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Adaptive modeling algorithm for energy optimization in nanosensor networks for smart IoT systems

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ABSTRACT

Efficient energy management in nanosensor networks remains a challenge in the design of intelligent IoT systems. This study proposed an adaptive modeling algorithm (NAMA) that dynamically adjusts the trade-off between energy consumption and stability in real-time nanosensor systems. The algorithm utilizes an energy-aware cost function combining total energy usage with a tunable parameter $\lambda(t)$ that is adapted based on consumption thresholds. The research focused on a sensor network model distributed across the artificial skin of a robotic system, consisting of nanosensors operating in the terahertz (THz) band. The model incorporates integral metrics to evaluate transmission, reception, and sensing power costs, and applies adaptive control rules, such as transmission suppression or reactive cut-off, to minimize global energy usage. Simulation results demonstrate that NAMA achieves reduction in energy variance and over 11% extension of operational lifetime, compared to fixed-weight energy strategies, measured at the 80% cumulative energy threshold. Moreover, under a realistic energy-per-operation cost of 1 μJ, the adaptive algorithm enables the system to execute over 23,000 operations, with more than 26,000 operations remaining within a 50 mJ energy limit. This confirms the capability of the algorithm to efficiently manage energy distribution while preserving network longevity. The adaptive trade-off coefficient $\lambda(t)$ responds effectively to environmental dynamics and energy saturation levels, maintaining network stability while optimizing power consumption. The proposed method contributes to the field by integrating control-theoretic adaptation with real-time nanosensor energy modeling, used Matlab/Python environment. It offers a practical and scalable solution for energy optimization in next-generation smart skin and embedded IoT systems.

Keywords: adaptive algorithms, energy optimization, nanosensor networks, smart IoT systems, terahertz communication, low-power sensing, computational modeling.

INTRODUCTION

The effective energy optimization strategy leads to the extend the nano-sensor networks (NSN) operational lifetime and ensure the reliability of their systems. The bottleneck is their limited power efficiency and energy consumption of communication over long periods of time. In this work, an adaptive modeling algorithm that dynamically estimates and controls the energy consumption of nanosensor networks was proposed. This allows each sensor node to adjust its activity based on current energy availability, predicted consumption trends, and global network constraints. The related works, mentioned below, show various approaches to optimizing and saving energy in nanosensor networks. In the paper [1], an optimization problem was defined to determine the optimal deployment of nanosensors (NSs) for the proper liver status description. The application of genetic algorithms allows finding the optimal number of nanosensors in the system, avoiding a large data volume. In the work [2], finding suitable routing paths in wireless nano- sensor networks (WNSNs) as a fundamental problem to be solved in energy-efficient Internet of Nano-things (IoNT) networks was described. Due to the nano- batteries having very limited capacity, the nano-sensor nodes should communicate through an energy-efficient routing scheme. In this paper, an energy-efficient routing path discovery algorithm between nanosensor node and receiver node was proposed for IoNT applications. The paper [3] investigated the effect of various parameters of energy consumption for communication in pulse-based wireless nanosensor networks. Through simulation, the effect of network parameters, i.e. energy for pulse transmission/reception, on the optimization problem was studied. The model enables optimum energy consumption design in wireless nanosensor networks. The next work [4] described WNSNs, i.e., networks of miniaturized devices with unprecedented sensing capabilities, are at the basis of applications in the biomedical and industrial fields.

Recent developments in plasmonic nano-antennas point to the Terahertz band (0.1–10 THz) as the frequency range of communication among nanosensors. The energy harvesting limits and the successful data transmission time are defined as the optimization problem constraints. According to [5] important feature of WNSNs is that the nanosensors are highly energy-constrained and it essential to develop energy efficient protocols for different layers of such networks. This paper examined the transmission energy minimization problem. In the paper [6] an energy optimization coding (EOC) for communication in WNSNs was proposed, and the energy model by jointly accounting for the energy consumption of both a transmitter and a receiver was presented. A novel energy-efficient distributed routing algorithm, in order to extend the lifetime of WNSNs in IoNT applications was proposed in the work [7]. This energy-efficient distributed protocol was compared with the traditional flooding based method and with an energy aware routing algorithm. The paper [8] presented novel signal integration methodologies that merge nanosensors with machine learning and reinforcement learning for better optimization. The application of reinforcement learning facilitates optimal sensor positioning as well as optimal knowledge with regards to what data should be processed. This approach is different from other competing ones because it is adaptive, self-learning and without loss of flexibility the amount of energy used is lowered greatly. Next paper [9] introduced an adaptive algorithm to equally cooperate in data transfer process between nanosensors. Each nanonode can adjust the broadcasting decision according to its local traffic condition. The aim is to decrease the energy consumption by balancing data transmission load between constrained-resources nanonodes. The paper [10] proposed an adaptive energy consumption modeling algorithm for IoT smart meters, dynamically adjusting the data transmission frequency to the reading variability. The solution uses LoRaWAN/NB-IoT technologies and allows for a significant reduction in the number of packets and energy consumption – experimentally, a decrease in the frequency of energy consumption spikes by ~87–88% was achieved, which extends the lifetime of IoT nodes. The paper [11] presented an adaptive control model that optimizes energy consumption in an IoT environment based on software-defined networks. The proposed algorithm used entropy for early detection of DDoS attacks and stochastic techniques for mitigation, while simultaneously monitoring and limiting device power consumption. Simulations achieved, among other things, an 18% reduction in energy consumption compared to existing solutions, while maintaining high network performance (improved threat detection accuracy and reduced latency). Publication [12] proposed a distributed clustering algorithm for a nanosensor network using the modern metaheuristic red deer algorithm (RDA). The designed nanoRDA algorithm adaptively determines optimal cluster heads in an IoNT network composed of nanosensors, balancing the energy load between nodes. Experimental results indicate improved energy efficiency and extended network lifetime compared to traditional clustering protocols. The paper [13] dealt with an intra-body nanosensor network where the developed algorithm predicts changes in channel quality within the body (e.g. due to movement or physiological changes) and accordingly reconfigures transmission paths to minimize packet loss and energy consumption. The use of link state prediction allows for avoiding unreliable connections and stabilizes energy consumption in the network, which translates into longer nanosensor lifetime and greater communication reliability.

