Sociedade Brasileira de Automática (SBA)
XXV Congresso Brasileiro de Automática - CBA 2024, 15 a 18 de outubro de 2024

Regression-Based Law of Energy Efficiency in Wireless Sensor Networks

Prado, F. 0. C. * **Brigato, M.** ** **Ferreira, A. A.** *** **Prado, A. J.** **** **Avila, A. R.** †

* *Sao Paulo State University (Unesp); School of Engineering; Campus of Sao Joao da Boa Vista, (e-mail: fabiano.prado@unesp.br).*
** *Sao Paulo State University (Unesp); School of Engineering; Campus of Sao Joao da Boa Vista, (e-mail: mauricio.brigato@unesp.br)*
*** *Sao Paulo State University (Unesp); School of Engineering; Campus of Sao Joao da Boa Vista, (e-mail: andre.alves@unesp.br)*
**** *Sao Paulo State University (Unesp); School of Engineering; Campus of Sao Joao da Boa Vista, (e-mail: afonso.prado@unesp.br)*
† *Institute National de la Recherche Scientifique, Montreal, Canada, (e-mail: anderson.avila@inrs.ca)*

Abstract:
Wireless Sensor Networks play a pivotal role in various applications, ranging from environmental monitoring to industrial automation. Efficient clustering of these network nodes is crucial for optimizing communication and energy consumption. In this study, we compare the performance of two clustering methods, namely k-means and grid-based clustering, in terms of energy efficiency. The nodes are assumed to be uniformly distributed across a two-dimensional area, and clusters are formed using the k-means algorithm. A baseline model is established using grid clustering for comparison purposes. To evaluate the efficiency of these clustering approaches, the energy consumption analysis is based on Friss law, and regression algorithms are employed to analyze energy consumption patterns within the network. Through regression analysis, an energy efficiency law is determined for all the cases analyzed. Our results underscore an approach to optimize energy consumption by formulating a functional relationship for total transmission power, derived from regression analyses conducted across diverse simulation scenarios.

Keywords: Statistical data analysis, Learning theory, Machine Learning, Data Science, Wireless Communication.

1. INTRODUCTION

In recent years, wireless sensor networks (WSNs) have garnered significant attention owing to their potential applications in diverse fields such as target tracking (Lu et al. (2023)), intelligent traffic control system (Hilmani et al. (2020)), and localization (Pagano et al. (2015)). A WSN comprises a large number of wireless nodes, typically dispersed in a deliberate or randomized manner across a designated region characterized by dynamic environmental conditions. These nodes are equipped with sensing capabilities to detect, process, and transmit data to adjacent nodes as well as to a central Base Station (BS), facilitating comprehensive data collection and transmission within the network. Given the need to transmit sensed data to the central BS for subsequent analysis and action, the routing process plays a crucial role in WSN architecture. Efficient routing mechanisms are essential to facilitate the seamless transmission of data between individual nodes and the BS, ensuring timely and reliable delivery of information for further processing and decision-making. In WSNs, various hierarchical techniques have been proposed to optimize resource utilization, particularly battery power, with the objectives of enhancing energy efficiency and prolonging network lifespan. Among these techniques, clustering stands out as a prevalent approach employed to achieve these overarching goals.

Efficient clustering techniques (Del-Valle-Soto et al. (2023); Jan et al. (2017); Sabor et al. (2017); Pantazis et al. (2013)), and strategic placement of relay nodes (Wan and Chen (2022)) play a vital role in maximizing energy utilization and prolonging the network lifetime of WSNs. Improving cluster structure and optimizing the selection of cluster heads (CHs) emerge as crucial challenges in clustering methodologies. Notably, the K-means algorithm stands out as a versatile tool for generating clusters, finding extensive practical applications including WSNs. Numerous approaches have been developed based on the K-means algorithm to enhance clustering effectiveness (El Khediri et al. (2020); Periyasamy et al. (2016)). This paper endeavors to establish an analytical framework for quantifying the total power transmitted within WSNs through regression analyses. Within the context of the LEACH (Low Energy Adaptive Clustering Hierarchy) protocol, we envision a scenario where WSN nodes are uniformly dispersed across a two-dimensional area, and clusters are organized utilizing the k-means algorithm. The energy consumption dynamics within the network are governed by the principles of

