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REDUCING WIRELESS SENSORS NETWORKS ENERGY CONSUMPTION USING P-MEDIAN MODELLING AND OPTIMIZATION

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Research Paper

Abstract: *Despite significant progress in wireless sensor network's (WSN) applications in recent years, major problems persist, notably the efficiency of the battery power use for data exchange. In fact, sensor nodes are known to be energy-limited, they are powered by a relatively low capacity, non-rechargeable battery, and in most cases, the nodes are deployed in inhospitable or hard-to-reach areas and are unlikely to be recoverable. Therefore, any program running on a smart sensor must consider energy management. This paper describes, for the first time, a comprehensive p-median based mathematical model of the WSN-IoT network's clustering problem. A set of decision variables is defined in order to express the objective of minimizing the energy consumption as a mathematical function to be minimized taking into consideration the residual energy of the nodes, among other constraints to be satisfied. Unlike most of the techniques proposed in the literature, this one is remarkably notable by being scalable to large sized networks with up to 90,000 nodes. Moreover, the proposed approach allows the dynamic determination of the optimal number "p" of clusters to be formed and the assignment of the sensor nodes to each cluster to decrease and balance energy consumption of the network even when the base station is located outside the network. A considerable energy savings of nearly 20% is obtained by applying our new proposed method compared to the literature results. This approach will undoubtedly play a key role in future studies in the field of IoT.*

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1. Introduction

Almost all electronic devices used in our daily lives are or will soon become smart to improve their energy efficiency and reduce carbon emissions. We do this through the optimization, management, live analysis and monitoring of their energy assets and installations remotely. Fears of climate change are now imposing the energy transition using smart energy. This is particularly noticeable in the case of Internet of Things (IoT) applications. Furthermore, this technology is in permanent progress and is widely used in several fields such as health, urban management, television, transportation, business management and industrial processes (Srinidhi, Kumar & Venugopal, 2018) (Ozturk et al., 2020). The current Internet of Things works principally through sensors, actuators and other connected objects placed in physical infrastructures. These objects emit and receive data that are uploaded through a wireless network onto IoT platforms. The data are analyzed and enriched to optimize the usage of the devices included in the network.

Sensor nodes are small components that remain active for a time that is limited by the capacity of energy source, mostly the batteries. In most applications, it is a big problem or even impossible in some cases to recharge or change the battery, and the node ends up being replaced entirely. Network interruption thus depends essentially on energy consumption by the sensor nodes.

Objects connected to the networks currently are in millions and their number is expected to reach billions in the forthcoming years, resulting the generation of unprecedented amounts of data (Azari & Cavdar, 2018). It is crucial to optimize the energy efficiency of IoT networks to allow data transmission without compromising network overall performance. Many research works have been carried out in this context, and have led to solutions in multiple directions, including Network routing, Energy conservation, Congestion control, Heterogeneity, Scalability, Data security and Quality of service.

However, few of the proposed techniques are applicable to large-scale networks and do not meet the objectives when the base station is located outside the network. In this paper, we propose a new dynamic clustering model based on the p-median problem to minimize the energy consumed by wireless IoT networks. The main contributions of this paper are as follows:

i. An integer linear mathematical model based on the p-median model is described for the clustering problem.
ii. A proposed mathematical model that allows to determine the ideal number of clusters to form, select the most appropriate node of each cluster to be cluster-head , and efficiently assign nodes to clusters.
iii. The energy needed to send data from the sensor nodes to the base station is reduced while considering residual energy of nodes, node positions, node-node and node-sink distances and base station constraints.
iv. An effective proposed approach for large networks with external base stations.

We present a brief review of recent works aiming to optimize IoT networks. After what, we identify the p-median problem, its classical mathematical formulation, complexity, and resolution methods. In the context of wireless network topologies and based on a distance dependent radio energy consumption model, a novel dynamic model for the wireless IoT network clustering problem is described in terms of decision variables, constraints, and the objective function. A considerable energy savings, compared to the literature results, of nearly 20% can be achieved by applying the proposed method.

