

Decentralized node selection approach for load-balanced data collection in photovoltaic monitoring systems

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Abstract—Solar panels are widely used in modern energy management systems as a key renewable energy source. However, their stochastic behavior necessitates performance monitoring to ensure their reliable operation. Wireless Sensor Networks (WSNs) provide an effective and scalable solution for real-time monitoring of solar panels, enabling efficient data acquisition, analysis, and fault detection. Despite their advantages, WSNs face different challenges affecting the longevity and the maintenance of the network. In solar panels monitoring applications, similar panel behavior leads to similar data transmission among sensor nodes. Such redundant data transmissions result in unnecessary communication overhead, increased energy consumption and accelerated depletion of node resources, thereby reducing the overall lifetime and efficiency of the network. Consequently, this work focuses on a decentralized sensor node selection approach, where a subset of nodes is selected for transmission. In this approach, a sensor node is able to locally decide whether to transmit or not, without inter-node coordination, by combining four metrics into a single score, reflecting its eligibility to participate in the transmission process. The results have shown an improved network performance across network densities of 15 and 30 nodes, with packet delivery ratio improvements of 12.8% and 21.8%, and end-to-end delay reductions of 47% and 56.6%, respectively.

Index Terms—Wireless Sensor Networks, Decentralized Decision Making, Weighted Sum, Node Selection.

I. INTRODUCTION

Monitoring solar panels is essential in energy management systems, to ensure their efficient operation and to understand their performance [1]. Wireless Sensor Networks (WSN) have been widely adopted as an efficient solution for real-time monitoring in various environments, including solar energy systems [1]. Deploying sensor nodes on individual solar modules enables per-panel productivity monitoring, and the early detection of potential faults. In practice, solar panels are installed over building rooftops, resulting in a large-scale network of solar modules and sensor nodes. In our scenario, we consider a WSN deployed for monitoring solar panels. Each solar module is equipped with a battery-powered sensor node, collecting module based parameters, such as current, voltage, module temperature and dust accumulation. Data collection is performed periodically through a multihop transmission to the destination. However, solar panels installed under shared environment tend to have a similar performance [2], and therefore generate spatially redundant data, as illustrated in Fig. 1. The periodic transmission of this redundant

data increases communication overhead, overloads the network with redundant transmission, and accelerates energy depletion of the battery powered nodes. As a result, this will degrade the network performance and reduce the overall network lifetime. This problem is even more critical in the context of Green IoT, where the main objective is the development of environmental friendly IoT applications, such as the Green WSN (GWSN). They focus on enhancing the network performance, and reducing the energy consumption, by reducing the redundant data transmissions [3].

One of the solutions is to periodically select a subset of nodes for transmission, rather than requiring all nodes in the network to transmit data periodically. However, centralized selection strategies require frequent information exchange and centralized processing, which increases communication overhead and energy consumption [4]. Decentralized strategies reduce the need for central control, but they may still require coordination among neighboring nodes to share selection decisions [5]. This leads to the following research question: *Can a sensor node autonomously decide whether to transmit or not using only local information, without coordinating with neighboring nodes? Can this approach reduce energy consumption, minimize overall transmissions, improve network efficiency, and still ensure a reliable end-to-end packet delivery?* In this paper, we propose a lightweight autonomous node selection approach based on the weighted sum method. Each node periodically computes an eligibility score using four locally measurable metrics: energy level, silence period, retransmission ratio, and relay factor. This score allows the node to decide whether to transmit its collected data while considering its own local state. The main contributions of this paper are twofold:

- The definition of four local metrics that allow each sensor node to evaluate its eligibility for data transmission. These metrics are chosen because they capture key local aspects affecting transmission suitability. The energy level metric reflects the remaining battery capacity, while the silence period metric prevents the same nodes from transmitting repeatedly. The retransmission ratio captures the node's recent retransmission behavior, and the relay factor accounts for its forwarding load.
- A decentralized node selection approach, that enables

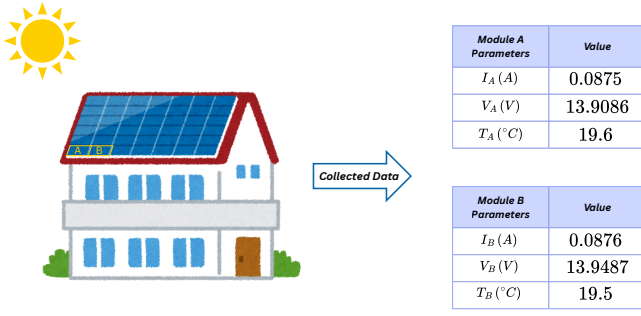


Fig. 1. Spatial data similarity among sensor nodes during a single period

each sensor node to decide whether it must transmit its collected data or not, without coordinating with other nodes.

