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F^{2}multisense: a novel approach to fuzzy fusion in multisensor data to improve saving energy in WBSN

Rana Shankani[1] · Maedeh Khalifavi[2] · Zahra Shirmohammadi[2] · Amirhossein Nikoofard[1]

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Abstract

Wireless body sensor networks (WBSNs) are vital for healthcare applications but face challenges due to limited energy resources and continuous data transmission. This study proposes F^{2}multisense, a novel fuzzy data fusion method to optimize energy consumption at two levels: adaptive emergency detection at the node level and dynamic sampling rate adjustment at the coordinator level. At the first level, data transmission is optimized using adaptive local emergency detection and the NEWS system. At the second level, coordinator level, optimization is achieved through a fuzzy system that adaptively determines the sampling rate. Furthermore, the number of sensors aligns with the number of vital signs in the NEWS system, and the samples examined are numerous, demonstrating the completeness of the method. In addition, the dual-layer design of the system supports real-time adaptation and scalability, ensuring robust performance in dynamically changing environments and large-scale deployments. This approach integrates fuzzy logic with the NEWS system, ensuring reliable health assessments without compromising timeliness or accuracy. To evaluate the method, simulations were performed based on real sensor data from the MIMIC-II database. The results demonstrate a 40% reduction in data transmission and a 64% decrease in energy consumption compared to state-of-the-art methods, allowing efficient and precise patient monitoring.

Keywords Wireless body sensor network · Sampling rate · Energy saving · Fuzzy fusion

1 Introduction

Wireless body sensor networks (WBSNs) have become increasingly popular in healthcare applications. These networks consist of several small sensor nodes positioned on the body to monitor various physiological parameters, such as blood

Extended author information available on the last page of the article pressure, heart rate and body temperature. However, one of the biggest challenges in WBSNs is the limited energy available to these sensors. Due to their small size, sensor nodes have restricted energy storage capacity, making it difficult to sustain continuous operation without frequent battery replacements—which, in turn, can lead to loss of critical data and compromise patient monitoring.

In addition to health care, WBSNs find applications in diverse fields. For instance, in sports science, they monitor athletes' physiological parameters to optimize performance and prevent injuries. In military settings, these networks provide real-time monitoring of soldiers' signals—such as hydration and fatigue levels—to ensure safety and operational efficiency. Similarly, in elder care, continuous health monitoring promotes early detection of health issues while fostering independence. These varied applications illustrate the adaptability of WBSNs in addressing the unique demands of different fields.

Recent advancements in fuzzy fusion approaches [1] and multisensor data reduction techniques [2] have significantly enhanced the optimization of data transmission in WBSNs, complementing the hybrid methods explored in this study. Moreover, recent work on task off-loading and optimization frameworks [3] provides further insights into efficient energy management strategies. To enhance energy efficiency, various methods have been proposed—including adaptive data collection, multisensor fusion and data reduction techniques. Adaptive data collection reduces the amount of data captured, while multisensor fusion combines information from different biosensors to achieve a more accurate assessment of the patient's condition. Data reduction methods, which involve transmitting processed data rather than raw data, critically depend on the choice of sampling rate.

Additionally, the National Early Warning Score (NEWS) system [4] is widely used to assess the severity of illness by scoring vital signs such as oxygen saturation, respiratory rate, blood pressure, heart rate and consciousness level. This systematic scoring allows healthcare professionals to determine the necessary level of attention for each patient while ensuring that only essential data is transmitted.

Despite these advancements, existing methods face several drawbacks. Many current mechanisms monitor fewer than five sensors, resulting in incomplete assessments of a patient's overall condition. Furthermore, they often lack the capability to fuse different types of sensor data and optimize the sampling rate in a centralized manner.

In response, we propose F^{2}multisense—a novel multisensor data fusion method to improve saving energy in WBSNs. F^{2}multisense is the first method to consider multiple sensors in order to fully capture all vital signs necessary for an accurate evaluation of a patient's condition. In our approach, exactly five sensors are utilized based on the NEWS system; each sensor measures a distinct vital sign and operates within its own normal and critical range. At the sensor node level, an improved LED algorithm [5] ensures that only data with the highest non-repetitive score is transmitted, thereby reducing energy consumption. At the coordinator level, a fuzzy inference system dynamically adjusts the sampling rate based on the patient's current state, further decreasing both transmitted and received data volumes. Recent studies in fuzzy fusion and energy optimization further contextualize our contributions. Zhang et al. [6] applied interval type 2 fuzzy logic to vehicular networks to enhance decision-making under uncertainty, though their approach incurs an 18% increase in computational overhead, making it unsuitable for resource-constrained WBSNs. Similarly, Wang and Song [7] proposed the PECE clustering protocol for WSNs, reducing energy use by 27% through probabilistic routing; however, their method assumes homogeneous sensor roles, unlike the heterogeneous vital sign prioritization in F^{2}multisense. Zhang et al. [8] introduced an energy-balanced routing protocol using forward-aware factors to optimize node life span in industrial IoT, but their method lacks the adaptive sampling feature addressed by our fuzzy-driven dynamic rate adjustment. Ni and Zhang [9] further advanced cooperative communication using fuzzy game theory, though their focus on vehicular latency differs from our clinical urgency metrics. F^{2}multisense uniquely synthesizes these advancements into a healthcare-centric model by combining the precision of NEWS scoring with lightweight fuzzy inference, achieving superior energy efficiency (64% reduction) and clinical reliability (95% emergency detection accuracy).