2. Related works

In order to improve the performance and extend the lifetime of IoT based networks, solution approaches must be implemented to solve the problems encountered in these networks considering the following directions :

1. Network routing, or the selection of the optimal path for sending sensor data across single or multiple networks.
2. Energy conservation, or energy saving methods and sleeping techniques to extend network lifetime;
3. Congestion control to minimize conflict between IoT devices and service types ;
4. Heterogeneity, or the ability to handle data generated by different types of objects in the network
5. Scalability, or the ability to keep up with constantly increasing numbers of network objects;
6. Data security that is effective mechanisms to secure data against unintended extraction and use ;
7. Quality of service, or IoT network performance measured in terms of parameters such as bandwidth, delay, packet loss rate, interference avoidance and destabilization (Escobar et al., 2019).

A brief history of the evolution of the IoT and a comprehensive survey of IoT network optimization challenges has been published (Azari & Cavdar, 2018).

Techniques of IoT energy efficiency optimization can be classified as follows (Azari & Cavdar, 2018) :

i. Radio optimization techniques : These techniques have an impact on the quality of the signal and hence on coverage and robustness by selecting dynamically channel and programming a cooperative reception/transmission. A novel context-aware approach using a Q-learning algorithm to decide the type of the wireless connection, choose the data processing unit and to determine the quantity of data to be scammed in the aim of meeting energy consumption, cost, response time, and security objectives has been published (Alonso et al., 2018). A distributed learning approach to operation control in long-range technology has been described, in which device communication parameters are adapted to the environment to minimize energy consumption and collision of data transmitted over shared channels (Sangaiah et al., 2020). An algorithm that uses the L system to draw a Hilbert curve has been developed for adaptive and dynamic optimizing of a central IoT network with increased Wi-Fi transmission range with parameter sharing to increase the energy efficiency of a smart home (Popli, Jha & Jain, 2019). The feasibility of applying the IoT technology to supervise and enhance the efficiency of the energy and the spectrum usage of broadcasting networks using the ultra-high frequency band has been investigated (Tekin et al., 2019). This involved a brand new network design with an IoT retroactive circuit and a 2-step long-range/NB-IoT-based algorithm that chooses the best base station set among several possibilities to minimize infrastructure and then optimizes power consumption by linking users to the operational base stations through the best routing pattern that minimizes both data loss and the effective isotropic radiated power. Power consumption by a broadcaster in Havana was thus reduced by 15–16.3% compared to current digital terrestrial multimedia broadcast networks while spectrum usage efficiency was increased by 32–35% and the availability of TVWS channel was increased by 34% in 90% of instances. A small cell allocation plan ensuring the mutual objectives of optimizing energy efficiency and maximizing data rate has been introduced for an IoT application in a smart city (Kashyap, Kumari & Chhikara, 2020). The proposed scheme is obtained based on the formulation of the problem as an integer programming multiobjective optimization problem wich has been resolved by a new algorithm based on the fusion of the branch-and-bound algorithm and the non-dominated sorting genetic metaheuristic (NSGAII) (Alazab et al., 2020).

ii. Data reduction techniques : These techniques work on latency by minimizing data transmission and use aggregation techniques to improve the quality of service. The allocation of the available resources in cloud computing is performed by applying the whale optimization heuristic which is inspired by the collective hunting method of the humpback whale (Chi & Radwan, 2020). An energy-efficient approach for optimal water use in irrigation and an energy-efficient health monitoring system (E2AHMS) for adaptively distributing the transmission power required to monitor patients are two novel examples of next-generation green-NBIoT (Alsaryrah, Mashal & Chung, 2018). In another hand, (Huang et al., 2015) provides a toolbox for the modelization and the simulation of the various methods of resource management in IoT, edge and fog computing, networks.

