{j+1} + v(V^{j+1} - V^j)$ ;
- 22              $j \leftarrow j + 1$ ;
- 23         **end**
- 24         Return Feasible sensor position.
- 25 **end**

---

TABLE II: Simulation setting parameters

Iteration cycle	$v_i$	$n$	$R_{v_i}$	TP	CB	CM
Iteration-1	25	5	0.15	23 dbm	20 MHz	IEEE Model E
Iteration-2	50	10	0.18	23dbm	25 MHz	IEEE Model E
Iteration-3	80	16	0.12	25 dbm	30 MHz	IEEE Model E

## A. Performance index

Subsequently, we have cross-validated the performance of our approach by comparing error measurement indexes and estimated as:

$$1) RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_i - Q_i)^2}$$

$$2) MAE = \frac{1}{N} \sum_{i=1}^N \|P_i - Q_i\|$$

Root mean square error (RMSE) means absolute error (MAE) has been used to assess distinction rates among real and anticipated estimates.  $P_i$  refers to sensed data, and  $Q_i$  refers to entail data.

We are conferencing the rank value and nonfeasance quality imperatives while assessing the Lyapunov approach's sensor rank value. It optimally defines the location of the high-rank un-labeled sensors by validating through *Theorem1*. The error measurement index values play a vital role in assessing the sensor's position over the network; it leads to generate accurate data to make an optimal decision of sensor location with moderate data cost and reliable response rate. The base-station positions are fixed with prognosticative portability models, and a sub-set of the sensor might fall in abnormal radio coverage conditions. Certainly, all three methods satisfy a high percentage of an area covering range.

If the quantity of hubs rises, the centralized model's compute time also rises to compare the distribution system performance. For instance, the CP-model grabs 25s to handle 50-sensors; in the worst case, it has taken 350s to process 85-sensors to accomplish the best solution. Likewise, the opportunity model has taken 3-iterations in test-1 in 46.7s; in test-2, it has taken 195.1s to finish 9- iterations. Simultaneously, in test-3, it consumes 1751s to complete 4-iterations. It sounds that the opportunity model does not have linear stability to accomplish our manuscript objective. Our proposed system  $DL_i - SRC$  has a low execution time of every active sensor, around 45s at both normal and abnormal cases, which addresses it numerously adaptable for an enormous scope of SUL concerns.

Fig. 3 illustrates response time analysis of our proposed system  $DL_i - SRC$  with three methodologies. CP-model has accurate response time because of less computation scope over multiple sensors framework, and opportunity model (Opt model) linearly executes searching process consistently. Our proposed system consumes moderate searching time even an increased count of active sensors, yet at the same time significantly far better than opportunity model simulation outcomes. The above conversation related to sensor count demonstrates that the heuristic directive approach would be fleeter than an opportunity model for most potential information search questions.  $DL_i - SRC$  has cost less response time than the opportunity model even at the higher time to check the requirements satisfaction. In-case, if the sensing radius increases ( $\pi$ ), the  $DL_i - SRC$  approach snips superfluous search time than among all state-of-art strategies.

CP-model has the quickest response time since it has a unique response system, and it has the most inconspicuous coverage ratio, as illustrated in Fig. 4. In particular, when the base coverage area is not equal to zero, most of the sensors did not make it possible to grab information, as we can observe in Fig. 4(b). It shows that CP-model does not have adequate information. Our proposed approach outcomes demonstrate the viability of the  $DL_i - SRC$  model, which enormously builds the coverage ratio. In the meantime, the standard sensor selection and coverage ratio outcomes of the opportunity model remain not potentially enrich than the  $DL_i - SRC$  approach, and it is achievable through sub-dividing the area optimally.