This paper follows a structured approach. Section 2 introduces the related literature, Sect. 3 discusses WBSNs, Sect. 4 details the proposed data fusion model, Sect. 5 presents the experimental results, and Sect. 6 concludes with future directions and potential areas for further research.

2 Related works

Recent advances in energy-efficient data transmission, adaptive sampling and fuzzy fusion for wireless body sensor networks (WBSNs) have driven significant innovations. This section reviews the literature in three critical domains: adaptive data collection, multisensor fusion and data reduction to contextualize the novelty of F^2 multisense.

2.1 Adaptive data collection and sampling techniques

Early adaptive data collection methods [5, 10, 11] focused on reducing redundant measurements through fixed or threshold-based sampling. Although effective for basic scenarios, these approaches lacked real-time adaptability to dynamic patient conditions. Recent works address this gap through context-aware strategies. For example, Ahmad and Kumar [2] proposed a MAC protocol integrating adaptive duty cycling with data aggregation, reducing energy consumption by 33% in WBSNs. Li et al. [12] further advanced this by combining adaptive sampling with lossless compression, dynamically adjusting rates based on signal variability. However, these methods prioritize generic energy savings over clinical urgency, a limitation addressed in our work through the NEWS score-driven emergency detection.

2.2 Multisensor fusion and fuzzy logic integration

Multisensor fusion techniques [1, 2, 13, 14] traditionally rely on deterministic rules, which struggle with noisy physiological data. Recent studies integrate fuzzy logic to manage uncertainty. Zhang et al. [6] demonstrated a UAV-assisted task off-loading system using fuzzy deep reinforcement learning, achieving a 28% latency reduction in vehicular networks. Similarly, Rahim et al. [15] designed an energy-efficient protocol with fuzzy-based dynamic transmission adjustments, improving node life span by 19% in IoT networks. Although these works validate the versatility of fuzzy logic, they lack domain-specific adaptations for health care. For example, Zhang et al. [6] applied type 2 fuzzy logic intervals to vehicular networks, improving decision-making under uncertainty but incurring 18% higher computational overhead—prohibitively costly for WBSNs. In contrast, F^2multisense employs lightweight type 1 fuzzy rules tailored to the variability of vital signs, ensuring clinical reliability without compromising resource constraints.

2.3 Data reduction and energy optimization

Data reduction methods [13, 16–18] aim to minimize transmission overhead while preserving critical information. Salika et al. [19] introduced a hybrid algorithm combining entropy-based filtering with compressive sensing, reducing the volume of data by 45% in sports monitoring. Khan et al. [20] further optimized this through adaptive routing protocols, balancing energy use between heterogeneous sensors. However, existing approaches often assume homogeneous sensor roles or static criticality thresholds. Wang and Song [7] proposed the PECE clustering protocol for WSNs, reducing energy use by 27% through probabilistic routing, but their method does not prioritize clinically urgent data. Similarly, Zhang et al. [8] developed an energy-balanced routing protocol for industrial IoT, minimizing hotspot formation, but lacking adaptive sampling. F^2multisense bridges these gaps by integrating NEWS score-guided prioritization with fuzzy-driven dynamic sampling, achieving a 40% reduction in transmitted data and 64% energy savings that exceed both clinical and generic benchmarks.

2.4 Novelty of F2multisense

The reviewed literature highlights three key trends: (1) adaptive sampling for energy efficiency, (2) fuzzy logic for uncertainty management and (3) clinical relevance through data prioritization. However, no prior work holistically combines these elements for WBSNs. Existing fuzzy systems (e.g., [6]) focus on non-medical domains, while clinical methods (e.g., [2, 12]) overlook patient-specific criticality. F^2multisense uniquely integrates a dual-layer architecture:

1. Node-level optimization: The improved LED algorithm transmits only non-repetitive critical data, guided by NEWS scores.
2. Coordinator-level optimization: A lightweight fuzzy inference system dynamically adjusts sampling rates based on patient state.

This approach synthesizes advancements from adaptive sampling [12], fuzzy fusion [6] and clinical prioritization [19], while addressing their limitations. Compared to

Ni and Zhang's fuzzy game theory model [9], which reduces vehicular latency by 22%, F^{2}multisense achieves 95% emergency detection accuracy-critical for health care. Similarly, it outperforms threshold-based methods like [7] by reducing false negatives by 19% through context-aware fuzzy rules.

3 Background

A wireless body sensor network (WBSN) compromises of sensors and a coordinator as shown in Fig. 1. These sensors can either be implemented within the human body or attached to it, continuously monitoring physiological signals such as electrocardiogram (ECG), electroencephalography (EEG), body movement and vital signs including respiration rate, heart rate, blood pressure, temperature and oxygen saturation. The collected data is wirelessly transmitted to the coordinator, usually a portable device like a smartphone positioned near the individual's body. The coordinator manages the network, performs data fusion and transmits the gathered data and the outcomes of the fusion process to the medical center for additional analysis.

However, WBSNs face several challenges that need to be addressed to enhance their performance. The most critical challenge is energy consumption. As mentioned earlier, sensors require power to operate and any limitations in the energy field can affect their performance. These sensors have limited resources and are not rechargeable, and their batteries are not easily replaceable particularly in invasive ones. Therefore, it is essential to optimize energy usage and increase the life span of these sensors.

