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ENERGY-SAVING METHOD IN WIRELESS SENSOR NETWORKS

Abstract. Relevance. WSNs are characterized by many autonomous nodes that are expected to operate for extended periods without battery replacement or recharging. This poses a significant challenge for researchers and developers to find effective energy-saving methods that can substantially extend the autonomous operating time of the nodes and ensure the stable and reliable functioning of the entire network. **The object of research** is the processes of energy consumption and functioning of Wireless Sensor Networks. **Purpose of the article** is the development and investigation of an energy-saving method in Wireless Sensor Networks based on the use of machine learning algorithms, particularly artificial neural networks of the Kohonen map type and their modifications, in order to ensure the most efficient utilization of node energy resources, optimize data transmission and processing processes, and increase the duration of autonomous operation and the reliability of sensor network functioning under variable operating conditions. **Research results.** An energy-saving method based on modified Kohonen maps has been developed. The proposed approach involves multifactor clustering of nodes considering their energy parameters, adaptive selection of transmission routes, regulation of node activity modes, and online retraining of the map. **Conclusions.** The energy consumption of nodes depends not only on the hardware configuration but also on the method of data exchange organization, the chosen network topology, transmission frequency, and environmental conditions. The issue of energy depletion in individual nodes is critical, as it can lead to network fragmentation or complete network failure. Therefore, there is a need for dynamic, intelligent management that considers both local and global characteristics of the network.

Keywords: wireless sensor network, energy consumption, Kohonen map, machine learning, clustering, adaptive routing, node.

Introduction

Modern wireless sensor networks are one of the key infrastructure components across various fields of human activity, such as environmental monitoring, industrial process control, healthcare, smart homes and cities, agriculture, and military applications. The widespread adoption of such networks is driven by their capability for continuous data collection, transmission, and analysis from many spatially distributed sensor nodes. At the same time, the growing number of sensor devices, the increasing volume of processed data, and the expansion of geographic deployment areas significantly raise the demand for energy autonomy of these systems.

One of the most critical challenges faced by wireless sensor networks is ensuring a prolonged operational period of the nodes without the need to replace power sources or recharge batteries. A typical solution is to power the nodes using autonomous batteries, the replacement of which in large-scale or hard-to-reach networks is a complex and economically inefficient task. This is why energy efficiency becomes a crucial factor that directly impacts the viability and practical applicability of sensor networks.

The issue of node energy consumption is further complicated by the fact that a typical sensor device expends energy not only for data transmission but also for data reception, processing, and maintaining functionality in standby mode. Given the limited power supply resources, the need for a comprehensive approach to energy efficiency is evident. Therefore, the relevance of researching energy-saving methods lies in finding a balance between performance, reliability, and the duration of autonomous node operation.

This work presents a detailed analysis of modern methods for reducing energy consumption in wireless sensor networks. Particular attention is given to energy-efficient routing protocols, algorithms for managing node and sensor operating modes, strategies for reducing the volume of data to be transmitted, methods of adaptive signal power control, and the potential for using renewable energy sources to ensure maximum autonomy of sensor devices. The results of this analysis will help formulate recommendations for the integrated use of various technologies and approaches, which will significantly enhance the efficiency of wireless sensor networks under real-world conditions.

The purpose of this work is the development and investigation of an energy-saving method in wireless sensor networks based on the use of machine learning algorithms, particularly artificial neural networks of the Kohonen map type and their modifications, to ensure the most efficient utilization of node energy resources, optimize data transmission and processing processes, and increase the duration of autonomous operation and the reliability of sensor network functioning under variable operating conditions.

