AGV-Assisted Data Collection Strategies in Industrial IoT: A Value of Information Perspective

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***Abstract*—With the advent of the Industry 4.0 era, the widespread deployment of Automated Guided Vehicles (AGVs) in factories has enabled them to serve as sensor relays, assisting in collecting sensor data in areas with poor signal quality. Traditionally, the objective of sensor data collection has been primarily to reduce the delay in data acquisition. However, latency alone offers an incomplete reflection of the significance of sensor data to industrial tasks. Value of information (VoI) has emerged as a novel metric that more accurately reflects the impact of sensor data on the performance of upstream tasks. In this background, we introduce an innovative AGV-assisted sensor data collection strategy to minimize the loss of sensor data VoI. This strategy encompasses the selection of data fusion nodes, choice of transmission modes, and AGV path planning. We introduce a new metric called structural value entropy, which effectively reduces VoI loss during the data fusion process, and through the design of a metaheuristic algorithm based on ant colony optimization, achieves the selection of transmission modes and the planning of AGV paths with minimal VoI loss. Simulation experiments validate the effectiveness of the proposed strategy in maintaining VoI, demonstrating significant performance enhancements and acceptable convergence speed compared to baseline strategies, affirming the strategy's efficiency and feasibility in handling large-scale sensor data collection tasks.**

***Index Terms*—Internet of Things, Automated Guided Vehicle, Value of Information, Sensor Data Collection**

I. Introduction

In the era of Industry 4.0, a large number of automated guided vehicles (AGVs) are deployed in factories to assist in carrying out factory operations [1]. In addition to performing transportation tasks, AGVs often also serve as sensors to collect data, aiding in data transmission in areas with poor channel conditions [2], [3]. Traditional sensor data collection objectives aim to minimize the collection delay of sensor data or enhance the freshness of sensor information data, such as minimizing the age of information (AoI)[1] [4]. However, recent research indicates that data freshness alone cannot fully reflect the importance of sensor data for industrial tasks [5]. Drawing insights from new research in the field of network control, the *value of information* (VoI) metric is considered a novel indicator that more accurately reflects the impact of sensor data on upstream task performance [6]. VoI is defined as assigning a specific value to the information, representing the impact or importance of that information to a specific decision-maker in a particular system. Based on VoI, information gathering for control purposes has demonstrated superior performance compared to traditional strategies in terms of control accuracy and collection costs [5]–[8].

The VoI, as a novel metric, possesses characteristics fundamentally distinct from time delay. Studies suggest that VoI has a strong task correlation and non-linear variation over time [9], [10], presenting challenges for leveraging AGVs in assisting sensor data collection: minimizing VoI loss in sensor data fusion and AGV path planning. Due to limitations in sensor battery capacity, it is impractical for all sensors to simultaneously transmit data to the control center. Opting to fuse data from a subset of sensors for centralized transmission is undoubtedly a more economical approach [11]; nevertheless, sensor data fusion is accompanied by VoI loss. Furthermore, the path selection of AGVs can also result in varying degrees of VoI loss. Strategies to reduce VoI loss in collected sensor data have not been a primary focus in existing literature. Traditional data fusion methods and path planning algorithms struggle to achieve lower VoI loss, even when collecting the freshest sensor data and following the shortest AGV paths. Thus, the development of an effective sensor data collection strategy that minimizes VoI loss is crucial for optimizing the performance of upstream tasks that rely on sensor data collection.

In this paper, we introduce a novel collaborative AGV sensor data collection strategy that aims to minimize the loss of sensor data VoI. This strategy encompasses the selection of data fusion nodes, transmission mode selection, and AGV path planning. Specifically, we introduce a metric called structural value entropy, which evaluates the VoI loss after data fusion based on sensor data VoI and sensor network topology. This evaluation assists in determining transmission nodes and data fusion scopes. Subsequently, by formulating the minimum VoI collection loss problem and jointly considering the selection of fusion node transmission modes and AGV path planning, a metaheuristic algorithm based on ant colony optimization is designed to achieve the selection of transmission modes and the determination of AGV paths with low VoI loss. This approach not only reduces sensor energy consumption and

[1]AoI metric is defined as the time elapsed since the generation time of the last received information.