We performed simulations using OMNET++, and the results show an improvement in terms of packet delivery ratio, and end-to-end delay, in addition to the reduction of energy consumed for data transmissions. Fairness index was also measured to evaluate how evenly the sent packets were distributed among the nodes. Furthermore, our approach minimized the transmission of redundant information, by distributing communication tasks across sensor nodes. The rest of the paper is organized as follows: Section II provides an overview of the different node selection techniques. Section III describes our network architecture, and in Section IV, the spatial redundancy in solar systems is discussed. In Section V, our proposed selection approach is described, and the simulation results are presented in Section VI. Finally, Section VII concludes the paper while highlighting future work.

II. RELATED WORKS

Node selection in WSN consists of selecting specific nodes within the deployed ones, to efficiently organize and maintain the network. This process can be applied for different purposes, such as selecting nodes for data transmission, or for routing objectives. Selections can be carried out based on a single metric, or a combination of different metrics, in both centralized and decentralized manners.

A. Centralized node selection approaches

Centralized node selection approaches relies on a central decision making unit to perform the decision making, after collecting the needed information from the deployed sensor nodes. Authors in [6] proposed a node selection mechanism, Energy-Aware Matrix Completion-based data gathering approach (EAMC), in order to improve the energy efficiency in wireless sensor networks. The method combines inter-node data correlation with residual energy information in a cost function for selecting transmitting sensor nodes at the sink. A correlation based sensor node selection has been also developed in [7]. It consists of correlated regions where sensor node selection algorithm is applied to reduce redundant transmissions from nearby nodes. Correlated regions are identified

through overlapping coverage areas, and the selection algorithm favors nodes with higher energy levels. To reduce energy consumption during periodic real-time data collection in clustered WSNs [8], the authors propose alternating nodes between active and sleep modes based on spatio-temporal correlation and residual energy. The cluster head identifies correlated nodes using spatial distance and measurement similarity, then selects active nodes according to their coverage capability and energy level. This approach reduces redundant transmissions by allowing only selected nodes to remain active. Authors in [9] proposed a centralized linear combination of three metrics to compute a node's potential for selection as an energy efficient forwarding node. These methods are effective in limiting transmissions to selected nodes, thereby reducing overall energy consumption, however their centralized nature increases network overhead due to the required additional information exchange.

B. Decentralized Node Selection Approaches

In decentralized node selection approaches, sensor nodes collaboratively participate in the decision-making process. Pearson Data Correlation and Prediction (PDCP), a data reduction algorithm introduced in [10], is another sensor node selection approach that relies on correlation and energy level. Each node makes its own decision based on its energy level and the correlation with neighboring nodes, selecting the node with the highest residual energy when high correlation is observed. Although PDCP avoids extra control packets by piggybacking the required information on Hello messages, incorporating additional selection metrics would increase packet size and communication overhead. Reinforcement learning (RL) for cooperative computing and sleep scheduling has been introduced in [11]. By formulating cooperative node selection as a multi-agent Q-learning problem, their approach balances energy consumption across the network and maximizes the number of completed events. A scoring based routing protocol has been introduced in [5], where each node is ranked based on the combination of different metrics, including energy level, ETX, to form a score. The information required to compute this score is exchanged between a node and its one-hop neighbors, allowing each node to maintain awareness of its neighbors states and to select the forwarder with the highest score. A relay node selection scheme for WBSN was proposed in [12] to reduce sensor energy consumption. The authors formulated relay selection as a multi-criteria decision-making problem using AHP and TOPSIS, considering metrics such as residual energy, traffic load, neighborhood size, SNR, hop distance, node criticality, and node location. These parameters are exchanged between neighboring nodes through Hello control messages using Carrier Sense Multiple Access (CSMA). While existing approaches adopt decentralized selection, they typically require inter-node information exchange to coordinate decisions and share selection outcomes. In our work, a decentralized node selection approach that enables each sensor node to autonomously decide whether to transmit is proposed. This mechanism operates without coordination or