Main part

The operation of sensor nodes in wireless sensor networks is determined by a combination of hardware, software, and environmental factors, each of which affects performance, stability, energy consumption, and the duration of autonomous operation. Key factors include: the type and sensitivity of the sensor (the choice of sensor depends on the type of physical quantity being measured. The higher the resolution and sensitivity, the more energy the sensor may consume); the power and architecture of the microcontroller (the processor’s computing power determines the ability to locally process data before transmission. More powerful microcontrollers reduce the amount of data transmitted but may consume more energy themselves); the type and capacity of the power source (the battery or energy storage device limits the node's operation time. The type of power source and the possibility of energy harvesting are also important); energy consumption modes (the availability of sleep, wake-up, standby, and active communication modes are critical for optimizing energy usage. Switching between modes must be controlled and adaptive); the communication protocol (the selected protocol affects transmission range, speed, and energy cost. Low-energy protocols are often chosen for long-term deployments); network topology and routing algorithms (a node may be an endpoint or a relay. Acting as a relay for others increases its energy consumption. Uneven load distribution among nodes leads to early depletion of certain elements in the network); data collection and transmission frequency (frequent measurements and transmissions increase energy usage. Optimizing this frequency is critical in designing energy-efficient algorithms); environmental conditions (temperature, humidity, interference levels, terrain, and other physical factors can affect sensor reliability and communication quality, causing additional energy expenditures); node software (optimized software, task schedulers, and adaptive algorithms can significantly reduce energy usage); local decision-making capability (nodes capable of analyzing collected data independently – e.g., classifying events or filtering noise – can reduce the number of transmitted packets and save energy).

In traditional wireless sensor network systems, decisions regarding routing, energy management, and node operation modes are made based on rigid rules or statistical models. This approach often fails to account for the complex dynamics of the network, changing environmental conditions, battery degradation, or unexpected overloads of individual nodes. Therefore, the application of machine learning algorithms, which allow adaptive optimization of network operation considering variable parameters and accumulated experience, is gaining increasing relevance.

One of the key tasks in the context of energy saving is node clustering, i.e., grouping nodes into clusters based on such features as battery level, geographic location, traffic density, and load. Machine learning enables this clustering to be performed dynamically rather than statically, with the structure of the clusters being updated as the network state changes. For instance, k-means methods, hierarchical clustering, or algorithms based on self-organizing maps can automatically determine the optimal number and configuration of clusters, helping reduce energy losses from routing and prevent overload of individual nodes.

Another important area is activity prediction of nodes and intelligent scheduling of sleep/wake cycles. Using historical activity data, typical sensing patterns, or external parameters (e.g., daily temperature variations, movement, or noise), learning algorithms can predict when a node is likely to be heavily loaded and adjust its operating mode accordingly. This approach maintains a balance between energy consumption and data transmission quality.

In addition, the use of classification and regression methods enables real-time assessment of the network state and decision-making regarding route changes or switching nodes to energy-saving modes.

Reinforcement learning-based approaches also deserve attention. In such models, nodes or node groups learn to make energy-efficient decisions through interaction with the environment – by trial and error. For example, an agent can learn to deactivate secondary nodes or adjust transmission power in response to changing network conditions, receiving “rewards” for saving energy without compromising service quality.

Finally, recent research focuses on integrating deep learning to detect complex dependencies in the large volumes of data generated by the network. For example, convolutional neural networks enable the identification of recurring traffic patterns, while recurrent neural networks allow for forecasting future node loads. This creates the foundation for proactive energy and transmission management.

In article [1], a modified Kohonen map method is proposed to improve the performance of artificial neural networks through the clustering of sensor nodes—parameters such as hop count, energy levels, sensitivity, and delay are calculated. The author suggests using artificial neural network-based clustering of sensor data, which leads to enhanced energy saving in wireless sensor networks.

In article [2], the DL-GMA approach is proposed, which is a deep learning-based grouping model aimed at improving energy efficiency in wireless sensor networks. By utilizing advanced grouping and clustering techniques, DL-GMA optimizes energy consumption, enhances network stability and scalability, reduces congestion, and improves quality of service. However, the authors note certain limitations in their work, including network heterogeneity, mobile nodes, communication overhead, and the limited scale of the evaluation, which require further investigation.

In article [3], an integrated concept is proposed to enhance energy efficiency based on machine learning methods and intelligent data analysis. The author states that a unified model for sensor selection and event detection can learn from historical data and solve operational tasks such as energy efficiency, event detection accuracy, and service quality assurance in the case of sensor failures. However, the work has some shortcomings, as many functional and practical issues remain unresolved, particularly those related to network retraining.