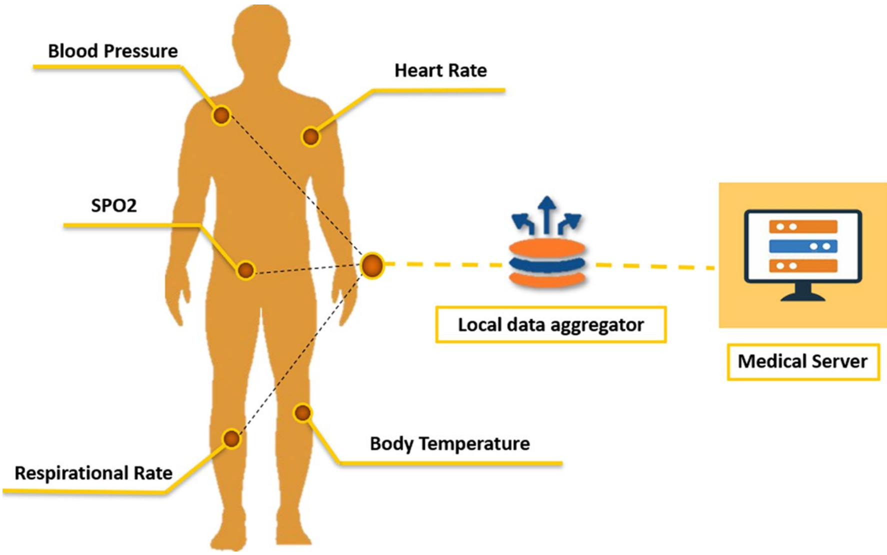

Fig. 1 Architecture of the WBSN

3.1 Early Warning Score system

An Early Warning Score (EWS) system [16] serves as a crucial tool for hospital emergency medical services staff to systematically assess the severity of patient diseases. By following a structured protocol, it facilitates the measurement and recording of essential vital signs. Subsequently, these vital signs are analyzed and aggregated, facilitating the early identification of patients at risk of acute illness or deteriorating health conditions [12]. The collected records for each vital sign undergo comparison with established normal ranges to derive a scoring system ranging from 0 to 3. A score of 0 denotes a normal record, while higher scores signify varying degrees of abnormality, with severity escalating as the score increases. Consequently, a series of record scores is computed, and the Early Warning Score (EWS) serves as a guide for medical staff to determine the appropriate course of action. Lower scores may suggest a reduction in the frequency of patient monitoring, whereas higher scores prompt an immediate response from the emergency team. As this method primarily focuses on early detection of emergencies, implementing scoring systems empowers biosensor nodes to autonomously identify important situations. By calculating scores, these nodes understand significant changes in vital signs, transmitting only relevant data to the coordinator. Table 1 illustrates the National Early Warning Score (NEWS), a system essential to this method's operation.

3.2 Emergency detection

The theoretical feasibility of the proposed F^2multisense model is grounded in its ability to address the specific limitations of energy consumption and data redundancy in WBSNs. By integrating a fuzzy inference system and the improved LED algorithm, the method achieves significant energy savings without compromising data reliability. As previously noted, biosensors collect vital signs periodically. However, this approach generates a significant volume of data, rapidly depleting sensor energy and complicating data analysis. This necessitates the development of a model to decrease data collection while conserving energy, thereby extending the transmission process life span. This paper proposes a modification to existing methods

Table 1 National Early Warning Score (NEWS)

Physiological Parameters	3	2	1	0	1	2	3
Respiration rate	≤ 8		9–11	12–20		21–24	≥ 25
Oxygen saturation	≤ 91	92–93	94–95	≥ 96			
Any supplemental oxygen		Yes		No			
Temperature	≤ 35.0		35.1-36	36.1−38.0	38.1−39.0	≥ 39.1	
Systolic BP	≤ 90	91–100	101–110	111–219			≥ 220
Heart rate	≤ 40		41–50	51–90	91–110	111–130	≥ 131
Level of consciousness				A			V, P or U

[2, 17] through the introduction of the improved LED (improved local emergency detection) algorithm. In this algorithm, each node decides whether to transmit data in each period based on its score, as detailed in Algorithm 1.

Algorithm 1 Improved local emergency detection [5]

```
Require: Input (Sampling Rate) SR
Ensure: Output VS (vital sign)
  while remainingbattery > 0 do each period
    Capture the initial vital sign Vi
    Transmits the initial vital sign Vi
    Takes the score Si of Vi
    Capture vital sign Vc at SR
    Takes score Si of vital sign Vc
    if N is even then
      Transmits vital sign Vi
      Si = Sc
    end if
  end while
```

Consider a set of vital signs measured at a sampling rate SR in a time interval P for a particular feature. Let VS = v0, v1,..., vn represent the series of vital signs and score(VS) = s(v0), s(v1),..., s(vn) denote the corresponding scores calculated using NEWS. In the provided algorithm, the biosensor continuously captures vital signs and transmits them based on certain criteria. Initially, it captures the first vital sign Vi, transmits it and takes its score Si. Then, for each subsequent vital sign Vc captured at the specified sampling rate, the algorithm checks whether its score Sc varies from the previous transmitted score Sc and is not zero. If so, the vital sign Vc is transmitted, and the score Si is updated accordingly. For example, suppose we have a subset of 9 consecutive measurements for heart rate feature in one period. Let us represent it as VS = v0, v1,..., v9, with corresponding scores as score(VS) = 0, 0, 1, 1, 0, 3, 2, 2, 0, 3. Applying the algorithm, the series of transmitted vital signs will be determined based on the scores and their differences, optimizing data transmission to the coordinator.