iii. Sleep and wake techniques : The problem of scheduling and controling productive activity periods in IoT has been addressed using Max-plus dioid algebra with tuning systems that adjust and schedule activity and sleep periods to avoid useless wake-up calls and provide data as required by the application. The network was modeled using a timed event graph in which a vertice represents the node state, the edges correspond to the links between the states and the weight on each edge represents the transition times from one state to another. Such a system allows optimizing of energy consumption, increases IoT lifetime, reduces unnecessary data production, storage and transmission and preserves data quality (Mehran, Kimovski & Prodan, 2019).

iv. Energy-efficient routing has an impact on IoT scalability and robustness either by clustering the network and choosing the cluster-head appropriately or by opting for a data transmission protocol. A multi-objective optimization model for cluster-heads selection, called the fitness-averaged rider optimization algorithm, has been introduced to ensure energy efficiency by considering the best candidate nodes, the amount of remaining energy and the energetic balance level (Dhumane & Prasad, 2017). The performance in terms of standardized energy, alive nodes, delay, and cost function metrics was verified through comparative analysis with state-of-the-art models such as artificial bee colony algorithm (Li et al., 2009), genetic algorithm (Liu et al., 2011), particle swarm optimization (Mostafaei, 2019), gravitational search (Mahmood et al., 2019), moth flame optimization (Guangshun et al., 2019), moth flame/ant lion optimization (Binu & Kariyappa, 2018), whale optimization (Guangshun et al., 2019), self-adaptive whale optimization (Xu, Fan & Yuan, 2013), and rider optimization algorithms (McCall, 2005). The superior efficiency of the described cluster-heads selection strategyl was thus confirmed. The multi-objective fractional gravitational search algorithm was developed to provide an energy-efficient transmission protocol in IoT (Pedersen & Chipperfield, 2010). The energy available in each node is measured initially, then the algorithm, which combines the fractional theory and thegravitational search, determines the cluster-head iteratively. Multiple objectives such as distance, energy, delay, and link lifetime were considered to define the fitness function for the selection of the cluster-heads. Furthermore, (Rashedi, Nezamabadi-Pour & Saryazdi, 2009) proposes a multiobjective metaheuristic to design an energy efficient routing protocol in IoT networks called the multiobjective fractional gravitational search. In another hand, (Chu, Horng & Chang, 2019) proposed a data transmission balance model for WSN networks that uses an improved version of the ant colony algorithm to describe a multi-hop communication method to reduce energy consumption and improve network reliability. This proposed approach is superior to the conventional ant colony algorithm and the traditional WSN. (Abbad et al., 2022) proposed a new weighted Markov chain-based clustering protocol that decreases the intra-cluster energy consumption. This protocol considers the abundance of sensors for the selection of cluster heads to reduce redundant data sending in regions with high sensor density and to select the sensors to be queried in low density areas. Tests show that the proposed protocol reduces energy consumption efficiently and extends the lifetime of sensor-poor regions. In addition, (Mahmoudi, Zioui & Belbachir, 2022) proposed a novel quantum-inspired clustering metaheuristic that optimizes energy consumption in IoT wireless networks. The authors used qubits to encode the cluster head choice solution, and explored the research area using firefly motion and PSO motion. This approach offers significant energy savings and an exponential computational speedup as based on quantum computing's tools.

v. The service composition problem is encountered frequently in IoT networks when a user makes a complicated request that a device cannot answer by itself and a composite service therefore must be created. The IoT use of multi-objective metaheuristic search algorithms has been described, especially the very popular non-dominated sorting genetic algorithm, which has been shown to deliver an optimal solution to the service composition problem (Praveen Kumar Reddy & Rajasekhara Babu, 2017). A bi-objective shortest path selection scheme for IoT service composition problem has been applied to the task of maximizing quality of service (in terms of run time, cost, and network latency) while minimizing energy consumption using a pulse algorithm with four built-in pruning procedures developed for the purpose (Mirjalili, 2015). One novel multi-objective approach for the resource provision and application placement problem in IoT application placement in fog, is based on the multi-objective genetic optimization algorithm considering energy consumption, the execution time, and the the economic cost (three conflicting criteria) to get the closest to the Pareto front of application-component optimized placements on the available fog devices (Mirjalili & Lewi, 2016). The proposed approach is claimed to be effective after comparaison with a couple of related state-of-the art methods (Escobar et al., 2019) (Gupta et &l., 2017) in terms of communication data size, component CPU workload, quality, and algorithm scalability.