The analysis of the sources confirms the relevance of using artificial neural networks of the Kohonen map type to improve energy efficiency in wireless sensor networks.

The essence of using Kohonen maps in energy-saving tasks lies in building an optimized model for distributing functions among network nodes. In typical wireless sensor networks, only a portion of the nodes perform critical tasks such as routing or data aggregation. The use of Kohonen maps enables the identification of nodes best suited to perform these functions based on a set of criteria: battery charge level, call frequency, signal quality, transmission intensity, load level, etc. Thus, node clusters are formed, within which cluster heads or relays are selected to minimize energy consumption across the entire system.

A key advantage of using Kohonen maps in this task is their ability for unsupervised learning, meaning such a neural network does not require pre-labeled data to function. This is especially important in scenarios where reliable a priori information about the network status may not be available. During the learning process, the Kohonen map forms a topologically ordered structure where nodes with similar characteristics are grouped together, allowing for effective dynamic clustering in real time.

Moreover, this type of artificial neural network is well suited for adaptation to changes within the network. For example, if certain nodes fail or the environmental configuration changes, the Kohonen map can be retrained or adapted to the new conditions without requiring a complete system restart. This ensures the resilience and survivability of wireless sensor networks, which is critically important in remote or hard-to-reach environments.

Despite the effectiveness of classical self-organizing Kohonen maps for clustering tasks and reducing energy consumption in wireless sensor networks, for complex, dynamic, and large-scale environments, the standard Kohonen map architecture or its sequential learning process may prove insufficiently flexible [4]. This has led to the emergence of a few modifications that improve adaptability, scalability, and real-time accuracy. Such enhanced models open new horizons for implementing energy-efficient management in sensor networks, considering changes in network topology, load levels, power element status, and external influences.

There are also several architectures that are modifications of the classical Kohonen map. In hierarchical architecture, the network consists of multiple organizational levels, where each successive level refines the previous one. This approach is particularly effective for large sensor networks with heterogeneous node distribution. A hierarchical structure enables multilevel clustering – first dividing the network into regions based on their position on the grid and then forming energy-optimal clusters within each region. This significantly simplifies routing, reduces the number of inter-cluster transmissions, and allows for localized network adaptation.

Another promising direction involves adaptive maps that change their structure during the learning process. Unlike classical maps with a fixed number of neurons, adaptive maps can add or remove neurons in response to changes in data input. This is critically important for sensor networks where the number of active nodes can vary over time due to energy depletion, physical damage, or changes in the environmental configuration. Adaptive topology modification allows the system to maintain clustering accuracy and effective network management without the need for complete retraining. Another type of modification enables dynamic map expansion in the direction of highest data complexity. In sensor networks, this allows more attention to be automatically devoted to areas with high traffic or a high risk of overload, providing more detailed energy management in critical regions.

An alternative approach to improving the efficiency of Kohonen maps is the modification of the training process. The standard Kohonen map training algorithm is based on unsupervised learning with gradual reduction of the neighborhood radius and learning rate. Classical training requires a significant number of iterations and constant processing of input data, which may result in excessive energy consumption when implemented on real nodes with limited resources. Therefore, several modifications have been proposed to improve energy efficiency and adaptation to sensor network conditions.

Training on data subsets suggests using random or statistically representative subsets instead of the entire input dataset. This reduces the amount of information transmitted to the main node or computing center, thereby lowering energy costs for communication. Additionally, local training on nodes or clusters with limited data reduces the number of iterations and improves scalability.

The classical Kohonen map algorithm requires preprocessing of the entire training set. Incremental learning, in contrast, allows the map to adapt to each new input vector individually. This approach accounts for changes in network state in real time without full retraining and also reduces the need for storing large data volumes on the nodes. Training with a dynamic neighborhood radius implies that the neighborhood radius is adapted dynamically – for example, depending on the variance of the input data or the energy resource level of the sensor nodes. This allows for the reduction of unnecessary updates and focuses the training process only on those nodes where changes are truly significant, thereby saving energy. In energy-aware learning, an additional parameter is introduced into the weight update function that accounts for the current battery charge level of a node. If a node has a low charge, its participation in the training process is reduced or excluded. In this way, the system automatically avoids overloading the resources of nodes that are close to depletion and ensures a more balanced load distribution across the network.

