

Evaluating Heterogeneous and Homogeneous Sampling for Energy-Accuracy Trade-Offs in Multi-Sensor IoT Systems

Kammery Tagat
Faculty of Computer Science and
Information Technology (FCSIT)
Universiti Malaysia Sarawak
(UNIMAS)
Kuching, Malaysia
23020157@siswa.unimas.my

Lau Sei Ping
Institute of Social Informatics and
Technological Innovations (ISITI)
Universiti Malaysia Sarawak
(UNIMAS)
Kuching, Malaysia
splau@unimas.my

Tan Chong Eng
Institute of Social Informatics and
Technological Innovations (ISITI)
Universiti Malaysia Sarawak
(UNIMAS)
Kuching, Malaysia
cetan@unimas.my

Abstract—Energy-constrained Internet of Things (IoT) nodes commonly use homogeneous sampling, where all sensors operate at the same fixed intervals. This often leads to inefficient energy utilization and suboptimal sensing accuracy because it does not account for the different temporal characteristics of individual sensors. This limitation highlights the need to adopt adaptive strategies capable of accounting for sensor-specific behaviours. This paper investigates the energy accuracy trade-off of optimized homogeneous and heterogeneous sampling strategies using Greedy and Random Search methods. Experimental results show that both optimized samplings reduce energy consumption from approximately 70% to below 9% of battery capacity while maintaining comparable sensing accuracy. In addition, heterogeneous sampling improves sensing accuracy by approximately 2 percentage points over optimized homogeneous sampling without increasing energy consumption by adapting sampling intervals to the characteristics of individual sensors. These results highlight that heterogeneous sampling provides a more effective balance between energy efficiency and sensing accuracy, making it better choice for multi-sensor IoT applications.

Keywords—Heterogeneous Sampling; Homogeneous Sampling; Fixed-rated; Multi-sensor Internet of Things (IoT); Energy Accuracy Trade-off; Adaptive Sampling; Energy-Aware Sensing

I. INTRODUCTION

Designing energy efficiency in multi-sensor Internet of Things (IoT) systems for sensor nodes operating under limited and dynamic energy conditions poses a significant challenge. To emulate real-world deployments for monitoring environment and coastal sensing, sensor nodes integrate heterogeneous sensing modalities which include temperature, humidity, air quality (AQI) and tide sensors. There are inherent differences in sensing dynamics, variability and energy consumption among these modalities. Most current systems utilize a homogeneous sampling strategy and all the sensors operate at a uniform sampling interval. This simplification of system design and synchronisation fail to capture the inherent heterogeneity of multi-sensor environment. This leads to inefficiencies in energy utilization and sensing performance [1], [2].

From technicalities, fixed-rate or homogeneous sampling exhibits fundamental limitations. Sensors with slow temporal variation tend to oversample, which leads to unnecessary energy utilization with minimal information gain. In contrast,

highly dynamic sensors may cause under sampling, which leads to loss of critical temporal information and reduced sensing accuracy. The research gap shows that existing sampling strategies do not effectively balance energy consumption and sensing fidelity due to the assumption of uniform temporal behaviours across sensors [3], [4]. As a result, to maintain an optimal balance between energy consumption and sensing fidelity becomes more difficult under fixed-rate or homogeneous sampling schemes.

Energy-aware sensing and adaptive monitoring have shown the benefits of adjusting sensing behaviour based on recent research in system conditions and energy availability [5], [6]. Such approaches utilise optimization techniques to improve energy efficiency. However, these approaches are primarily designed for node-level adaptation, such as uniform duty-cycling across all sensors. It does not take the heterogeneous characteristics of individual sensors into account. As a result, it fails to address sensor-level heterogeneity where each sensing modality may require a specific sampling strategy. Another research gap is focused on optimized homogeneous sampling approaches where it does not take into consideration the diverse characteristics of individual sensors within a multi-sensor system.