vi. In related research, an efficient multi-objective optimization algorithm based on the chaotic ant swarm has been developed (Gupta et &l, 2017), in which the concepts of “neighbors” and “neighbor selecting” rules are redefined, and an archive-based approach is incorporated to allow fast convergence to the true Pareto front with an evenly-distributed set of solutions. For solving most well-known multi-objective optimization problems, chaotic ant swarming outperformed state-of-the-art peer algorithms such as particle swarm and the non-dominated sorting genetic algorithm, in terms of generational distance, spacing, and error ratio.

It is important to note that in the context of energy consumption's optimization in IoT enabled networks involving clustering architecture, none of the above-mentioned works has established a complete mathematical formulation based on an adequate definition of the decision variables thus allowing to appropriately model the objective as well as all constraints. In addition, the majority of these methods were designed for small networks with base stations located in the area covered by the nodes and performed poorly when used in networks with peripheral base stations. Therefor this work proposes a comprehensive mathematical modelling of the the problem and resolve it with an exact approach that delivers a better solution in terms of solution’s quality and energy savings than approximative methods previously proposed.

3. Tools and materials

3.1. P-median problem: definition, mathematical formulation, and complexity

The p-median localizaion problem was first described in 1964 by Hakimi in the field of combinatorial optimization (Skarlat et al., 2017). Given a graph □ = (□, □) defined by V a set of n nodes (|V|=n) and E the set of all possible links between all pairs of nodes of V, with d_{ij} as the distance between two vertices □ and □ of □, the task is to select □ vertices of □ to be "medians" or “centers” and the □ − □ remaining vertices of □ called "clients" or “customers” with minimal total distance between centers and clients. The p-median problem is known as an NP-complete problem (Mahmoudi, 2017). It is usually formulated as independent sets of arcs (Kariv & Hakimi, 1979) or in classical mathematical terms (Avella & Sassano, 2000). The latter approach generally takes the following form this latter classical mathematical formulation usually takes the form of the following model Integer Program (IP):

$$(IP)\begin{cases} Min \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} & & \\ \sum_{j=1}^{n} y_j \quad = p & & (1.1) \\ \sum_{j=1}^{n} x_{ij} \quad = 1 & i=\overline{1,n} & (1.2) \\ x_{ij} \quad \le y_j & i,j=\overline{1,n} & (1.3) \\ x_{ij},\ y_j \quad \in \{0,1\} & i,j=\overline{1,n} & (1.4) \end{cases} \qquad (1)$$

- **Where:**
- $x_{ij} = 1$ if and only if customer j is served by median i,

- $y_j = 1$ if and only if center j is open,
- Constraints 1.1 limit the number of selected medians to p,
- Constraints 1.2 ensure that each client is supplied by a single median,
- Constraints 1.3 ensure that clients are assigned to open medians.

Although the p-median problem is widely studied in operations research, its polytope has yet to be described fully. Partial descriptions have been proposed for various types of trees (Zhao, B.S., & M.S., 2007), subclasses of facets in general, or the case of forkless graphs (Baiou & Barahona, 2005) (Varnamkhasti, 2012). In an extended formulation with two additional sets of variables, existing facets can be generalized, new facets can be developed, and the polytope can be completely described when $p = n - 2$ (Zhao, B.S., & M.S., 2007).

Several exact methods have been proposed for the resolution of the p-median problem based mainly on the branching strategies (Reese, 2006) (Garcia, Labbe & Marin, 2011) (Elloumi, 2010) (Elloumi & Plateau, 2010). Since the p-median problem in np-hard on a general network, it is not solvable using precedent methods for large networks or/and an arbitrary p in a reasonable time (Mladenovic et al., 2007), several heuristic and meta-heuristic approximate methods have been devised (Mladenovic et al., 2007) (Basu, Sharma & Ghosh, 2015). A branch-price-cut algorithm based on Lagrangian relaxation has been proposed for large scales (Avella & Sassano, 2000).

