

Overhead- and energy-aware integrated sensing and communication for IoT: A dual-mode edge-intelligent framework

Oday Abdulhusein Abdaumran¹, Isam Aameer Ibrahim², Ibtihal Razaq Niama ALRubeei³, Hussain Ali Mutar^{4*}, Haider TH. Salim ALRikabi⁵

¹ Department of Construction and Projects, Wasit University, Wasit, Iraq

² Electrical Engineering Department, College of Engineering, Thi-Qar University, Nasiriyah, Iraq

^{3,5} Electrical Engineering Department, College of Engineering, Wasit University, Wasit, Iraq

⁴ Computer Department, College of Computer Science and Information Technology, Wasit University, Wasit, Iraq

*Corresponding author E-mail: hmutar@uowasit.edu.iq

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Abstract

The Integrated Sensing and Communication (ISAC) is an important direction for Internet of Things (IoT) networks because it uses the same radio infrastructure for data delivery and environmental awareness through shared spectrum, pilots, and hardware. There are many IoT-specific challenges that have not yet been resolved. Specifically, the assumptions regarding sensing overhead, latency, memory burden, and energy feasibility of passive nodes have not been adequately considered in prior ISAC formulations. This paper proposed an overhead and energy-aware ISAC framework that switches between passive, active, and hybrid sensing modes based on traffic load, scene dynamics, and harvested energy feasibility. A simulation campaign of 1500 Monte Carlo episodes, between the proposed framework and dedicated sensing plus communication, and static ISAC baselines, was performed. OEA-ISAC achieved the highest system utility (41.10 ± 0.12), the highest sensing F1-score (0.937 ± 0.001), the lowest latency (22.32 ± 0.20 ms), and the lowest energy per delivered Mbit (0.536 ± 0.003 J/Mb). OEA-ISAC has a 19.9% utility improvement over static ISAC, while it has a 27.3% utility improvement over dedicated sensing plus communication. The findings suggest that including sensing overhead as a primary control variable is a valuable area of future research in the context of hybrid active/passive IoT systems.

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Keywords: Integrated sensing and communication, Internet of Things, Edge intelligence, Backscatter, Wi-Fi sensing, Energy efficiency

1. Introduction

Internet of Things can be defined as the progression from basic telemetry into a cyber-physical medium that's capable of providing contextually aware cyber-physical platforms that require the network to carry not only packets of information, but also sense variables such as motion, occupancy, position, vibration, anomalous events, and changes in the environment [1, 2]. Typically, these functions are implemented in conventional systems using individual pieces of sensing hardware and separate communications links, resulting in an increased number of devices, higher deployment costs, increased power consumption, and increased fragmentation of available spectrum. Integrated Sensing and Communications (ISAC) aims to eliminate the

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inefficiency of separate devices by enabling the use of a common wireless platform to provide both connectivity and environmental awareness using shared signals and shared radio resources [3].

This shift is important to IoT due to the resource limitations present during practical IoT deployments. As such, IoT systems communicate through short packet lengths, with intermittent active timeframes in addition to being powered by a small battery or by harvesting energy [4]. In these environments, the operational costs associated with the acquisition and storage of sensing data can equal the benefit of obtaining insight from that sensor data. Wi-Fi sensing deployments have also revealed that both airtime, memory, and coordination can be impacted through the active use of Wi-Fi to sense, as well as that the ideal design for both Wi-Fi and IPv6 would be the one that optimizes total system utility after all associated overheads are taken into account [5].

This paper has a specific target: many ISAC (Integrated Sensing and Communication) studies have focused on optimizing the rates of communication and the quality of sensing, and also consider energy efficiency, but very few consider the joint treatment of all three variables in regard to the overhead associated with sensing, latency, and the feasibility of harvested energy in hybrid active and passive IoT (Internet of Things) networks [6]. The paper will present an overhead- and energy-aware ISAC framework, which enables the adaptive selection of passive, active, and hybrid sensing modes through edge control [7, 8]. Figure 1 illustrates the relationship between sensing benefit and sensing overhead in IoT-oriented ISAC systems [9]. The figure highlights the central intuition of this paper: although stronger sensing can improve environmental awareness, the associated increase in protocol burden, latency, and processing cost may reduce the net system utility. This observation provides the foundation for the proposed overhead-aware design [10, 11].

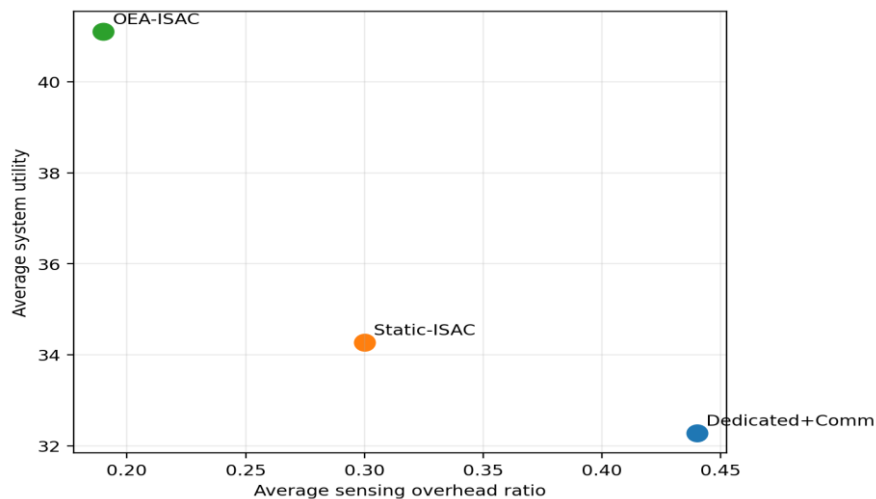


Figure 1. Conceptual utility-overhead relationship motivating the proposed overhead-aware ISAC design

Table 1 summarizes the main contributions of this study. The table is intended to give a concise overview of the identified research gap, the proposed OEA-ISAC method, the adopted simulation framework, and the principal findings obtained from the evaluation. In this way, it clarifies both the methodological novelty and the practical significance of the work.

