Journal of Innovations in Computer Science and Engineering
Shahid Beheshti Unversity

January 2026, Volume 3, Issue 2

An Efficient Energy Consumption Mechanism for Wireless Body Area Networks

Mohammadjavad Khani, **CODE ORCID:** 0000-0002-3643-7824
Razi University, Kermanshah, Iran, e-mail: m.khani@razi.ac.ir
Zahra Shirmohammadi✉, **CODE ORCID:** 0000-0003-2607-4940
Faculty of Computer Engineering, Shahid Rajaee Teacher Training University, Tehran, Iran,
e-mail: shirmohammadi@sru.ac.ir
Maedeh Rostamnezhad, **CODE ORCID:** 0000-0000-0000-0000
Faculty of Computer Engineering, Shahid Rajaee Teacher Training University, Tehran, Iran, e-mail: rostmnezhad@sru.ac.ir

ABSTRACT
Wireless Body Area Networks (WBANs) enable continuous and remote physiological monitoring, but their practical lifetime is constrained by the limited energy available at body-worn or implanted sensor nodes. Because wireless transmission is a major contributor to node energy use, reducing repeated transmission of redundant physiological representations is an important design objective.
This study presents a lightweight PCM-based transmission-reduction mechanism for WBAN sensors. The mechanism combines bandwidth-consistent sampling, scalar quantization, and Pulse Code Modulation (PCM) with a simple transmission rule: a PCM code is transmitted when it differs from the previously transmitted code, while repeated codes are suppressed. The method was evaluated in MATLAB using three hours of real physiological data from four signals in the MIMIC/PhysioNet dataset.
Across the four evaluated physiological traces, the proposed mechanism reduces transmitted 8-bit code volume by 69.81%-97.27% and achieves modeled energy savings of 53.70%-74.82%. Under the same 8-bit-equivalent transmission accounting, the adapted NIS baseline achieves 20.31%-32.59% energy saving and the code-aligned SRCM implementation achieves 48.75%-73.66%. PCM therefore gives the lowest transmitted payload and modeled energy consumption for all four evaluated signals. Signal-specific N, N_{tx}, MAE, and RMSE are also reported.
The results indicate that combining standard PCM representation with a lightweight state-change transmission rule can reduce redundant radio activity in resource-constrained WBANs, particularly for slowly varying physiological signals. The energy benefit must be considered together with signal fidelity because aggressive quantization may remove clinically relevant variations. Future work should validate the energy-quality trade-off on additional subjects and physical WBAN hardware.

KEYWORDS
Wireless Body Area Networks, Adaptive Sampling, Pulse Code Modulation, Physiological Signals, Energy Efficiency.

1. INTRODUCTION

Population aging and the increasing demand for continuous healthcare monitoring have intensified interest in remote and wearable health technologies [1]. Wireless Body Area Networks (WBANs) provide a practical architecture in which compact physiological sensors acquire vital signs and forward them to a coordinator, gateway, or healthcare service for subsequent analysis.
A WBAN typically contains sensors placed on, near, or inside the body to monitor variables such as heart rate, respiration, blood pressure, oxygen saturation, temperature, or motion [2]. Continuous acquisition can improve the timeliness of clinical observation, but it also produces a large stream of measurements that must be processed and communicated under strict constraints on battery capacity, computation, memory, and radio bandwidth.
Energy consumption is therefore a central limitation of WBAN operation. Sensing and local processing consume energy, but repeated wireless transmission of samples can dominate the energy budget when measurements are collected continuously. Reducing the number of unnecessary or redundant transmissions can consequently extend operating time without requiring larger batteries or frequent battery replacement.
Previous studies have addressed this issue through adaptive data collection, sensing-rate control, compression, sensor scheduling, and local emergency detection [1-7], [17-22], [34-37]. These methods demonstrate that transmission workload can be reduced by exploiting temporal or spatial redundancy. However, some approaches require continuous sensor activity, assume rechargeable nodes, introduce non-trivial processing overhead, or focus on emergency detection rather than a simple signal-representation mechanism suitable for constrained WBAN nodes.

Submit Date: 2026-01-06
Revise Date: 2026-10-10
Accept Date: 2026-10-18
✉ Corresponding author

The present work focuses on a complementary design point: a low-complexity signal-processing and transmission chain that reduces repeated radio transmissions when physiological measurements map to the same discrete representation. Nyquist-guided sampling is used to avoid unnecessary oversampling, after which quantization and PCM encoding map samples to discrete code words. A lightweight transmission rule then suppresses consecutive transmissions of an unchanged PCM code. The contribution is therefore the WBAN-oriented integration of these operations with an explicit transmission-reduction rule, rather than a new sampling theorem or a new PCM formulation.

This positioning also clarifies the scope of the proposed mechanism. It is not intended to replace adaptive emergency-aware protocols or advanced compression algorithms. Instead, it provides a lightweight front-end mechanism that can be combined with higher-layer WBAN protocols when computational simplicity and communication reduction are primary requirements.

The experimental study uses three hours of MIMIC/PhysioNet data from respiration rate, systolic blood pressure, heart rate, and oxygen saturation signals. These signals exhibit different levels of temporal variation, allowing the proposed mechanism to be examined under both highly redundant and more dynamic physiological behavior.

The study evaluates two directly relevant outcomes: the reduction in represented/transmitted data and the corresponding reduction in energy consumption under the energy model adopted in this work. The analysis also identifies an important limitation: larger reductions can be accompanied by lower signal fidelity, so energy savings should not be interpreted independently of the information preserved in the physiological waveform.

The methodological contribution is the PCM-based transmission-reduction mechanism: the PCM code sequence is used as the local state for a simple event rule that suppresses repeated radio transmissions. PCM and Nyquist sampling are established techniques; the contribution here is their low-complexity integration with an explicit code-change transmission rule and a quantitative link between transmission count, reconstruction fidelity, and modeled energy consumption.

The main contributions of this work are the following:

• A lightweight WBAN-oriented PCM-based transmission mechanism that combines Nyquist-guided sampling, amplitude quantization, PCM encoding, and a code-change transmission rule to suppress repeated radio transmissions without requiring a computationally intensive prediction or reconstruction model.