VoI loss but also demonstrates rapid convergence. The main contributions of this paper are summarized as follows:

1) An innovative sensor data fusion approach is proposed, based on structural value entropy, effectively reducing VoI loss in the data fusion process. Through precise control over the number of transmission nodes and the data fusion scope, this scheme maintains information integrity while significantly decreasing energy consumption in sensor data collection, thereby achieving an optimized balance between VoI and energy efficiency.
2) We propose an AGV-assisted sensor data collection scheme. This scheme, by optimizing data transmission modes and path planning, successfully minimizes VoI loss during data transmission. Notably, the chosen transmission modes and path-planning algorithms have swift convergence speed.
3) Simulation experiments underscore the efficacy of the proposed strategy in preserving VoI. Compared to baseline strategies, this approach demonstrates significant performance enhancements and maintains an acceptable convergence speed. These findings validate the efficiency and feasibility of the proposed strategy in managing extensive sensor data collection tasks.

The remainder of this paper is organized as follows: The system model is introduced in Section II. Sensor mode selection and the AGV path planning algorithm are discussed in Section III. Simulation results and analysis are presented in Section IV. The paper is concluded in Section V.

II. System Model and Problem Formulation

In the factory depicted in Fig. 1, several groups of sensing devices are dispersed, each group executing a sensing task in concert and geographically proximate to one another. Their internal nodes are interconnected via a wired network. The sensors are required to periodically transmit the data collected through a wireless channel to a control center for subsequent tasks.

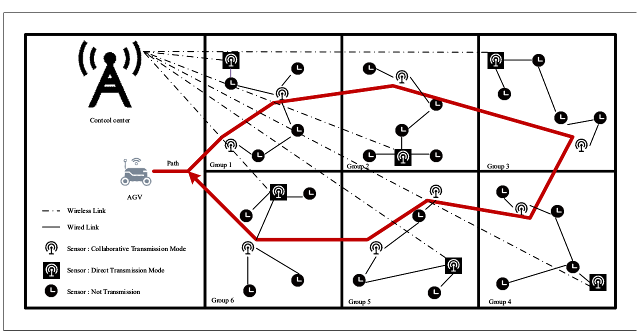

Fig. 1. AGV-assisted industrial IoT sensing data collection system model.

In the factory, it is supposed that there are N different groups of sensor devices, represented as $\boldsymbol{G} = \{\boldsymbol{G}_1, \dots, \boldsymbol{G}_N\}$. The graph $\boldsymbol{G}_n = (\boldsymbol{S}_n, \boldsymbol{E}_n)$ depicts the topological structure of the n^{th} group of sensor devices, where $\boldsymbol{S}_n$ denotes the set of nodes, and $\boldsymbol{E}_n$ represents the set of edges. The term $s_{n,m} \in \boldsymbol{S}_n$ refers to the sensor node m within the group n, with each group comprising a distinct number of sensor nodes connected by stable topological wired communication links for data fusion within the group.

The VoI of the data from the node m in the group n of sensor devices is designated by $v_{n,m}$, with the data size being measured in $c_{n,m}$ bits. According to the paper [9], the VoI highlights the impact of sensor data on the efficiency of task performance at a higher level. In this context, VoI is considered an inherent characteristic of sensor data, independently assessed by the sensor nodes and reported to the control center before the commencement of data collection tasks. Due to the specificity that VoI evaluation is dependent on particular upstream tasks, the detailed methodology for VoI evaluation is not discussed. It has been observed that the fusion of data from neighboring sensor nodes by any node within the n-th group leads to a reduction in the data VoI. This reduction, as discussed in the papers [7], [12], can be attributed to the requisite feature extraction in the fusion of multimodal data. This process inevitably results in some loss of information, thereby affecting the VoI of the fused data. The function $\hat{v}_{n,m} = f_n(\boldsymbol{G}_{n,m})$ represents the VoI changes after data fusion in node $s_{n,m}$, where $\boldsymbol{G}_{n,m}$ denotes the topological structure of neighboring nodes involved in the fusion process, and the function $f_n(.)$ represents a task-specific function related to the upstream tasks of sensor data and characteristic of each sensor device group. Furthermore, data transmission is also found to cause a loss in VoI, mainly due to transmission time delays. As described in the literature [8], the decline in VoI over time can be modeled using a negative exponential function as