This paper systematically evaluates to overcome limitations of different sampling strategies within a unified experimental framework. Specifically, this study investigates whether assigning independent sampling rates to heterogeneous sampling sensors offers measurable performance advantages over homogeneous sampling sensors under identical energy constraints or whether homogeneous sampling remains equally effective. The analysis evaluates the performance of fixed-rate sampling, optimized homogeneous sampling and heterogeneous sampling configurations across multiple sensing modalities using Total Energy Consumption (TEC) and Mean Reconstruction Error (MRE) to capture both energy efficiency and sensing accuracy. The main contributions of this paper are as follows:

- **Comparative Evaluation of Sampling Strategies:** A systematic comparison of fixed-rate, optimized homogeneous and heterogeneous sampling strategies in a multi-sensor IoT node, highlighting the limitations of uniform sampling and the benefits of adaptive approaches.
- **Unified Energy-Accuracy Evaluation:** Total Energy Consumption (TEC) and Mean Reconstruction Error (MRE) are used to quantitatively assess the trade-off

between energy efficiency and sensing accuracy across different sampling strategies.

- **Quantitative Analysis of Optimisation Impact:** Experimental results demonstrate that optimized sampling strategies significantly reduce energy consumption from approximately 70% under fixed-rate sampling to below 9% of battery capacity while maintaining comparable accuracy.
- **Effectiveness of Heterogeneous Sampling:** It is shown that heterogeneous sampling further improves sensing accuracy compared to optimized homogeneous strategies under similar energy constraints, confirming the advantage of sensor-specific sampling adaptation.
- **Sensor-Level Sampling Behaviour Insights:** A detailed analysis of sensor-specific sampling distributions reveals that optimal sampling rates vary across sensing modalities and contribute towards improvement system efficiency.

II. RELATED WORK

Fixed-rate or homogeneous sampling has traditionally been widely used in Internet of Things (IoT) system due to its simplicity, easy to implement and predictable system behaviour. In this perspective, all sensors operate at a uniform sampling interval, regardless of their individual sensing characteristics or environmental context, to reduce overhead and facilitate straightforward system design. However, this assumption inherently treats all sensing modalities as uniform in function, which is seldom the case in practical multi-sensor deployments. Sensors to detect temperature and humidity often exhibit slow and smooth temporal variations. Meanwhile, Air quality and tide measurements sensors experience more dynamic fluctuations depending on environmental conditions. As a result, fixed-rate sampling often leads to inefficient system operation. This is because energy resources are not fully utilized and sensing performance is not optimized [1], [7]. These limitations become obvious in energy-constrained IoT nodes because unnecessary sampling reduces the system lifetime.

To mitigate these problems, researchers have focused on adaptive and energy-aware sampling strategies. These approaches aim to adaptively adjust sensing rates based on environmental conditions such as environmental variability, data importance and available energy resources. Energy-aware adaptive sampling techniques are effective to improve and extend operational lifetime in resource-constrained IoT systems through the reduction of sensing and communication activities [8]. Data aggregation and intelligent scheduling are proposed to minimize unnecessary data transmission and optimize overall network efficiency [4]. These strategies rely on residual energy, global error thresholds and network conditions to regulate sampling behaviours. They can be effective in improving overall system efficiency by typically using a unified control policy across all sensors. However, these strategies assume that a single adaptive strategy is sufficient to manage the entire sensing system.

Similarly, research involving multi-sensor and application-specific IoT domains has amplified the importance of adaptive sensing. For instance, in healthcare and environmental sensing applications, dynamic sensing strategies have effectively reduced energy consumption and

enable to maintain acceptable levels of data quality and reliability [9]. In addition, distributed adaptive communication frameworks and clustering-based sampling techniques have shown the benefits gained from decentralized sensing decisions which enable localized adaptation within sensor networks [7], [10], [11]. These approaches emphasize flexibility and scalability in heterogeneous environments especially when sensing conditions vary across spatial and temporal dimensions. Despite acknowledging environmental heterogeneity, many of these frameworks continue to operate like the sensor node as a homogeneous entity. It means a single sampling policy is applied uniformly across all sensors within a node. It does not account for differences in sensor-specific temporal dynamics, measurement variability and energy consumption. This simplification limits the ability of such systems to exploit the potential gains achievable through fine-grained and sensor-level adaptation [12], [13].