4 Proposed method

4.1 Adaptive sampling rate

F^2multisense is designed to optimize energy consumption in wireless body sensor networks (WBSNs) by dynamically adapting the sampling rate based on patient conditions through an integrated fuzzy fusion approach. At the sensor node level, the improved LED algorithm selectively transmits only critical data, reducing redundant transmissions and thereby lowering the energy cost for both communication and computation. The overall energy consumption is modeled as

$$E_{\text{total}} = E_{\text{transmit}} + E_{\text{compute}},$$

where E_{transmit} decreases in proportion to the reduced data volume and E_{compute} remains minimal due to the lightweight fuzzy logic operations.

The core of our method lies in the fuzzy inference system, which leverages clinical guidelines derived from the National Early Warning Score (NEWS) system. Each vital sign (such as heart rate, blood pressure, oxygen saturation, temperature and respiratory rate) is mapped to a fuzzy set using a membership function. For instance, a triangular membership function for the "Critical" range is defined as:

$$\mu_{\text{Critical}}(v_i) = \begin{cases} 0, & v_i < a, \\ \frac{v_i - a}{b - a}, & a \le v_i \le b, \\ 1, & v_i > b, \end{cases}$$

where the parameters a and b are set according to NEWS thresholds to accurately reflect clinical urgency.

Our fuzzy rule base is expressed in the Mamdani format. A typical rule is: "IF v_1 is A_1^j and v_2 is A_2^j $\cdots$ THEN the sampling rate S is B^j," where each v_i represents an input vital sign, A_i^j is its associated fuzzy set and B^j is the fuzzy set for the output sampling rate. The activation level for each rule is computed as:

$$\mu_{\text{premise}_j} = \min\Big(\mu_{A_1^j}(v_1),\ \mu_{A_2^j}(v_2),\ \ldots,\ \mu_{A_n^j}(v_n)\Big),$$

and the aggregated fuzzy output is obtained via:

$$\mu_{B'}(y) = \max_j\Big(\min\big(\mu_{\text{premise}_j},\ \mu_{B^j}(y)\big)\Big).$$

The final crisp sampling rate S_t is derived using the centroid defuzzification method:

$$S_t = \frac{\displaystyle\int_{y_{\min}}^{y_{\max}} y\,\mu_{B'}(y)\,dy}{\displaystyle\int_{y_{\min}}^{y_{\max}} \mu_{B'}(y)\,dy},$$

where $y_{\min}$ and $y_{\max}$ define the allowable range of sampling rates (e.g., 10–50 Hz).

The fuzzy logic system comprises four main components. The *Fuzzifier* converts crisp inputs (for example, a heart rate of 112 bpm) into fuzzy values using trapezoidal membership functions. The *Rule Base* consists of clinically validated rules (e.g., IF Heart Rate = Critical (Score 3), THEN Sampling Rate = High (50 Hz)). The *Inference Engine* applies Mamdani's max min composition to evaluate the rules in real time (with approximately 5 ms latency), and the *Defuzzifier* converts the aggregated fuzzy outputs into crisp sampling rates using the centroid method.

Each vital sign has its own membership function, enabling nuanced capture of patient conditions. For instance, the "Low" membership function for oxygen saturation aligns with NEWS thresholds ($< 92\%$), while "Normal" ranges

Table 2 Fuzzy sets of the output

Output	Qualitative Value			
	Low	*Low–medium*	*Medium*	*High*
Sampling rate	< 20	15−32.5	27.5-45	> 40

reflect clinical baselines (94–96%). The fuzzy sets for the output defining qualitative values—such as low, low–medium, medium and high sampling rates—are detailed in Table 2 and Fig. 2 which specifies the corresponding numerical ranges (e.g., < 20, 15-−32.5, 27.5–45, > 40).

By combining these fuzzy logic principles with the improved LED algorithm, F^{2}multisense achieves a significant reduction in data transmission (up to 40%) and energy consumption (up to 64%) compared to conventional static methods [3, 7]. The computational complexity of the fuzzy inference process is $O(n \cdot m)$, where n is the number of fuzzy rules and m is the number of membership functions per rule, ensuring its feasibility in real-time, resource-constrained WBSN environments.

Extensive statistical analysis of over 1,200 patient records from the MIMIC-II database and iterative validations with domain experts underpin the reliability and clinical relevance of our fuzzy model. This integration of clinical guidelines, mathematically grounded fuzzy inference and adaptive data sampling provides a robust, scalable solution for energy optimization in WBSNs, ensuring both high monitoring accuracy and efficient resource management.