The paper [14] indicated that seamless interconnectivity among nanonetworks with the available communication networks and the Internet requires developing new network architectures and new communication paradigms while addressing the various energy challenges. The next study in [15] presents the adaptive ant colony method, which improves energy efficiency by determining the ideal cluster count using connectedness and distributed cluster-based sensing, which is important from the point of view of the nanosensor network. The method significantly reduces the energy consumption of nodes by several percentage points. The next paper [16] proposed a hybrid approach combining fuzzy clustering with optimization algorithms to improve energy management in IoT sensor networks. The proposed solution adaptively minimizes energy losses by reducing unnecessary transmissions and balancing node load and the network implementing this method was characterized by slower battery power decay and longer lifetime compared to traditional protocols. The publication highlighted the effectiveness of intelligent techniques (AI/ML) in energy management in large IoT networks.

In [17], the problem of limited energy in nanosensors was addressed by integrating simultaneous information transfer and power supply techniques. The authors propose a cluster network framework in which nanosensor nodes can harvest energy from radio signals during data transmission. Additionally, an algorithm was introduced to ensure uniform energy consumption within clusters and this approach extends the lifetime of nanonodes, standardizes the energy consumption level in the network, and reduces the transmission error rate. Publication [18] presented an adaptive sleep scheduling algorithm for IoT nodes based on a learning automaton. The solution demonstrated significant energy savings – up to 16% lower power consumption with longer sleep cycles. The finite state machine-based adaptive sampling algorithm proposed in [19] controls the sampling rate of IoT devices while maintaining a sustainable level of energy consumption. Validation under real-world conditions demonstrated energy self-sufficiency with minimal energy consumption. In the following paper [20], a heuristic resource management algorithm for hierarchical federated learning, taking into account wireless power, was proposed. The model optimizes energy allocation and training schedules for IoT devices with minimal energy cost. Another publication [21] addressed intra-body communication channels between nanosensors flowing in the bloodstream and gates attached to the skin using the terahertz (THz) spectrum. To optimize the communication performance, this work investigated the impact of noise and mobility, and subsequently derives the trade-off between them. This paper [22] presented a comprehensive treatment and technology survey on THz communications and sensing in terms of advantages, applications, propagation characterization, antennas, transceiver devices, networking including those for applications in nanonetworks. The paper gave a holistic view of the current state of the art and highlights the open research challenges towards 6G and beyond. In [23], the properties of graphene nanoantennas and SPP signal propagation in the 0.1–10 THz band were discussed in the context of nanonetworks, highlighting the real possibility of miniaturizing nanosized communication structures.

In [24], THz sensor technologies, their sensitivity, tuning, and applications in medicine and IoT were analyzed in a review. Advanced materials (graphene, photonic fibers) were highlighted and directions for the development of ultrafast, high-performance sensors were proposed. A review [25] presented pioneering metamaterial structures for THz sensors. The impact of high-quality THz resonance and tunneling on improved sensitivity was emphasized, with applications in IoT skin nanosensors and smart skin. The authors in [26] developed an adaptive energy threshold strategy for IoT nodes that takes into account battery power levels and data priority. Depending on the threshold, the node adjusts when and what it transmits, allowing for intelligent redirection of network resources. Simulations demonstrate energy savings while maintaining critical data traffic. The paper [27] presented a model for simultaneous optimization of routing, bandwidth, and subband allocation in THz nanosensor networks. The study showed that optimal multi-hop routing and variable bandwidths allow for reduced energy consumption in transmission-dominant situations, while maintaining a low energy cost for the entire network. The paper specifically addresseed the technology of nanonetworks with THz communication, taking into account aspects of routing and energy effects, complementary to the adaptive modeling algorithm. The study [28] introduced a robust model of IoT-integrated multi-sensors to ensure functionality and seamless IoT integration. It was shown how changes in the sensor-object distance affect the optimization of the integrated sensor behavior. The proposed model integrates an intelligent skin sensor with an autonomous IoT system. This model shows significant potential for miniaturization and scalability, making it particularly suitable for IoT applications.

MATERIALS AND METHODS

In the presented study, a nanosensor adaptive modeling algorithm (NAMA) for an embedded network was developed.

For the purposes of this work, it was assumed that the "lifetime" of a network is the time it takes to reach 80% of its cumulative energy cost. The network can be embedded on the artificial skin of a humanoid robot or a flexible smart skin surface.

NAMA algorithm

The pseudocode of the adaptive algorithm is shown in Figure 1. The coefficients denote: α_i is a weighting factor for the energy consumption of data transmission, which determines how strongly the transmission (e.g. sending packets) affects the overall energy loss of the i-th sensor; βi, is a weighting factor for energy consumption by measuring and processing data, which determines how much the "sensing" itself contributes to the total energy loss; η is the adaptation/learning constant and denotes the rate at which the sensor changes its operating parameters (e.g. sampling) – the larger η, the faster it responds to a decrease in energy, but may be less stable. Next, $P_{comm}(t)$ is the power consumed for data transmission, $P_{sense}(t)$ is the power consumed for measurement (e.g. touch, pressure, temperature), derivative (d/dt) $(E_i(t))$ is the rate of energy decrease over time. In the *NAMA* algorithm, these coefficients, with which the energy changes of a network node is described, are as follows:

$$\frac{dE_i(t)}{dt} = \alpha_i(t) \cdot P_{comm}(t) + \beta_i(t) \cdot P_{sense}(t) \quad (1)$$

Therefore, in the NAMA algorithm, the energy consumption of i-th sensor at time t is modeled by Equation 1 and $P_{comm}(t)$ is the current power needed to transmit data from the nanosensor, $P_{sense}(t)$ current minimum accumulated power needed to perform the measurement. On this basis, the nanosensor locally adjusts its operating parameter u_i(t) (e.g. operating frequency):

$$u_i(t + \Delta t) = u_i(t) - \eta \cdot \frac{dE_i(t)}{dt} \quad (2)$$

These factors are important for: local adaptation (sensors can dynamically adjust (t) based on local conditions, e.g., motion load or touch intensity), optimization (this helps balance energy between transmission and measurement tasks, e.g., if a nanosensor is overloaded with measurements, it is increased to better predict future consumption) and distributed management (it does not need to be coordinated globally, but the sensor itself "learns" the proportions of the impact of different actions on energy loss). The NAMA algorithm implements local energy control of the nanosensor node, allowing it to intelligently