• A mathematical formulation that links the PCM code-change indicator directly to the number of transmission events and the communication-energy term, making the mechanism responsible for the energy saving explicit.

• A common-model comparison with NIS and SRCM on the same four physiological records. All three methods use the corrected 8-bit quantized representation and the same sensing/transmission accounting. PCM achieves 53.70%-74.82% modeled energy saving, compared with 20.31%-32.59% for the 8-bit NIS adaptation and 48.75%-73.66% for the code-aligned SRCM implementation.

The remainder of the paper is organized as follows. Section 2 reviews adaptive sampling, data-reduction, and compression approaches and identifies the research gap addressed here. Section 3 describes the proposed sampling, quantization, and encoding mechanism. Section 4 presents the dataset, evaluation procedure, signal-level results, energy analysis, and limitations. Section 5 concludes the paper and outlines future work.

2. RELATED WORKS

Figure 1 shows an example of figures. Energy-efficient data acquisition in sensor and body-area networks has mainly been studied through adaptive sampling, data compression, and sensor-management strategies. Adaptive collection methods modify sensing or reporting rates according to signal variability, residual energy, or application requirements. Laiymani and Makhoul [1] and Makhoul et al. [3] used measurement variation and residual energy to adapt data collection, while Lee et al. [15] proposed energy-aware sampling mechanisms for self-sustainable sensor networks. Lu et al. [5] addressed distributed sampling-rate allocation in rechargeable sensor networks.

For health-oriented sensing, adaptive strategies have also incorporated patient state or emergency information. Salim et al. [7] combined adaptive sampling with local emergency detection, and Qi et al. [16] adapted sampling rates for activity recognition. More recent WBAN-oriented studies have investigated sampling-rate prediction and context-aware sampling using learning-based or self-adaptive mechanisms [34], [36], [37], while recent 2025-2026 work has expanded the design space toward redundancy-aware coding, threshold-triggered transmission, ML-assisted selective communication, and adaptive data-rate control [39-42]. These approaches can be effective, but their computational requirements and control logic may be more demanding than a simple PCM-code-change transmission rule.

A second research direction reduces the amount of information transmitted through compression or signal representation. Yoon and Noh [2], [35] considered joint control of sensing and compression rates. Zhou and Chen [17] combined compressed sensing with node-sleep strategies, while Azar et al. [18] used a DWT lifting scheme for lossless WBAN compression. Compressed sensing has also been investigated for physiological acquisition, including heart-sound signals [25]. Such methods can achieve strong reduction, but the processing complexity, reconstruction requirements, and suitability for resource-constrained nodes vary considerably.

Other studies address network-level energy efficiency through scheduling, aggregation, sensor selection, or local decision making [11], [12], [14], [19-24]. These techniques are valuable at the protocol level, although they do not directly eliminate oversampling or repeated signal representations at the acquisition stage. Consequently, signal-level and network-level techniques can be viewed as complementary rather than mutually exclusive. Recent work further confirms that energy-efficient WBAN communication is being addressed through threshold-based transmission control, lightweight compression, machine-learning-assisted selective transmission, and adaptive data-rate control. Alatawi [40] introduced threshold-triggered transmission and sleep control for energy-efficient health monitoring, while Hajiloo Vakil and Shirmohammadi [39] proposed LPRLC, combining prediction and run-length coding to reduce redundant physiological data. Aljohani [41] used machine-learning-based

transmission relevance estimation for selective communication, and Ye et al. [42] proposed health- and link-aware adaptive data-rate control. These recent methods reinforce the importance of suppressing redundant communication, but they rely on prediction, learning, protocol-level control, or multi-factor rate adaptation rather than a minimal PCM-code-change rule. Table 1 shows that existing approaches reduce communication through adaptive sampling, compression, prediction, or network-level control. The proposed PCM-based mechanism differs in that the transmission decision is made directly from the PCM code sequence using a single stored code and a change comparison. This design avoids the forecasting, transform/reconstruction, machine-learning, or multi-factor control overhead required by several recent approaches, while retaining compatibility with conventional WBAN sensing pipelines.

Research gap and positioning. The literature demonstrates that adaptive sampling, compression, prediction, and network-level scheduling can reduce communication energy, but these approaches often introduce dynamic control logic, transform/reconstruction stages, learning models, or protocol-level coordination. The present study investigates a simpler sensor-side design: a PCM representation is used as a discrete local state, and transmission is triggered only when that state changes. The resulting mechanism retains the low implementation cost of conventional sampling and PCM while adding an explicit communication-reduction rule tailored to temporally redundant physiological signals.

The proposed mechanism is especially intended for signals with substantial temporal redundancy. For rapidly changing signals, more PCM-code transitions occur and the achievable transmission reduction decreases. Likewise, aggressive quantization can reduce fidelity. The method should therefore be interpreted as an energy-quality trade-off mechanism rather than a universally lossless compression technique. This limitation is examined again in Section 4.

Table 1. Comparison of the proposed PCM-based mechanism with representative energy-efficient WBAN/data-reduction approaches.

Method	Main strategy	Adaptive sampling	Compression / quantization	Redundant transmission reduction	Additional computation	Evaluation context
Laiymani and Makhoul [1]	Adaptive data collection based on measurement variation	✓	—	✓	Low–Medium	Periodic sensor networks
Salim et al. [7]	Adaptive sampling with local emergency detection	✓	—	✓	Medium	Wireless body sensor networks
Zhou and Chen [17]	Data compression combined with node sleeping	—	✓	✓	Medium	WBAN
Azar et al. [18]	DWT-based lossless data compression	—	✓	✓	Medium–High	Wireless body sensor networks
Mehrani et al. [34]	Deep-learning-based sampling-rate prediction	✓	—	✓	High	WBAN biosensors
Mehdi et al. [37]	Self-adaptive sampling with context recognition	✓	—	✓	Medium	Wireless body sensor networks
Hajiloo Vakil and Shirmohammadi [39]	Prediction + run-length coding for redundant physiological data	—	✓	✓	Medium	Real physiological WBAN signals
Alatawi [40]	Threshold-based transmission and sleep control	—	—	✓	Low–Medium	Simulated WBAN health monitoring
Aljohani [41]	ML-based transmission-relevance estimation	—	—	✓	High	Wearable health monitoring
Ye et al. [42]	Health- and link-aware adaptive data-rate control	✓	—	✓	Medium	IEEE 802.15.6-compatible WBAN
Proposed PCM-based mechanism	PCM representation with code-change transmission gating	✓	✓	✓	Low	Real physiological data (MIMIC/PhysioNet)