Of late, optimization-based approaches have been introduced to identify efficient sampling configurations in IoT systems. Random and Greedy Search techniques provide practical and computationally efficient methods of exploring the sampling configuration space. Such optimization problems can be difficult to solve analytically because they involve discrete decision variables, competing objectives, time-varying conditions and a large sampling-configuration space. By using these methods, near-optimal solutions can be discovered by iteratively evaluating candidate configurations based on predefined objective functions. It helps to minimize energy consumption and maximize data accuracy. As for adaptive sensing, optimization-based strategies provide a flexible framework for balancing competing objectives and constraints. In the most recent studies, these optimization techniques are applied at a global and node level. As a result, a single optimized sampling rate is shared across all sensors. Furthermore, in the exploration of heterogeneous configurations, each sensor is assigned an independent sampling interval, which remains limited and the potential benefits are not fully quantified.

Despite advances in adaptive, energy-aware and optimization-driven sensing, a critical gap remains in the current body of literature. To be specific, existing studies fail to provide a systematic and quantitative comparison between fixed-rate, optimized homogeneous and heterogeneous sampling strategies within a unified evaluation framework. Although previous studies have shown the benefits of adaptive sampling, it remains uncertain whether sensor-specific sampling outperforms homogeneous sampling in terms of energy efficiency and sensing accuracy. Moreover, the absence of a standardized evaluation framework that computes Total Energy Consumption (TEC) and Mean Reconstruction Error (MRE) makes it difficult to assess the effectiveness of heterogeneous sampling. To overcome this gap, it is essential to modernize the design of the next generation IoT sensing systems that take into consideration both energy efficiency and context-aware which forms primary stimulus for the present study.

III. METHODOLOGY

The method involved in this study consists of a multi-sensor Internet of Things (IoT) node equipped with four

sensing modalities temperature, humidity, air quality index (AQI) and tide sensors. These sensors exhibit heterogeneous temporal dynamics and energy consumption characteristics. It reflects realistic conditions for environmental monitoring and coastal sensing. The system operates over a fixed time horizon of 1440 minutes, to correspond a full-day monitoring cycle. It is assumed that the available battery capacity is sufficient to sustain a baseline configuration of fixed 5-minute sampling across all sensors. It is important to provide a consistent reference for performance comparison.

The effectiveness of different sampling strategies is evaluated using three sampling configurations. First, fixed-rate sampling applies a uniform sampling interval selected from 5, 10, 15, 30 and 60 minutes across all sensors. Second, optimized homogeneous sampling determines a single global sampling interval using Random Search (RS) and Greedy Search (GS), where the same optimised sampling interval is assigned to all sensors. Third, heterogeneous sampling assigns independent sampling intervals to each sensor, where the optimal sensor-specific configuration is also obtained using RS and GS. For optimized homogeneous and heterogeneous strategies, the sampling interval search space is defined from 1 to 200 minutes. This formulation enables direct comparison between fixed-rate, optimized homogeneous and sensor-specific heterogeneous sampling under consistent evaluation conditions. To jointly evaluate energy efficiency and sensing accuracy, a composite fitness function Equation (1) is defined as:

$$Fitness = w_1(1 - TEC_{norm}) + (1 - w_1)(1 - MRE_{norm}) \quad (1)$$

where $w_1 \in [0,1]$ is a weighting factor controlling the trade-off between energy consumption and sensing error. TEC_{norm} and MRE_{norm} represent the normalised total energy consumption and normalised mean reconstruction error respectively. In this study, equal weighting is adopted ($w_1 = 0.5$), to ensure a balanced optimization objective. A higher fitness value indicates a better trade-off and that reflects a reduction in energy usage and improved reconstruction accuracy.

Total Energy Consumption (TEC) over a 24-hour period is used to capture sensor-level heterogeneity is shown in Equation (2):

$$TEC = \sum_{s=1}^S \left(\frac{1440}{R_s} \cdot E_s \right) \quad (2)$$

where S represents the total number of sensors, R_s represents the sampling interval of the sensor s , and E_s represents the energy consumed per sampling. This formula reflects the inverse relationship between sampling interval and energy consumption. Shorter intervals mean higher sampling frequency and increased energy usage. In homogeneous sampling, $R_s = R$ for all sensors. In heterogeneous sampling, each sensor operates with a distinct sampling interval. Sensing accuracy is evaluated using Mean Reconstruction Error (MRE). It quantifies the deviation between actual and reconstructed sensor readings. For each sensor, the normalized reconstruction error is represented in Equation (3):

