Cluster-based routing in Wireless Sensor Networks with reduced energy consumption: A Systematic Review

William Castro da Rosa, Waldir Sabino da Silva Júnior and Celso Barbosa Carvalho

Abstract – The energy consumption of electronic devices is a determining factor in the development of routing algorithms for Wireless Sensor Networks (WSNs). Among several strategies, the construction of community clusters has been successfully used to reduce energy consumption in WSNs. The objective of this research is to perform a systematic review of routing algorithms for WSNs based on clusters. We have chosen three databases that cover journals focused on Computer Science and Engineering – Web of Science, IEEE Xplore and Science Direct. The selection of cluster heads based on residual energy, fitness functions and sensor placement increases the effectiveness of cluster-based routing.

Keywords – Wireless sensor networks, Routing, Clusters, Energy consumption.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are made up of devices powered by batteries, capable of extracting information from the environments where they are inserted, generating data that are passed on to other devices on the network or to base stations [1]. WSNs are one of the pillars of the Internet of Things (IoT), which mixes technologies for sensoring and managing network resources to offer solutions with several practical applications.

IoT is widely used in industry, being important in quality control processes [2-3]. In addition to industrial purposes, IoT can also be used in encrypted communication [4], management of smart cities [5], remote medical monitoring [6], traffic control through vehicular networks (VANET) [7], among other possibilities.

Many sensors of a WSN can be installed in mobile devices or machines. In this case, the connectivity between nodes of the network may be intermittent and the network topology may be subjected to changes/disconnections, making end-to-end routing ineffective. Several algorithms address the routing problem in WSNs and other mobile networks [8-15], being able to deliver messages between devices on a network with varying levels of efficiency.

The advancement of routing techniques increased the use of WSNs. Consequently, the demand for sensors has grown in recent years [16]. WSN routing is a complex operation, requiring power and network resources. Thus, the influence of energy consumption of devices with sensors on WSN routing has become the subject of research. Strategies are varied [17-26], with the aim of reducing the energy consumption of connected devices.

Some approaches are based on the building of community clusters. The hierarchy of nodes in communities is a strategy that has been showing reductions in energy consumption in different test scenarios.

The large number of recent developments in this area of research motivates the periodic elaboration of systematic reviews to organize and summarize state of the art methodologies. Therefore, there is a need to identify and analyze recently developed cluster-based WSN routing algorithms, their respective proposals and their results. The present research is a systematic review of these algorithms, which are expected to offer reductions in the energy consumption of sensors and other connected devices.

This paper is organized as follows: Section II describes the research model and strategy, the inclusion and exclusion criteria for this systematic review and the study selection process. Section III presents the results and a brief explanation of selected studies. Conclusions are given is Section IV.

II. MATERIALS AND METHODS

A. *Research model and strategy*

A systematic review was performed based on an adaptation of the recommendations of the PRISMA 2020 (*Preferred Reporting Items for Systematic Reviews and Meta-Analyses*) [27] review guide flowchart. The search for articles was done through databases with a wide range of journals focused on Computer Science and Engineering. Three databases were selected: Web of Science, IEEE Xplore and Science Direct. They were accessed from the CAPES journal portal, through the Federated Academic Community (CAFe).

Web of Science, by Clarivate Analytics, has more than 9000 indexed journals and informs, for each article, the documents cited by it. IEEE Xplore provides more than 4 million periodicals, conference/congress proceedings and technical standards, published by the Institute of Electrical and Electronic Engineers (IEEE-USA) and the Institute of Engineering and Technology (IET-UK). Elsevier's Science Direct contains articles from over 37,000 book titles, with links to external datasets such as Scopus.

The search pattern for articles was based on the terms "wireless sensor networks" AND "energy consumption" AND "clustering" AND "routing" AND "mobile" NOT "review" NOT "survey". The search was performed in March and April 2023.

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B. Inclusion and exclusion criteria

To be included in the review, each study met the following criteria: (1) propose at least one routing algorithm in wireless sensor networks based on clusters, (2) reduce the energy consumption of devices, (3) show comparisons with existing techniques, (4) be written in English, (5) be published in the latest five years, from 2019 onwards.