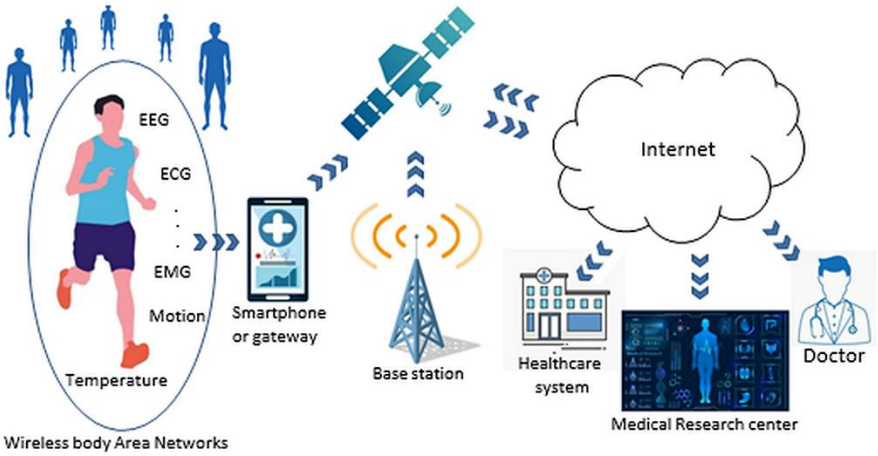


Figure 1. The Architecture of the Wireless Body Area Networks [37]

3. PROPOSED METHOD

The proposed mechanism is designed to reduce the communication workload before physiological measurements are transmitted by a WBAN sensor. Its processing chain consists of four logical stages: (i) selection of a sampling rate consistent with the highest relevant signal frequency, (ii) amplitude quantization, (iii) PCM encoding of the quantized samples, and (iv) transmission gating based on PCM-code changes. The first three stages use established low-complexity operations; the fourth stage determines whether the current PCM representation generates a radio transmission event.

Nyquist-Guided Sampling

Let T_s denote the sampling interval and f_s the sampling frequency. The sampling frequency is defined as $f_s = \frac{1}{T_s}$. To avoid avoidable oversampling while preserving the frequency content represented by the selected signal bandwidth, the sampling rate is chosen to satisfy the Nyquist condition relative to the highest relevant frequency component B. The relationship between the sampling interval and sampling frequency is given in Equation (1).

$$f_s = {}^{1}/_{T_s} \quad (1)$$

where f_s is the sampling frequency and T_s is the sampling interval. According to the Nyquist criterion, the sampling frequency should be at least twice the highest relevant signal frequency B. Sampling substantially above this level increases the number of acquired and potentially transmitted samples, whereas sampling below it can introduce aliasing and information loss. The Nyquist sampling constraint used in this work is expressed in Equation (2).

$$f_s > 2B \quad (2)$$

where B denotes the highest relevant frequency component of the physiological signal. In practice, B should be determined from the signal bandwidth or an appropriate preprocessing step rather than from the raw amplitude range. The resulting samples are then passed to the quantization stage.

Energy-Saving Rationale and Scope

The mechanism does not claim to make PCM itself energy efficient. Rather, the energy benefit arises from using the PCM code sequence as a compact local representation and suppressing radio transmissions when the current code is identical to the last transmitted code. This benefit is expected to be larger for slowly varying signals and smaller for signals containing frequent abrupt changes. Increasing quantization coarseness can further reduce the number of code changes but may also distort clinically relevant variations; consequently, the operating point must be selected with both energy and signal fidelity in mind.

Quantization and PCM Encoding

Let x_{min} and x_{max}note the minimum and maximum amplitudes represented in the current signal interval, and let L be the number of quantization levels. The quantization step is $\Delta = \frac{x_{max} - x_{min}}{L}$ each sampled amplitude is mapped to its nearest permitted level and then encoded as a PCM code word c[k]. Samples that map to the same quantization level therefore share the same discrete representation.

Let x_{min} and x_{max} denote the minimum and maximum amplitudes of the evaluated signal and let b = 8 bits, giving $L = 2^b = 256$ quantization levels. The quantization step is $\Delta = \frac{x_{max} - x_{min}}{L}$. For each sample x[k], the PCM index is $q[k] = floor\left(\frac{x[k] - x_{min}}{\Delta}\right)$, clipped to the interval [0, L−1]. For visualization and fidelity evaluation, the reconstructed amplitude is x_{hat}[k] = x_{min} +(q[k] + 0.5) Δ. The index q[k] is then represented by its 8-bit PCM code word c[k]. This amplitude-based formulation prevents the saturation produced when a fixed quantizer range is used for physiological signals with different amplitude ranges.

Let c[k] denote the PCM code word generated for sample k. The transmission indicator u[k] is defined as u[k] = 1 for the first sample and whenever c[k] differs from the last transmitted code; otherwise, u[k] = 0. The total number of transmission events is therefore $N_{tx} = \Sigma u[k]$. Only samples associated with a PCM-code change are transmitted, while consecutive repeated code words are suppressed. This rule is the central transmission-level contribution of the proposed mechanism because it converts

temporal redundancy in the physiological signal into direct radio-activity reduction using only a code comparison and one stored value per sensor.

The experimental analysis focuses on communication reduction rather than clinical diagnosis. Consequently, physiological ranges are not used as decision thresholds in the proposed mechanism. Figures 3-6 compare the original physiological traces with their PCM-quantized representations. Slowly varying signals, particularly oxygen saturation, contain long runs of similar PCM codes, whereas signals with larger or more frequent variations generate more code changes. This signal-dependent persistence determines the number of transmission events under the proposed rule.