Friss law, with regression algorithms utilized to dissect and discern intricate energy consumption patterns. This comprehensive analysis seeks to unravel the underlying mechanisms driving energy consumption within WSNs, thereby providing valuable insights into the optimization of power transmission strategies under the LEACH protocol.

The subsequent sections of this article are structured as follows: In Section 2 lays the foundation by presenting the fundamental theory guiding the simulations conducted WSN. Following this, the Section 3 provides a comprehensive overview of the experimental setup and implementation details, including the utilization of the Python programming language and the specification of parameter values. Subsequently, in the Section 4, we delve into the regression process and highlight the derived energy efficiency law, demonstrating its interpretability and efficacy in optimizing network energy utilization. Lastly, the Section 5 synthesizes our contributions to the existing literature and outlines potential future research avenues in this domain.

2. THEORETICAL FRAMEWORK

This work is based on the LEACH protocol (Heinzelman et al. (2000); Verma (2023)) to structure the communication of the WSN which is a pioneering protocol, adept at managing energy consumption and extending network lifespan through decentralized organization by setting CHs responsible for coordinating and aggregating data from neighboring sensor nodes within their respective clusters before transmitting them to the BS.

Originally the LEACH protocol establishes that the sensor nodes initially self-elect as CHs probabilistically, aiming for equitable energy distribution. Recent advancements have expanded its efficacy by integrating supplementary clustering algorithms. Here, we consider the K-Means (KM) clustering method as a means to decentralize the WSN architecture, aiming to optimize energy consumption. We designate the nearest network node to each cluster centroid as the CH, thereby facilitating efficient data aggregation and transmission while minimizing energy expenditure.

We establish a comparative framework, herein referred to as the Grid Method (GM), which serves as the foundational baseline for comprehensive evaluation. While KM clustering categorizes nodes into clusters based on geometrical approximation between nodes, the grid method spatially organizes nodes into a grid structure. These techniques enhance resource utilization by facilitating efficient data aggregation at CHs before transmission to the BS.

2.1 Spatial Distribution of WSN Nodes

In this study, we are supposing that the spatial distribution of N_n nodes, over an area $A = L \times L$, is following a uniform probability density function

$$F(x, y) = \frac{1}{L^2}, \tag{1}$$

satisfying the normalization $\iint F(x, y)\, dx\, dy = 1$. Under this distribution condition, we sampled the N_n nodes coordinates to perform our experiments by considering N_r realizations of the spatial configuration of the nodes, thus ensuring that distribution is authentically uniform.

2.2 Friis Law and WSN Energy Consumption

Friis Law, also known as the Friis transmission equation (FTE), plays a pivotal role in understanding the propagation of electromagnetic signals in WSNs. In our analysis, we utilize the FTE to quantify the transmitted power P_t of each node in the WSN, considering factors such as received power P_r, antenna transmission and reception gains G_t and G_r, wavelength λ, and the distance d between the transmitter (node) and receiver (head). For our purposes, we express the aforementioned equation as follows:

$$P_t = \kappa d^2, \tag{2}$$

where

$$\kappa = \frac{P_r}{G_t G_r} \left(\frac{4\pi}{\lambda} \right)^2 \tag{3}$$

is a constant factor, since it is assumed that: **(1)** the antenna performances are stable across the network deployment area (constant gains); **(2)** the P_r values at the CHs remains constant, by reflecting the stable reception conditions from all nodes; **(3)** all nodes transmit with the same value of wavelength.