$$MRE_s = \frac{1}{N} \sum_{i=1}^N \left| \frac{x_{s,i} - \hat{x}_{s,i}}{x_{s,max} - x_{s,min}} \right| \quad (3)$$

where $x_{s,i}$ represents the actual measurement, $\hat{x}_{s,i}$ represents the reconstructed value and normalization ensures comparability across sensors with different measurement ranges. The system-level MRE is computed in Equation (4):

$$MRE = \frac{1}{S} \sum_{s=1}^S MRE_s \quad (4)$$

This formula is to ensure that each sensor can contribute fair amount to the overall accuracy metric no matter its scalability or variability. Sensing accuracy is expressed as in Equation (5):

$$Accuracy = (1 - MRE) \times 100\% \quad (5)$$

where lower MRE indicates higher accuracy. Random Search generates candidate sampling configurations within the defined search space. It evaluates each candidate using the composite fitness function. In contrast, Greedy Search helps to improve the sampling configuration by selecting changes that can increase the fitness value at each step. Both optimization methods are relevant to homogeneous and heterogeneous sampling configurations under identical evaluation conditions to ensure a fair output.

The experiment is conducted and evaluated under controlled simulation conditions to ensure reliable results. The sampling interval search space for each sensor ranges from 1 to 200 minutes to enable the optimization algorithms to explore both high-frequency sensing and energy-efficient sampling configurations. To identify suitable sampling configurations, each optimization algorithm is executed for 200 iterations. The dataset used is synthetically generated to emulate realistic sensor behavior, temporal variability and measurement noise. Performance is evaluated using Total Energy Consumption (TEC), Mean Reconstruction Error (MRE) and sensor-specific sampling rates. This provides a comprehensive assessment for both system-level energy efficiency and sensor-level adaptation.

IV. RESULTS AND DISCUSSION

This section examines the performance of fixed-rate, optimized homogeneous and optimized heterogeneous sampling strategies through a comparative analysis. The analysis focuses on energy accuracy trade-off, sensing accuracy distribution, battery consumption, sensor-level sampling behaviors and convergence characteristics of the optimization methods. The analysis is carried out under the selected experimental setting of weight = 5 with sunny weather and the environment changes every minute.

A. Energy Accuracy Trade-off

Fig. 1 shows the trade-off between energy consumption and sensing accuracy for all the evaluated sampling strategies. The fixed-rate baselines showed the expected relationship between sampling frequency, battery consumption and sensing accuracy. For instance, the fixed 5-minute sampling baseline achieves high sensing accuracy but consumes almost 70% of the total battery capacity. This suggests that frequent fixed-rate sampling can preserve sensing fidelity and it is not efficient for energy constrained multi-sensor IoT nodes.

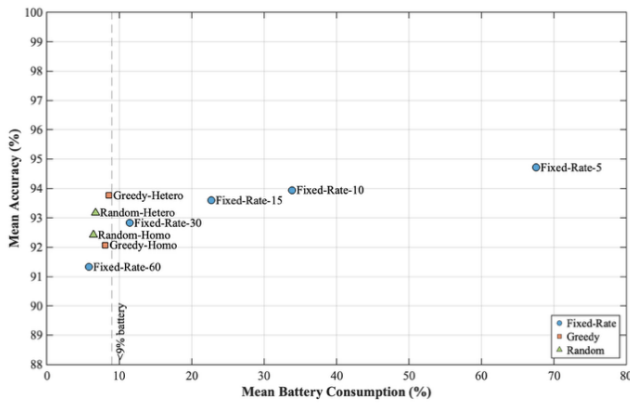


Fig. 1. Energy accuracy trade-off among various fixed-rate, optimized homogeneous and optimized heterogeneous sampling strategies. Each point represents the mean battery consumption and mean accuracy over 200 iterations.

In comparison, the optimized homogeneous and heterogeneous strategies substantially reduce battery consumption to below 9% while maintaining comparable accuracy. This result confirms that optimized sampling is effective in identifying sampling configurations that reduced unnecessary sensing activity without severely degrading reconstruction quality. Therefore, fixed-rate sampling is not an efficient strategy when the objective is to balance energy consumption and sensing accuracy.