Table 1. Main contributions of the study

Contribution	Description
Gap identification	Establishes the need to jointly model sensing overhead, latency, and passive-node feasibility for IoT ISAC.
Novel method	Introduces OEA-ISAC, a dual-mode edge-intelligent scheduler with passive-tag admission control.
Simulation framework	Evaluates mixed active/passive IoT behavior over 1,500 Monte Carlo episodes per method.
Main finding	Shows that overhead-aware adaptation yields higher utility, lower latency, and lower energy than static ISAC.

2. Related work

Research on wireless networks within the ISAC field is typically categorized into three different categories (classical Physical Layer ISAC is a subset of wireless) [12, 13]. This category deals with the development of joint designs of both the waveforms and the covariances (a mathematical measure of a random vector's degree of correlation) and provides a mathematical basis for ISAC [14, 15]. Most of this research assumes that all nodes in the network are functioning at or above their capabilities to be able to get maximum utility from all of the ISAC processes [16, 17]

The second direction for handling is realizing practical Wi-Fi and WLAN sensing of IoT devices, as such exposes the implementation burden of real-world Wi-Fi sensing implementation in real protocol stacks [18, 19], and describes how sound procedures, CSI feedback, buffering, and the storage of sensed data can reduce the data throughput of communication to an increase in latency [20, 21]. Thus, this practical overhead is a core gap to be addressed throughout this paper [22, 23].

The third area of interest is “backscatter or passive ISAC and ambient IoT”. These types of studies are appealing because they provide a means by which to participate in sensing activities with very low/zero power, or battery-less sensing [24, 25]. However, most of these studies do not make an explicit connection between the feasibility of using passive nodes, edge-based adaptation capabilities, and control of sensing-overhead in one unified IoT scheduling architecture. To position the proposed work within the broader research landscape, Figure 2 presents a taxonomy of representative ISAC-for-IoT research directions. The figure groups prior studies according to their dominant focus, including classical PHY-centric ISAC, Wi-Fi/WLAN sensing, backscatter-based ISAC, and edge-intelligent ISAC [26, 27]. By organizing the literature in this way, the figure helps reveal the gap addressed in this paper, namely the limited joint treatment of sensing overhead, latency, and passive-node feasibility [28, 29].

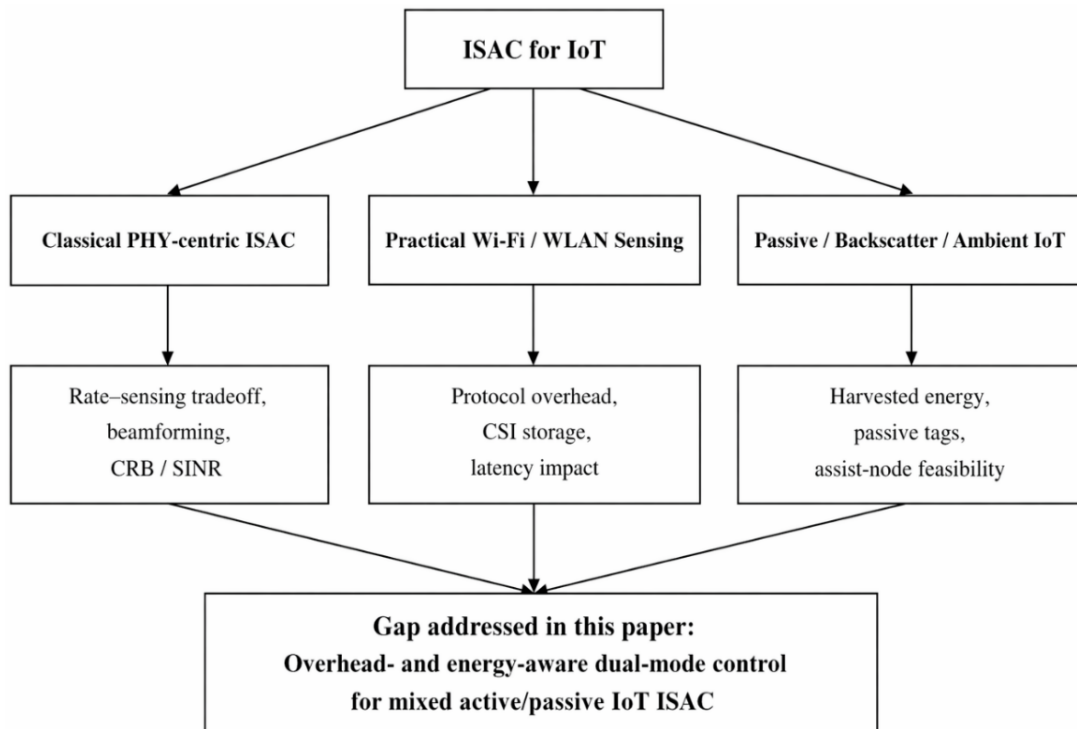


Figure 2. Taxonomy of the representative ISAC-for-IoT literature and the gap addressed by the paper

To complement the taxonomy in Figure 2, Table 2 provides a structured comparative critique of the main research directions in the existing ISAC literature. The table contrasts their primary objectives, strengths, and IoT-specific limitations, thereby making clear why an overhead- and energy-aware framework is needed. This comparison also helps justify the design choices adopted in the proposed OEA-ISAC approach.

Table 2. Comparative critique of related ISAC research directions.

Study direction	Primary objective	Strength	IoT-specific limitation
Classical PHY-centric ISAC	Rate-sensing co-design	Strong mathematical foundation	Often ignores protocol overhead and low-end device feasibility
Wi-Fi / WLAN sensing	Practical protocol realization	Commodity hardware relevance and deployment realism	Adds sensing airtime, storage, and latency burden
Backscatter / ambient-IoT ISAC	Low-power integrated perception	Excellent energy profile for large-scale IoT	Weak mixed active/passive scheduling treatment
Edge-intelligent ISAC	Adaptive control under dynamics	Can react to varying traffic and scene conditions	May overlook overhead as a direct cost term

A consensus view of the literature suggests that there is an emerging gap at the junction of IoT realistic usage and ISAC optimization, which is currently exploitable and still publishable in terms of new knowledge creation. Overhead, latency, and passive nodes should be treated as first-class control variables, rather than as obscured implementation management variables.