Exclusion criteria are: (1) not proposing a new algorithm or a new approach to perform routing in wireless sensor networks based on clusters, (2) not showing reductions in energy consumption, (3) not making comparisons with previous work, (4) having been published before 2019.

The process of identifying and sorting articles is described by the steps illustrated in Fig. 1, adapted from the PRISMA 2020 flowchart.

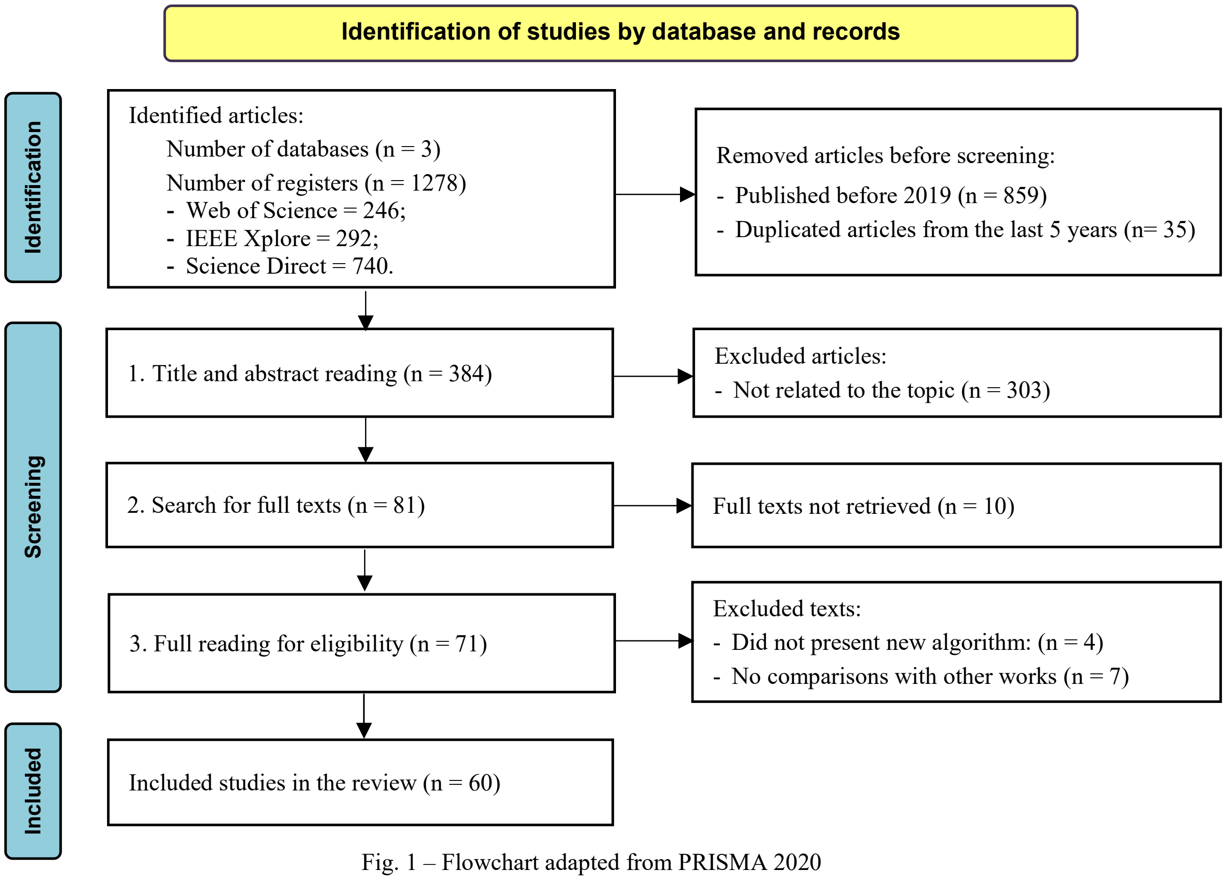

Fig. 1 – Flowchart adapted from PRISMA 2020

C. Study selection

The selection process was related to the identification and screening phases of Fig.1. Screening took place in three steps: 1 – Title and abstract reading, where studies not related to the topic were discarded; 2 – Search for full texts; 3 – Full text reading, where the main contributions of the works (introductions) and the results (figures, graphs and tables) were emphasized. After screening, a final number of n = 60 studies were approved and included in the review.