More importantly, the heterogeneous strategies provide an additional improvement over optimized homogeneous strategies. Although both optimized approaches operate within a similar energy range, heterogeneous sampling achieves higher accuracy by assigning independent sampling intervals to different sensors. This demonstrates that sensor-specific sampling provides a better energy–accuracy balance than applying a single uniformly optimized sampling interval across all sensors.

B. Accuracy Distribution

Fig. 2 presents the distribution of sensing accuracy across the fixed-rate, optimized homogeneous and optimized heterogeneous sampling strategies over 200 iterations. The fixed 5-minute baseline provides strong accuracy performance but this is achieved at the expense of substantially higher battery consumption. As the fixed sampling interval increases, energy consumption decreases but the accuracy performance becomes more sensitive to information loss caused by less frequent sampling.

The optimized homogeneous strategies achieve competitive accuracy while significantly reducing energy consumption. However, because optimized homogeneous applies a single sampling interval to all sensors, it cannot fully account for differences in sensor dynamics. The accuracy distribution shows that the optimized homogeneous methods perform slightly lower accuracy than the heterogeneous methods.

Heterogeneous strategies achieve higher sensing accuracy than homogeneous strategies. Sensor-specific sampling improves accuracy while preserving sensing fidelity under similar energy constraints. The results show that optimization can reduce energy consumption and heterogeneous sampling

enhances sensing accuracy through sensor-specific adaptation.

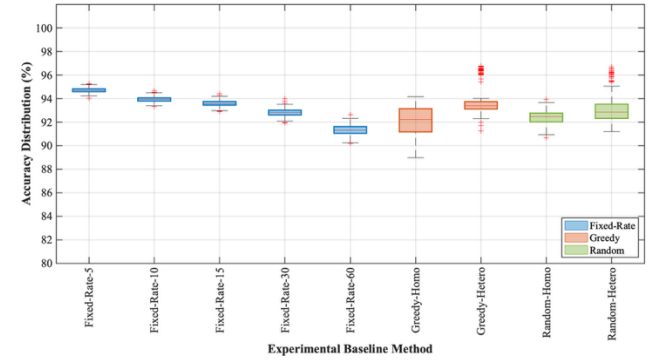


Fig. 2. Distribution of mean sensing accuracy for various fixed-rate, optimized homogeneous and optimized heterogeneous sampling strategies over 200 iterations. The boxplots present the median, interquartile range (IQR) and outliers for each strategy.

C. Battery Consumption Comparison

Fig. 3 compares the battery consumption of the evaluated strategies. The fixed 5-minute baseline consumes almost 70% of the available battery capacity and that represents the highest energy demand among the tested configurations. This happens because all sensors are always sampled at a uniform interval. Although longer fixed-rate intervals can reduce energy consumption, the fixed-rate does not consider the different temporal behaviours of individual sensors. In contrast, both optimized homogeneous and optimized heterogeneous strategies consume less than 9% of the battery capacity. This substantial reduction highlights the effectiveness of optimization in energy-constrained IoT sensing. The results show that adaptive optimization can identify sampling intervals that significantly reduce energy consumption compared with fixed-rate sampling.

The optimized homogeneous and heterogeneous strategies exhibit similar battery consumption. This is an important finding because the accuracy improvement achieved by heterogeneous sampling is obtained without increasing battery consumption. Therefore, heterogeneous sampling improves the energy–accuracy trade-off not by consuming more energy but by allocating sampling effort more efficiently across individual sensors.

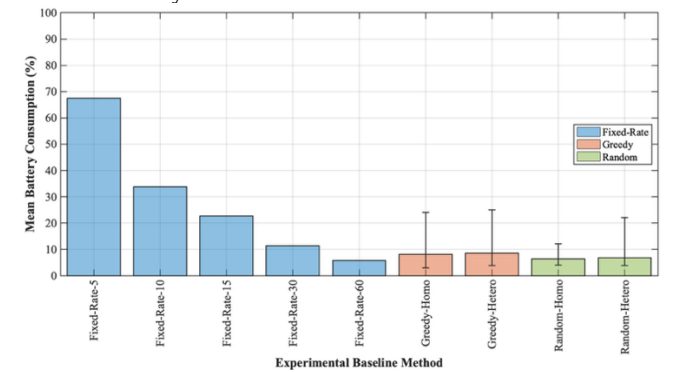


Fig. 3. Mean battery consumption across fixed-rate, optimized homogeneous and optimized heterogeneous sampling strategies. Error bars represent the minimum and maximum values obtained over 200 iterations.