In priority-based learning, the weight coefficients are updated more frequently for inputs corresponding to high-priority events or clusters with high energy consumption. This allows computational resources to be focused on more energy-intensive areas and enables quicker adaptation to change that may threaten the network's viability. In the quantized Kohonen map, discretization of the input data space is introduced, which reduces the dimensionality of the training dataset and computational costs. In WSNs, this lowers the need for precise measurement of physical quantities and allows nodes to operate with coarser but more energy-efficient sensors or to transmit smaller-sized data packets.

The development of an effective energy-saving method for wireless sensor networks requires a combination of adaptive input data analysis, consideration of node energy constraints, and the network's ability to self-adjust [4]. In this context, modified Kohonen maps serve as a key component of the intelligent energy management model. A method is proposed based on dynamic node clustering using an adapted Kohonen map training algorithm [5], which considers the energy state of nodes, traffic density, position on the coordinate grid, and transmission history. The concept of the method involves building an energy-weighted Kohonen map that is updated in online mode and makes decisions regarding the formation of node clusters, selection of energy-optimal cluster centers, determination of efficient transmission routes with minimal energy loss, and adaptation of node operating modes (active, idle, sleep). The implementation stages of the method (Fig. 1) are as follows:

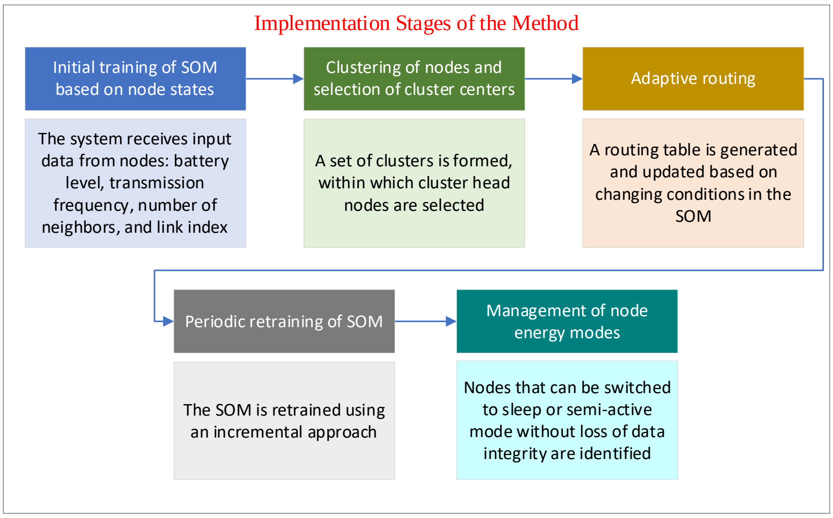

Fig. 1. Implementation Stages of the Method

1) Initial SOM Training Based on Node States. In the first stage, the system receives input data from the nodes: battery level, transmission frequency, number of neighbors, and link index. Based on these features, a Kohonen map is created with a dynamically adapted neighborhood radius and energy-weighted weight updates, where nodes with lower battery levels have reduced influence on the formation of the topology.

2) Node Clustering and Cluster Head Selection. After training, the map forms a set of clusters within which cluster head nodes are selected. The cluster head selection algorithm considers the maximum remaining energy, minimum distance to other nodes in the cluster, and load history. This ensures balanced distribution of balanced load and avoids premature exhaustion of individual nodes.

3) Adaptive Routing. Within each cluster, a routing table is formed and updated considering changing conditions such as energy depletion in a node or traffic increase. SOM is used not only for clustering but also for building a network-wide load-weighted map. This enables traffic redirection to avoid overloaded or low-energy nodes.

4) Periodic Retraining of the Kohonen Map. The method includes cyclic retraining of the map using an incremental online approach. This allows the system to remain adaptive even in dynamic conditions, such as changes in network topology or partial node failures. The learning radius and update coefficient are reduced depending on the stability of the cluster structure.