D. Data extraction

Some studies selected in the flowchart of Fig.1 were of special interest for their creative approaches to energy consumption and clear comprehension. They had their main data organized in Table 1, using the following information: (1) authors and year of publication, (2) proposal, (3) references for comparison, (4) results. A textual summary of ten selected articles is given in the next section.

III. RESULTS

The initial search provided n = 1278 articles. After removing duplicate papers and those that did not meet the inclusion criteria, n = 60 studies were approved and included in the review. Among these works, ten articles were selected (Table 1) for a more detailed description. They provided new routing algorithms for WSNs, capable of reducing the energy consumption of electronic devices.

The EEDMS algorithm [17] adopts two methods to collect normal or emergency data in a sensor network: 1 - It builds a spanning tree to forward emergency data to a base station; 2 – It divides the network into cells of the same size, which are managed by cell heads (CH) that collect normal data and forwards them to a mobile sink. The CH selection mechanism considers a cost function based on residual energy of nodes and their respective distances to the cell center. To avoid unbalanced consumption of energy among nodes, cells are shifted periodically. The combination of the two mentioned methods reduces latency for emergency data and increases the cost-effectiveness of normal data collection.

Table 1 - Characteristics of cluster-based routing algorithms

Authors, Year	Proposal	References for comparison	Energy consumption reduction compared to reference (R)
Farzinvash et al, [17], 2019	Distributed data collection with mobile sinks: EEDMS	Fault-tolerant virtual backbone tree (FTVBT), Energy-aware path construction (EAPC), Optimized low-energy adaptive clustering hierarchy (LEACH), Weighted rendezvous planning (WRP), Caching point-oriented iterative routing (CB)	50% (FTVBT), 14% (EAPC), 34% (Opt LEACH), 48% (WRP), 59% (CB)
Elshrkawey et al, [18], 2022	Enhanced routing based on a reposition particle swarm optimization: RA-RPSO	Particle swarm optimization (PSO), Genetic algorithm (GA), Grey wolf optimization (GWO), Ant-Lion optimization (ALO)	Up to: 68,1% (PSO), 65,9% (GA), 61,6% (GWO), 60% (CB)
Sadrishojaei et al, [19], 2021	Clustering and location prediction routing based on multiple mobile sinks: CLRP-MMS	Location predictive data gathering (HALPDGSMS), Energy efficient routing with mobile sink support (EERAMSS)	28,1% (HALPDGSMS), 34,6% (EERAMSS)
Aftab et al, [20], 2019	Clustering for Internet of Drones (IoD) based on dragonfly algorithm: BICIoD	Ant colony optimization (ACO), Grey wolf optimization (GWO)	23% (ACO), 33% (GWO)
Elmonser et al, [21], 2020	Dynamic multihop LEACH: DMH-LEACH	Singlehop LEACH, Multihop LEACH	Up to: 29% (Singlehop LEACH), 16% (Multihop LEACH)
Wei et al, [22], 2022	Dynamic spanning tree with mobile sink: DSTMS	Centralized energy efficient distance based routing (CEED), Distributed, multi-hop, adaptive, tree-based energy-balanced routing (DMATEB), Improved LEACH (ILEACH)	58,4% (CEED), 72,4% (DMATEB), 13,4% (ILEACH)
Amutha et al, [23], 2022	Hybrid optimization with unequal clustering: HOUCMS	Competitive swarm optimization unequal clust. (CSO-UCRA), Particle swarm optimization (PSO) unequal clust.(PSO-UCRA), Energy- and proximity- based unequal clust. (EPUC), Energy aware unequal fuzzy clust. (EAUCF), Energy balanced unequal clust. (EBUC)	8,3% (CSO-UCRA), 11,1% (PSO-UCRA), 20,6% (EPUC), 21,4% (EAUCF), 21,4% (EBUC)
Najjar-Ghabel et al, [24], 2019	High-performance data harvesting in MS-based WSNs: HPDMS	Energy aware path construction (EAPC), Multiobjective PSO (MOPSO), Delay bound reduced K-means (DBRkM)	59,9% (EAPC), 39,7% (MOPSO), 32,6% (DBRkM)
Ojha et al, [25], 2022	Multiobjective GWO: MOGWO	Multiobjective PSO (MOPSO), Dynamic clustering ACO (DC-ACO), Energy aware path construction (EAPC), Weighted rendezvous planning (WRP)	25% (MOPSO) 30% (DC-ACO) 37% (EAPC) 45% (WRP) (scenario with 200 nodes)
Tirani et al, [26], 2020	Weighted data aggregation trees with optimal mobile sinks: WDAT-OMS	Centralized clustering algorithm (CCA), Energy-aware CS-based data aggregation (ECDA), Energy-balanced high-level data aggregation tree (EHDT)	66% (CCA) 62% (ECDA) 63% (EHDT)