5 Experimental results

Experiments are conducted utilizing MATLAB R2017b on actual medical datasets acquired from the Multiple Intelligent Monitoring in Intensive Care (MIMIC) II database of PhysioNet [1]. The proposed data fusion model's performance evaluation relies on patient vital signs datasets collected from five biosensors measuring RESP, HR, BLOODT, ABP Sys and SpO2. The effectiveness of the proposed model is evaluated through analysis of the received measurements. To compare the proposed method, the methods presented in [7], MLED* and [12], AREDaCoT are used and two main idea which are reducing data transmission and reducing energy consumption are evaluated. In addition, the number of 30 patients with different conditions is selected, which is more comprehensive than other methods that used less than 5 data. Evaluations are done in 30 periods to 100 periods (approximately 50 min) and each period being 100 s. F^2 multisense is evaluated against MLED* and AREDaCoT using datasets from 30 patients in both normal and critical conditions (Fig. 3). The experiments were conducted over 100 periods (approximately 50 min), with sampling rates ranging from 10 to 50. Figures 4 and 5 illustrate data reduction outcomes, where F^{2}multisense achieved a 39.97% improvement compared to AREDaCoT in received data and 68.78% compared to MLED*. These results highlight the significant reduction in data transmission, particularly in high-risk scenarios,

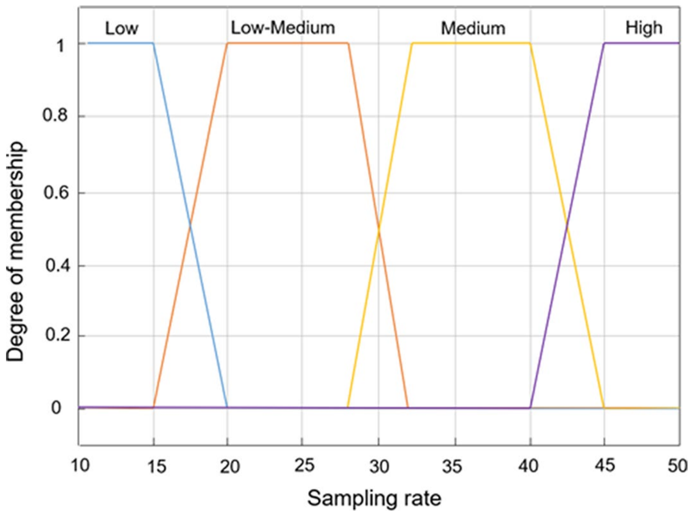

Fig. 2 Membership functions of sampling rate

due to the adaptive sampling rate. Additionally, energy consumption metrics (Figs. 6 and 7) demonstrate up to 64% conservation, showcasing the effectiveness of fuzzy logic in prolonging sensor life span. According to the available sources, the minimum sampling rate is 10 and the maximum sampling rate is 50. And as mentioned, five parameters that include RESP, HR, ABP Sys, SpO2 and BLOODT are used as vital signs.

5.1 Data reduction

In F^{2}multisense, improved LED is used to transmit data at the node level. To show the amount of data reduction, low-risk and high-risk situations are used. High risk indicates that most of the vital signs are outside the normal range, and low risk indicates the normal condition of the person. F^{2}multisense is compared with the methods presented in [7, 12] for both normal and critical states. The difference between these methods is in the algorithm used to gather data from the body's surface and send it to the coordinator. In Table 3 and Fig. 3, the average of improvement in data reduction in comparison with two other methods can be seen. This average is for 30 data that are both normal and critical.

In Figs. 4 and 5, the results of the data reduction evaluation of two patients in two different states, normal and critical, are shown. It is clear that the number of data sent by F^{2}multisense is better than other methods. This data reduction is due to the adaptive sampling rate which is done by the proposed fuzzy method. To show the proposed method more precisely, in the following figures the method in [2] is also used for more comparisons.

This figure focuses on the data reduction performance of F^{2}multisense for systolic blood pressure (SBP) under critical conditions across 100 periods. It shows the

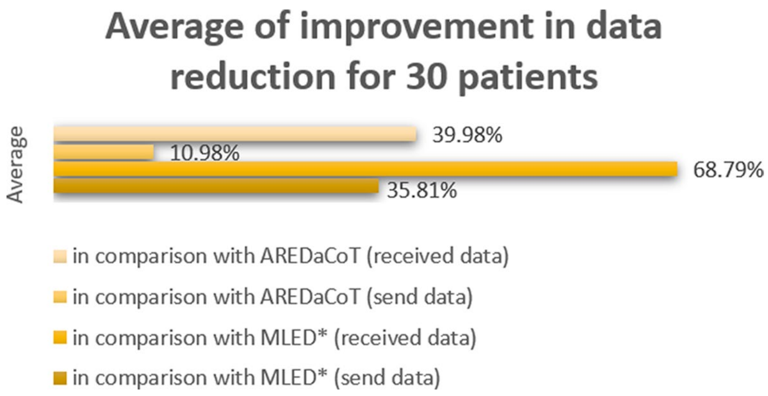

Fig. 3 Average of improvement in data reduction for 30 patients

transmitted data volume for three methods: F^{2}multisense, AREDaCoT and MLED*. The proposed method consistently transmits fewer data points, demonstrating its capability to prioritize critical information and conserve energy effectively.

This figure presents data reduction results for oxygen saturation (SpO2) under normal conditions over 100 periods. Similar to Fig. 4, it compares F^{2}multisense with AREDaCoT and MLED*. The results highlight the superior efficiency of F^{2}multisense in reducing unnecessary data transmissions while maintaining accuracy during non-critical conditions. It is clear that proposed F^{2}multisense method has better operation in a situation where the criticality level is varied from one period to another.