Since the WSN communication is established using the N_c clusters from the two methods, the WSN energy consumption from nodes is accomplished through a double summation of (2) as follows:

$$\mathcal{P}_{nodes} = \sum_{i=1}^{N_c} \sum_{j=1}^{N_n(i)} P_t^{i,j}, \tag{4}$$

where the outer summation is with respect to the N_c clusters and the inner summation is with respect to the $N_n(i)$ nodes of the i-th cluster. On the other hand, the energy consumption from CHs transmitting to the BS is accomplished through a single summation of (2) as follows:

$$\mathcal{P}_{heads} = \sum_{i=1}^{N_c} P_t^{i}, \tag{5}$$

where the summation is with respect to N_c clusters. Therefore, the WSN energy consumption is the sum $\mathcal{P}_{nodes} + \mathcal{P}_{heads}$. As will be seen, both $\mathcal{P}_{nodes}$ and $\mathcal{P}_{heads}$ are functions of the cluster quantity N_c and the number of nodes N_n, and after the data generation from our simulations we obtain a regression function for both powers.

2.3 K-means Method

The KM method is one of the best-known and popular clustering approaches. In this method, the objective is to partition the dataset comprising observations into a predetermined number of clusters ($K = N_c$), aiming to minimize the within-cluster sum of squares by assigning each observation to the cluster with the nearest mean centroid. Considering that the features used in clustering are the spatial coordinates of the network nodes, the minimization is with respect to the sum of Euclidean distances between WSN nodes. The Figure 1 illustrates the clustering of the WSN setting $N_c = 6$. Further elucidation on the operational intricacies of the method is available in the subsequent reference (James et al. (2021)). As the

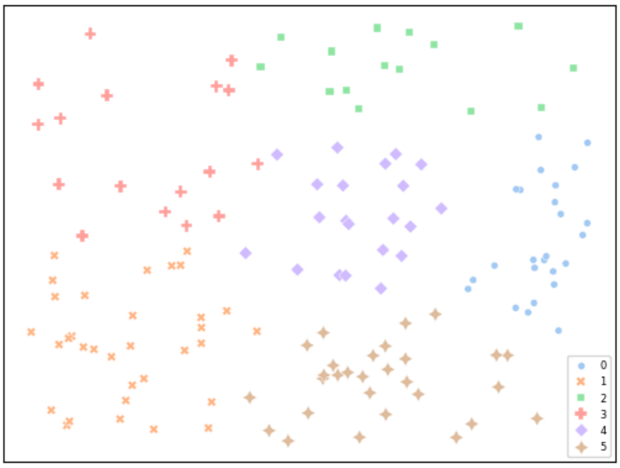

Figure 1. clustering of 140 nodes according to the kmeans method for $N_c = 6$.

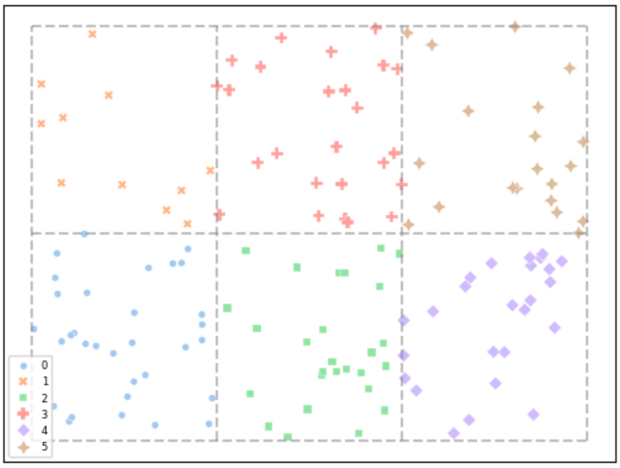

Figure 2. clustering of 140 nodes according to the grid method for $N_c = 6$.

referred method lacks an intrinsic criterion for determining the optimal number of partitions, it necessitates simulation across a range of number of clusters.