3. Problem formulation

Consider a single-cell ISAC-enabled IoT network in which one access point (AP) is equipped with M antennas serve K_a active IoT devices and coordinates K_p passive or backscatter tags over a shared bandwidth B . The AP emits dual-purpose waveforms that simultaneously support uplink or downlink communication and environmental sensing. In contrast to conventional formulations that mainly optimize rate and sensing fidelity, the present work explicitly models sensing overhead, latency, and passive-node energy feasibility as first-class design factors. This is important in IoT deployments because the gain obtained from additional sensing can be offset by CSI acquisition burden, pilot occupation, control signaling, local buffering, and edge-processing cost.

Let R_k denote the achievable throughput of the active device k , and let the aggregate communication utility be represented by $\sum_{k=1}^{K_a} R_k$. Let $Q_s \in [0,1]$ denote normalized sensing quality, measured in this work through a proxy consistent with event detection fidelity, while E_b represents the energy expenditure per delivered Mbit, L denotes end-to-end latency, and O_s denotes the sensing overhead ratio. The system controller selects an operating mode $m \in [\text{passive}, \text{active}, \text{hybrid}]$, a sensing duty factor $\tau \in [0,1]$, a beamforming matrix $\mathbf{W} = [\mathbf{w}_1, \dots, \mathbf{w}_{K_a}]$, and a passive-tag admission vector $\boldsymbol{\rho} = [\rho_1, \dots, \rho_{K_p}]$, where $\rho_i \in \{0,1\}$ indicates whether passive tag i is admitted for participation during the frame.

The overall system objective is to maximize a weighted utility that rewards communication and sensing performance while penalizing energy use, latency, and sensing-induced overhead. The optimization problem can therefore be written as:

$$\max_{\mathbf{w}, \tau, m, \boldsymbol{\rho}} U = \alpha \sum_{k=1}^{K_a} R_k + \beta Q_s - \gamma E_b - \delta L - \eta O_s$$

subject to the following practical constraints:

$$\sum_{k=1}^{K_a} \|\mathbf{w}_k\|^2 \leq P_{\max}$$

$$\begin{aligned}
R_k &\geq R_k^{\min}, \forall k = 1, \dots, K_a \\
Q_s &\geq Q_s^{\min} \\
L &\leq L_{\max} \\
\rho_i = 1 &\Rightarrow E_{h,i} \geq E_i^{\min}, \forall i = 1, \dots, K_p
\end{aligned}$$

where P_{\max} is the AP transmit-power budget, R_k^{\min} is the minimum service requirement of an active device k , Q_s^{\min} is the minimum acceptable sensing quality, L_{\max} is the latency bound imposed by delay-sensitive IoT traffic, and $E_{h,i}$ and E_i^{\min} denote harvested and required energy, respectively, for the passive tag i . The coefficients $\alpha, \beta, \gamma, \delta, \eta > 0$ are design weights controlling the trade-off among system objectives.

To expose the role of sensing burden more explicitly, the overhead term O_s can be interpreted as a normalized combination of pilot occupation, control signaling, sensing storage cost, and additional processing demand, namely

$$O_s = \lambda_1 O_{\text{air}} + \lambda_2 O_{\text{ctrl}} + \lambda_3 O_{\text{mem}} + \lambda_4 O_{\text{proc}},$$

where O_{air} denotes sensing airtime consumption, O_{ctrl} denotes coordination or signaling overhead, O_{mem} denotes buffering and storage burden, and O_{proc} denotes edge-computation load, with λ_j being non-negative normalization weights. This decomposition reflects the practical fact that IoT sensing is not free even when it shares the same radio platform as communication.

Because the mode variable m and the admission vector $\boldsymbol{\rho}$ are discrete, while \mathbf{W} and τ are continuous, the final empirical formulation contains both discrete and continuous variables that create a nonlinear mixed integer programming problem. Because finding the complete global optimum solution for all variables at once would introduce a prohibitively high level of computational complexity to small and inexpensive IoT cell devices, OEA- uses an Edge-Based Intelligent Scheduling (EBS) approach to estimate states and select modes quickly instead of doing a high number of iterations through computational optimization. The controller's estimated output will maintain the basic form of the original utility maximizing programme while at the same time maintaining computational feasibility for use in real-time applications. The core notation used in the proposed OEA-ISAC formulation is shown in Table 3.

Table 3. Core notation used in the proposed OEA-ISAC formulation

Symbol	Definition	Optimization Role
R_k	Achievable throughput of active IoT device k	Promotes communication performance in the objective function
Q_s	Normalized sensing-quality metric	Encourages accurate and reliable environmental sensing
E_b	Energy consumed per successfully delivered Mbit	Penalizes energy-inefficient system operation
L	End-to-end communication and processing latency	Penalizes delay and discourages latency-sensitive degradation
O_s	Sensing overhead ratio	Captures the protocol and processing burden introduced by sensing
ρ_i	Admission indicator for passive tag i	Ensures participation only when passive-node operation is energy feasible

The formulation's incorporation of an explicit overhead term is unique among the available formulations. The majority of previously developed models contain implicit or concealed costs that are either "built in" to the resource assumptions or otherwise unaccounted for. Therefore, there are no trade-offs that can be optimized directly from the models using overhead as a part of the trade-off discussion. This model explicitly allows the scheduler to select low-cost passive sensing during high traffic periods and to use active sensing during those times where the scene dynamics warrant the overhead incurred by active sensing as opposed to passive sensing.

4. Proposed OEA-ISAC method

The proposed framework contains four coordinated layers: mixed active/passive IoT devices, a multi-antenna access point, a joint communication-decoding and sensing-processing engine, and an edge-intelligence scheduler. The access point emits a shared waveform that simultaneously supports communication and environment sensing, while the edge controller updates beam patterns, sensing duty cycle, and operating mode on a frame-by-frame basis. After establishing the research gap and problem setting, Figure 3 presents the overall architecture of the proposed OEA-ISAC framework. The figure illustrates the interaction among active IoT devices, passive/backscatter tags, the multi-antenna access point, the joint communication-and-sensing engine, and the edge-intelligent scheduler. It therefore provides a system-level view of how the proposed design integrates communication, sensing, and adaptive control within a unified IoT architecture.