$$v_t = v \times e^{-\alpha_n t}, \tag{1}$$

where v represents the original VoI, t the time spent in transmission, and α_n is the decay coefficient specific to the sensor VoI for particular tasks.

The set of nodes requiring AGV collaborative transmission is denoted as $\boldsymbol{S}_{AGV}$, and the set of edges representing the actual road within the factory is symbolized as $\boldsymbol{E}_{AGV}$. Together, nodes and edges constitute the AGV route map $\boldsymbol{G}_{AGV}$. Originating from a fixed starting point, the AGV traverses on a predefined path at a uniform speed, passing through nodes that require collaborative transmission, and returning to the starting point later. To simplify the analysis, it is assumed that the data collection cycles of all sensor nodes are synchronized. Following each data collection cycle, it is first necessary to perform data fusion (if required by the sensor device group) before initiating the data transmission. Sensors utilize orthogonal frequency bands, and both the transmission power P_S and allocated bandwidth B are fixed. The transmission rate from sensor $s_{n,m}$ to the control center can be calculated as

$$R^D_{n,m} = B\log_2(1 + SNR^D_{n,m}), \tag{2}$$

and $SNR^D_{n,m} = \frac{g^{DSC}_{n,m} l^{DSC}_{n,m} P_S}{\sigma^2}$, where $g^{DSC}_{n,m}$ denotes the Rayleigh small scale fading satisfying $g^{DSC}_{n,m} \sim \mathcal{CN}(0,1)$ and σ^2 denotes the noise power, the path loss $l^{DSC}_{n,m}$ is characterized using the multi-slope bounded path loss model (MBPM), which is computationally represented as

$$l_{n,m}^{DSC} = \mu_i (1 + (d_{n,m})^{\beta})^{-1}. \tag{3}$$

Within the framework of MBPM, the transmission distance is segmented into k segments which i-th segment denoted by D_i. The term $d_{n,m}$ in the formula represents the distance between the sensor and the control center, with the path loss exponent $\beta = \beta_i$ being applicable for distances within the range $D_i \leq d \leq D_{i+1}$. The variable μ_i signifies the cumulative effect of the overall losses incurred from the starting point up to the distance range of the i-th segment, and is calculated as

$$\mu_i = \prod_{j=1}^{i} \frac{1 + D_j^{\beta_j}}{1 + D_j^{\beta_{j-1}}}. \tag{4}$$

The sensor data transmission process assisted by AGVs is delineated into two distinct phases. Initially, in the first phase, sensors utilize a direct communication mode to transmit data directly to the control center. Upon the AGV's completion of its current data transmission task and when the distance between the AGV and the sensor falls below the predefined threshold D_c, the process transitions into the second phase, known as collaborative transmission mode. During this phase, sensors broadcast data while the AGV operates in a half-duplex mode. The AGV receives the sensor's broadcast signal, processes it, and then relays it. The control center receives both the original signals from the sensors and the enhanced signals from the AGV, employing maximum ratio combining techniques to fuse them and enhance the signal-to-noise ratio (SNR) of the received signal. As described in [13], the rate of collaborative transmission can be calculated as

$$R_{n,m}^{C} = \frac{1}{2} B \log_2 (1 + SNR_{n,m}^{D} + SNR_{n,m}^{C}), \tag{5}$$