5) Management of Node Energy Modes. Based on the cluster structure and the state of the network, the algorithm identifies nodes that can be switched to sleep or semi-active mode without compromising data integrity. This implements a cyclic wake-up strategy for the nodes, which significantly reduces average energy consumption.

The proposed method represents a practical and promising approach to resource management in wireless sensor networks.

Conclusions

During this research, an analysis of the energy-saving problem in wireless sensor networks was conducted, and the rationale for using machine learning methods – particularly modified Kohonen maps – as an effective tool for adaptive network resource management was substantiated. The energy consumption of nodes depends not only on the hardware configuration but also on the organization of data exchange, the selected network topology, transmission frequency, and environmental conditions. The problem of energy depletion in individual nodes is critical, as it can lead to network fragmentation or complete system failure. Therefore, there is a need for dynamic, intelligent management that considers both local and global characteristics of the network.

Clustering, prediction, and adaptive control models – especially those implemented through reinforcement learning or deep learning – can enhance both the energy resilience of the network and the overall quality of service.

As a result, machine learning not only provides energy savings but also creates the foundation for building self-learning, autonomous next-generation systems.

Thanks to their topological ordering and unsupervised learning capability, Kohonen maps enable the formation of energy-optimal clusters, the selection of the most suitable nodes to act as cluster heads, and the dynamic reconfiguration of network structure based on changes in energy states. This ensures balanced load distribution and reduces the number of transmissions within the network.

Machine learning algorithms offer qualitatively new opportunities for adaptive, self-learning, and energy-efficient functioning of wireless sensor networks. Their implementation results in reduced energy consumption, increased reliability, and minimized human intervention in the operation of such systems.

Modified Kohonen maps are an effective, scalable, and adaptive tool for managing energy consumption in wireless sensor networks. They not only enhance energy efficiency but also ensure fault tolerance, adaptability, and integration with other intelligent technologies.

An energy-saving method based on modified Kohonen maps has been developed.

The proposed approach involves multifactor clustering of nodes considering energy parameters, adaptive selection of transmission routes, regulation of node activity modes, and online retraining of the map. Thus, modified Kohonen maps, integrated into the architecture of the sensor network, represent an effective means for building energy-efficient, self-learning, and flexible sensor systems.

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Метод енергозбереження в безпровідних сенсорних мережах

В. С. Гармаш, В. О. Дяченко, О. П. Міхаль, В. Г. Знайдюк

Анотація. Актуальність. Безпровідні сенсорні мережі характеризуються великою кількістю автономних вузлів, які повинні тривалий час працювати без заміни або підзарядки джерел живлення. Це ставить перед дослідниками і розробниками завдання пошуку ефективних методів енергозбереження, здатних суттєво продовжити період автономної роботи вузлів та забезпечити стабільну й надійну роботу всієї мережі. **Об'єкт дослідження**: процеси енергоспоживання та функціонування безпровідних сенсорних мереж. **Мета статті**: розробка методу багатоваріантного синтезу дискретно-казуальних моделей елементарних функцій операцій керованих інформацією який розширить можливості проектування мало ресурсних пристроїв реалізації СЕТ-операцій для побудови криптографічних систем з подвійним управлінням процесом шифрування. **Результати дослідження.** Розроблено метод енергозбереження, що базується на модифікованих картах Кохонена. Запропонований підхід передбачає багатофакторну кластеризацію вузлів з урахуванням енергетичних параметрів, адаптивний вибір маршрутів передачі, регулювання режимів активності вузлів і онлайнове перенавчання карти. **Висновки.** Енергоспоживання вузлів залежить не лише від апаратної конфігурації, а й від способу організації обміну даними, обраної топології мережі, частоти передач та умов навколишнього середовища. Проблема енергетичного виснаження окремих вузлів є критичною, оскільки вона здатна спричинити фрагментацію або повний вихід мережі з ладу. Саме тому виникає потреба в динамічному, інтелектуальному управлінні, яке враховує як локальні, так і глобальні характеристики мережі.

Ключові слова: безпровідна сенсорна мережа, енергоспоживання, карта Кохонена, машинне навчання, кластеризація, адаптивна маршрутизація, вузол.