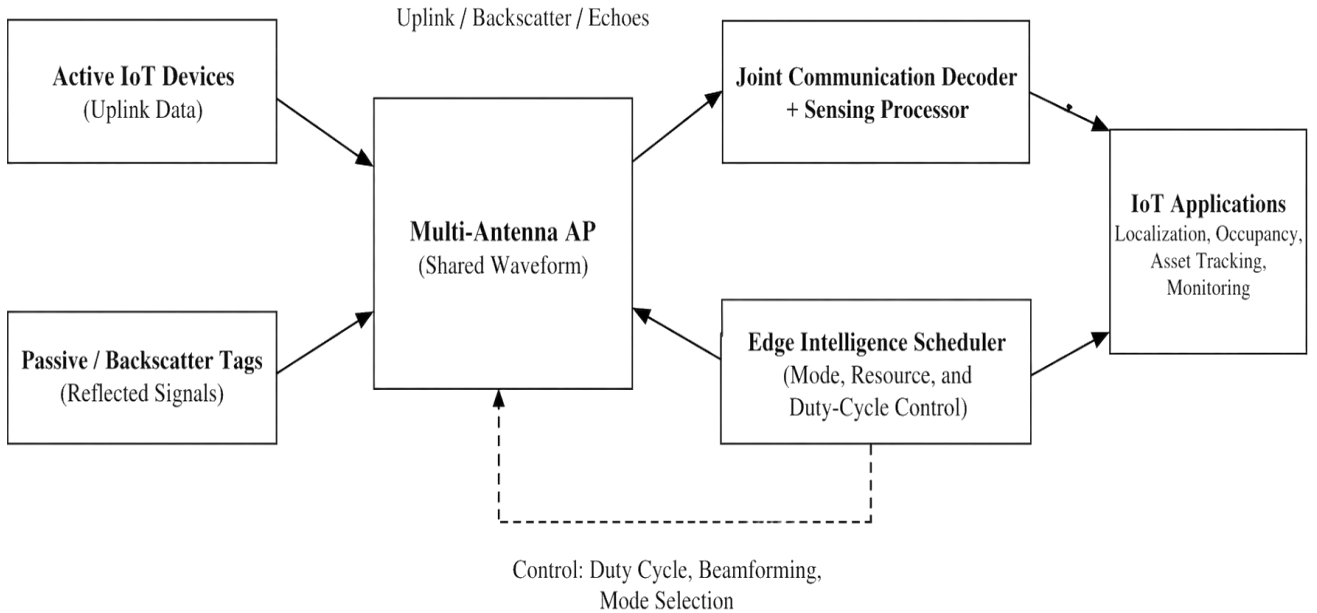


Figure 3. Architecture of the proposed OEA-ISAC framework

4.1. Dual-mode scheduling logic

Each frame of data is used to estimate the three state variables, which are x , the traffic load, s , the scene-dynamics score, and h , the passive-feasibility score at the edge controller. If there is a large amount of traffic in the system and the environment is stable, the controller will switch to passive sensing mode to conserve resources. When either the environment is changing rapidly, or the sensing objective is not achieved, then the controller will enter into either a mode of active sensing or a hybrid mode combining limited active probing with passive tag participation by the sensors. To clarify the operational logic of the proposed method, Figure 4 depicts the frame-level decision process of OEA-ISAC. The figure shows how the controller uses traffic load, scene dynamics, and passive-feasibility information to choose among passive, active, and hybrid sensing modes. This visualization is important because it explains how the proposed system converts the optimization objective into a practical and lightweight scheduling strategy.