$$SNR_{n,m}^{C} = \frac{g_{n,m}^{DSA} l_{n,m}^{DSA} P_S g_{n,m}^{C} l_{n,m}^{C} P_{AGV}}{\sigma^2 (g_{n,m}^{DSA} l_{n,m}^{DSA} P_S + g_{n,m}^{C} l_{n,m}^{C} P_{AGV})}, \tag{6}$$

where P_{AGV} represents the transmission power of the AGV, the $g_{n,m}^{DSA}$ and $g_{n,m}^{C}$ denote the Rayleigh small scale decays between the sensor and the AGV and between the AGV and the control center. Additionally, $l_{n,m}^{DSA}$ and $l_{n,m}^{C}$ correspond to the average path losses from the sensor to the AGV and from the AGV to the control center, respectively. To simplify the impact of AGV mobility on the changing channel conditions, we estimate the average path losses $l_{n,m}^{DSA}$ and $l_{n,m}^{C}$ based on the maximum collaborative distance threshold D_c, and the distance $d_{n,m}$ from the sensor to the AGV and from the AGV to the control center are calculated in the same way as Eq. (3). The direct transmission delay $T^D = \frac{C}{R^D}$, while the cooperative transmission delay $T^C = T^S + \frac{C - R^D T^S}{R^C}$, where T^S represents the time from the initiation of the transmission cycle to when the sensor engages in cooperative transmission with the AGV and C represents sensor data size.

Therefore, the problem of maximizing the VoI collected from sensors can be formalized as Problem 1, where Eqs. (7a - 7d) articulate the relationship between the optimization of AGV routes and the timing aspects of cooperative transmissions. Eq. (7a) identifies the time-related impacts of selecting certain transmission methods; Eq. (7b) quantifies the cooperative transmission time; Eq. (7c) based on the cooperation sub-graph with AGV path, iterating paths $\boldsymbol{\zeta}$ to build the mapping from AGV cooperative decision to the cooperation wait time; Eq. (7d) exposes the influence of sensor data fusion on the volume of data payloads.

Problem 1.

$$\max_{\boldsymbol{\eta},\boldsymbol{\delta},\boldsymbol{\theta},\boldsymbol{\zeta}} \sum_{n=1}^{N} \sum_{m=1}^{M} \eta_{n,m} \times (\delta_{n,m} v_{n,m} + (1 - \delta_{n,m}) \hat{v}_{n,m}) \times e^{-\alpha_n T_{n,m}}, \tag{7}$$

$$\text{where} \quad T_{n,m} = \theta_{n,m} T_{n,m}^{D} + (1 - \theta_{n,m}) T_{n,m}^{C}, \tag{7a}$$

$$T_{n,m}^{C} = T_{n,m}^{S} + \frac{C_{n,m} - R_{n,m}^{D} T_{n,m}^{S}}{R_{n,m}^{C}}, \tag{7b}$$

$$T_{n,m}^{S} = acc(G_{AGV}(G, \delta, \theta), \boldsymbol{\zeta}, s_{n,m}), \tag{7c}$$

$$C_{n,m} = \delta_{n,m} c_{n,m} + (1 - \delta_{n,m}) \hat{c}_{n,m}, \tag{7d}$$

$$\text{s.t.} \quad \eta_{n,m},\ \delta_{n,m},\ \theta_{n,m} \in \{0, 1\}, \tag{7e}$$

$$\boldsymbol{\zeta} = (\hat{s}_1, \cdots, \hat{s}_{\hat{n}}), \tag{7f}$$

$$\hat{s}_i \in \boldsymbol{S}_{AGV}, \forall i \in \{1, \cdots, \hat{n}\}, \tag{7g}$$

$$(\hat{s}_i, \hat{s}_{i+1}) \in \boldsymbol{E}_{AGV}, \forall i \in \{1, \cdots, \hat{n}\}, \tag{7h}$$