Essentially, Fig. 5 delineates that  $DL_i - SRC$  has feasible

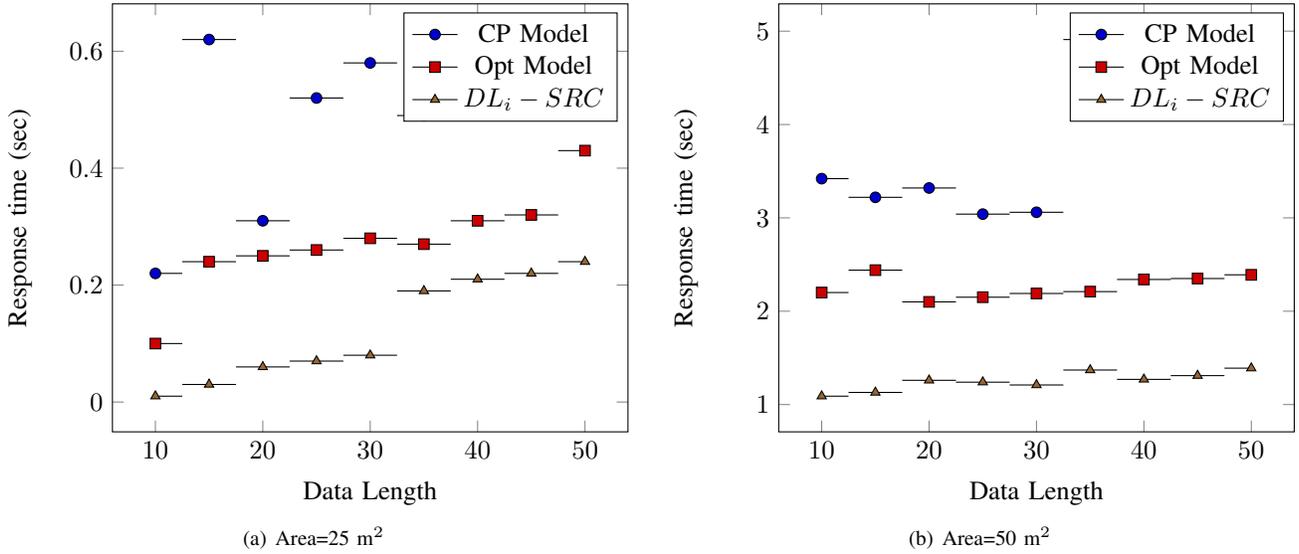


Fig. 3: Load and response time analysis

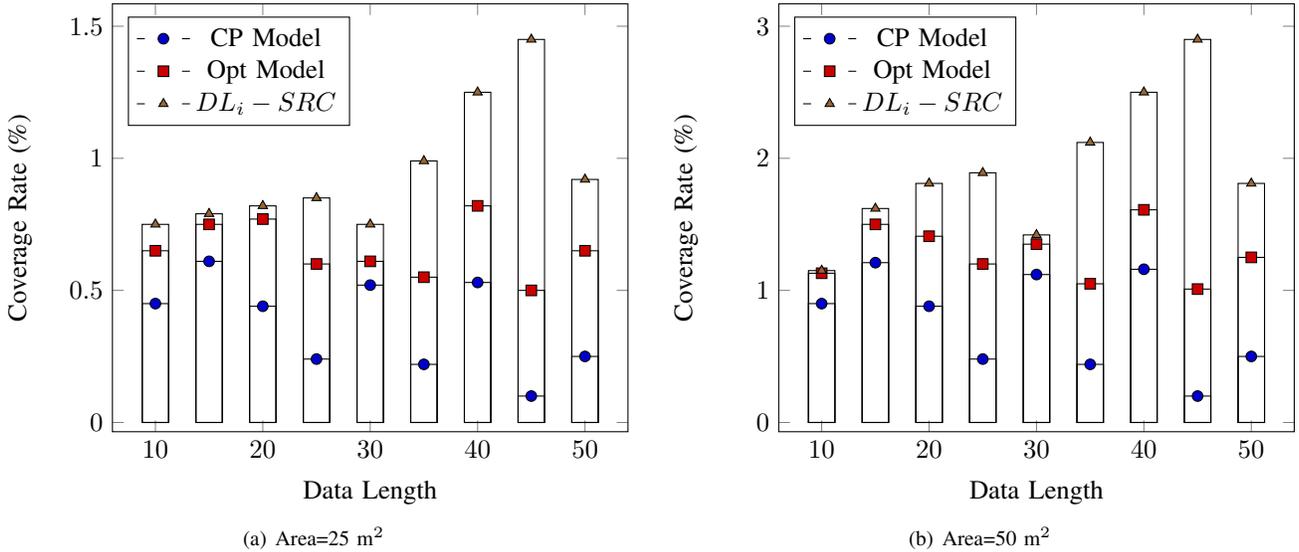


Fig. 4: Load and coverage rate analysis

functioning cost better than opportunity model and CP model due to initial cross verification and validation of multi-sensor framework characteristics (node degree, link quality, sensor residual energy, sensor data loss rate, sensor data redundancy rate, number of re-transmissions are must leverage before allowing sensor into the network for being active). These parameters impact network sustainability with quality data search that leads to optimizing the system cost.

The  $DL_i - SRC$  approach enables a prognostic sensor rank system based on a feedback model to optimize the search accuracy, data quality, and system cost than the CP-model and Opportunity model. Our approach has a positive  $\pi$  value during area coverage ratio estimation, and it can observe in Fig. 5(b). The results indicate a trade-off between system cost, data quality, and search accuracy w.r.t response time;