The RA-RPSO algorithm [18] is based on particle swarm optimization (PSO), which was originally designed to model the social behavior of fish schools and bird flocks. The RA-RPSO is divided into three phases: 1 - Initialization, 2 - Setup and 3 - Transmission. In the initialization phase, a base station (BS) uses the K-means algorithm to create a set of sensor nodes (SN) clusters and a sensor information table that keeps, among other information, the identifier, position and energy of each SN. The setup and transmission phases are executed through successive rounds. In the setup phase, the BS employs the RPSO method to pick the SN that represents the optimal cluster head (CH). The process of CH selection uses a fitness function that has to meet four objectives: 1 - Keep high residual energy in SNs, 2 – Reduce intra-distances between cluster members (CMs) and their CHs, 3 – Minimize distances between CHs and BS and 4 – Properly rotate the role of CH among different SNs through successive rounds. For this multiobjective purpose, the RPSO modifies native equations of PSO for position, velocity and inertia weight. In the transmission phase, the CHs use TDMA technology to aggregate data from their respective cluster members in a single hop and send them to the BS via CSMA protocol.

The CLRP-MMS method [19] partitions the network into segments and allocates nodes in different communities based on their positions. For the selection of cluster heads (CH), a function based on the distance between nodes, residual energy and speed of movement in the network determines the CH of each community, at each round of execution of the algorithm. The reconstruction of the clusters is done locally and in situations where the residual energy of the CH becomes lower than a given threshold, to balance the energy consumption of the devices. The position prediction of CHs in other clusters reduces the distances to be traveled by nodes for message transmission between communities.

BICIoD's dragonfly-style clustering [20] considers five factors to update a drone's position vector – separation, alignment, cohesion, attraction, and distraction. Position and residual energy determine a drone's fitness. The selection of a CH is performed as a function of each candidate's fitness and connectivity to the base station. Position and residual energy are also critical for message forwarding, extending the lifetime of clusters.

The DMH-LEACH protocol [21] is executed in intervals, called “rounds”. At the beginning of each round, the number of clusters in the network is dynamically calculated, determining the threshold value that defines which nodes will be elected cluster heads (CHs). To prevent CHs close to the sinks from quickly consuming their energy reserves, DMH-LEACH resorts to node mobility to balance consumption in the network. The selection of CHs considers the mobility factor, avoiding nodes with high mobility and volatile connectivity. Thus, the election of the CHs considers the threshold obtained by the number of clusters, the residual energy of the nodes and the mobility factors, providing better energy balance to the sensors.

The DSTMS algorithm [22] builds a multilayer transmission framework between a mobile sink and sensors spread across a monitoring area. The process is organized in two stages. The first consists of creating a dynamic “rendezvous layer”, composed of the sink and some selected nodes called “rendezvous points”, responsible for communication between sink and sensors. The second stage is based on the LEACH protocol and the energy consumption of sensor nodes, performing the construction of a dynamic minimum spanning tree (MST). The MST consists of the rendezvous layer and an inter-cluster transport layer, where most nodes are organized in clusters. Connections between cluster heads and rendezvous points interconnect the two layers. The resulting MST is capable of connecting any sensor to the sink, extending the useful life of the network and saving energy.