$$\sum_{n=1}^{N} \sum_{m=1}^{M} \eta_{n,m} \leq \eta_{max}. \tag{7i}$$

The optimization problem described above introduces three decision sets, where the decision variables, as indicated by constraint (7e) are binary integer decision variables. The set $\boldsymbol{\eta}$ is used to signify whether a sensor transmits data to the control center, where $\eta_{n,m} = 1$ indicates the node should transmit data, otherwise indicating that the node should either fuse data with other nodes or refrain from data transmission during the current cycle. The set $\boldsymbol{\delta}$ represents whether a sensor fuses data from neighboring nodes, with $\delta_{n,m} = 1$ indicating data fusion and 0 implying the node should only transmit its own data. The set $\boldsymbol{\theta}$ determines whether sensor transmission is assisted by AGVs, with $\theta_{n,m} = 0$ indicating the need for AGV-assisted transmission, and 1 meaning data is directly transmitted from the sensor to the control center. Furthermore, the AGV's path planning is represented by the list $\boldsymbol{\zeta}$ as the constraint (7f), where the number of nodes $\hat{n}$ in the path depends on the number of sensor nodes requiring AGV cooperation. Constraints (7g) and (7h) ensure that the nodes and edges in the AGV's path belong to the predefined node set $\boldsymbol{S}_{AGV}$ and edge set $\boldsymbol{E}_{AGV}$ of the AGV cooperative transmission sub-graph, respectively. Lastly, to preserve the battery life of sensor nodes and extend the overall network operational time, constraint (7i) restricts the maximum number of sensor nodes participating in transmission during each collection cycle, thereby safeguarding the longevity of the sensor network.

III. AGV-assisted sensory data collection strategy based on the VoI

Problem 1 involves a complex relation of interconnected decision variables, significantly complicating any direct attempt at a solution. This section proposes a methodical decoupling of these variables for problem 1 by breaking it down into two sub-problems: the fusion of sensory data and the determination of an appropriate transmission mode, each to be solved independently.

A. Data Fusion Strategy Based on Structural Value Entropy

We begin by examining the issue of sensor data fusion. To separate it from later decision-making, we gauge the VoI loss during sensor data transmission based on a fixed transmission rate, R. The sensor data fusion problem can be expressed as

Problem 2.

$$\max_{\boldsymbol{\eta},\boldsymbol{\delta}} \sum_{n=1}^{N}\sum_{m=1}^{M} \eta_{n,m}\times (\delta_{n,m}v_{n,m} + (1-\delta_{n,m})\hat{v}_{n,m}) \times e^{-\alpha_n T_{n,m}}, \tag{8}$$

$$s.t. \quad (7e), (7i).$$

However, in practice, since the fusion functions for the sensors are not shared with the control center, such as completing federated learning scenarios using sensor data [14], addressing this issue requires the center to estimate the VoI after fusing the data. Leveraging the stationary nature of sensors in the IIoT, the center can pre-emptively understand the topological information to evaluate the trend of data VoI after fusion. At this juncture, we introduce the notion of structural value entropy (SVE), which is an adaptation of local structure entropy (LSE) from graph theory, calculated as

$$H_i = -VD_i(\sum_{j=1}^{N_i} p_{ij}\log_2 p_{ij} + \frac{2\lambda Tr_i}{k_i(k_i-1)}), \tag{9}$$

$$p_{ij} = \frac{VD_i}{\sum\limits_{j=1}^{N_i} VD_j}, \tag{10}$$

where H_i represents the SVE of a node i, equivalent to node $s_{n,m}$ referenced earlier. The probability that a node i fuses sensory data from node j is given by p_{ij}. Tr_i counts the triangular closures involving node i and its neighboring nodes. N_i is the set of node i's immediate neighbors, k_i is its degree, and VD_i is its VoI weighted degree, expressed as $VD_i = \sum_{j\in N_i} v_j$. Formula $\frac{2\lambda Tr_i}{k_i(k_i-1)}$ represents the clustering coefficient, reflecting a node's irreplaceability: a lower coefficient indicates higher irreplaceability, hence a larger structural value entropy. Employing these indices, the sensor data fusion problem can be addressed via a greedy algorithm which optimizes the SVE as algorithm 1.