Step	Operation
1	Initialize parameters: energy $E_i(0)$, sampling level $u_i(0)$, learning constant η, coefficients α_i, β_i, time t=0
2	Collect measurement data and measure current energy $E_i(t)$
3	Estimate instantaneous energy consumption $dE_i(t)/dt = \alpha_i P_{comm}(t) + \beta_i P_{sense}(t)$
4	Update nanosensor operating parameters: $u_i(t + \Delta t) = u_i(t) - \eta \cdot dE_i(t)/dt$, where η is the local learning constant that controls the rate of change
5	Send data packet if $u_i(t + \Delta t)$ exceeds the set threshold
6	Update energy level $E_i(t + \Delta t) = E_i(t) - E_{tx} - E_{sense}$
7	Go to next iteration $t \leftarrow t + \Delta t$, back to step 2
8	Stop, when $E_i(t) < E_{min}$ or max simulation time reached

Figure 1. Nanosensor adaptive modeling algorithm

adapt operating parameters (e.g., sampling rate) to the rate of energy consumption. Each sensor initializes initial values for energy, operational settings, and adaptation factors. In each time iteration, the nanosensor performs a measurement, estimates instantaneous energy consumption based on communication and sensor activity, then modifies its operating mode to minimize further energy degradation. A key element is a local differential model describing the rate of energy change, which controls behavioral modifications without the need for global communication. If the adaptation level reaches a predetermined threshold (e.g., an operating parameter drops below a threshold), the sensor decides to transmit data. Its energy budget is then updated. This process repeats until the energy is depleted or the simulation ends. This approach ensures distributed and independent energy management of nodes, which leads to extending its lifetime, reducing energy fluctuations and increasing the uniformity of system operation.

Example

If the parameters are distributed such that a touch nanosensor with frequent transmission has: $\alpha_i = 0.8$, $\beta_i = 0.2$ → data transmission is the main source of energy consumption. If the nanosensor is sparse transmission: $\alpha_i = 0.3$, $\beta_i = 0.7$ → energy consumption dominates the sensor operation side. It was assumed that the network consists of an average of 300 sensors distributed irregular over an area of approximately 100 cm², which corresponds to a realistic sensory density for biomimetic haptic applications (e.g., the surface of a human hand). In nanosensor applications, THz communication is increasingly being chosen for the following reasons, based on both physical properties and practical design requirements: 1st – high network throughput and bandwidth, 2nd – nanoscale antennas, 3rd - short distances and low power, 4th – minimal interference and high locality. Firstly, the THz band (0.1–10 THz) offers exceptionally wide transmission channels, enabling simultaneous, high-speed communication of hundreds of bits from multiple sensors operating in a small area—for example, approximately 300 nanosensors on the palm of a hand (100 cm²). This is ideal for IoT applications. Secondly, nanostructures, such as graphene nanoantennas, have dimensions close to the THz wavelength. This allows for the construction of efficient, miniaturized antennas compatible with nanoscale devices, as confirmed by the literature on THz nanonetworks, particularly those based on graphene nanoantennas and surface waves in the 0.1–1 THz band. Thirdly, in skin-like sensor applications, communication distances typically range from 1 to 20 mm. The THz band enables efficient transmission over such distances, with minimal latency and low transmission power, owing to its strong directivity and data rate. Fourthly, due to significant signal attenuation in air and biological materials, the THz band promotes local operation—ideal for dense networks of sensor strips, where high transmission precision is required with limited impact on the surroundings. Nanosensors often utilize THz communication, because it offers high throughput, compact antenna design, and efficient, local data exchange at low power consumption. The validity of this assumption is confirmed by current research and literature reviews, as mentioned above.

The benefits of THz communication in nanonetworks are summarized in Tables 1 and 2, based on the literature listed in Related Works. A summary of both tables above is

Table 1. The benefits of THz communication in nanonetworks

N.	Feature	Importance for nano-sensors
1	Very wide bandwidth	Data transmission from multiple sensors
2	Nanoantenna compatibility	Physical Implementation; THz wavelength compatible with nanomaterial antennas (e.g., graphene, CNT)
3	Short range	Short range = advantage: Effective transmission at 1–20 mm, ideal for dense skin networks
4	Minimal latency	Useful for tactile feedback
5	High directivity	Reduces interference, increases local communication
6	Low transmission power	Reduces energy consumption—crucial in battery-powered systems
7	IoNT compatible (Internet of Nano-Things)	A natural choice for the Internet of Nano-Things and artificial skin

provided in the Results and Discussion section. The conclusions to the both tables are provided in the Conclusion section. It was assumed that each nanosensor has a limited energy resource (E_0 = 0.3 mJ) and measures contact parameters (pressure, temperature, microvibrations) and then transmits the data to a local edge node (Edge Hub) located in the wrist or PCB integration area.

Communication occurs in the THz band, over short distances of 1–15 mm, in single- or multi-hop mode. The energy consumption of each sensor is described by the classical model:

$$E_{tx} = E_{elec} \cdot k + \varepsilon_{amp} \cdot k \cdot d^n \tag{3}$$

and

$$E_{rx} = E_{elec} \cdot k \tag{4}$$

where: the parameters adopted for consideration are: E_{elec} = 35 nJ/bit is the energy of electronic systems, ε_{amp} = 90 pJ/bit/mm² is the amplifier energy in the transmitter, k = 256 bits is the data packet length, d is the average distance between nodes, and n = 2 is the propagation loss exponent.

The difference between E_{tx} (energy for transmission) and E_{rx} (energy for reception) is a key issue in energy modeling of nanosensor networks in general (e.g. WSN, IoT), in Table 3.

System optimization with total energy consumption and variability in time

The system is optimized with respect to a cost function that takes into account both the total energy consumption and its variability over time:

$$J_i = \frac{1}{T}\int_0^T [\, \alpha \cdot P_{tx,i}(t) + \beta \cdot P_{rx,i}(t) + \gamma \cdot P_{sense,i}(t)]\, dt \tag{5}$$

or in discrete form (for implementation):

$$J_i = \frac{1}{N}\sum_{k=1}^{N}(\, \alpha \cdot P_{tx,i}[k] + \beta \cdot P_{rx,i}[k] + \gamma \cdot P_{sense,i}[k]\,) \tag{6}$$

where: α, β, γ are the weights assigned to different activity types and $P_{tx,i}$, $P_{rx,i}$, $P_{sense,i}$ are the instantaneous power of the corresponding operations of the *i*-th nanosensor. The J_i function allows for the evaluation of a node's energy consumption in different modes. It also serves as the basis for optimization in the adaptive NAMA algorithm, where J_i is minimized while maintaining specified functionality. The Equation 5 with the factor (1/T) is the total power consumed by the *i*-th node during time T, expressed in watts [W], i.e., energy cost per unit of time. Without factor (1/T) the total energy consumed by the *i*-th node during time T is obtained:

Table 2. Comparison with other communication technologies

Technology	Advantages	Disadvantages
0.1–10 THz	Massive throughput A size-compatible nanoantenna Ideal for short distances	High air attenuation Requires precise targeting
IR (infrared)	Easily available Low power consumption Suitable for simple sensors	Sensitive to optical obstructions Poor scalability in multi-node networks
RF (MHz–GHz)	Stable transmission over longer distances	Antennas too large for the nanoscale. Interference and noise in dense environments
Piezooptic	Compatible with micro/nanostructures They can be used as sensors and data transmitters	Very limited transmission speed Complexities of integrating optoelectronics on the skin

Table 3. Comparison of E_{tx} with E_{rx}

Parameter	Energy E_{tx}	Energy E_{rx}
Definition	Energy consumed by the sensor while sending data	Energy consumed while receiving data from another node
Dependence	Depends on distance d, number of bits k and propagation losses d^(n)	Depends mainly on the number of bits k; does not depend on the distance
Typical eq.	$E_{tx} > E_{rx}$	
Wear	Typically greater than reception, especially at longer distances	Smaller and more stable—depending solely on the electronics
Meaning in NAMA	It strongly influences the energy decay rate and is an important adaptation factor	It has a lesser impact on the NAMA algorithm, but is important for routing and multi-hop

$$J_i = \int_0^T [\alpha \cdot P_{tx,i}(t) + \\ + \beta \cdot P_{rx,i}(t) + \gamma \cdot P_{sense,i}(t)]\, dt \qquad (7)$$

where: the expression under integral J_i represents the instantaneous total power of each network node.

$$P_{total}(t) = [\alpha \cdot P_{tx,i}(t) + \\ + \beta \cdot P_{rx,i}(t) + \gamma \cdot P_{sense,i}(t)] \qquad (8)$$

with energy weights ($\alpha = 0.8$, $\beta = 0.4$, $\gamma = 0.6$) depending on the task priorities of the nanosensor network and $P_{tx,i}(t)$, $P_{rx,i}(t)$, $P_{sense,i}(t)$ are randomly fluctuating power waveforms (simulating transmission, reception, and measurement).

Formulas (5) and (7) differ in what they measure. The version with the factor (1/T) describes the nanosensor's temporal energy consumption density [W] and is used to compare efficiency and adapt over time. The version without the factor (1/T) represents the total energy and is used for energy balance as well as calculation of the nanosensor's duty cycle. The formulas can be explained based on physics and electronics, as energy is the product of power and time, instantaneous power is the instantaneous energy consumption, and combining (summing) power over time yields the nanosensor's energy effect. Standard energy models are used in the literature. From these models, the energy components of transmission, reception, and measurement are summed, resulting in the following formula:

$$J_i = E_{tx,i} + E_{rx,i} + E_{sense,i} \qquad (9)$$

On the basis of this, it can be summarized that using weights (α,β,γ) is a common technique in adaptive and optimization algorithms to adjust the importance of individual cost components. If the goal is no longer just to minimize energy consumption but also to ensure operational stability, for example, avoiding large fluctuations in power, control, or energy levels, then the lambda trade-off factor $\lambda \in [0,1]$ controlling the trade-off between energy saving and its uniform distribution is introduced. If $\lambda = 0$ → full focus on energy minimization, if $\lambda = 1$ → full focus on stability (e.g., equal workload distribution), intermediate values represent a compromise between the two. Here, the formula becomes:

$$J_i = (1 - \lambda) \cdot E_i + \lambda \cdot V_i \qquad (10)$$

where: E_i is the energy consumption component (e.g., total nanosensor energy), and V_i is the stability component (e.g., power variance, fluctuations).

The factor (1 - λ) emphasizes energy efficiency, and λ emphasizes stability. This can be interpreted as meaning that the system may act more aggressively when energy is the primary objective ($\lambda \to 0$). When stability is important (e.g., to avoid sensor overheating or destabilizing the system), the weight λ increases. The parameter λ can even be dynamically adjusted depending on battery level, load, or node priorities. To further model the energy cost function J_i, which reflects the energy consumption of a single nanosensor i- node, depending on relevant system parameters, let us assume that the energy cost J_i depends on: E_{tx}, E_{rx}, E_{sense} and operating time T, if the cost is calculated as average consumption. Introducing the trade-off factor λ into the cost function J_i is a typical step in multi-objective optimization, particularly in adaptive energy-saving algorithms. In practice, two cost functions were defined: $J_i^{fix}(t)$ for a fixed lambda λ value of 0.5 and $J_i^{adap}(t)$ for a variable lambda. The time index at which each of these functions reaches 80% of its maximum value was checked.

Example

In this case *lifetime_fixed* = 142 (i.e. the 142nd point in the t vector)and *lifetime_adaptive* = 158. What does this mean in terms of time? The time vector t contains 200 points evenly spaced between 0 and 10 seconds and the time interval is:

$$dt = \frac{10 - 0}{200 - 1} \approx 50.25\, ms$$

so $t_{142} = 142 \cdot dt \approx 7.13$s and $t_{158} \approx 7.95$s. It was assumed that the system terminates when it reaches 80% of its maximum cost, so we have Extending Network Lifetime ENL:

- life time for $\lambda = 0.5$ → $t = 142$ point of simulation,
- life time for adaptive λ → $t = 158$ point of simulation.

Therefore, ENL = 100% · (158 – 142)/142 = + 11.18%. The conclusion is that the adaptive strategy increased network lifetime by over 11%. This shows that adaptive regulation allows the system to operate longer with the same energy limit, justifying the claim of an extension of network lifetime by over 11% (see on the Figure). On the basis of Equation 8 it was calculated the cumulative energy by integration (discrete summation):

$$E_{integral}(t_i) = \sum_{j=0}^{i} P_{total}(t_j) \cdot \Delta t \quad (11)$$

At the end is $E_{total\ max} = \max(E_{integral})$ the maximum value of this curve. In the considered case, $E_{total\ max} \approx 23.57$ mJ. This corresponds to the maximum energy consumption over the entire simulation duration (10 seconds).

Adaptive rule

The function $u_i(t + \Delta t)$ (see Equation 2) represents the adaptive control of a single nanosensor. As the rate of energy consumption changes (due to variable transmission and measurement power), the control value is dynamically adjusted. An increase in instantaneous energy consumption leads to a faster decrease in $u(t)$, which may symbolize, for example, an automatic limitation of the frequency of measurements, transmissions or sensor activity.