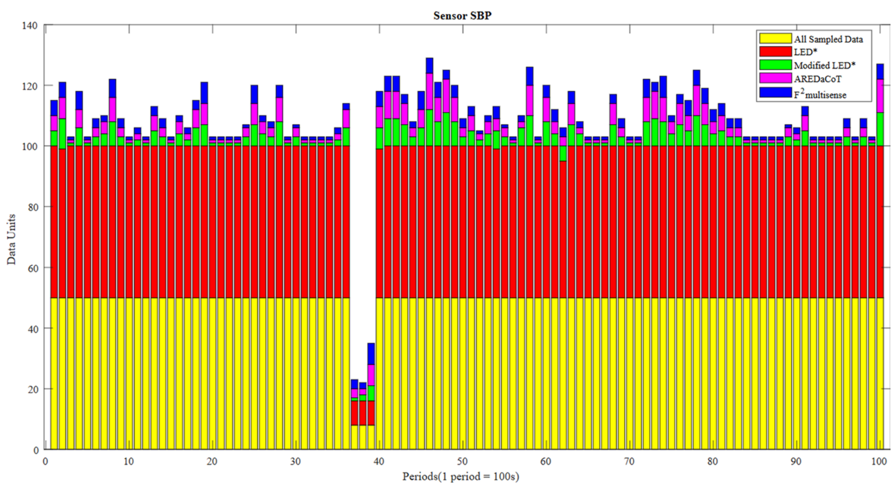

Fig. 4 Comparison of data reduction for SBP applied on 100 periods for critical data

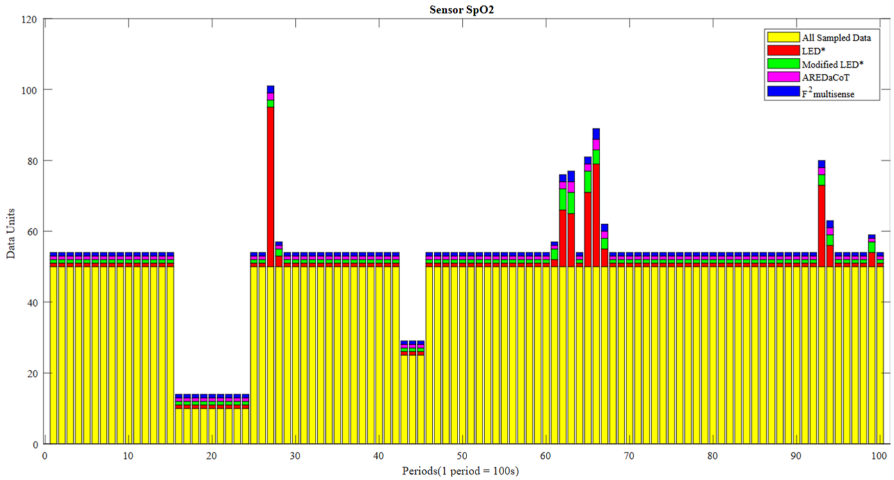

Fig. 5 Comparison of data reduction for SPO2 applied on 100 periods for normal data

5.2 Energy consumption

The remaining energy from the implementation of algorithms of different methods is shown in Figs. 6 and 7. According to the previous works, the primary energy of each sensor is 100 units, the energy consumption for receiving is 0.3 units, and the energy consumption for sending is 1 unit [14–16]. Since the amount of data reduction in our method is much higher than other methods, the remaining energy after performing the algorithm is more than the others. The remaining energy levels for