Table I summarizes the main performance trends observed from Fig. 1 to Fig. 3. The fixed 5-minute baseline achieves high sensing accuracy but consumes almost 70% of the battery capacity. Optimized homogeneous and heterogeneous strategies reduce battery consumption to below 9%. Among the optimized approaches, heterogeneous sampling achieves higher sensing accuracy than homogeneous sampling under similar battery consumption and as a result, it achieves a better energy–accuracy trade-off.

TABLE I. SUMMARY OF PERFORMANCE COMPARISON

Method	Sampling Type	Accuracy (%)	Energy (%)	Remarks
Fixed 5 min	Homogeneous fixed-rate	~ 93	~ 70	High accuracy but very high energy consumption
Fixed 10–60 min	Homogeneous fixed-rate	Decreases as interval increases	Decreases as interval increases	Demonstrates the fixed-rate energy–accuracy trade-off
Optimized Homogeneous	Homogeneous optimised	91.2–92.0	< 9	Substantially reduces energy with moderate accuracy loss
Optimized Heterogeneous	Heterogeneous optimised	92.5–93.1	< 9	Improves accuracy over optimized homogeneous at similar energy cost

D. Sensor-Level Sampling Behaviour

Fig. 4 illustrates the sensor-level sampling interval distributions for optimized homogeneous and heterogeneous strategies. In the homogeneous strategy, all sensors are assigned to the same sampling intervals because a single global sampling rate is applied across the entire nodes. This limits the ability of the system to respond to differences in sensor variability, sensing importance and energy demand.

In contrast, the heterogeneous strategy assigns different sampling intervals to the temperature, humidity, AQI and tide sensors. This confirms that different sensing modalities require different sampling behaviours to achieve a better balance between energy consumption and sensing accuracy. Instead of applying the same interval to all sensors, heterogeneous optimization allows each sensor to operate according to its individual characteristics and contribution to the overall optimization objectives.

These differentiated sampling patterns explain the improved accuracy observed in heterogeneous strategies. By allocating sampling intervals according to sensor-level characteristics, heterogeneous sampling reduces redundant measurements while preserving important temporal information. These findings highlight the value of sensor-specific sampling adaptation for improving the performance of multi-sensor IoT systems.

E. Convergence Behaviour of Optimised Methods

Fig. 5 shows the convergence behaviour of random and greedy search methods under homogeneous and heterogeneous sampling configurations.

heterogeneous configurations. The greedy-based methods converge rapidly, reaching stable fitness scores within the early iterations. This suggests that Greedy Search is able to identify high performing sampling configurations more quickly than Random Search.

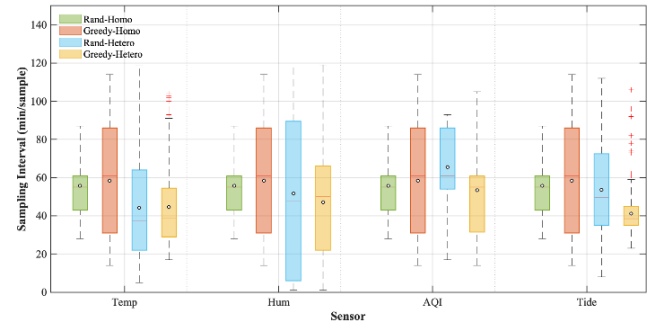


Fig. 4. Sensor-level sampling interval distributions for optimized homogeneous and heterogeneous strategies over 200 iterations. The boxplots show the distribution of selected sampling intervals for temperature, humidity, AQI and tide sensors and the circular markers indicate mean values.