4. EXPERIMENTAL RESULTS

4.1. Dataset and Evaluation Setup

The proposed mechanism was evaluated in MATLAB using three hours of physiological measurements from the MIMIC/PhysioNet resource [33]. The dataset contains N = 10,800 samples for each of four signals: systolic blood pressure, heart rate, respiration rate, and oxygen saturation (SpO2). The corrected experiments use the 8-bit, 256-level amplitude quantizer defined in Section 3 for every signal. No imputation was applied; zero-valued observations present in the source record were retained. For the comparative experiment, the same corrected 8-bit quantized sequence is supplied to PCM, NIS, and SRCM so that differences arise from the representation/transmission mechanism rather than from different input records or quantizer ranges.

NIS [43] is a lossless single-character compression method based on 0/1 neighborhood traversal. The supplied NIS implementation operates on seven-bit character representations; because the present physiological codes span the full 0-255 range, its traversal rule was extended to eight-bit words while retaining the same control-bit and relative-position coding principle. SRCM [44] combines sampling, quantization, 8-bit encoding, and compression. In accordance with the supplied SRCM code, consecutive identical corrected quantized codes are represented as runs, with one 8-bit code value and a binary run length per run. This implementation choice is stated explicitly because the cross-correlation similarity stage in the SRCM article is not parameterized sufficiently in the supplied MATLAB code for an exact independent reconstruction.

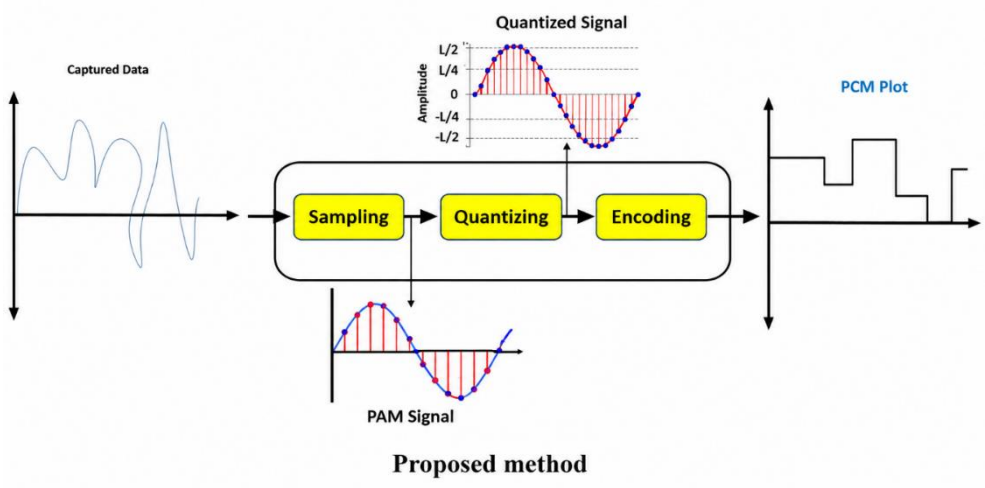


Figure 2. Graphical abstract of the proposed method

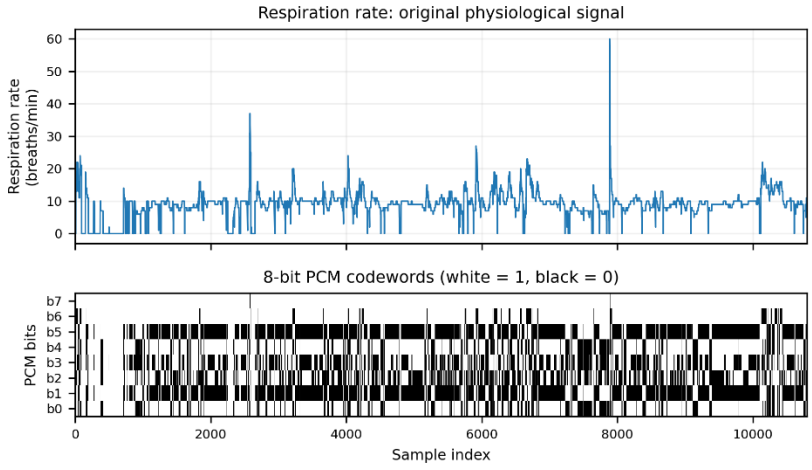


Figure 3. Original respiration-rate signal and its corresponding 8-bit PCM binary codewords.

4.2. Signal-Level Data Reduction

Figures 3–6 were regenerated using the corrected amplitude-based 8-bit quantizer. For Figures 4–6, the upper panels show the original physiological amplitudes and the lower panels show the actual 8-bit PCM codewords (b7–b0) generated for each

sample. This code-domain representation avoids visually conflating the quantized amplitude reconstruction with the PCM output. The signal-dependent number of code changes determines N_{tx}. Oxygen saturation has the fewest transmission events (295 of 10,800), while systolic blood pressure has the most (3,260 of 10,800).

Quantitative fidelity was evaluated using mean absolute error (MAE) and root mean square error (RMSE) between each original signal and its reconstructed PCM amplitude. The resulting errors are small relative to the observed signal ranges, but they are reported explicitly because transmission reduction must be interpreted together with reconstruction fidelity.

Table 2 summarizes N, N_{tx}, transmission reduction, MAE, RMSE, and modeled energy saving for the proposed PCM mechanism. Table 3 then compares PCM, NIS, and SRCM on the same 10,800-sample records under a common transmitted-bit and energy accounting model.

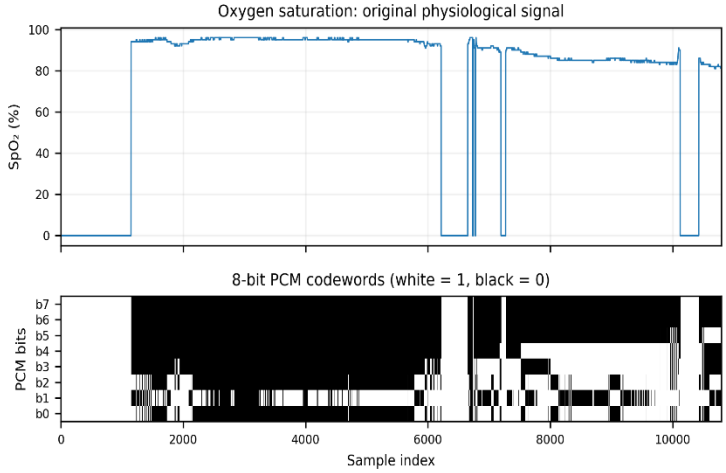


Figure 4. Original oxygen-saturation signal and its corresponding 8-bit PCM binary codewords.