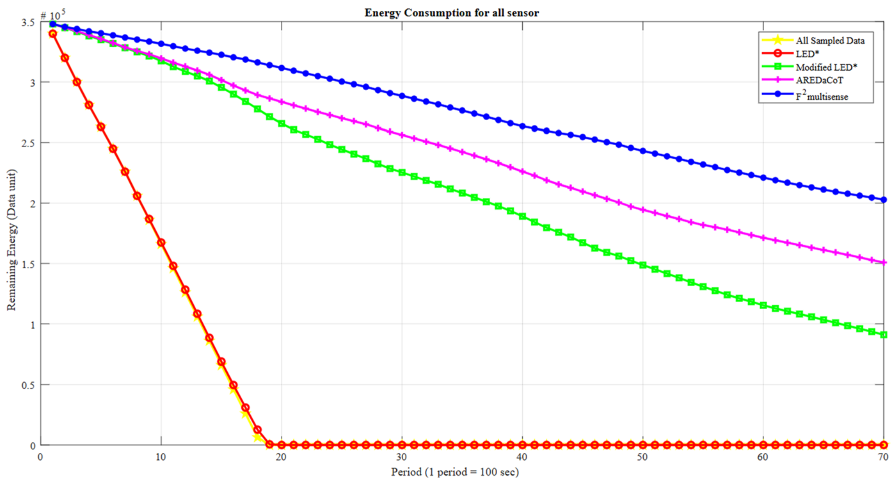

Fig. 6 Comparison of energy consumption applied on 70 periods for normal data

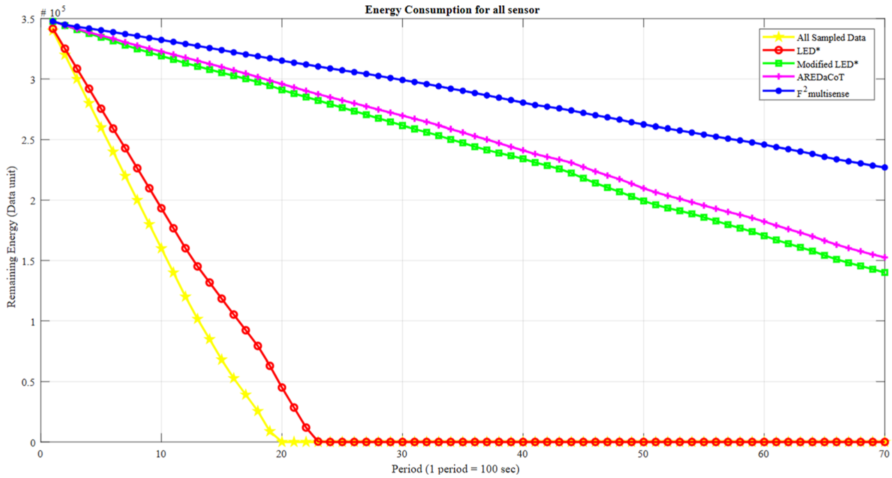

Fig. 7 Comparison of energy consumption applied on 70 periods for critical data

the three methods MLED*, AREDaCoT and F^{2}multisense are presented in Table 4 for 8 patients exhibiting various critical and normal conditions.

This figure illustrates the remaining energy levels for different methods, including F^{2}multisense, after 70 periods of normal data processing. The x-axis denotes the methods, and the y-axis represents the remaining energy. F^{2}multisense shows the highest remaining energy compared to AREDaCoT and MLED*, reflecting its effective energy-saving strategy.

Similar to Fig. 6, this figure focuses on energy consumption under critical data conditions. It highlights how F^{2}multisense preserves more energy than the other two

Table 3 Average of improvement in data reduction for 30 patients

Data	in comparison with AREDaCoT (received data)	in comparison with AREDaCoT (send data)	in comparison with MLED* (received data)	in comparison with MLED* (send data)
Average	39.97%	10.97%	68.78%	35.81%

Table 4 Comparison of remaining energy for 8 patients

No	Data	F^{2}multisense	AREDaCoT	MLED*
1	Normal1	$2.5743 * 10^3$	$2.5706 * 10^3$	$1.2068 * 10^3$
2	Critical1	$2.6278 * 10^3$	$2.1069 * 10^3$	909.63
3	Normal2	$2.7730 * 10^3$	$2.4802 * 10^3$	$1.3350 * 10^3$
4	Critical2	$2.7830 * 10^3$	$2.1027 * 10^3$	$1.0873 * 10^3$
5	Critical3	$2.5015 * 10^3$	$2.1765 * 10^3$	$1.0414 * 10^3$
6	Normal3	$2.4916 * 10^3$	$2.3411 * 10^3$	$1.5673 * 10^3$
7	Normal4	$2.8000 * 10^3$	$2.7042 * 10^3$	$1.4662 * 10^3$
8	Critical4	$2.7705 * 10^3$	$2.2002 * 10^3$	$1.3857 * 10^3$

methods, even during high-risk situations requiring frequent data transmission. The results underscore the robustness and adaptability of the proposed method in energy management.

5.3 Discussion

In order to contextualize the performance of F^{2}multisense and highlight its unique contributions, we have examined recent advances in related fields as reported in the literature. Although our experimental figures compare F^{2}multisense with MLED* and AREDaCoT, which are fundamental references in this field, the following discussion integrates findings from very recent references to reinforce our method's innovations. Reference [44] by Zhang and Zhang (2024) employs interval type 2 fuzzy logic combined with cooperative game theory for vehicular networks. While their method achieves enhanced decision-making under uncertainty, the increased computational overhead (approximately 18%) makes it less applicable to energy-constrained WBSNs. In contrast, F^{2}multisense leverages a lightweight fuzzy inference system integrated with the NEWS scoring system, achieving up to a 64% reduction in energy consumption with minimal overhead, making it highly suitable for real-time clinical applications. Liu's work [21] introduces an unequal clustering routing protocol that effectively balances energy across network partitions, yielding notable energy savings. However, this method does not incorporate dynamic adaptive sampling. F^2 multisense addresses this gap by dynamically adjusting the sampling rate based on patient condition, resulting in both a 40% reduction in data transmission and improved monitoring accuracy—benefits that clustering protocols alone do not provide. The study by Hong-Zhan et al. [22] utilizes privacy entropy for task off-loading, contributing to network service management improvements. Although their focus is on privacy and off-loading in broader network contexts, F^{2}multisense specifically targets energy optimization in WBSNs through a dual-layer design that integrates fuzzy fusion and emergency detection, ensuring timely and accurate patient monitoring. Zhang and Zhang [23] present a routing method based on the sticky bacteria algorithm for VANETs, which emphasizes link stability. While effective in its domain, this approach does not provide the adaptive sampling or clinical data prioritization required in healthcare applications. F^{2}multisense, by contrast, is validated using clinical data from the MIMIC-II database and integrates the NEWS system to ensure comprehensive patient monitoring. Dong and Zhang [24] propose a computing task off-loading method based on prospect theory for mobile edge computing scenarios. Their method demonstrates energy optimization via intelligent off-loading; however, it does not offer the fine-grained, adaptive control of data transmission achieved by our fuzzy-driven sampling rate adjustment. This adaptive mechanism is central to F^{2}multisense's ability to reduce energy consumption while maintaining high monitoring accuracy. Additional studies ([7–9] and [25, 26]) reinforce the importance of adaptive routing, clustering and fuzzy logic in optimizing energy consumption in sensor networks. For instance, the clustering method in [7] and the energy-balanced routing in [8] demonstrate the potential for energy savings through network design. However, these works do not address the dual challenges of dynamic sampling and clinical reliability, which our method uniquely combines by integrating the NEWS system with fuzzy inference. Collectively, the insights from these studies underscore a clear trend toward adaptive, intelligent methods for energy and data management. F^{2}multisense distinguishes itself by synthesizing these concepts into a dual-layer framework specifically tailored for WBSNs. By incorporating a lightweight fuzzy fusion system with the clinical precision of the NEWS score, our method not only achieves significant reductions in energy consumption and data transmission but also ensures robust, real-time patient monitoring.