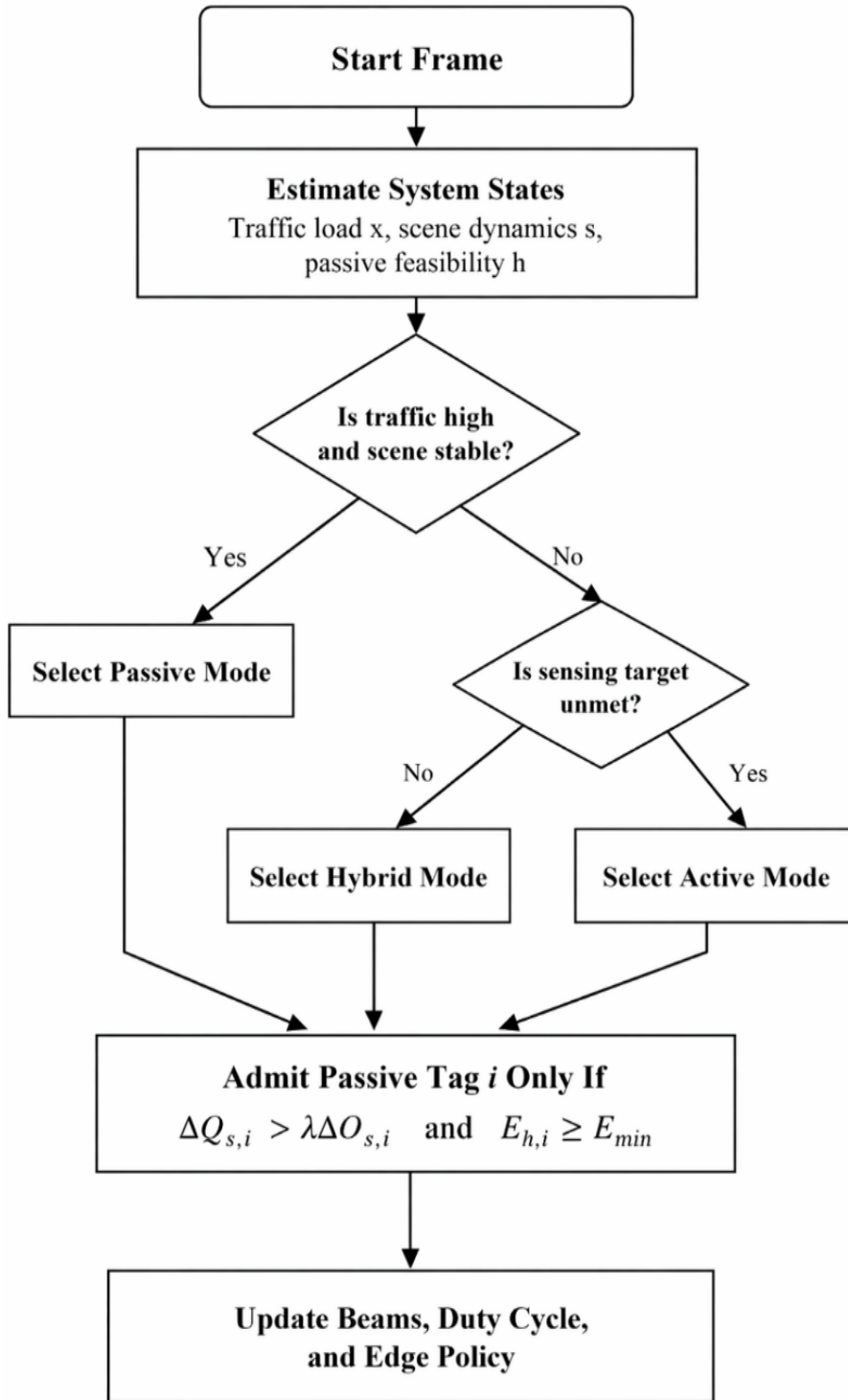


Figure 4. Frame-level decision process of OEA-ISAC

4.2. Complexity and resources

The proposed OEA-ISAC framework is lightweight and suitable for edge deployment. At each frame, it performs state acquisition, passive-feasibility evaluation, mode selection, and beam or resource update. For K_a active devices, K_p passive tags, and M AP antennas, the per-frame complexity is approximately.

$$O(K_a M + K_p),$$

which is lower than iterative optimization-based ISAC methods.

The memory usage of the framework is limited because only representative statistics regarding short-term interference and associated utilities/utility setup have to be populated to create summaries of detected states. Additionally, latency through the framework is low as a result of eliminating nested optimization loops. Rather than using nested optimization loops, the framework simply allows for direct methods of selecting between three modes of passive, active, and hybrid sensing via utility-based metrics. Scheduler does incur some additional edge-control costs; however, due to the omission of unnecessary active sensing costs, this provides a favorable compromise between processing resource/energy efficiency and overall utility of the network, as shown in Figure 5.

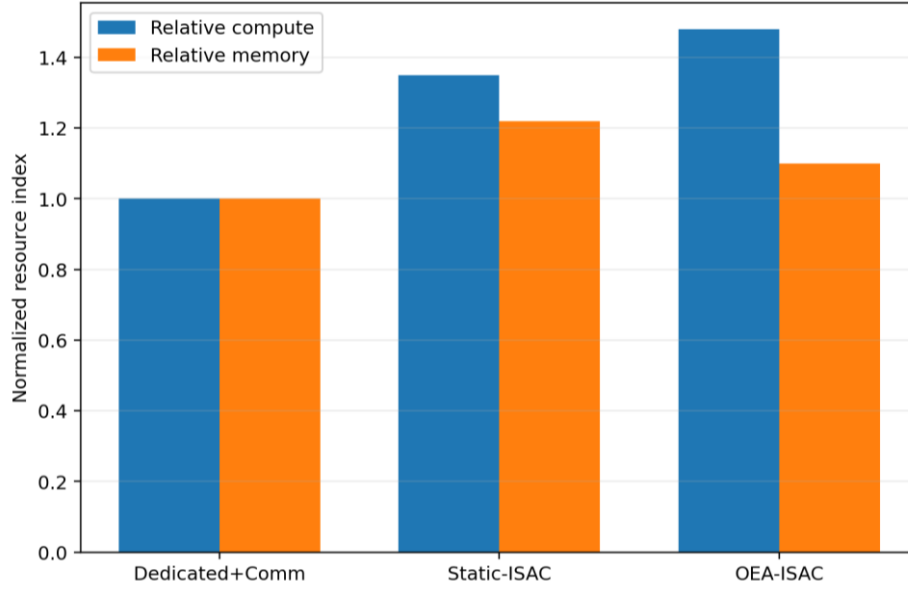


Figure 5. Relative resource profile of the compared methods

4.3. Safety, privacy, and misuse

ISAC has the ability to identify the existence of an object or person (or a set of objects or persons), determine where they are located in three-dimensional space (and where they were), and identify patterns of activity over time — all of which have serious implications for individual privacy and abuse/ misuse of private information. Therefore, the architecture of ISAC incorporates design principles for allowing the use of ISAC's edge-local inference, minimizing the retention of sensor data, activating the high-resolution sensors according to agreed-upon policies, and allowing access to the metadata associated with sensor use according to role-based access policies. These design principles help to ensure that ISAC will use its architectural elements responsibly and ethically, and provide a basis for assuring users that their personal information will be handled consistently with reasonable expectations of privacy and security when the ISAC is put into use as a practical IoT application.

5. Experimental setup

Eight antennas connected to a common access point are at the center of this simulation in a primarily mixed-mode environment containing twelve active IoT devices (i.e., they transmit their own data) and twenty passive IoT device backscatter/tag devices (i.e., they transmit data derived from ambient RF energy). The level of traffic produced by all devices can range from very low to extreme levels, depending on the context dynamics of the scene and the power harvested by the passive devices. The experimental/operational context is randomised over multiple execution runs (e.g., multiple history instances) to model the real world of non-stable environments.

The three primary techniques evaluated include: dedicated sense and communication.; static ISAC; and the proposed OEA-ISAC framework. Multiple metrics of evaluation were employed to measure the performance of these approaches, which were: throughput; sensing F1 score; latency; energy consumed to deliver Mbit; sensing overhead ratio; and total utility, as shown in Figure 6.