RESULTS AND DISCUSSION

On the basis of Table 2 it can be concluded that communication in the terahertz (THz) band is becoming the preferred technology for sensor nanonetworks, especially where sensors are very small, operate over short distances (1–20 mm), and fast and local data transmission is required. The THz band offers a very wide transmission bandwidth, allowing for the parallel operation of a large number of sensors. An additional advantage is their physical compatibility with nanoantennas – THz waves have wavelengths comparable to the dimensions of nanomaterials such as graphene or carbon nanotubes, enabling the creation of microscopic antennas. Due to their limited range and high directivity, THz communication is well-suited to dense and local networks, such as the skin of a robot hand or the flexible surface of a smartphone, where the distances between elements are minimal.

System optimization with total energy consumption and variability in time

Let us consider the following calculation example with the data as below. Example. Let be E_{elec} = 50 nJ/bit, ε_{amp} = 100 pJ/bit/mm², k = 256 bits, d = 5 mm, n = 2. For this data we have: $E_{tx} = 50 \cdot 256 + 100 \cdot 10^{-3} \cdot 256 \cdot 8^2 = 12.8$ µJ + 1.64 µJ = 14.4 µJ and $E_{rx} = 50 \cdot 256 = 12.8$ µJ.

One can see that transmission costs more and more the further the data needs to be sent. For E_{tx} this is a quadratic curve (Figure 2). For short distances (1–5 mm), energy consumption increases slowly. For longer distances (10–20 mm), energy increases drastically—illustrating how expensive it is to transmit data long distances in nanonetworks. The red dashed line (E_{rx}) is a horizontal line and the receiving energy independent of distance can be seen. The data reception energy,

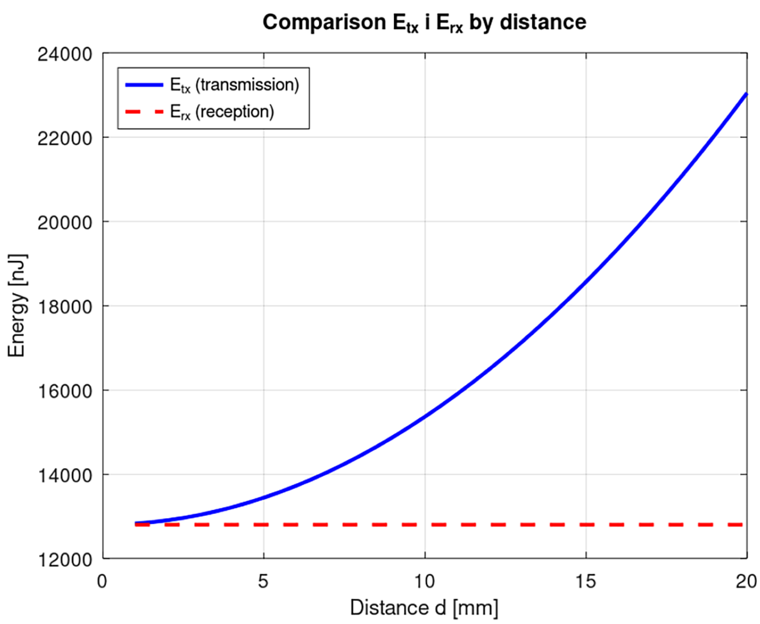

Figure 2. Energy changes with distance: for E_{tx} and E_{rx}

although independent of the transmission distance, is not absolutely constant. Therefore, we will get a linear graph and the more bits are sent to a node, the more energy it must use to receive them (Figure 3). For example, for:

$k = 256 \rightarrow E_{rx} = 12.8$ μJ,

$k = 1024 \rightarrow E_{rx} = 51.2$ μJ.

It can then draw conclusions by taking into account other factors indicated in Table 4. In nanosensor networks (e.g., on the surface of a robot hand, smartphone, or electronic skin), the typical clock frequency of a microcontroller, transmitter, or receiver depends on the technology and the tradeoff between speed and power consumption. When working with energy modeling, one can assume the standby mode is 32 kHz (negligible consumption), active reception: 4 MHz or 8 MHz for a balance between speed and energy saving. This is important because the higher the clock frequency, the faster the data is received, but also the higher the power consumption (e.g., $P \sim f \cdot V^2$ for CMOS).

The parameter $E_{\_tx}$ dominates the cost function for long-distance transmissions or central nodes, $E_{\_rx}$ is important in multi-hop models where sensors receive data from neighbors. The energy required to receive data by a nanosensor depends on several important technical factors. The most important is the number of received bits k, and the longer the data packet, the more energy the receiver consumes. This relationship is linear. Therefore, frequency scaling (DFS) or dynamic power management (DPM) are often used. On the basis of Table 4 it can be noticed that although E_{rx} does not depend on the distance between nodes, it is strongly dependent on the data size, hardware technology, and receiver operating parameters. In practice, nanosensor systems and intelligent IoT devices use different clock frequencies, depending on energy efficiency requirements, operating speed, and the technology used.

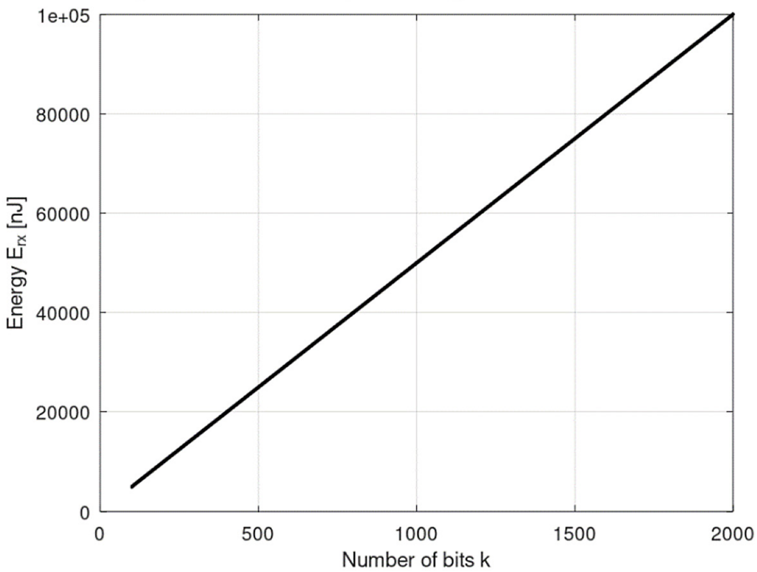

Figure 3. Energy E_{rx} changes with the k-number of bits

Table 4. Reception energy E_{rx} dependence for nanosensors in the network

Factor	Impact on E_{rx}
Number of bits	Main factor - energy increases linearly with the length of the received packet $E_{rx} = E_{elec} \cdot k$
Manufacturing technology	Different technologies (CMOS, graphene, nano-MEMS) have different values of E_{elec} — this affects the cost per bit
Operation mode	In standby mode (sleep mode) consumption is close to zero; in active mode - full reception energy
Clock frequency	Faster clock speeds speed up reception but increases power consumption per bit
Supply voltage	Higher operating voltage of electronics increases energy consumption
Channel conditions (BER, SNR)	High interference (low SNR, high BER) causes retransmissions or error corrections — increases the real E_{rx}