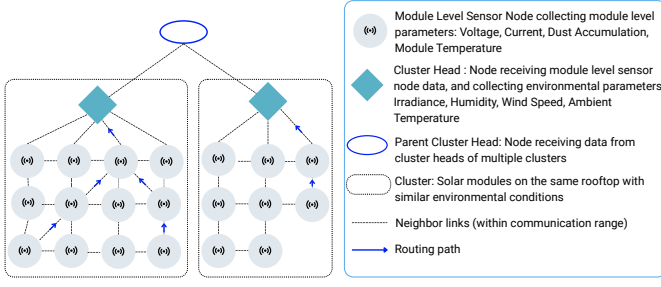


Fig. 2. Network architecture

information exchange among neighboring nodes, by relying on local metrics that reflect the transmission state of each node.

III. NETWORK ARCHITECTURE

Solar panels that are installed within the same area are subject to similar environmental conditions, such as meteorological state and obstacles, and can be geographically grouped into clusters that share the same environmental conditions. Accordingly, as described in Fig. 2, our architecture is based on a clustered environment, where each solar panel is equipped with one sensor node to collect data. We suppose then that N sensor nodes are deployed within each cluster. Each sensor node periodically collects module level parameters such as the current and the voltage being produced, the dust accumulation as well as the module temperature, and forwards them towards the cluster head via a multihop transmission. While cluster heads receive module-level data, they also collect environmental parameters, such as the irradiance, humidity, wind speed and temperature.

IV. DATA REDUNDANCY IN SENSOR BASED SOLAR MONITORING SYSTEMS

In sensor based solar monitoring system, a periodic data collection allows the system to continuously track the operating state of each solar module and capture both gradual and sudden performance variations. Since the panels exhibit similar performance within the same area, this leads to the periodic collection of redundant information. However, variations can still arise from different types of changes affecting the photovoltaic modules. We can distinguish two types of changes that may occur in solar panels: physical changes at the level of a single PV module, such as cracks or degradation, and environmental changes affecting a group of solar panels, such as cloud movement or shading [13]. From a spatial perspective, these changes can be classified as local changes, which occur at an individual module, and global changes, which affect a set of modules. Local changes may indicate abnormal behavior or faults in a specific module, whereas global changes usually affect several modules simultaneously. As a result, global changes may lead to similar performance variations across multiple panels, thereby preserving spatial redundancy among the sensed data. In this work, the resulting redundancy is considered from a spatial perspective, where different sensor nodes transmit similar information during the same reporting

period, rather than from a temporal perspective, where a single node repeatedly reports similar values over time. Although temporal redundancy exists in periodic transmissions, addressing redundancy from a temporal perspective does not eliminate redundancy across the network, as similar information may still be transmitted simultaneously by multiple neighboring nodes.

V. THE PROPOSED NODE SELECTION APPROACH

While transmission is affected by several network conditions, additional aspects related to the sensor node's operation and activity need to be considered. We primarily focus on locally available metrics, with low computational complexity that can be calculated by each node.

A. Decision making process

Before making a decision, a node must first compute a score that reflects its transmission eligibility, emphasizing its ability to successfully complete a data transmission. The score is calculated using the weighted sum method, that consists of combining multiple objectives by assigning a weight to each one, to reflect its importance in the overall score calculation [14], [15]. The weighted sum function is defined as in (1), where n represents the number of decision making metrics, w_i represents the weight associated to the i^{th} metric, and s_i represents the value of the i^{th} metric. The metrics that we considered in our study will be further explained in Section V-B. After calculating the score, each node will compare it to a specific threshold in order to decide whether it transmits its own data or not. The threshold value represents the minimum eligibility score for transmission, determined by the combined strength of the weighted metrics. Its value was determined experimentally by evaluating the effect of different values on the selection.

$$\text{Score} = \sum_{i=1}^n w_i s_i, \quad \text{with} \quad \sum_{i=1}^n w_i = 1 \quad (1)$$

B. Decision making parameters

In this section, the four selection metrics are presented: energy level, silence period, retransmission ratio and relay factor. Each metric represents a specific aspect of the sensor node, without requiring global network knowledge or additional communication overhead. The energy level of a sensor node is a key indicator of the node's capacity in performing data transmissions. However, additional metrics reflect as well how a node has performed in previous transmissions, such as the relay factor and the retransmission ratio. A high number of retransmissions may indicate instability or poor link quality, while the relay factor reflects the node's usage in forwarding data. Additionally, to reduce the number of successive transmissions among nodes, the silence period of a node is considered as well. Together, these four metrics provide a representation of the main trade-offs involved in transmission selection: energy preservation, fairness among nodes, link reliability, and load balancing.