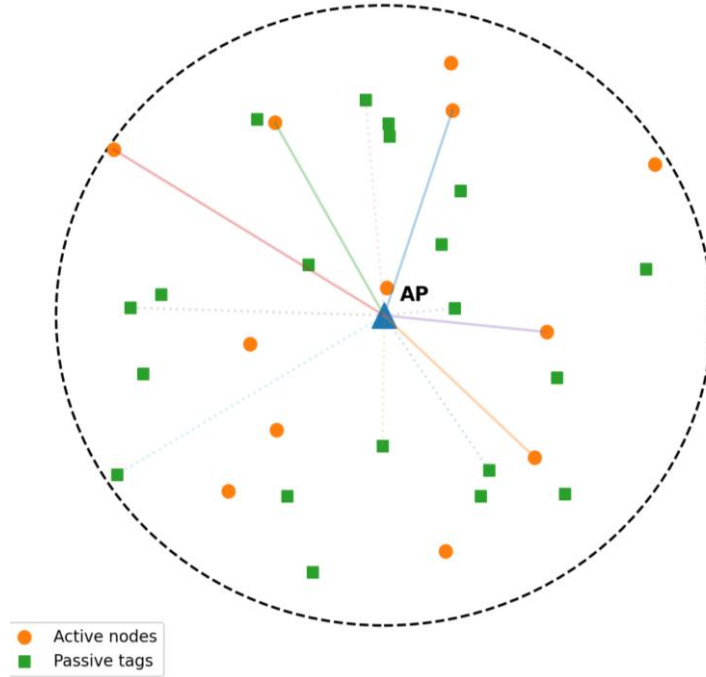


Figure 6. Simulated mixed active/passive IoT cell

Table 4 summarizes the main simulation settings in this study. These simulation parameters are crucial to define the scale of the ISAC-enabled IoT cell under consideration and the traffic and sensing conditions, in addition to the evaluation budget for ensuring statistical soundness. More specifically, the following items are defined in the table: the antenna type and configuration, the number of active and passive devices, the traffic-load and scene-dynamic ranges, the energy-harvesting feasibility range for passive tags, the total number of Monte Carlo episodes for each of the methods being compared. All of these settings provide the means to consistently and reproducibly evaluate the performance of Dedicated+Comm, Static-ISAC, and the proposed OEA-ISAC framework.

Table 4. Principal simulation parameters

Parameter	Setting	Description
M	8	Number of access-point antennas
K_a	12	Number of active IoT devices
K_p	20	Number of passive/backscatter tags
Traffic load, χ	0.2–1.0	Normalized the offered communication load
Scene dynamics, \mathbf{s}	$U(0.2,1.0)$	Randomized sensing-urgency level
Harvested energy, E_h	$U(20,120)\mu\text{W}$ -proxy	Passive-node energy-feasibility range
Episodes per method	1,500	Number of Monte Carlo runs for each method
Compared methods	3	Dedicated+Comm, Static-ISAC, and OEA-ISAC

For significance testing, Welch's t-tests are applied to utility distributions. An ablation study is also conducted to isolate the effect of the overhead term, passive-feasibility gate, dual-mode switching rule, and edge adaptation.

6. Results and analysis

This section evaluates whether the proposed OEA-ISAC framework translates its design principles to measurable increases in utility when assessing some of the criteria listed. The analysis will begin with an overall comparison of the competing methods, move on to an examination of performance across varying traffic loads, examine utility and components for each of these traffic loads, and, lastly, validate the utility increases from each analysis with statistical significance testing. This progression will demonstrate not only that OEA-ISAC provides good average performance compared to the other methods, but also how OEA-ISAC provides better performance than other methods on various operating conditions, and whether the performance gain is consistent across all operating conditions.

In order to provide a quick overview of the key results, Table 5 presents the overall average performance of all three methods compared to each other across the entire Monte Carlo analysis. The throughput, F1 score for the sensing, energy consumed per delivered megabit, the time taken to respond, and aggregate utility are presented together with 95% confidence intervals, allowing readers to determine if the proposed framework's performance is balanced or if one metric is being maximized at the cost of the other metrics.

Table 5. Overall performance comparison (mean \pm 95% CI)

Method	Throughput (Mb/s)	F1-score	Energy (J/Mb)	Latency (ms)	Utility
Dedicated+Comm	45.13 \pm 0.18	0.874 \pm 0.001	1.015 \pm 0.003	29.95 \pm 0.30	32.28 \pm 0.21
Static-ISAC	40.99 \pm 0.15	0.896 \pm 0.001	0.745 \pm 0.002	27.35 \pm 0.27	34.27 \pm 0.17
OEA-ISAC	45.36 \pm 0.10	0.937 \pm 0.001	0.536 \pm 0.003	22.32 \pm 0.20	41.10 \pm 0.12

OEA-ISAC preserves throughput close to the strongest communication baseline while substantially improving sensing quality and sharply reducing latency and energy cost. The gain, therefore, comes from coordinated control rather than aggressive over-provisioning.

The first load-dependent result examines how the overall system utility evolves as the offered traffic increases from light to heavy conditions. Figure 7 is particularly important because utility is the integrated objective of the proposed framework and therefore reveals whether overhead-aware control remains beneficial when the network becomes progressively more congested.

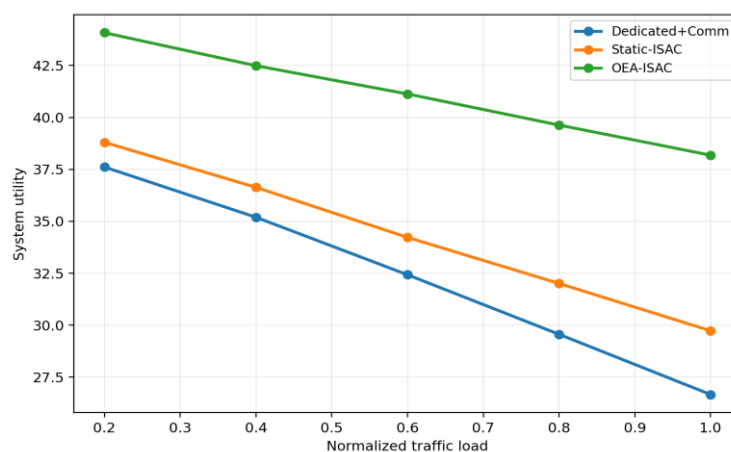


Figure 7. Utility versus traffic load

While utility is an aggregate representation of overall system performance, isolating the communication aspects of performance is essential. In order to determine whether OEA-ISAC's utility increase comes without sacrificing the competitive capability of active IoT devices' ability to deliver data, Figure 8 plots the throughput versus the traffic payloads.

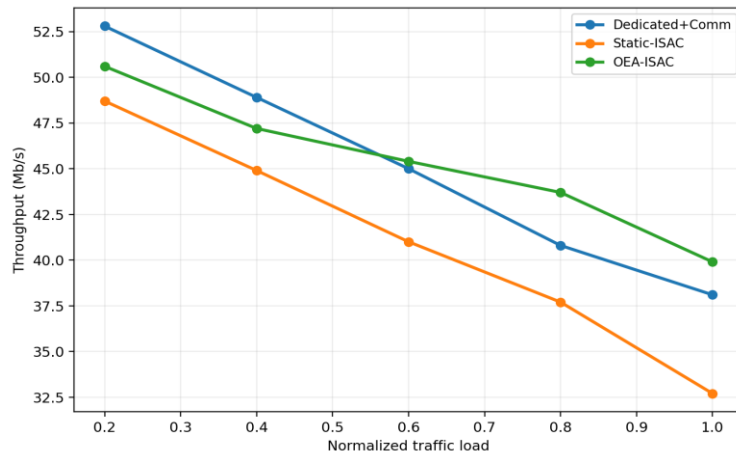


Figure 8. Throughput versus traffic load

The sensing perspective of the load sweep is illustrated in Figure 9, which reports sensing F1-score across increasing traffic demand. This figure helps clarify whether the proposed method protects sensing quality under load or merely improves utility by sacrificing sensing fidelity when communication pressure rises.