3.2. Smart network topologies

A wireless sensor network is made of a set of sensor nodes numbering from a few dozen to several thousand communicating with each other via radio waves to route data acquired from a geographical area to a collection node called a base station (or sink). The base station then transmits the data to the end user via other networks such as the Internet or satellite for analysis and decision-making.

In the simplest case, all sensors are close enough to the base station for data to be routed in single direct hops. However, in large networks, many sensors are far from the base station and data must hop through other nodes. The two principal types of sensor network topology are described below (Messai, 2019).

Flat topology: A flat wireless sensor network (Figure 1) is homogeneous, meaning that all nodes have the same functionality and possess the same resources. Depending on the service and the type and number of sensors, multi-hop communication may be required. This architecture allows high fault tolerance but is not scalable.

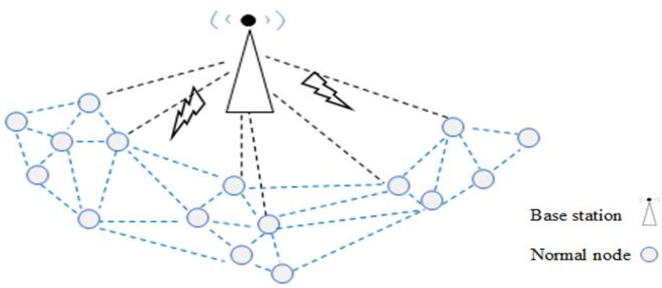


Figure 1 A wireless sensor network with a flat topology

Hierarchical topology: Sensor nodes can be grouped into clusters that correspond to different levels of responsibility. A cluster consists of a cluster-head and member nodes, which acquire and send data to the heads, which act as relays between nodes and the base station directly or via other heads as shown in Figure 2. Clustered architectures improve energy efficiency and network scalability by maintaining a hierarchy in the network and offer possibilities such as aggregation of collected data.

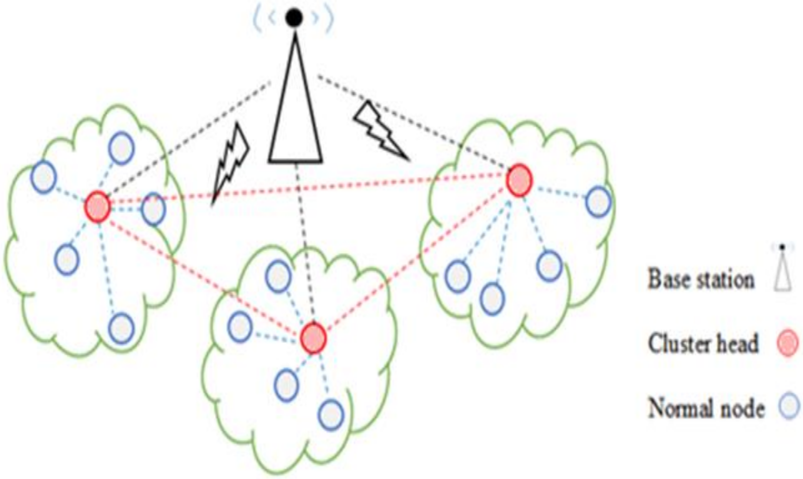


Figure 2 A wireless sensor network with a hierarchical topology

Another possibility is the chain (Braginsky & Estrin, 2002), in which each node can communicate with only two neighbors. Architectures that combine clusters and chains are also possible (Figure 3).