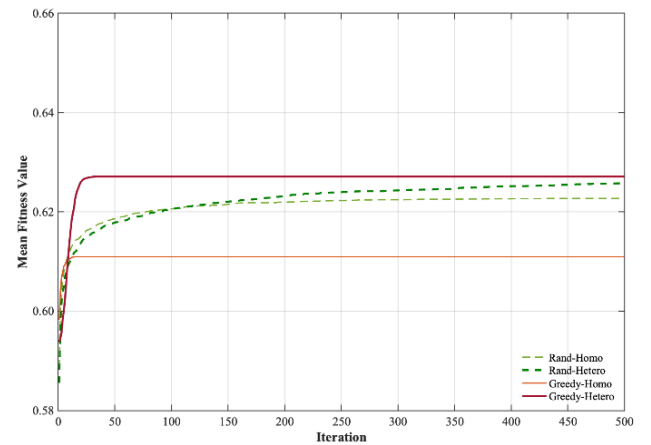


Fig. 5. Convergence behaviour of random and greedy search strategies under homogeneous and heterogeneous sampling configurations.

In contrast, random search exhibits slower and more gradual improvement across iterations. This behaviour is expected because random search explores the sampling space without directional guidance. Although random search continues to improve over time, it requires more iterations to approach competitive fitness scores.

Heterogeneous configurations generally achieve better final fitness scores than their homogeneous counterparts. This indicates that sensor-specific sampling provides a more favourable configuration space for balancing energy consumption and sensing accuracy. The convergence behaviour supports the earlier results by showing that heterogeneous strategies are not only more accurate but can also be effectively identified through optimization.

F. Experimental Scope and Limitations

This study is focused on a controlled experimental setting using a balanced energy accuracy weighting ($w = 0.5$), sunny weather and a fixed environmental resolution setting.

Therefore, the reported results primarily demonstrate the effectiveness of heterogeneous sampling under a representative baseline scenario rather than all possible operating conditions. Different weighting values may shift the optimization preference towards either lower energy consumption or higher sensing accuracy while cloudy or rainy conditions may affect energy availability and the optimal sampling configuration. Future evaluation should therefore consider multiple weighting settings, weather conditions, battery initial states and real-world deployment constraints to further validate the general applicability of the proposed approaches.

G. Discussion

Overall, the results demonstrate two important findings. First, optimized sampling is necessary for reducing energy consumption in energy-constrained multi-sensor IoT nodes. Compared with fixed-rate sampling, optimized homogeneous and heterogeneous strategies reduce battery consumption from approximately 70% to below 9% while maintaining comparable accuracy. Second, heterogeneous sampling provides an additional advantage over homogeneous sampling under similar energy constraints. By assigning independent sampling intervals to individual sensors, heterogeneous strategies improve sensing accuracy without increasing battery consumption. The sensor-level analysis further shows that different sensors benefit from different sampling intervals, confirming that uniform sampling is suboptimal for heterogeneous multi-sensor environments. These findings support the central argument of this paper that is optimization improves energy efficiency but sensor-level heterogeneity is required to further improve the energy accuracy trade-off in multi-sensor IoT systems.

V. CONCLUSION

This paper demonstrated the importance of heterogeneous sampling in improving the energy-accuracy trade-off for energy-constrained multi-sensor IoT nodes. The results show that optimized sampling reduces battery consumption from approximately 70% under the fixed 5-minute baseline to below 9%, while maintaining comparable accuracy. Furthermore, homogeneous sampling improves accuracy from 91.2% – 92.0%, and under optimized heterogeneous sampling, accuracy improves from 92.5% – 93.1% at similar energy consumption levels. These findings confirm that optimized heterogeneous sampling is more efficient than optimized homogeneous sampling for same resource allocation. The current evaluation is based on a controlled experimental setting, balanced energy-accuracy weighting, sunny weather conditions and a fixed environmental resolution. Future work will extend the evaluation to a wider range of weight settings, weather conditions and initial battery capacities. Further investigation will also consider real-world deployment factors, including communication overhead, battery dynamics, hardware-level energy behaviour and other optimization methods such as metaheuristic and learning-based approaches.

ACKNOWLEDGMENT

This research was supported by Universiti Malaysia Sarawak under the VC-High Impact Research Grant, Grant No. UNI/F08/VC-HIRG/85502/P08-03/2022. The authors gratefully acknowledge the said university for providing the approved funding that supported the successful completion of this research.