2.4 Grid Method

The grid method (Farman et al. (2016); Meng et al. (2016)) entails the straightforward subdivision of the WSN area into smaller spatial units, accomplished by a grid structure delineated by intersecting horizontal and vertical evenly spaced lines. These delineated grid cells serve as foundational spatial criteria for clustering network nodes uniformly distributed. By partitioning the WSN deployment area into discrete grid cells, the method establishes a structured framework for node organization and communication. Each grid cell represents a distinct spatial region, facilitating the allocation of nodes to specific clusters based on their spatial proximity to the centroid of respective grid cells. The Figure 2 illustrates the clustering of the WSN setting $N_c = 6$ according to this method. This approach serves as a baseline technique for clustering in WSNs, providing a structured and intuitive approach to node organization and spatial partitioning that can be compared against the KM method for performance evaluation and benchmarking.

3. METHODOLOGY AND EXPERIMENTAL SETUP

To conduct simulations and derive the findings presented in this article, we employed the Python programming language, leveraging its versatility and extensive libraries. Specifically, we utilized prominent data analysis and machine learning libraries including *numpy* for numerical computations, *pandas* for data manipulation and analysis, and *sklearn* for machine learning algorithms implementation (Géron (2019)), ensuring robustness and reproducibility in our experimental framework. The initial step of the simulation involved importing functionalities from the *numpy.random* module to regulate the generation of pseudo-random numbers, thereby facilitating reproducibility through seed creation and data draw control. In what follows, the *uniform* function from the *numpy* library is employed to generate bidimensional coordinates for N_n nodes distributed uniformly across an area $A = L \times L$. The primary simulation parameters include the dimensions of the area under observation (L), the number of nodes deployed within the network (N_n), the count of clusters formed (N_c), and the number of experimental realizations conducted (N_r). The experimental design involves systematic variations in both N_n and N_c parameters to comprehensively assess their impact on network performance. The other parameters were kept at a constant value, namely, $N_r = 200$ and $L = 200$m.

We utilized the KM clustering algorithm from the cluster module of *sklearn* Python package. Specifically, we instantiated the *KMeans()* class with the parameter $n_{init} = 20$ to ensure convergence to the global minimum through multiple initialization. Subsequently, we employed the *DataFrame* data structure from the *pandas* package to systematically organize and structure all output data for further analysis and interpretation. Following the training of the KM algorithm, the *predict()* method is applied to ascertain the label corresponding to each node, subsequently appending this information into a new column within the aforementioned *DataFrame* for comprehensive data organization and analysis.

Simultaneously, clustering was executed employing the grid method. Unlike the K-means algorithm, the grid method relies on a straightforward heuristic approach, as elucidated in the Subsection 2.4, devoid of reliance on node-specific data.

Upon establishing clustering using both methods, the node nearest to the centroid of each cluster was selected as the CH. Subsequently, Euclidean distances between each node and its respective CH were computed for further analysis. These outputs were then included in the *DataFrame* for comprehensive data management and interpretation. The above procedure was repeated to calculate the distances from the CHs to the BS which is located in the corner of the experiment area. Finally, we segment into two distinct *DataFrames*, one to delineate the transmissions from nodes to CHs and other for the transmissions from CHs to the BS.

With the Euclidean distances readily available, we proceed to compute the transmitted powers P_t according to equation (2). Furthermore, the kappa constant (κ) was computed considering the gains (G_t and G_r) equal to unity, the wavelength $\lambda \approx 0.13\text{m}$, and a received power $P_r = 10^{-7}\text{mW}$, where the milliWatts scale is appropriate as the nodes are IoT devices operating at very low power levels. Once more, the feature P_t was stored as new columns within the aforementioned *DataFrames*.