Algorithm 1 Sensor Data Fusion and Transmission Strategies

Input: sensor set $\boldsymbol{S}$, sensor VoI set $\boldsymbol{V}$, η_{max}.
Output: $\boldsymbol{\eta}$, $\boldsymbol{\delta}$.
Initial transmission rate R, $\boldsymbol{\eta} = \mathbf{0}$, $\boldsymbol{\delta} = \mathbf{0}$.
Calculate VoI weighted degree and SVE in G.
for i in $\boldsymbol{S}$ **do**
    $T_i = \frac{c_i}{R}$, $\hat{T}_i = \frac{\sum_{j\in N_i} c_j}{R}$
    if $H_i e^{T_i} > v_i e^{Ti}$ **then**
        $\delta_i = 1$
        $v_i = H_i$, $T_i = \hat{T}_i$
    end if
end for
D = New Dictionary(key=$\boldsymbol{S}$, value=$\boldsymbol{V}$)
$D.sort()$ based on value
$\eta_{num} = 0$
for i in $D.key$ **do**
    if $\eta_{num} \le \eta_{max}$ **then**
        $\eta_i = 1$
        $\eta_{num} = \eta_{num} + 1$
    end if
end for
return $\boldsymbol{\eta}$, $\boldsymbol{\delta}$

B. Transmission Mode Selection and AGV Path Planning Based on the VoI

Once the sensor data fusion scheme is determined, the original problem is reformulated as follows:

Problem 3.

$$\max_{\boldsymbol{\theta},\boldsymbol{\zeta}} \sum_{k\in \boldsymbol{S}_{Tr}} v_k \times e^{-\alpha_k(\theta_k T_k^D + (1-\theta_k)T_k^C)}, \tag{11}$$

$$s.t. \quad (7e), (7f), (7g), (7h).$$

$\boldsymbol{S}_{Tr}$ represents the set of sensor nodes to be transmitted, and v_k is the VoI after δ and θ are determined. For this problem, we further decompose it into two sub-problems: transmission mode selection and AGV path planning, and solve them in an interleaved iterative method as algorithm 2.

Algorithm 2 Alternate Iterative

Initialize: AGV-to-sensor time set $\boldsymbol{T}$, $\boldsymbol{S}_{Tr}$, Sensor channel status set $\boldsymbol{g}$.
while true **do**
    $\boldsymbol{S}_{AGV}$ = ALGORITHM 3($\boldsymbol{T}$, $\boldsymbol{S}_{Tr}$, $\boldsymbol{g}$)
    $\boldsymbol{T}_{new}$, $\boldsymbol{\zeta}$ = ALGORITHM 4($\boldsymbol{S}_{AGV}$)
    if Termination conditions is True **then**
        break
    end if
    $\boldsymbol{T} = (1-\omega)\cdot \boldsymbol{T} + \omega \cdot \boldsymbol{T}_{new}$
end while

In the above formulation, $T_i \in \boldsymbol{T}$ is an estimate of the true value T_i^S, initialized based on the distance between the sensors and the AGV starting point, and continuously refined through interleaved iterations, ω is a soft update parameter.

The transmission mode selection sub-problem is a 0-1 integer nonlinear programming problem that can be solved using the VoI greedy strategy as algorithm 3.

Algorithm 3 Transmission Mode Selection

Initialize: $\boldsymbol{\theta} = \mathbf{1}$
for i in $\boldsymbol{S}_{Tr}$ **do**
    $T_i^S = T_i$
    Get T_i^C, T_i^D based on (7a) and (7b)
    if $T_i^C \leq T_i^D$ **then**
        $\theta_i = 0$
    end if
end for
Return: $\boldsymbol{S}_{AGV}$ based on $\boldsymbol{\theta}$.