in return, the system shares reliable required data as per the service request.

Fig. 6 represents the report of  $DL_i - SRC$  approach response time concerning the service request rate with a top-sensors ( $v_i$ ), which share quality data as per the type of service request. We can observe that, when  $v_i = 8$ , the response time is high in all service request rate cases. Subsequently, we can observe the response time is moderately low even at the top-sensors are  $v_i = 20$  because all three algorithms are consolidated the coverage rate, sensor stability based on sensor-rank, and sensor positioning system. Table III shows the comparative performance analysis between our system and two existing systems. Feasible Sensor Rate (FSR) represents how many sensors can share exact entail data per

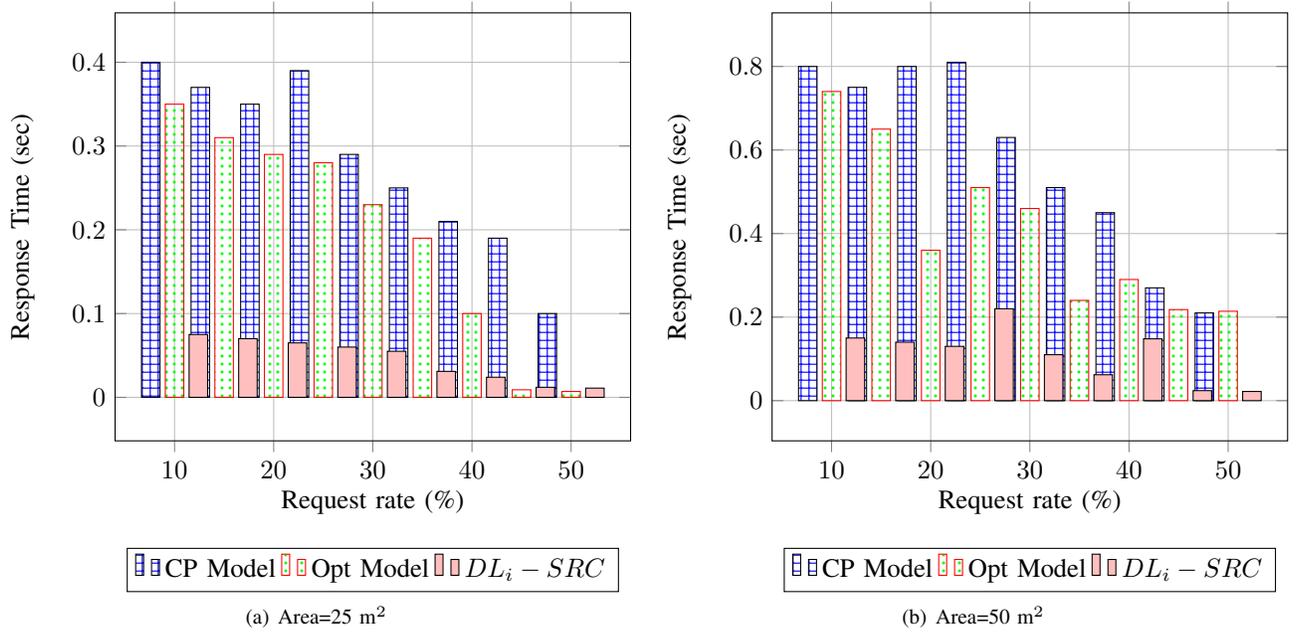


Fig. 5: Load and cost rate analysis

TABLE III: Comparative performance analysis summary with various simulation values