Lastly, to quantify the energy consumption of the WSN as defined by equations (4) and (5), the summation of the columns corresponding to the variable P_t is accomplished using the sum() method of the *pandas DataFrame*. Therefore, these summations correspond to the $\mathcal{P}_{nodes}$ and $\mathcal{P}_{heads}$ which can be understood as functions of parameters N_c and N_n. It is pertinent to highlight that the experiments were repeated N_r times, where N_r represents the number of realizations of spatial configurations of the WSN nodes. The referred parameter was tested for various values, and it was observed that values exceeding $N_r = 200$ did not result in any significant changes in the experimental outcomes. These realizations were generated from a uniform probability distribution, ensuring robust statistical representation and reliability in the experimental outcomes.

The source code utilized in this study is accessible via the following link for comprehensive review and reproducibility of our findings: *github*.

4. RESULTS AND DISCUSSION

Utilizing the data derived from the experiments outlined in the preceding section, supervised datasets are constructed to train a regressor. These datasets consist of input variables N_n or N_c, and output variables $\mathcal{P}_{nodes}$ and $\mathcal{P}_{heads}$. Consequently, two regression analyses will be conducted: one to ascertain the relationship $\mathcal{P}_{nodes}(N_c, N_n)$ and another to establish $\mathcal{P}_{heads}(N_c, N_n)$.

4.1 Regression Modeling

Prior to conducting the final regression analysis, an extensive exploratory data analysis and residual assessment of provisional models were undertaken. This investigation revealed an absence of cross-dependency between the powers of the features N_n (number of nodes) and N_c (number of clusters) (James et al. (2021)). Notably, while the $\mathcal{P}_{nodes}$ exhibited non-linear behavior in relation to the number of clusters, exhibiting a decay rate associated with the N_c utilized in the experiment, the $\mathcal{P}_{heads}$ demonstrated a linear relationship. Based on these initial findings, a decision was made to employ the linear regression model for both node and cluster-head powers. However, it was noted that the linear regression of node power necessitates the incorporation of additional features constituted by the powers of feature N_c, indicating a more nuanced modeling approach to accomplish the decaying behavior.

4.2 Law Derivation From Regression Results

For regression analysis, the *LinearRegression()* class from the linear-models module of the sklearn package was

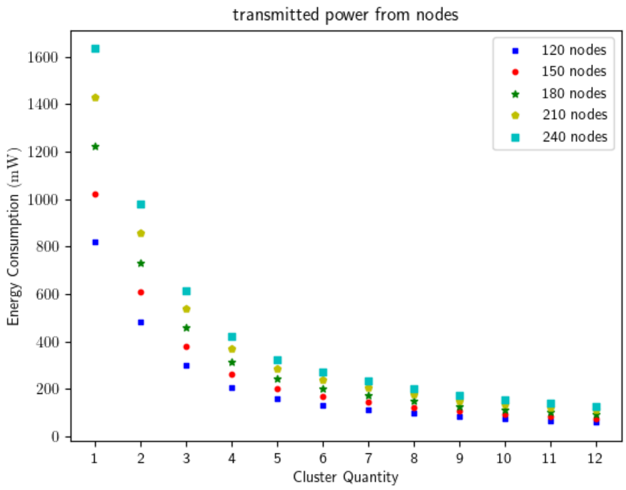

Figure 3. $\mathcal{P}_{nodes}$ power exponential decaying as N_c for $N_n = 120, 150, 180, 210, 240$

employed. The regression of $\mathcal{P}_{nodes}$ on N_c involved the utilization of this feature up to the sixth power to capture the nonlinear relationships.

K-Means Case Figure 3 depicts the outcomes of the regression analysis of $\mathcal{P}_{node}$ on N_c across five distinct values of network node counts for the supervised data using the method K-means. Visual inspection reveals a discernible exponential decay pattern in all the functions $\mathcal{P}_{node}(N_c)$. This decay phenomenon is attributed to the reduction in average distances from nodes to CHs, which correlates with the augmentation of N_c within the network. Based on the observed exponential trend described from regression, inference of an energy consumption law for $\mathcal{P}_{node}$ was conducted through mathematical function modeling. The resulting expression is provided below:

$$\mathcal{P}_{\textbf{nodes}} = C(N_n) \exp\left[-K(N_c)N_c\right], \tag{6}$$

where $C(N_n)$ represents the amplitude of the exponential decay coupled with linear growth relative to the parameter N_n. Additionally, $K(N_c)$ denotes the decay rate, which exhibits variability across different values of N_c, ranging from 0.2 to 0.4.