- **Node Energy Level:** Residual energy is an important factor because it indicates whether the node has enough energy to participate in transmission. This metric represents the remaining energy fraction of the sensor node and is defined as the ratio of the remaining energy level of the node to its initial energy level.
- **Silence Period:** Repeated transmissions by the same node may accelerate energy depletion and lead to an unbalanced load distribution. This metric quantifies how recently a node last transmitted, penalizing recent consecutive transmissions while promoting fairness among the nodes. A sensor node can be silent for a specific maximum period of time, after which it is required to transmit its collected data, to ensure its availability. This metric is calculated according to (2), where t represents the current transmission time, t_{last} represents the last transmission time of the node, and t_{max} the maximum silence time.

$$TX = \begin{cases} 1, & \text{never transmitted} \\ 0, & \text{transmitted in the previous period} \\ \frac{(t - t_{\text{last}})}{t_{\text{max}}}, & \text{otherwise} \end{cases} \quad (2)$$

- **Retransmission Ratio:** Link reliability is a key factor in determining whether a node can transmit successfully, as poor link quality can increase the likelihood of retransmissions. If a node exhibits a high number of retransmissions, this reduces its possibility of being selected. This metric is used for this evaluation, and is calculated as follows:

$$RTX = \begin{cases} 1, & \text{never retransmitted} \\ \frac{R_P}{T_P}, & \text{otherwise} \end{cases} \quad (3)$$

where R_P is the number of all retransmission attempts done by the node, including retransmission of forwarded packets, and T_P is the number of all transmission attempts completed by the node, including transmissions of locally originated packets, retransmissions, and forwarded packets.

- **Relay Factor:** In the context of a multihop transmission, a sensor node may play a dual role by transmitting its own sensed data while also forwarding data received from neighboring nodes. When a node has a high relay load, this reduces the likelihood of being selected, avoiding additional transmission overhead. This metric is used for this evaluation, and is calculated as follows:

$$RelayFactor = \begin{cases} 1, & \text{not a relay node} \\ \frac{F_P}{T_P}, & \text{otherwise} \end{cases} \quad (4)$$

where F_P is the number of packets received from other sensor nodes, and forwarded by the node towards the CH, and T_P is the number of all transmissions attempted by

TABLE I
WSN CONFIGURATION PARAMETERS USED FOR SIMULATION IN OMNET++.

Parameter	Value
Routing Protocol	DSDV
Period	300s
Communication Technology	802.15.4
Bit rate	250 Kb/s
Deployment Model	Grid
Grid Size	$m \times n$
Metric Weight	0.25
Confidence Interval (CI)	95%
Number of Runs	30
Simulation Time	18000s

the node, including transmissions of locally originated packets, and forwarded packets.

VI. SIMULATION AND RESULTS

Simulations were performed using OMNeT++ simulator [16] [17] with the INET framework [18] to evaluate the proposed approach. INET is an open source library implemented in OMNET++ environment, that offers protocols and models for wired and wireless networks. The WSN is configured according to the parameters in Table I, where each node is communicating with a cluster head via a multihop transmission. The transmission decision is made periodically at each transmission interval, where each sensor node computes its score to assess its eligibility for transmission. During the first decision making period, nodes have very close energy levels and similar values for the remaining metrics, leading to nearly equivalent scores. To address this, we introduced a randomized mechanism where each node generates a random value in the interval $[0,1]$, and then transmits if the value is lower than a predefined probability p . The selection is performed independently of the selection metrics at this stage.

We consider the following two scenarios in our study:

- Scenario 1: A baseline scenario in which all sensor nodes periodically transmit data.
- Scenario 2: A selective transmission scenario in which the proposed node selection mechanism is applied. We used an equal weights distribution for all the metrics to maintain a balanced contribution among them, without prioritization.