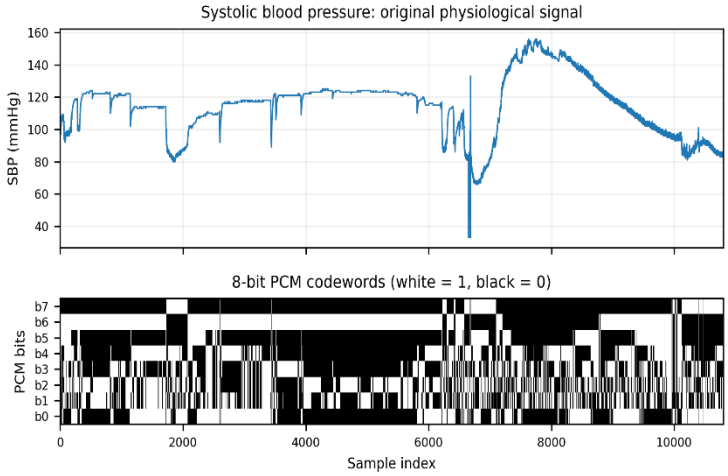


Figure 5. Original systolic blood-pressure signal and its corresponding 8-bit PCM binary codewords.

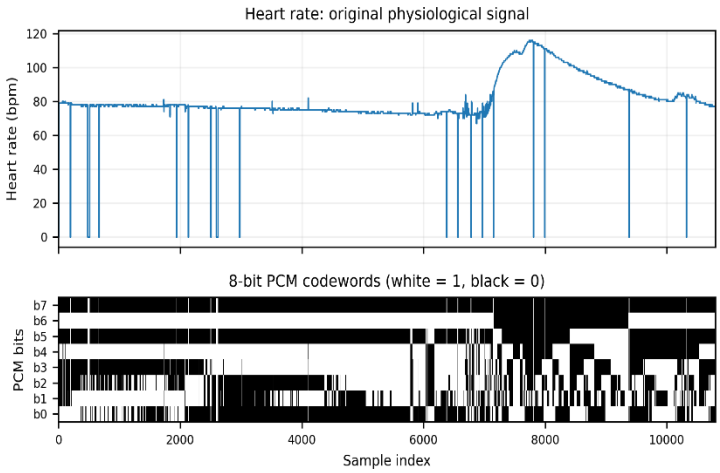


Figure 6. Original heart-rate signal and its corresponding 8-bit PCM binary codewords.

Table 2. Per-signal transmission reduction, reconstruction fidelity, and modeled energy saving with the corrected 8-bit PCM implementation.

Signal	N	N_{tx}	Tx reduction (%)	MAE	RMSE	Energy saving (%)
Systolic blood pressure	10,800	3,260	69.81	0.118	0.134	53.70
Heart rate	10,800	844	92.19	0.123	0.139	70.91
Respiration rate	10,800	1,330	87.69	0.059	0.069	67.45
Oxygen saturation	10,800	295	97.27	0.115	0.131	74.82

Table 3. Common-model comparison of PCM, NIS, and SRCM on the same corrected 8-bit physiological sequences.

Signal	Method	Payload bits	Eq. 8-bit Tx	Data reduction (%)	Energy saving (%)
Systolic blood pressure	PCM	26,080	3,260.000	69.81	53.70
Systolic blood pressure	NIS	60,261	7,532.625	30.25	23.27
Systolic blood pressure	SRCM	31,642	3,955.250	63.38	48.75
Heart rate	PCM	6,752	844.000	92.19	70.91
Heart rate	NIS	63,584	7,948.000	26.41	20.31
Heart rate	SRCM	9,205	1,150.625	89.35	68.73
Respiration rate	PCM	10,640	1,330.000	87.69	67.45
Respiration rate	NIS	56,045	7,005.625	35.13	27.03
Respiration rate	SRCM	13,922	1,740.250	83.89	64.53
SpO2	PCM	2,360	295.000	97.27	74.82
SpO2	NIS	49,794	6,224.250	42.37	32.59
SpO2	SRCM	3,666	458.250	95.76	73.66

4.3. Energy-Consumption Analysis

For a fair comparison, energy consumption is normalized to $E_s = 0.3$ unit per acquired sample and $E_{t8} = 1$ unit per transmitted 8-bit equivalent. The non-optimized case sends 8N bits and consumes $E_{base} = 0.3N + N$. For each compression/transmission method m with B_m transmitted payload bits, $E_m = 0.3N + \frac{B_m}{8}$. PCM contributes 8 bits for each transmitted code-change event. NIS contributes the actual encoded bit count produced by the adapted neighborhood traversal. SRCM contributes 8 bits for each run symbol plus the minimum binary representation of its run length. This bit-normalized model avoids the inconsistent method-specific energy formulas in the legacy scripts.

Figures 7-10 were regenerated using the common model and now compare the non-optimized case, PCM, NIS, and SRCM for each physiological signal. PCM has the lowest modeled energy consumption in all four cases. Its savings are 53.70%, 70.91%, 67.45%, and 74.82% for systolic blood pressure, heart rate, respiration rate, and SpO2, respectively. The corresponding NIS savings are 23.27%, 20.31%, 27.03%, and 32.59%, while SRCM achieves 48.75%, 68.73%, 64.53%, and 73.66%.

The advantage of PCM over SRCM is modest for the slowly varying heart-rate, respiration, and SpO2 traces because both methods exploit consecutive repetition; however, SRCM must additionally transmit run-length information. NIS is less effective on these numerical 8-bit physiological codes because it compresses each word independently rather than suppressing temporal repetition across samples. The maximum PCM saving of 74.82% remains below the theoretical 76.92% upper bound imposed by the sensing term in the adopted model. The per-signal savings are 53.70% for systolic blood pressure, 70.91% for heart rate, 67.45% for respiration rate, and 74.82% for oxygen saturation. These values replace the earlier 88% claim, which was incompatible with the stated sensing and transmission costs.