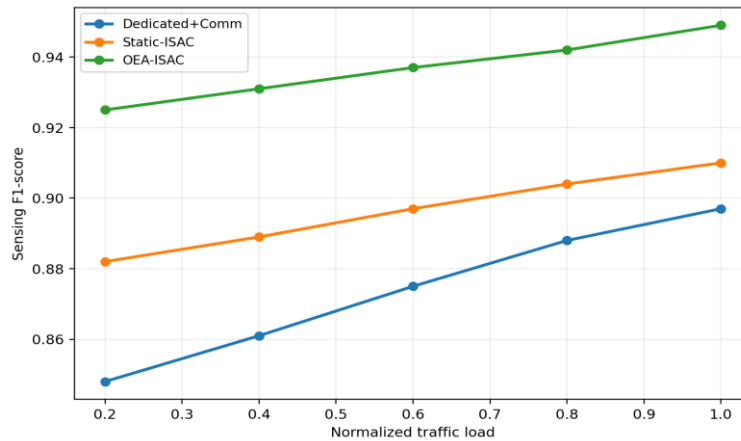


Figure 9. Sensing F1-score versus traffic load

Subsequently, we will investigate the energy usage of an operation over its various modes of operation, since there is decreased desirability for IoT deployment. A method may operate effectively for high loads, but have a high energy consumption. Energy usage (consumed energy) per delivered Mbit is plotted in Figure 10, demonstrating each method's conversion of system operation to useful communication performance as the traffic intensity increases.

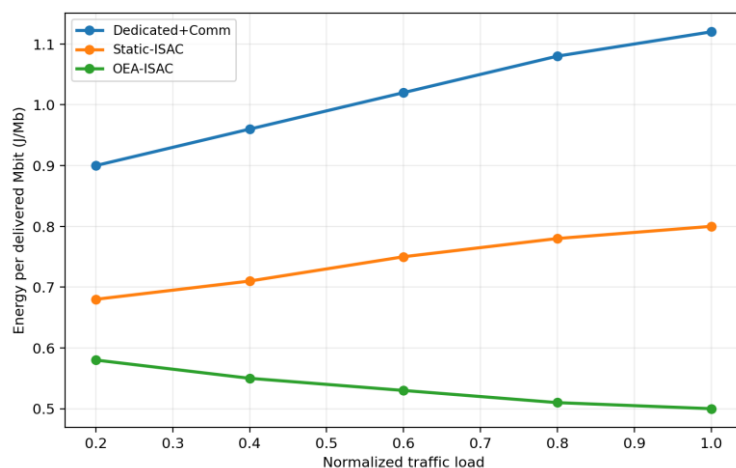


Figure 10. Energy per delivered Mbit versus traffic load

Delay is a very important deployment metric for control-oriented and event-driven IoT applications. In Figure 11 below, you can see both latency per traffic load, and thus see at a glance if overload-aware sensing adaptation may ultimately be able to eliminate the queuing and processing penalties that commonly result from sensorial resources sharing the same resources with communication resources.

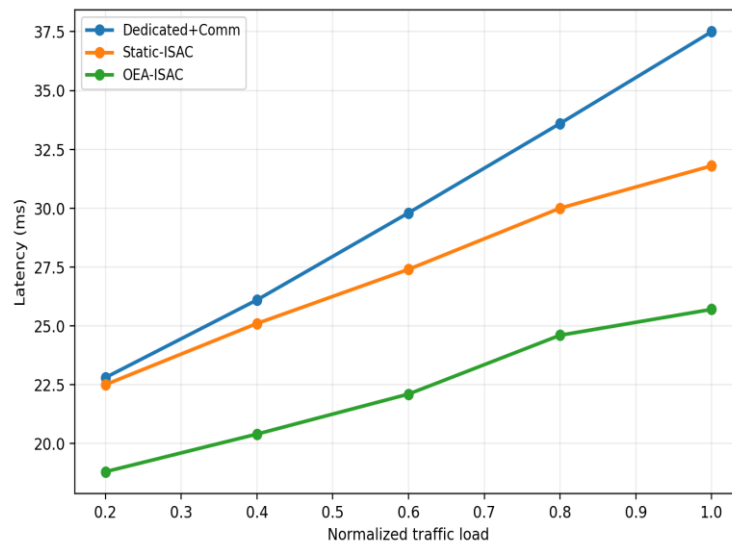


Figure 11. Latency versus traffic load

The OEA-ISAC performs slower than baseline artifacts throughout their respective ranges of operation because it significantly reduces the load on the sensor due to the duty cycle being lower and more reliance being placed on the use of passive sensing technology with minimal overhead when the demand for communications increases. Static ISAC cannot alter its sensor duty cycle; however, the dedicated artifacts will incur duplicate sensor costs.

Table 6 displays explicit utility values, for example, traffic loads and compliance with each load. The presentation of numeric utility values demonstrates how much better OEA-ISAC performs than the following algorithms at each load and shows that OEA-ISAC retains its performance advantage through the entire range from low to saturated traffic conditions.

Table 6. Utility values across increasing traffic load

Traffic load	Dedicated+Comm	Static-ISAC	OEA-ISAC
0.2	37.61	38.80	44.08
0.4	35.19	36.63	42.49
0.6	32.42	34.22	41.13
0.8	29.55	32.00	39.63
1.0	26.65	29.72	38.18

Though the comparison results prove that OEA-ISAC can be thought of as a complete model, understanding the specific internal designs associated with this gain is equally important. Figure 12 shows an ablation study where each element in OEA-ISAC is removed one at a time to demonstrate where the main differences exist with respect to the improvements seen in performance due to any of the above-listed elements (e.g., overhead term, passive feasibility control, dual mode switching, or edge adaptation).