Figure 4 illustrates the regression analysis of cluster-head power $\mathcal{P}_{\text{heads}}$ on the number of clusters N_c across five distinct values of network node counts. Notably, the parameter N_n exhibits negligible influence, given the inherent relationship between the number of CHs transmitting to the base station and the number of clusters. Specifically, with the addition of each new cluster, a corresponding CH is automatically generated within the system, resulting in an intrinsic one-to-one correspondence between these variables.

Deriving a function to model the linear behavior of energy consumption $\mathcal{P}_{\text{heads}}$ is straightforward, as demonstrated by the expression provided below:

$$\mathcal{P}_{\textbf{heads}} = \mathcal{A}N_c + \mathcal{B}, \tag{7}$$

where $\mathcal{A}$ represents the linear variation rate, quantifying the rate at which power increases with the addition of each CH during clustering. Meanwhile, parameter $\mathcal{B}$ denotes the intercept of the functional model, a value that has been

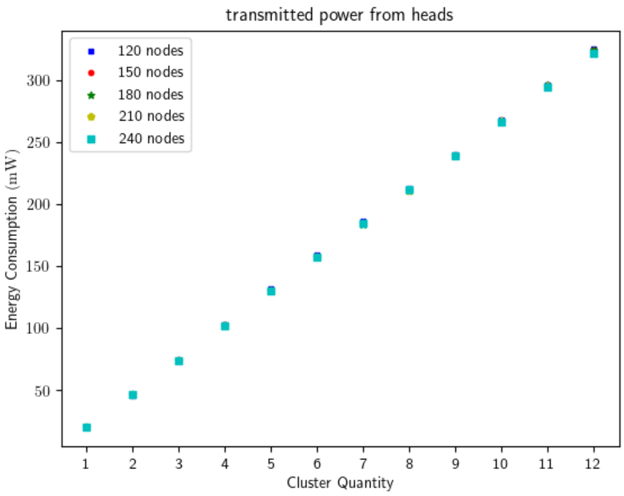

Figure 4. $\mathcal{P}_{heads}$ power linear increasing as N_c for $N_n = 120, 150, 180, 210, 240$

statistically proven to be null by the F-statistic (James et al. (2021)).

The parameters and dependencies outlined in equations (6) and (7) are highly adaptable, allowing for easy adjustment based on regression outcomes. Upon establishing well-defined functions for both equations, a closed-form optimization of the cluster count N_c can be achieved through the following equation:

$$\left.\frac{\partial \mathcal{P}_{\textbf{total}}}{\partial N_c}\right|_{N_n=cte} = 0, \tag{8}$$

where $\mathcal{P}_{\textbf{total}} = \mathcal{P}_{\textbf{nodes}} + \mathcal{P}_{\textbf{heads}}$. It is noteworthy that, despite the $\mathcal{P}_{\textbf{total}}$ function involving two variables, its minimum can be computed as if it were a function of a single variable. This simplification arises from the linearly increasing dependence on N_n due to the behaviour of $C(N_n)$ in (6).

Employing equation (8), the optimal cluster quantity for a given configuration can be determined. For instance, in a WSN configuration with $N_n = 120$, the minimum energy consumption, as dictated by equation (1), occurs at $N_c = 5$. Conversely, for $N_n = 240$, the minimum shifts to $N_c = 9$. These findings are corroborated and validated by the addition of two regressions outcomes themselves, depicted in the graph presented in figure 5.