The lowest frequencies, in the range of 32 kHz to 1 MHz, are found in ultra-low-power devices such as real-time clocks (RTCs), simple nano-MEMS controllers, or standby nodes. They enable very long system lifetimes at the expense of limited timing functionality. Typical microcontrollers used in the IoT typically have clock frequencies in the range of 1–16 MHz. In modern nanonetworks, especially those operating in the THz band, local clocks or pulse generators can reach even higher speeds – from 100 MHz to 1 GHz. The graph in Figure 4a finds the value of λ^* that minimizes the cost. It plots the graph with a red dot at the minimum point. Figure 4b shows a model with a dynamically changing trade-off factor $\lambda(t)$. The top graph is the λ(t): the value of λ decreases over time, as we assume the node consumes energy. Initially, there is a greater emphasis on stability (large λ), later on, a greater emphasis on savings (small λ). The middle graph is the power consumption $P\text{total}(t)$: random fluctuations in transmit, receive, and measurement power. The bottom graph is the energy cost $J_i(t)$: the cost variation over time, reflecting how changing $\lambda(t)$ affects the preferred operating mode (stable vs. cost-saving). The following graph (in Figure 4c) shows an adaptive strategy with a threshold-controlled tradeoff λ(t). The tradeoff factor $\lambda(t)$ is initially set to 1 (increasing the emphasis on energy consumption stability). When total energy consumption exceeds 60% of the maximum value, $\lambda(t)$) suddenly decreases to 0.3. This indicates a transition to energy-saving mode, where the total energy E_i, rather than its fluctuations, becomes the dominant

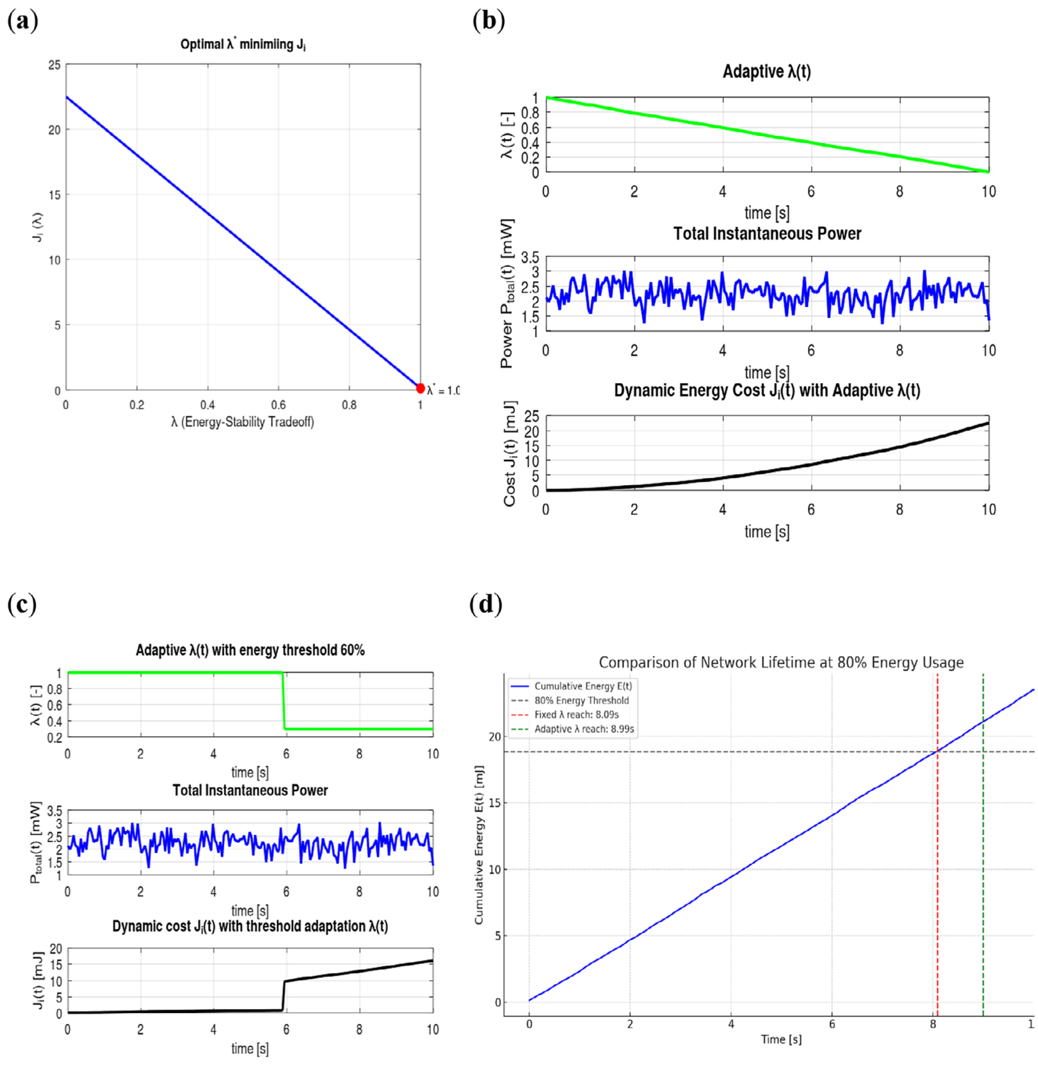

Figure 4. (a) Finding the optimal value of λ^* that minimizes the energy cost function $J_i(\lambda)$ with a static trade-off λ factor, (b) is the model with a dynamically changing trade-off factor $\lambda(t)$, (c) Adaptive strategy with threshold-controlled compromise λ(t). (d) Comparison of the moments when strategies reach 80% energy consumption

cost factor. The top graph $\lambda(t)$ changes suddenly after the threshold is crossed. The middle graph shows the instantaneous power consumed by the sensor. The bottom graph shows the resulting cost $J_i(t)$, reflecting the change in strategy. A comparison of the moments at which the strategies reach 80% energy consumption is shown in Figure 4d. The red line is the strategy with a fixed $\lambda = 0.5$ and reaches the threshold earlier (~7.13 s). The green line is the adaptive strategy with a dynamic $\lambda(t)$ and reaches the threshold later (~7.95 s).