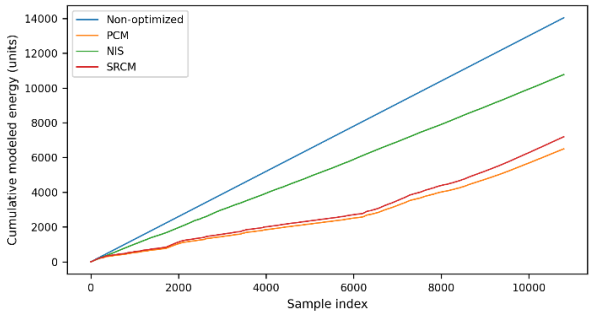


Figure 7. Common-model cumulative energy comparison for systolic blood pressure: non-optimized, PCM, NIS, and SRCM.

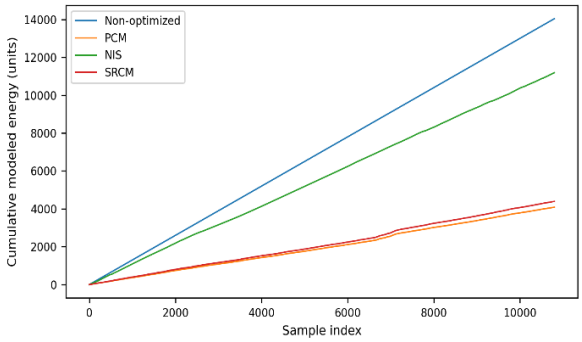


Figure 8. Common-model cumulative energy comparison for heart rate: non-optimized, PCM, NIS, and SRCM.

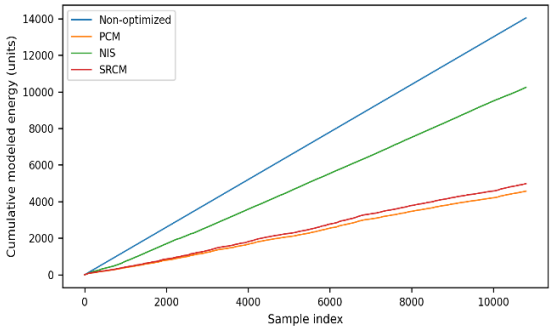


Figure 9. Common-model cumulative energy comparison for respiration rate: non-optimized, PCM, NIS, and SRCM.

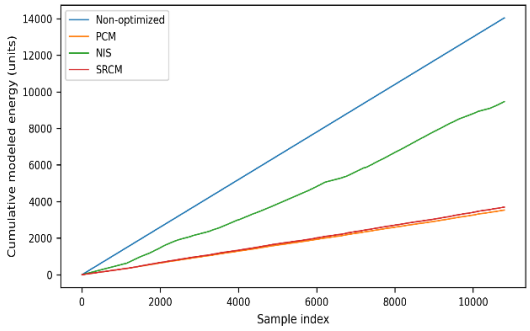


Figure 10. Common-model cumulative energy comparison for oxygen saturation: non-optimized, PCM, NIS, and SRCM

.The results have important limitations. First, the evaluation uses a three-hour record from a single patient, so the reported reductions should not be generalized to all subjects, pathologies, or sensor modalities. Second, energy consumption is calculated from an abstract unit-cost model rather than measured on physical WBAN hardware. Third, the NIS comparison is an explicit 8-bit extension of a method originally described for seven-bit printable characters, and the SRCM comparison follows the supplied run-length implementation after correction of the quantizer; therefore, the baseline results should be interpreted as reproducible same-data implementations rather than exact reproductions of every experiment reported in [43] and [44]. Finally, zero-valued observations in the source record were retained without imputation.

The experiments support the intended use of the proposed mechanism as a lightweight transmission-reduction front end. Its main advantage is computational simplicity: the transmission decision requires only one comparison with the last transmitted PCM code and a state update when a new code is sent; no forecasting model, iterative optimizer, or complex receiver-side reconstruction is required for the decision itself. The mechanism is consequently attractive when communication energy is more expensive than a small amount of local processing.

5. CONCLUSION

This study presented a lightweight WBAN-oriented PCM-based mechanism for reducing communication workload by combining Nyquist-guided sampling, 8-bit amplitude quantization, PCM encoding, and a code-change transmission rule. Using three hours of MIMIC/PhysioNet measurements from four physiological signals, the corrected implementation produced data/transmission reductions from 69.81% to 97.27% and modeled energy savings from 53.70% to 74.82%. Under the same bit-normalized energy model and the same corrected input sequences, the adapted NIS implementation achieved 20.31%-32.59% energy saving and the code-aligned SRCM implementation achieved 48.75%-73.66%. Thus, PCM produced the lowest modeled energy consumption for all four evaluated traces, while requiring only a code comparison and state update. These results remain subject to the limitations of a single-patient record, an abstract energy model, and implementation adaptations required for the two literature baselines. Future work should validate all methods on additional subjects and physical WBAN hardware.

6. ACKNOWLEDGMENT

The authors would like to express their sincere appreciation to SRTTU University for its support and for providing the facilities necessary to conduct this research.

7. REFERENCES

[1] Laiymani, David and Makhoul, Abdallah, "Adaptive data collection ap- proach for periodic sensor networks," in *9th International Wireless Com- munications and Mobile Computing Conference (IWCMC),* 2013, pp. 1448– 1453.

[2] Yoon, Ikjune and Yi, Jun Min and Jeong, Semi and Noh, Dong Kun, "Adap- tive sensing and compression rate selection scheme for energy-harvesting wireless sensor networks," in International Journal of Distributed Sensor Networks, vol. 13, SAGE Publications Sage UK: London, England, 2017, pp. 155-165.

[3] Makhoul, Abdallah and Harb, Hassan and Laiymani, David, "Residual energy-based adaptive data collection approach for periodic sensor net- works," in Ad Hoc Networks, vol. 35, Elsevier, 2015, pp. 149–160.

[4] Silva, Joao Marco C and Bispo, Kalil Araujo and Carvalho, Paulo and Lima, Solange Rito, "LiteSense: An adaptive sensing scheme for WSNs," in IEEE Symposium on Computers and Communications (ISCC), IEEE, 2017, pp. 1209–1212.