The hybrid optimization HOUCMS [23] merges meta-heuristics based on butterflies and ant colonies to transmit data with energy efficiency. The algorithm determines the CHs by applying the butterfly metaheuristic, through a fitness function that considers five factors: residual energy, distance from the nodes to the CHs, distance from the CHs to the mobile sink, degrees of the nodes and centrality. Then, an unequal clustering is performed, followed by a route calculation based on the ant colony metaheuristic.

The HPDMS technique [24] employs two methods to balance collection delays and energy consumption. The first, KMACO-DH, uses k-medoids to organize the sensors into clusters and ant colony-based optimization (ACO) to calculate a route between CHs, to be traversed by the mobile sink. The second method, LW-DH, is a greedy algorithm that uses the clusters and routes obtained by KMACO-DH to refine the routes, aiming to reduce the overload in the multihop network.

The methodology proposed by the multiobjective gray wolf optimization, MOGWO [25], is based on the hunting and leadership behavior of wolves. They are classified into four categories: alpha, beta, delta and omega. The first three have more aptitude and represent the best solutions for an optimization problem. The fitness function adopted by MOGWO must balance three conflicting goals: The first is to minimize the maximum average transmission distance of sensor nodes. The second is to minimize the maximum average hop counts. The third objective is to minimize the maximum average transmission distance between sensor nodes in the same cluster. Considering the fitness values and the multiobjective nature of the problem, MOGWO resorts to Pareto dominance to determine a set of non-dominated search agents, from which the alpha, beta and delta are selected. Optimized solutions are selected and transformed into rendezvous points (RPs). The lowest cost route is calculated so that the mobile sink can visit the RPs. After collecting data from the sensors, the algorithm calculates their residual energy to rotate the RPs within the clusters.

The WDAT-OMS algorithm [26] partitions the network sensors into a given number of clusters, based on their positions. For this purpose, an initial, non-optimized set of selected nodes (SN) is randomly created. Other sensors are linked to the nearest SN, forming initial clusters. For each cluster, a new SN is determined such that the sum of the Euclidean distances of all its sensors to the new SN is minimal. Thus, the other sensors are linked again to the closest SN. This cycle is repeated until the sensors gradually converge to the best clusters. A “round” is defined as the interval between two instants of time in which the sensors collect data from the environment. In each round, the WDAT-OMS is run in three phases. In the first, the cluster heads (CHs) are determined from the residual energy and the Euclidean distance between the sensors, in addition to a punishment factor created to control the trade-off between energy consumption and load balance in the network. In the second phase, each sensor transmits its data to the corresponding CH through a data aggregation tree. In the third phase, mobile sinks traverse the network in optimized routes to collect data from CHs.

The works discussed in this review [17-26] present reductions in energy consumption in relation to reference works in the literature, according to Table 1. Since some nodes may be highly requested to transmit data or messages to mobile devices, their energy levels may be quickly depleted. In order to avoid this, routing algorithms often resort to CH calculation functions based on residual energies of the nodes. Some techniques perform the calculation of fitness functions, being more common in optimization algorithms based on biological models [20,23,25]. The preservation of sensors with a lower energy level contributes to extending the lifetime of the network.

IV. CONCLUSIONS

The Internet of Things and wireless sensor networks are related research areas that present many possibilities for practical applications. In this review, several studies developed with the objective of reducing the energy consumption of devices in wireless sensor networks were selected. Among the approaches found in the literature, the construction of network clusters is emphasized. Clusters can be determined according to several strategies and methodologies, such as colony optimizations [20,23], construction of multilayer frameworks [22], dynamic adjustment of the status of sensors within clusters [18], position prediction [19], use of k-medoids [24], among others. These strategies may be combined with each other, creating additional advantages that can be further analyzed in future works.

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Conflicts of interest: The authors declare that there are no conflicts of interest.

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