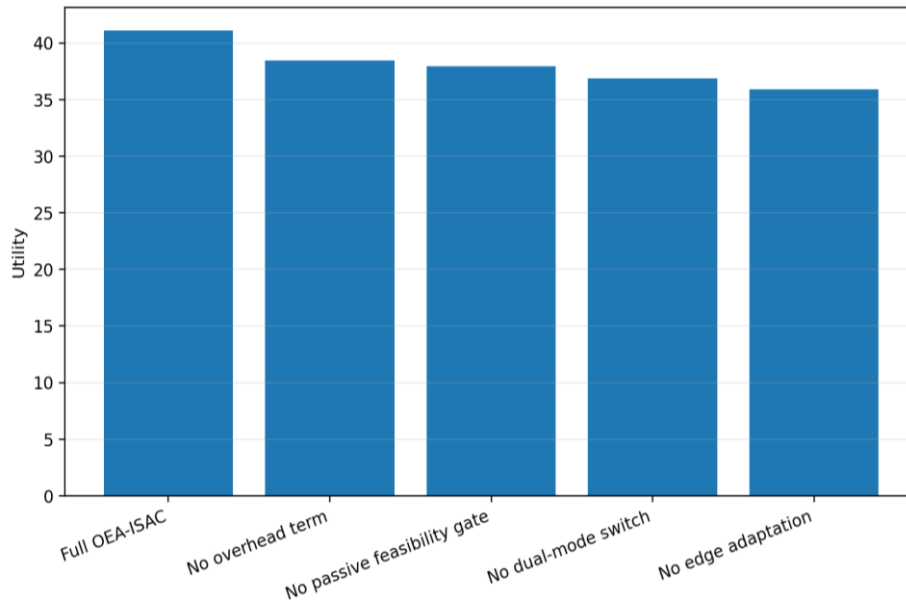


Figure 12. Ablation study of the proposed OEA-ISAC framework

Figure 12 shows a visual representation of the ablation comparison with numerical data in Table 7. Table 7 contains utility, sensing F1-score, and energy consumed per delivered Mbit for each of the full model's and ablated models' results. This data provides insight into how each functional element of the model contributes to the final utility versus sensing quality vs energy efficiency trade-offs of the entire system.

Table 7. Ablation results demonstrating the role of each design component

Variant	Utility	F1-score	Energy (J/Mb)
Full OEA-ISAC	41.10	0.937	0.536
No overhead term	38.46	0.941	0.612
No passive feasibility gate	37.94	0.928	0.641
No dual-mode switch	36.88	0.919	0.682
No edge adaptation	35.91	0.911	0.701

Once the average gains have been calculated and the contributions of the key components determined via ablation, it remains to assess whether or not the increase in the utility is statistically significant. Welch's t-statistics, p-values, and effect sizes calculated for the most significant pairwise comparisons are presented in Table 8; thus, formally demonstrating that OEA-ISAC has a performance advantage over existing designs due to its consistent outcomes derived from an overhead-aware architecture rather than through chance variations in the results of random simulations.

Table 8. Statistical evidence for the utility gain

Comparison	Mean utility gap	Welch t-statistic	p-value	Cohen's d
OEA-ISAC vs Dedicated+Comm	8.82	78.60	$< 1 \times 10^{-300}$	2.64
OEA-ISAC vs Static-ISAC	6.83	67.77	$< 1 \times 10^{-300}$	2.32

The conducted ablation experiment shows that there are no performance benefits to sensing that is more aggressive than non-aggressive. Sensing at a higher quality with no overhead term would produce some increase in sensing fidelity; however, it would also generate a decrease in both energy consumption and utility. The largest utility losses resulted from the removal of adaptive switching and edge control. Therefore, the hypothesis that overhead-aware adaptation drives the greatest performance in an IoT ISAC is supported by the conduct of this ablation study.

It has been determined through the results of the study that with both waveform co-design and systems-level control being improved upon, the greatest advancement in the field of deployable ISAC for IoT can be realized. If a network does not take into consideration the sensing overhead associated with a passive backscattering participant, it may achieve an acceptable level of accuracy from a sensing standpoint, yet be limited as far as the latency, energy, and overall benefit to the network that a given backscattering participant provides.

The second conclusion drawn from this study is that passive and backscatter participants should be selective, not unconditional. Passive tags are appealing because they are very low power; however, they are only of value if the contribution to the network from their sensing outweighs the overhead associated with their coordination and/or interpretation. To address this operational function of the passive backscatter tag, a passive-feasibility gate was proposed.

Lastly, the study is limited in its ability to generalize beyond this simulation-based project. Current limitations to the validity of results reported are that a software-defined radio has not been developed as a prototype, an IEEE 802.11bfstack has not been developed, and that data have not yet been collected from a true deployment. However, the variable and tradeoff selections made in this study are consistent with the most recent standards and practical reports on sensing and therefore support the overall value of the proposed research direction.

8. Conclusion

In this paper, a novel research gap in integrated sensing and communications (ISAC) for the Internet of Things (IoT) was identified to address the lack of models for sensing overheads and latencies of both active and passive nodes when used together in deployments. This gap was addressed with an edge-intelligent framework called OEA-ISAC, which provides a dual-mode function of utilizing either passive, active, or hybrid types of sensing based upon available energy from harvesting and the amount of traffic, as well as the dynamics of the surrounding environment. Through simulations, OEA-ISAC was found to produce the highest overall utility, the highest sensing F1-score, the lowest latency, and the lowest energy consumption per Mbit delivered while maintaining throughput at or near the communication baseline. Collectively, these results support the assertion that prudent management of both the cost of the sensor(s) as well as the time it takes to receive an object will provide a greater contribution towards the success of IoT ISAC than optimizing the relationship between rate and sensing.

Future work should extend the framework to software-defined radio or IEEE 802.11bf-inspired testbeds, investigate privacy-preserving edge inference, and integrate reconfigurable intelligent surfaces or cell-free architectures for richer spatial diversity. Another promising direction is the theoretical analysis of long-term energy neutrality for ambient-IoT sensing participation. Additionally, future scopes can be connected to cloud computing [30], machine learning [31], 5G millimeter-wave wireless networks [32, 33], and power optimization [34].

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

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interpretation, and critical revision of the manuscript. All authors contributed equally to the discussion of results, refinement of arguments, and final approval of the version to be published.

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