[5] Lu, Ting and Liu, Guohua and Li, Wei and Chang, Shan and Guo, Wen- jing, "Distributed sampling rate allocation for data quality maximization in rechargeable sensor networks," in Journal of Network and Computer Applications, vol. 80, Elsevier, 2017, pp. 1–9.

[6] Fathy, Yasmin and Barnaghi, Payam and Tafazolli, Rahim, "An adaptive method for data reduction in the internet of things," in IEEE 4th World Forum on Internet of things (WF-IoT)., 2018, pp. 729–735.

[7] Salim, Christian and Makhoul, Abdallah and Darazi, Rony and Couturier, Raphaël, "Adaptive sampling algorithms with local emergency detection for energy saving in wireless body sensor networks," in NOMS 2016-2016 IEEE/IFIP Network Operations and Management Symposium. 2016, pp. 745–749.

[8] Dieter, William R and Datta, Srabosti and Kai, Wong Key, "Power reduc- tion by varying sampling rate," in Proceedings of the 2005 international symposium on Low power electronics and design. 2005, pp. 227–232.

[9] Krause, Andreas and Ihmig, Matthias and Rankin, Edward and Leong, Derek and Gupta, Smriti and Siewiorek, Daniel and Smailagic, Asim and Deisher, Michael and Sengupta, Uttam, "Trading off prediction accuracy and power consumption for context-aware wearable computing," in Ninth IEEE International Symposium on Wearable Computers (ISWC'05). 2005, pp. 20–26.

[10] Chen, Shih-Yeh and Lai, Chin-Feng and Hwang, Ren-Hung and Lai, Ying- Hsun and Wang, Ming-Shi, "An adaptive sensor data segments selection method for wearable health care services," in Journal of medical systems, vol. 39, Springer, 2015, pp. 1–11.

[11] Wang, Hui and Choi, Hyeok-soo and Agoulmine, Nazim and Deen, M Jamal and Hong, James Won-Ki, "Information-based energy efficient sensor selection in wireless body area networks," in IEEE International Conference on Communications (ICC). 2011, pp. 1–6.

[12] Habib, Carol and Makhoul, Abdallah and Darazi, Rony and Salim, Chris- tian, "Self-adaptive data collection and fusion for health monitoring based on body sensor networks," in IEEE transactions on Industrial Informatics, vol. 12, 2016, pp. 2342–2352.

[13] Harb, Hassan and Makhoul, Abdallah and Couturier, Raphaël, "An en- hanced K-means and ANOVA-based clustering approach for similarity aggregation in underwater wireless sensor networks," in IEEE Sensors Journal, vol. 15, 2015, pp. 5483–5493.

[14] Bradai, Nourchène and Fourati, Lamia Chaari and Kamoun, Lotfi, "WBAN data scheduling and aggregation under WBAN/WLAN healthcare network," in Ad Hoc Networks, vol. 25, Elsevier, 2015, pp. 251–262.

[15] Lee, Changmin and Lee, Jaiyong, "Harvesting and energy aware adap- tive sampling algorithm for guaranteeing self-sustainability in wireless sensor networks," in International Conference on Information Networking (ICOIN). IEEE, 2017, pp. 57–62.

[16] Qi, Xin and Keally, Matthew and Zhou, Gang and Li, Yantao and Ren, Zhen, "AdaSense: Adapting sampling rates for activity recognition in body sensor networks," in IEEE 19th Real-Time and Embedded Technology and Applications Symposium (RTAS), 2013, pp. 163–172.

[17] Zhou, Yue-Bin and Chen, Jia-Shun, "WBAN node sleep strategy and energy conservation method based on data compression," in Journal of Interdisciplinary Mathematics, vol.21, Taylor & Francis, 2018, pp. 1073– 1078.

[18] Azar, Joseph and Darazi, Rony and Habib, Carol and Makhoul, Abdallah and Demerjian, Jacques, "Using dwt lifting scheme for lossless data com- pression in wireless body sensor networks," in 14th International wireless communications & mobile computing conference (IWCMC), IEEE, 2018, pp. 1465–1470.

[19] Elghers, Sabrina and Makhoul, Abdallah and Laiymani, David, "Local emergency detection approach for saving energy in wireless body sensor networks," in IEEE 10th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob). 2014, pp. 585-591.

[20] Zhou, Ying and Yang, Lihua and Yang, Longxiang and Ni, Meng, "Novel energy-efficient data gathering scheme exploiting spatial-temporal correla- tion for wireless sensor networks," in Wireless Communications and Mobile Computing. Hindawi, 2019.

[21] Kortas, Manel and Habachi, Oussama and Bouallegue, Ammar and Megh- dadi, Vahid and Ezzedine, Tahar and Cances, Jean-Pierre, "Energy efficient data gathering schema for wireless sensor network: A matrix completion based approach," in International Conference on Software, Telecommuni- cations and Computer Networks (SoftCOM). IEEE, 2019, pp. 1–6.

[22] Ogawa, Keigo and Kanai, Kenji and Takeuchi, Masaru and Katto, Jiro and Tsuda, Toshitaka, "Edge-centric field monitoring system for energy- efficient and network-friendly field sensing," in 15th IEEE Annual Con- sumer Communications & Networking Conference (CCNC). 2018, pp. 1–6.