Iterations	CP model				Opt Model				$DL_i - SRC$			
	RMSE	MAE	FSR(%)	ACT(s)	RMSE	MAE	FSR(%)	ACT(s)	RMSE	MAE	FSR(%)	ACT(s)
Iteration-1	0.0532	0.357	83	31.56	0.0691	0.0769	88	25.15	0.0015	0.0191	95	19.12
Iteration-2	0.0481	0.291	79	28.5	0.0501	0.063	82	19.01	0.0043	0.0861	69	15.59
Iteration-3	0.0356	0.199	85	39.99	0.0496	0.051	89	95.12	0.0312	0.1675	96	23.84

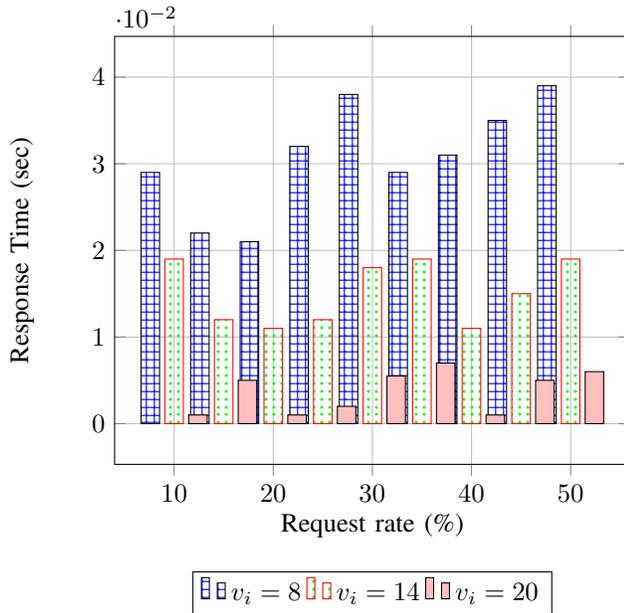


Fig. 6: Request-based reliable response analysis

the service request; Average Completion Time (ACT) speaks about the entail time to complete the service request. The statistical analysis illustrates that our approach has 96% of FSR, 23.84 seconds of ACT, and 0.1675% of MAE than

other approaches under iteration-3. In a simulation, iteration-3 enables 80 sensors, 16 Access Points (APs), the average coverage area is 0.12 meter/sensor, transmission power is 25dbm, the channel bandwidth is 30MHz with IEEE Model-E channel mode.

## V. CONCLUSION AND FEATURE WORK

The proposed deep learning-inspired sensor-rank consolidation ( $DL_i - SRC$ ) system is a combination of three approaches. Our  $DL_i - SRC$  system resembles an optimal solution for sensor cohesion, unique sensor localization, search accuracy by segmenting the problem into sub-problems. Initially, the sensor cohesion algorithm accelerates 81% sensor stability by selecting top rank sensors to fetch reliable matching information based on Lyapunov approach. Second, sensor unique localization algorithm partially works on the sensor rank; if the rank not in the potential sensor list, then the respective sensor is re-positioned based on the rank-inferior measurement index to avoid data redundancy and data loss. Third, a heuristic directive algorithm enhances data search efficiency by 61%, which returns from relevant ranked sensor data as per searching specifications. The simulation outcome describes that our  $DL_i - SRC$  system has 87.21% efficiency. The performance measurement index outcomes reveal that our approach has search efficiency 91%, service quality, sensor existence rate enhancement by 91%, and sensor energy gain

by 49% than benchmark standard approaches. Controlling the generation of fault data at the level of edge devices and making a feasible decision at the device level is a keen task. The functionality based on classical computing with multiple sensor environments is notable research-work; we wish to work on embedded-echo system by streamlining device level decision analysis with low redundant data, which further uses for fog computing.

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