We implemented our method on two network densities, 15 and 30 nodes. Nodes are deployed in a grid topology of size $m \times n$, where m represents the number of rows and n represents the number of columns. We compared both scenarios using the following performance metrics: network fairness, packet delivery ratio (PDR), end-to-end delay and energy consumption. Additionally, we evaluated the effect of different score threshold values on the selection approach through simulations.

A. Threshold sensitivity analysis

The threshold value in the proposed selection approach represents the eligibility of a sensor node to participate in

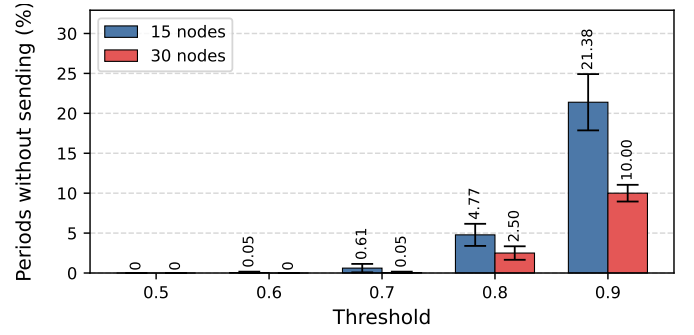
TABLE II
PERFORMANCE METRICS COMPARISON

Scenario	Nodes	PDR [95% CI]	Delay (ms) [95% CI]
Baseline	15	0.834 [0.829, 0.839]	190.782 [188.868, 192.696]
Selective	15	0.941 [0.936, 0.946]	101.381 [98.904, 103.858]
Baseline	30	0.733 [0.729, 0.736]	489.688 [486.172, 493.204]
Selective	30	0.893 [0.887, 0.899]	212.699 [209.512, 215.886]

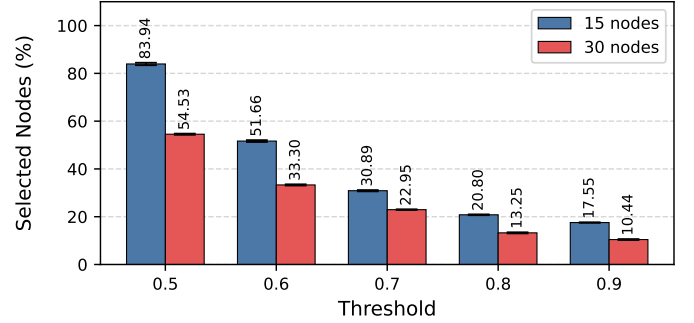
the transmission process. It influences both the nodes selected for transmission and the total number of transmissions carried out in the network. Accordingly, we compared threshold values ranging from 0.5 to 0.9 to evaluate their impact on the selection process in terms of two evaluation metrics: the average number of selected nodes per period and the average number of periods in which no node was selected. The first metric reflects the ability of the selection approach to reduce redundant transmissions, while the second indicates whether the threshold is too restrictive and may prevent data reporting in some periods. The experimental results are shown in Fig. 3. As the threshold value increases, the percentage of periods in which no node is selected also increases, while the percentage of selected nodes decreases. This confirms that higher threshold values reduce redundant transmissions but may also increase the occurrence of periods with no data transmission, particularly at threshold values of 0.8 and 0.9. For a threshold value of 0.6, the percentage of periods with no selected node remains very low, reaching only 0.05% for the 15 nodes network and 0% for the 30 nodes network. However, increasing the threshold to 0.7 further reduces the percentage of selected nodes from 51.66% to 30.89% for the 15 nodes network and from 33.30% to 22.95% for the 30 nodes network, while keeping the percentage of periods with no transmission relatively low, namely 0.61% and 0.05%, respectively. In comparison, the threshold value of 0.7 represents a good trade-off between reducing redundant transmissions and maintaining node participation, as it decreases redundant data while keeping the percentage of periods with no transmission relatively low. This value was therefore chosen for our simulations.