Table 5 contains the values of the dynamic cost $J_i(t)$, instantaneous power $P_{total}(t)$, and the adaptive trade-off factor $\lambda(t)$ at subsequent points in time. It can be used to analyze changes in energy cost depending on the adaptation strategy. The estimated on the cumulated energy value of 23.57 mJ is the correctly calculated total energy consumed by the nanosensor network during 10 seconds of operation, based on the variable transmit, receive, and measurement power waveforms. It is now possible to convert energy into the number of operations/signals in a nanosensor.

Example

It was assumed that a single operation/signal (e.g., reading or transmitting) consumes E_{op} = 1 µJ per operation, which is typical for nano-transmission. The energy consumed in the simulation

Table 5. The dynamic cost $J_i(t)$ depending on time and coefficient λ(t), for the first 30 rows out of 200 in total

Records	t [s]	λ(t)	$P_{total}(t)$ [mW]	$J_i(t)$ [mJ]
1	0.00	1.00	2.61	0.00
2	0.05	1.00	2.21	0.00
3	0.10	1.00	2.11	0.01
4	0.15	1.00	2.34	0.01
5	0.20	1.00	2.37	0.01
6	0.25	1.00	1.36	0.06
7	0.30	1.00	2.40	0.06
8	0.35	1.00	1.85	0.07
9	0.40	1.00	2.32	0.07
10	0.45	1.00	2.59	0.07
11	0.50	1.00	2.69	0.08
12	0.55	1.00	1.73	0.10
13	0.60	1.00	2.54	0.10
14	0.65	1.00	2.10	0.10
15	0.70	1.00	2.22	0.10
16	0.75	1.00	1.84	0.12
17	0.80	1.00	2.23	0.12
18	0.85	1.00	2.10	0.12
19	0.90	1.00	2.52	0.12
20	0.95	1.00	2.25	0.12
21	1.01	1.00	2.11	0.12
22	1.06	1.00	2.92	0.14
23	1.11	1.00	2.73	0.15
24	1.16	1.00	2.38	0.15
25	1.21	1.00	2.69	0.15
26	1.26	1.00	2.38	0.15
27	1.31	1.00	2.14	0.16
28	1.36	1.00	2.02	0.16
29	1.41	1.00	2.13	0.16
30	1.46	1.00	2.39	0.16
…	…	…	…	…

Source: own research.

is 23.57 mJ. The number of possible operations is 23.57 mJ/0.001 mJ = 23,567 operations. The maximum number of operations with the assumed limit of 50 mJ is 50,000 operations. Then, the remaining reserve of operations will be 50,000 -23,567 = 26,433 operations.

Adaptive rule

The graph in Figure 5 illustrates how the adaptive mechanism works in nanosensor networks – responding to local energy conditions in real time. In simulations such as this, sinusoidal functions (e.g. sin(t) and cos(t)) were assumed. This is because they represent the variability of the environment over time, and in real nanonetworks, the operating conditions of sensors change cyclically – for example, in response to hand movements (if the sensors are on the skin), temperature/pressure changes (e.g., in the environment), and cyclical system operations (e.g., a data collection schedule every few seconds).

Furthermore, sinusoids accurately represent such periodic phenomena in a simplified but realistic manner. They are mathematically stable and smooth. Using harmony allows checking whether the u(t) control algorithm reacts dynamically, how quickly it adapts to power increases/decreases, and whether the algorithm does not cause instability or too slow reactions.

Figure 5 shows a decreasing curve of the function $u(t)$, which represents the adaptive control of the nanosensor. As the energy consumption rate changes (due to variable transmission and measurement power), the control value is dynamically adjusted to the needs of each sensor. The top graph shows how the transmission and sensing power changes over time (periodically). The bottom graph shows how the adaptive control value $u(t)$ decreases in response to these consumption variables. This visualization shows how the nanosensor node adaptively adapts to local energy conditions. For larger values of $P_{comm}(t)$ and P_{sense}(t), the decline in $u(t)$ is faster. When consumption temporarily decreases, the rate of change in $u(t)$ also slows down. In noisy environments, the receiver may be forced to re-receive data or perform additional error correction, which increases the total energy cost of reception.

Table 6 for adaptive control with the transmission threshold contains the data for the threshold change $\lambda(t)$ after exceeding 60% of energy consumption, instantaneous power $P_{total}(t)$ and calculated dynamic cost $J_i(t)$. The variable $\lambda(t)$ allows for dynamic control of the trade-off between stability and energy efficiency where the

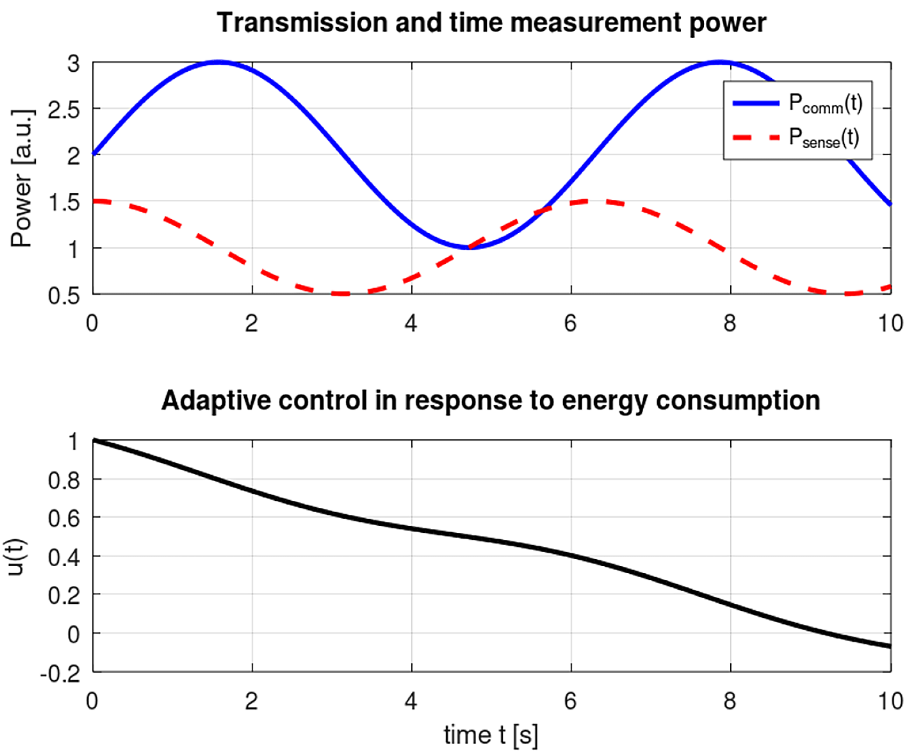

Figure 5. The adaptive control rule's performance over time in response to the *i*-th nanosensor's varying energy consumption