REFERENCES

- [1] C. Rodriguez-Pabon, G. Riva, C. Zerbini, J. Ruiz-Rosero, G. Ramirez-Gonzalez, and J. C. Corrales, "An Adaptive Sampling Period Approach for Management of IoT Energy Consumption: Case Study Approach," *Sensors*, vol. 22, no. 4, p. 1472, Feb. 2022, doi: 10.3390/s22041472.
- [2] E. Oliveira, A. R. da Rocha, M. Mattoso, and F. C. Delicato, "Latency and Energy-Awareness in Data Stream Processing for Edge Based IoT Systems," *J. Grid Comput.*, vol. 20, no. 3, p. 27, Sep. 2022, doi: 10.1007/s10723-022-09611-4.
- [3] D. Arnaiz, F. Moll, E. Alarcón, and X. Vilajosana, "Energy and relevance-aware adaptive monitoring method for wireless sensor nodes with hard energy constraints," *Integration, the VLSI Journal*, vol. 94, Art. no. 102097, Jan. 2024, doi: 10.1016/j.vlsi.2023.102097.
- [4] M. Ibrahim, H. Harb, A. Nasser, A. Mansour, and C. Osswald, "Aggregation-Scheduling Based Mechanism for Energy-Efficient Multivariate Sensor Networks," *IEEE Sens. J.*, vol. 22, no. 16, pp. 16662–16672, Aug. 2022, doi: 10.1109/JSEN.2022.3189431.
- [5] W. Chen, F. Tang, F. Cui, and C. Chen, "Research on Energy Harvesting Mechanism and Low Power Technology in Wireless Sensor Networks," *Sensors*, vol. 24, no. 1, p. 47, Dec. 2023, doi: 10.3390/s24010047.
- [6] S. Naifar, O. Kanoun, and C. Trigona, "Energy Harvesting Technologies and Applications for the Internet of Things and Wireless Sensor Networks," *Sensors*, vol. 24, no. 14, p. 4688, Jul. 2024, doi: 10.3390/s24144688.
- [7] J. Oh, D. Lee, D. S. Lakew, and S. Cho, "DACODE: Distributed adaptive communication framework for energy efficient industrial IoT-based heterogeneous WSN," *ICT Express*, vol. 9, no. 6, pp. 1085–1094, Dec. 2023, doi: 10.1016/j.icte.2023.02.009.
- [8] M. Giordano, S. Cortesi, P.-V. Mekikis, M. Crabolu, G. Bellusci, and M. Magno, "Energy-Aware Adaptive Sampling for Self-Sustainability in Resource-Constrained IoT Devices," in *Proceedings of the 11th International Workshop on Energy Harvesting & Energy-Neutral Sensing Systems*, New York, NY, USA: ACM, Nov. 2023, pp. 65–71. doi: 10.1145/3628353.3628545.
- [9] A. Kadhun Idrees, D. A. Alhussein, and H. Harb, "Energy-efficient multisensor adaptive sampling and aggregation for patient monitoring in edge computing based IoT networks," *J. Ambient Intell. Smart Environ.*, vol. 15, no. 3, pp. 235–253, Sep. 2023, doi: 10.3233/AIS-220610.
- [10] R. Damaševičius and R. Maskeliūnas, "Adaptive sensor clustering for environmental monitoring in dynamic forest ecosystems," *Peer. Peer. Netw. Appl.*, vol. 18, no. 3, p. 149, May 2025, doi: 10.1007/s12083-025-01974-1.
- [11] H. Harb et al., "CLARA: A cluster-based node correlation for sampling rate adaptation and fault tolerance in sensor networks," *Internet of Things*, vol. 28, p. 101345, Dec. 2024, doi: 10.1016/j.iot.2024.101345.
- [12] T. Shafique, A.-H. Soliman, A. Amjad, L. Uden, and D. M. Roberts, "Node Role Selection and Rotation Scheme for Energy Efficiency in Multi-Level IoT-Based Heterogeneous Wireless Sensor Networks (HWSNs)," *Sensors*, vol. 24, no. 17, p. 5642, Aug. 2024, doi: 10.3390/s24175642.
- [13] Y. E. M. Hamouda, "Optimally sensors nodes selection for adaptive heterogeneous precision agriculture using wireless sensor networks based on genetic algorithm and extended kalman filter," *Physical Communication*, vol. 63, p. 102290, Apr. 2024, doi: 10.1016/j.phycom.2024.102290.