The problem of AGV path planning is a variant of the travelling salesman problem (TSP), which can be solved using the ant colony optimization (ACO) algorithm. The basic idea of the ACO algorithm is to map the problem to be solved into a graph problem in graph theory, simulating the search behavior of ants in the solution space. Ants select the direction of the next move during the search process based on the concentration of pheromone and heuristic factor, achieving a balance between global search and local search. In this problem, the heuristic factor q_{ij}, the transition probability p_{ij}, and the pheromone update formula are set as

$$q_{ij} = v_i \cdot e^{-\frac{d_{ij}}{vel}}, \tag{12}$$

$$p_{ij}^{ACO} = \frac{(\tau_{ij})^{\gamma_1} \cdot (q_{ij})^{\gamma_2}}{\sum_{k \in N_i} (\tau_{ik})^{\gamma_1} \cdot (q_{ik})^{\gamma_2}}, \tag{13}$$

$$\tau_{ij} = (1 - \rho) \cdot \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^k. \tag{14}$$

Here, vel is the travel speed of the AGV, τ_{ij} represents the concentration of pheromone on the path from node i to node j, ρ is the pheromone evaporation coefficient, $\Delta\tau_{ij}^k$ is the amount of pheromone released by the k-th ant on the path from node i to node j. γ_1 and γ_2 are parameters controlling the weight of pheromone and heuristic factor in the selection probability. N_i represents the set of all unvisited nodes that can be transitioned from node i. The ACO algorithm can be summarized as algorithm 4.

Algorithm 4 Path Planning

Initialize pheromone trails.
Set best path $\boldsymbol{\zeta}$ to an empty tour.
for $iteration = 1$ **to** $iterations$ **do**
    for each ant i **do**
        Initialize ant i at AGV starting point.
        while unvisited nodes remain **do**
            Calculate probabilities of moving to unvisited nodes.
            Select the next node based on probabilities based on Eq. (13).
            Move ant to the selected node.
            Update pheromone trails based on Eq. (14).
        end while
        Calculate tour VoI of ant i.
        if VoI $>$ VoI of $\boldsymbol{\zeta}^*$ **then**
            Update best tour $\boldsymbol{\zeta}^*$.
        end if
        Return ant i to start node.
    end for
    Update pheromone trails globally.
end for
Calculate $\boldsymbol{T}_{new}$ based on $\boldsymbol{\zeta}^*$ and (11)
Return best tour $\boldsymbol{\zeta}^*$, $\boldsymbol{T}_{new}$.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
AGV Transmit Power P_{AGV}	20 dBm
Sensor Transmit Power P_S	10 dBm
Attenuation Coefficient α_n	0.002
Corner Distance $[D_0, D_1, D_2, D_3]$	[0, 50, 110]
Path Loss Exponent $[\beta_0, \beta_1, \beta_2]$	[2.8, 3.4, 4]
Noise Power σ^2	-42 dBm
Bandwidth B	180 kHz

IV. SIMULATION RESULTS AND DISCUSSION

The simulation is conducted in a factory setting covering an area of 200 meters by 200 meters. The distribution of sensors follows a Poisson point process, and the AGV commences its journey from the coordinates (0, 25). The AGV travels at a speed of 2 meters per second. The sensor data size C follows a Poisson distribution with a mean of 200 Kbits. Other parameters are summarized in the TABLE I. The fusion of VoI has been stratified into three forms: zero-order fusion, first-order fusion, and second-order fusion. The definitions of each form of fusion are as

$$f_{n,m} = \begin{cases} \max_{i \in N_m} \{v_1, \cdots, v_i, \cdots\}, \\ \sum_{i \in N_m} \psi_i \cdot v_i, \\ \sum_{i \in N_m} \psi_i \cdot (\sum_{j \in N_i} \epsilon_j \cdot v_j). \end{cases} \tag{15}$$

The order of the fusion function indicates the range of sensor fusion and the fusion functions for different sensor groups are randomly selected.