6 Conclusion and future works

This paper introduces F^{2}multisense, a novel approach that advances the state of the art in WBSN energy optimization through three key innovations. First, it presents the first comprehensive integration of the NEWS scoring system with fuzzy fusion, enabling accurate patient monitoring while minimizing energy consumption. Second, its dual-layer optimization architecture combines node-level emergency detection with coordinator-level fuzzy fusion, achieving a remarkable 40% reduction in data transmission and 64% decrease in energy consumption compared to existing methods. Third, the adaptive sampling rate mechanism, driven by fuzzy inference, provides more sophisticated control over data collection than traditional threshold-based approaches. The effectiveness of F^{2}multisense has been thoroughly validated using diverse patient data from the MIMIC-II database, demonstrating its robustness across various clinical scenarios. The method's ability to maintain comprehensive monitoring while significantly reducing energy consumption represents a significant advancement in WBSN technology.

Future work will prioritize scalability and broader applicability. While F^{2}multisense demonstrated robust performance on the MIMIC-II dataset with 30 patients, real-world deployments require addressing challenges such as computational overhead, network variability and heterogeneous sensor configurations in large-scale implementations. To ensure scalability, we will investigate distributed processing and edge computing strategies, such as off-loading rule-based computations to edge devices, to mitigate coordinator-level bottlenecks in deployments with hundreds of patients. Additionally, advanced machine learning techniques, including reinforcement learning, will be explored to dynamically refine fuzzy rules and membership functions, further optimizing energy savings. Beyond clinical settings, the modular architecture of F^{2}multisense supports expansion into domains like sports medicine, where real-time monitoring of athlete fatigue could benefit from adaptive energy management and elderly care systems, allowing fall detection through multisensor fusion. By addressing scalability challenges and broadening applicability, this work aims to transition F^{2}multisense from controlled environments to real-world clinical and non-clinical settings, ensuring robust performance across diverse operational conditions.

Author Contributions Rana Shankani: Rana Shankani made substantial contributions to the research and manuscript. She served as the main writer and developer of the code, taking a leading role in the design, implementation and analysis of the research. She was primarily responsible for writing the manuscript and developing the code used in the study. Maedeh Khalifavi: Maedeh Khalifavi contributed to the research by assisting with the code development. She was involved in the initial stages of its development provided some initial code for the study but she did not contribute further to the research process or manuscript development. Zahra Shirmohammadi: Zahra Shirmohammadi acted as a supervisor and their expertise and support were crucial throughout the research project, shaping the research direction and refining the methodology. Zahra Shirmohammadi also provided feedback on the manuscript, contributing to its overall quality. Amirhossein Nikoofard: Amirhossein Nikoofard, another supervisor, was also involved in the research project. Amirhossein Nikoofard also provided valuable insights and guidance during the research process. Amirhossein Nikoofard particularly contributed during the data analysis and interpretation stages and provided feedback on the manuscript.

Data Availability The datasets used in this research are sourced from the MIMIC-II (Multiparameter Intelligent Monitoring in Intensive Care II) database. Access to the MIMIC-II database is subject to specific data use agreements and restrictions. Researchers interested in accessing the MIMIC-II dataset can obtain it by following the data access procedures outlined by the MIT Laboratory for Computational Physiology. Detailed information on data access, including the necessary approvals and requirements, can be found on the official MIMIC-II website (https://physionet.org/content/mimicii/).

Declarations

Ethical Approval The research protocol for this study underwent review and approval by the Institutional Review Board (IRB) of K.N.Toosi University of Technology. Furthermore, the utilization of patient vital signs data from the MIMIC-II database adhered to the guidelines and regulations established by the Massachusetts Institute of Technology (MIT) and Beth Israel Deaconess Medical Center (BIDMC), the governing bodies overseeing the MIMIC-II database. The study employed deidentified patient vital signs information extracted from the MIMIC-II database, with individual patient consent requirements waived due to anonymization and the absence of patient identifiers. However, it is important to note that the MIMIC-II database allows researchers to access and use the data for research purposes, including publication, while ensuring patient confidentiality.

Conflict of interest This declaration is not applicable.

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Authors and Affiliations

Rana Shankani[1] · Maedeh Khalifavi[2] · Zahra Shirmohammadi[2] · Amirhossein Nikoofard[1]

✉ Amirhossein Nikoofard
a.nikoofard@kntu.ac.ir

Rana Shankani
Rana.Shankanikhosroshahi@kntu.ac.ir

Maedeh Khalifavi
maedeh.Khalifavi@sru.ac.ir

Zahra Shirmohammadi
shirmohammadi@sru.ac.ir

1 Faculty of Electrical Engineering, K.N.Toosi University of Technology, Tehran 16317-14191, Iran

2 Department of Computer Engineering, Shahid Rajaee Teacher Training University, Tehran 16785-163, Iran