B. Network fairness and load balancing

The proposed selection approach dynamically alternates among the selected nodes, introducing a load-balancing effect across the network. A sensor node is selected when it satisfies the minimum eligibility score. As a result, data transmission is distributed among different nodes rather than being assigned to the same subset of nodes. This helps improve network fairness and prevents excessive transmission load on specific sensor nodes. The network fairness is a metric that indicates whether the packets received at the destination are fairly distributed among the sensor nodes that participate in transmission [19]. It is computed as $\frac{(\sum_{i=1}^N r_i)^2}{N \times \sum_{i=1}^N r_i^2}$, where r_i is the average rate of packets delivered from the i^{th} sensor, and N is the total number of sensors [20]. The fairness value ranges between 0 and 1, where a value closer to 1 indicates a fairer distribution



(a) Average percentage of periods with no selected node



(b) Average percentage of selected nodes per period

Fig. 3. Impact of threshold values on the average percentage of periods with no selected node and the average percentage of selected nodes per period.

of transmissions among sensor nodes. Accordingly, fairness values of 0.91 and 0.92 were observed for the 15 nodes and 30 nodes networks, respectively. These results show that the proposed approach fairly selects nodes for transmission and distributes the transmission load across the network rather than concentrating it on a limited subset of nodes.

C. Energy consumption

Using INET's radio state energy consumption model, the energy consumption is calculated as $\Delta t \times P_{\text{cons}}$, where P_{cons} is the power consumption, and Δt is the time interval since the last energy update. As illustrated in Fig. 4, the total network energy consumption, including the energy used for both data packet transmission and reception, decreases when the selection mechanism is applied, for both network densities. Compared to the baseline scenario, enhancements of 68% and 75% are observed for 15 and 30 nodes respectively. This is primarily due to the reduction in the number of transmissions performed by each node, compared to the baseline scenario where each node periodically transmits data packets.

D. PDR and delay

In the baseline scenario, each node performs 60 transmissions during one simulation. This results in a total of 900 packets in the 15 nodes network and 1800 packets in the 30 nodes network. After applying the selection approach, the average number of transmitted packets decreases to 278 and 413, respectively, thereby reducing the redundancy of information transmitted toward the CH. As shown in Table

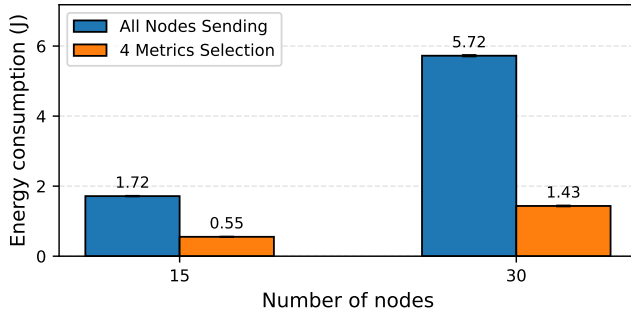


Fig. 4. Average total network energy consumption for data packets

II, the PDR increased to 94.1% in the 15 nodes network, and 89.3% in the 30 nodes network, corresponding to an improvement of 12.8% and 21.8%, respectively, compared with the baseline scenario for both network densities. This improvement is not solely due to traffic reduction during each decision making period, but rather to the proposed metric-driven scoring approach, which evaluates the node's retransmission risk together with additional selection metrics to guide the selection process, such as the energy level, the silence period and the relay factor. Furthermore, the observed end-to-end delay has decreased to 101.381 ms for the 15 nodes network, and 212.699 ms for the 30 nodes network after applying the node selection mechanism, corresponding to 47% and 56.6% improvement, respectively. In the baseline scenario, all nodes transmit periodically, regardless of their distance to the destination. As a result, a packet sent by a distant node may pass through relay nodes that are also transmitting their own data packets, increasing the queuing time before the packet is forwarded. In the selection approach, incorporating the relay factor allows to reduce the transmission load of a relay node, in addition to the remaining metrics considered, by favoring alternative nodes. This decreases the queuing time required for packet forwarding.

VII. CONCLUSION AND FUTURE WORKS

In this paper, we have presented our approach of a decentralized sensor node selection in a WSN applied for monitoring solar panels. The proposed approach consists on combining different metrics to compute a score for each sensor node, representing its eligibility in participating into the transmission process. In that manner, autonomous decision making is enabled on the sensor node level, without inter-node coordination. The results show that this decentralized method was able to effectively enhance the network performance and reduce the energy consumed for data transmission, while introducing a load balanced data transmission approach. For future work, we intend to extend the proposed method to account not only for spatial redundancy among sensor nodes, but also for local temporal changes observed at each individual node, such as the local faults. Moreover, we aim to improve our method by refining how the selection metrics weights are determined.

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