[23] Kankanamge, Nayomi and Yigitcanlar, Tan and Goonetilleke, Ashantha, "Public perceptions on artificial intelligence driven disaster management: Evidence from Sydney, Melbourne and Brisbane," in Telematics and Infor- matics, vol. 65, Elsevier, 2021, pp. 101729.
[24] Silva, João Marco and Carvalho, Paulo and Bispo, Kalil Araujo and Rito Lima, Solange, "e-LiteSense: Self-adaptive energy-aware data sensing in WSN environments," in International Journal of Communication Systems, vol. 33, Wiley Online Library, 2020, pp. e4153.
[25] Sun, Shuang and Xing, Jiazhu and Zhou, Zheng and Wang, Wei and Chen, Junxin, "Comparative Study of Compressed Sensing for Heart Sound Acquisition in Wireless Body Sensor Networks," in IEEE Access, vol. 8, 2020, pp. 22483–22492.
[26] Niaz, Fahim and Khalid, Muhammad and Ullah, Zahid and Aslam, Nau- man and Raza, Mohsin and Priyan, MK, "A bonded channel in cognitive wireless body area network based on IEEE 802.15. 6 and internet of things," in Computer Communications, vol. 150, Elsevier, 2020, pp. 131–143.
[27] Yessad, Nawel and Bouchelaghem, Siham and Ouada, Farah-Sarah and Omar, Mawloud, "Secure and reliable patient body motion based authenti- cation approach for medical body area networks," in Pervasive and Mobile Computing, vol. 42, Elsevier, 2017, pp. 351–370.
[28] Alkhayyat, Ahmed and Habeeb, Najmah A, "A cooperative MAC aware network coding toward improving throughput wireless body area network," in 2nd Scientific Conference of Computer Sciences (SCCS), IEEE, 2019, pp. 182–187.
[29] Al Attabi, Kassem and others, "Single Relay Selection in the Cognitive Cooperative Network: Toward Bandwidth Efficiency Improvement," in 4th Scientific International Conference Najaf (SICN), IEEE, 2019, pp. 222–226.
[30] Al-Mishmish, Hameed RM and Preveze, Barbaros and Alkhayyat, Ahmed, "Improvement of Underlay Cooperative Cognitive Networks Bandwidth Efficiency under Interference and Power Constraints," 2019.
[31] Alkhayyat, Ahmed and Mahmoud, Mahmoud Shuker, "Hybrid network coding and cooperative communication in WBAN," in 2nd International Conference on Engineering Technology and its Applications (IICETA), IEEE, 2019, pp. 79–82.
[32] Radie, A Hussien and Thabit, Ahmed A, "Energy harvesting based system: toward outage probability minimizing of WBSN," in 2nd International Conference on Engineering Technology and its Applications (IICETA), IEEE, 2019, pp. 89–93.
[33] Goldberger, Ary L and Amaral, Luis AN and Glass, Leon and Hausdorff, Jeffrey M and Ivanov, Plamen Ch and Mark, Roger G and Mietus, Joseph E and Moody, George B and Peng, Chung-Kang and Stanley, H Eugene, "PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals," in circulation, vol. 101, Am Heart Assoc, 2000, pp. e215–e220.
[34] Mehrani, Mohammad and Attarzadeh, Iman and Hosseinzadeh, Mehdi, "Sampling rate prediction of biosensors in wireless body area networks us- ing deep-learning methods," in Simulation Modelling Practice and Theory, vol. 105, Elsevier, 2020, pp. 102101.
[35] Yoon, Ikjune and Noh, Dong Kun, "Energy-aware control of data compres- sion and sensing rate for wireless rechargeable sensor networks," in Sensors, vol. 18, Multidisciplinary Digital Publishing Institute, 2018, pp. 2609.
[36] Mehrani, Mohammad and Attarzadeh, Iman and Hosseinzadeh, Mehdi, "Deep-learning based forecasting sampling frequency of biosensors in wireless body area networks," in Journal of Intelligent & Fuzzy Systems, vol. 39, MIOS Press, 2020, pp. 3195–3227.
[37] Mehdi, Hamid and Zarrabi, Houman and Zadeh, Ahmad Khadem and Rahmani, AmirMasoud, "Self-Adaptive sampling rate to improve network lifetime using watchdog sensor and context recognition in wireless body sensor networks," in Majlesi Journal of Electrical Engineering, vol. 14, 2020, pp. 11–22.
[38] Han, Youjun and Hu, Yueming and Huang, Xuejie, "Research and Appli- cation of K-means Clustering and DCT Double Compression Algorithm in Vibration Sensor," in 7th International Conference on Information, Cybernetics, and Computational Social Systems (ICCSS), IEEE, 2020, pp. 180–183.
[39] Hajiloo Vakil, Mahdieh and Shirmohammadi, Zahra, "LPRLC: Linear predictive run length coding to improve energy consumption of wireless body area networks," Results in Engineering, vol. 27, Art. no. 105622, 2025, doi: 10.1016/j.rineng.2025.105622.
[40] Alatawi, Mohammed Naif, "Optimizing security and energy efficiency in IoT-Based health monitoring systems for wireless body area networks," Scientific Reports, vol. 15, Art. no. 24921, 2025, doi: 10.1038/s41598-025-11253-x.
[41] Aljohani, Nasser, "An ML-driven framework for continuous wearable health surveillance and energy-efficient communication," Scientific Reports, vol. 16, Art. no. 21393, 2026, doi: 10.1038/s41598-026-52572-x.
[42] Ye, Bizhou, Zhou, Wei, and Liu, Qiliang, "A health- and link-aware adaptive data-rate method for enhancing quality of service in wireless body area networks," Discover Computing, vol. 29, Art. no. 635, 2026, doi: 10.1007/s10791-026-10513-2.
[43] Uthayakumar, J., Vengattaraman, T., and Dhavachelvan, P., "A New Lossless Neighborhood Indexing Sequence (NIS) Algorithm for Data Compression in Wireless Sensor Networks," Ad Hoc Networks, 2018, doi: 10.1016/j.adhoc.2018.09.009.
[44] Khani, M. J. and Shirmohammadi, Z., "SRCM: An Efficient Method for Energy Consumption Reduction in Wireless Body Area Networks based on Data Similarity," Ad Hoc & Sensor Wireless Networks, 2021.

AUTHOR BIOGRAPHY



Mohammadjavad Khani received B.Sc. in Computer Engineering (Software) from Shahid Rajaee Teacher Training University, Tehran, Iran, and M.Sc. in Computer Engineering (Software) from Shahid Rajaee Teacher Training University, Tehran, Iran. He is a lecturer professor and Ph.D. student at Razi University. His main research interests are Sampling, Compressing, Wireless Body Area Networks, Wireless Sensor Networks, Energy efficiency, Smart Agriculture.



Zahra Shirmohammadi received M.Sc. and Ph.D. degrees in Computer Engineering from Sharif University of Technology in 2011 and 2017 respectively. Her current research interests include dependability of SystemonChip (SoC) and Network-on-Chip (NoC) design and high-performance computer architecture.