Table 6. Adaptive control in response to energy consumption (the first 25 rows out of 200 in total)

Records	t [s]	λ(t)	$P_{total}(t)$ [mW]	$J_i(t)$ [mJ]
1	0.00	0.99	2.61	0.00
2	0.05	0.99	2.21	0.01
3	0.10	0.99	2.11	0.01
4	0.15	0.98	2.34	0.02
5	0.20	0.98	2.37	0.02
6	0.25	0.97	1.36	0.07
7	0.30	0.97	2.40	0.08
8	0.35	0.96	1.85	0.10
9	0.40	0.96	2.32	0.11
10	0.45	0.95	2.59	0.12
11	0.50	0.95	2.69	0.14
12	0.55	0.94	1.73	0.17
13	0.60	0.94	2.54	0.18
14	0.65	0.93	2.10	0.20
15	0.70	0.93	2.22	0.22
16	0.75	0.92	1.84	0.24
17	0.80	0.92	2.23	0.26
18	0.85	0.92	2.10	0.28
19	0.90	0.91	2.52	0.30
20	0.95	0.91	2.25	0.32
21	1.01	0.90	2.11	0.34
22	1.06	0.89	2.92	0.39
23	1.11	0.89	2.73	0.42
24	1.16	0.88	2.38	0.45
25	1.21	0.88	2.69	0.49
…	…	…	…	…

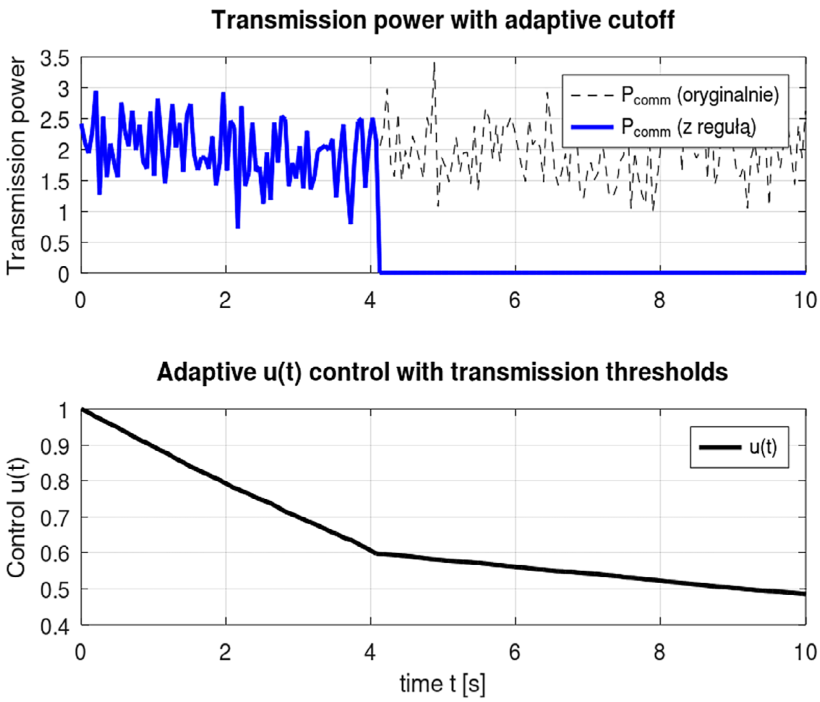

Figure 6. The adaptive control graph u(t) with transmission cut-off threshold

system operates precisely initially and then more economically later.

The graphs in Figure 6 (based on the Table 6) show the operation of an adaptive rule with a threshold cut-off of transmission, which operates in two stages. An adaptive rule with thresholds was used: If $u(t) < 0.6$ → transmission disabled (energy saving). If $u(t) > 0.75$ → transmission restored. The top graph shows the comparison: the gray dashed line is the original transmission (without any restrictions), the blue line is the transmission after the rule was implemented (transmission power before and after adaptation).

CONCLUSIONS

Simulation results indicate that NAMA significantly reduces energy fluctuations across the network and extends the effective system lifetime, defined as the time to reach 80% of cumulative energy consumption. This improvement is particularly critical for dense sensor arrays embedded in skin-like interfaces, such as humanoid hands or flexible wearable surfaces, where power availability is constrained and energy uniformity is essential for stable performance. The proposed model integrates terahertz communication principles, aligning with the emerging trend of utilizing nanoscale antennas for ultra-short-range, high-bandwidth, and low-power transmission. NAMA leverages local, real-time estimation of energy consumption rates to adaptively regulate the operating parameters of individual sensor nodes, such as sampling rate or transmission timing. By incorporating a differential model of energy flow, NAMA enables each nanosensor to autonomously balance the trade-off between sensing and communication costs using tunable coefficients (α_i, β_i) and a learning constant (η). By accounting for both communication and sensing energy in the adaptive model, NAMA offers a comprehensive framework for next-generation IoNT applications. The conducted work demonstrates that distributed, local energy control based on adaptive modeling and minimal coordination lead to measurable improvements in power stability, sensor longevity, and communication efficiency. These findings support the broader deployment of smart nanosensor networks in biomedical, wearable, and robotic systems.

For the adopted adaptive strategy with a threshold-controlled trade-off $\lambda(t)$, it is clearly visible that after exceeding 60% of the energy, the algorithm automatically reduces λ to save energy. At a realistic consumption of 1 µJ per operation (reading, transmitting, processing), such a system could still perform over 26,000 additional operations before reaching the energy limit of 50 mJ. This shows that the AMA algorithm works efficiently in terms of energy consumption in nanosensor systems. The operational resource utilization in the nanosensor network indicates that 47.1% of the energy has already been consumed (approximately 23,567 operations), while 52.9% of the energy remains (approximately 26,433 operations that can be performed with a 50 mJ limit). This demonstrates that the adaptive strategy leaves a significant energy reserve, which promotes longer system operation. According to the adaptive control rule as energy consumption increases, the control value decreases, which can represent a decrease in sensor activity, an extension of measurement intervals, or a reduction in transmission power. This mechanism allows for local adjustments to sensor operation without the need for central coordination. The introduction of threshold adaptation allows for dynamic adjustment of sensor activity. It also protects the node from complete energy depletion.

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