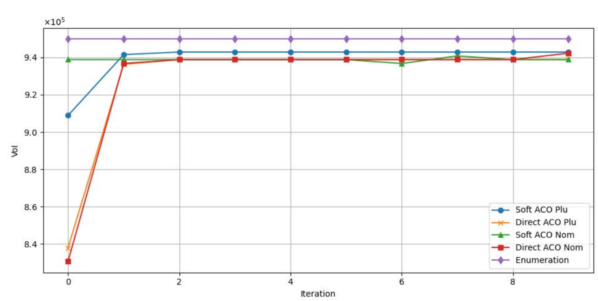

Fig. 2. Convergence speed and VoI comparison plots for the four algorithms.

As illustrated in Fig. 2, we first validate the convergence of our algorithm, by comparing it with four different algorithms to demonstrate the effectiveness of our proposed approach.

Soft ACO Plu denotes our proposed algorithm; Direct ACO Plu lacks the soft update mechanism and is otherwise identical to Soft ACO Plu; Soft ACO Nom lacks an improved heuristic factor for the ant colony algorithm; Direct ACO Nom removes both the soft update mechanism and the use of the improved heuristic factor. Notably, we used an enumeration method to represent the maximum VoI harvested. It is observable that, notwithstanding the eventual near-optimal performance of all four algorithms, the one equipped with a soft update mechanism and improved heuristic factor is able to achieve faster convergence while collecting the maximum VoI closest to that obtained by the enumeration algorithm.

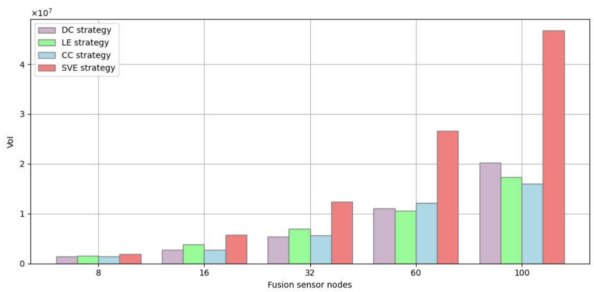

Fig. 3. Comparison of the effectiveness of fusion node selection: SVE Strategy Vs. DC, LE(LSE), and CC Strategies.

For a comparative analysis of the effect of the SVE for choosing fusion nodes, we first obtained the fusion nodes by node evaluation methods of SVE, Degree Centrality (DC), Local Structure Entropy (LSE), and Clustering Coefficient (CC) respectively; subsequently, we calculated the actual VoI after fusion of these groups of nodes. As depicted in Fig. 3, experimental results suggest that the SVE strategy is more effective than the conventional methods mentioned above in the assessment of fusion nodes. The selection of fusion nodes ensures the value of data collection while reducing the working scale of sensors, thereby effectively diminishing the energy consumption of sensor data collection.

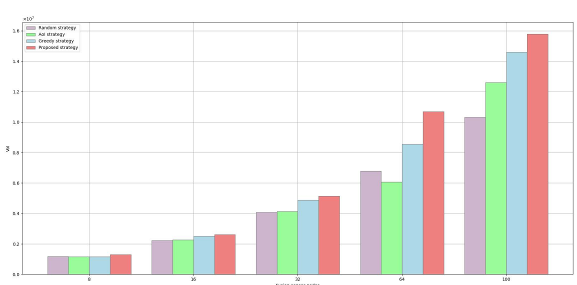

Fig. 4. Comparison of VoI collection under different sensor sizes: Proposed Strategy Vs. Strategies Based on Random, AoI, and Greedy Selections.

Fig. 4 showcases the preservation capacity of VoI in sensor data collection tasks by our proposed algorithm, considering different scales of fusion nodes. The abscissa represents the number of fusion nodes, while the ordinate quantifies the VoI obtained by transmitting the sensor data after selecting the co-transmission nodes using different strategies among the fusion nodes. The outcome reveals that as the scale of fusion nodes escalates, our proposed strategy results in lower VoI loss, capturing a greater extent of VoI.

V. Conclusion

This paper addresses the minimization of VoI loss during sensor data collection in the context of the IIoT, proposing an innovative AGV-assisted data collection strategy. Simulation results confirm that, while preserving VoI, the strategy demonstrates superior convergence speed over traditional methods, proving its efficiency and practicality in complex settings.

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