The rationale behind this shift in N_c can be readily elucidated through the structural characteristics of functions (6) and (7). Given that the linear function $\mathcal{P}_{\textbf{heads}}$ is the same across all parameter scenarios, the shift in N_c is attributed to the amplitude $C(N_c)$ of the function $\mathcal{P}_{\textbf{nodes}}$. This observation underscores the pivotal role of $C(N_c)$ in modulating the optimal cluster count N_c to minimize energy consumption across different network parameter settings.

Grid Case For comparative analysis, the grid method was implemented alongside the k-means approach. Consistently, the performance of the grid method was found to be inferior to that of k-means. Particularly, when the grid cell deviates from a square shape, its efficacy significantly diminishes. This decline in performance is attributed to the increasingly rectangular configuration, which hampers the minimization of distances between nodes and CHs, consequently leading to reduced energy efficiency. Conversely, when the grid cell approaches a perfect square shape, the outcome remains slightly less favorable than that achieved with k-means. In scenarios where performance between the grid method and alternative approaches is comparable, it becomes feasible to employ similar functional modeling techniques. By appropriately adjusting the parameters and dependencies to suit the specific context of the grid method, a consistent and rigorous analytical framework can be maintained as before.

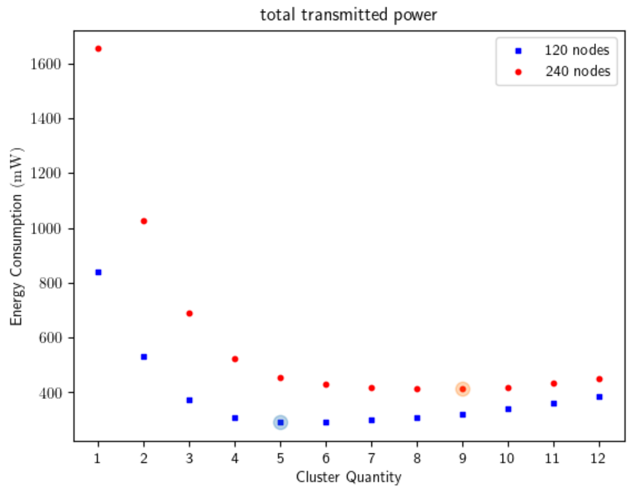

Figure 5. Combining the regression functions $\mathcal{P}_{nodes}$ and $\mathcal{P}_{heads}$, we derive the optimal values for N_c, which are $N_c = 5$ for $N_n = 120$ and $N_c = 9$ for $N_n = 240$.

5. CONCLUSION AND FUTURE DIRECTIONS

In this study, we introduced a sequence of procedures leveraging synthetic data generation and machine learning algorithms with the aim of optimizing and comprehending energy consumption in WSNs employing the classic LEACH scheme. Our approach involved utilizing data from linear regression analyses of energy consumption to formulate analytical functions, offering straightforward interpretations, and determining the total transmitted power of the wireless network as a function of parameters N_c and N_n. While our network context was deliberately simplified to streamline the presented procedures, we recognize the potential for future research to explore optimization strategies under more intricate conditions. Moving forward, we intend to investigate optimizations in scenarios featuring diverse spatial distributions for the nodes and transmission laws extending beyond FTE, thereby advancing the scope and applicability of our methodologies.

6. ACKNOWLEDGMENTS

The first author is grateful for the opportunity to be hosted by the aforementioned institution in 2023 (for 5 months) and 2024 (for 2 months) as a temporary professor, facilitating collaborative efforts with the second author, enabling a publication for the institution's research group. The authors extends their sincere appreciation to the

Inter-American Organization for Higher Education for fostering collaboration between Brazil and Canada.

Special acknowledgment is extended to professor Sandra C. C. Prado (FATEC-Mococa) for their valuable contribution to this manuscript by providing insightful feedback and assistance in the creation of graphics.

The authors disclose their utilization of LLM ChatGPT 3.5 as a writing assistant, emphasizing its role in generating original ideas throughout the course of this study.

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