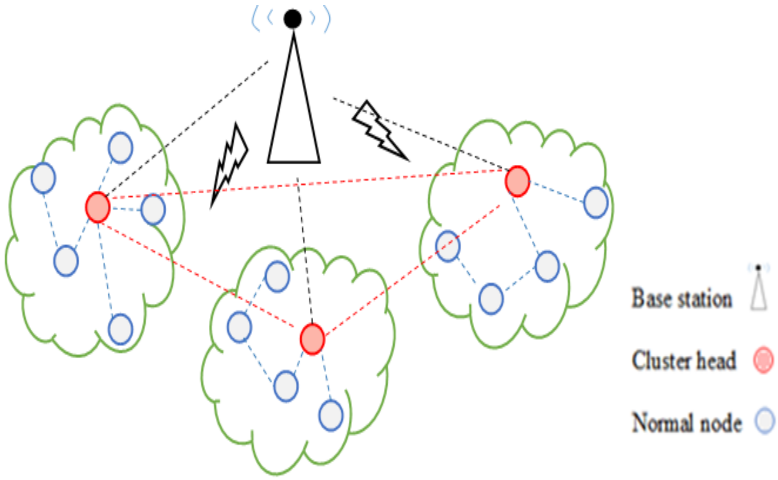


Figure 3 A wireless sensor network combining cluster and chain hierarchical topology.

Depending on network size and topology, one or more base stations can be in fixed locations or mobile within the network area. The base station is usually assumed to have a large computational capacity and no energy or storage constraints. The task of a sensor node may include creating packets of data for transmission to the base station or other sensor nodes.

When the battery energy of a sensor is depleted, the node can no longer provide any services, be it sensing, data pre-processing or data transmission. Such a node is considered dead ~~a~~nd must be excluded from the network topology until it can be serviced or replaced.

Conventional wireless sensor networks rely on static nodes. These networks can be used in commercial or environmental applications, for surveillance, monitoring, tracking, and so on. However, as technology advances, the expectation of mobility increases. Since the nodes in a wireless sensor network are small portable electronic devices, they can be easily coupled to mobile entities such as vehicles, robots, animals, or people.

Sensor nodes are resource-constrained devices characterized typically by:

Limited energy, typically a non-rechargeable low-capacity battery. In most cases, the nodes are deployed in inhospitable or hard-to-reach areas and are unlikely to be recoverable. Any program run on a sensor therefore must take into consideration energy management. However, most of the energy consumed is for wireless communication.

Low storage and processing power: A node comprises a sensing device, a processor, and a small storage unit. The processor allows the node to collaborate with other nodes and analyze the acquired data to lighten the load on the base station. However, processor speed and storage capacity are both limited, making most existing algorithms inapplicable.

Small transmission range: The distance over which data can be transmitted is limited by the signal strength and the radiating capacity of the antenna. Increased range requires additional power and is hence an expense that may or may not be justifiable (Mostafaei, 2019).

3.3. Energy consumption assessment

Energy consumption by the nodes can be measured using the distance-dependent radio model. Depending on the distance between transmitting and receiving nodes, free-space or multipath models can be used (Mostafaei, 2019). The energy to be consumed by a node to send a message of a given length *L* over a given distance *d* can be evaluated by (Abbad et al., 2022):

$$E_{TX}(L,d) = \begin{cases} E_{elec}{*}L + E_{AD}{*}L + E_{fs}{*}L{*}d^2, & d \le d_0 \\ E_{elec}{*}L + E_{AD}{*}L + E_{amp}{*}L{*}d^4, & d > d_0 \end{cases} \quad (2)$$

Where, E_{elec} is the energy consumed per bit sent or received by the electronic system, E_{AD} is the energy consumed for data aggregation, E_{fs} and E_{amp} represent the energy consumption of respectively free space propagation and multipath propagation in the sensor node's amplifier, and $d_0 = \sqrt{E_{fs}/E_{amp}}$ is the threshold distance between the transmitter and receiver (Abbad et al., 2022).

The energy to be consumed by the node while recieving a message of length L bits is given by (Abbad et al., 2022):

$$E_{RX}(L) = E_{elec} * L \quad (3)$$

3. Methodology

3.1. Clustering

Clustering is used widely to optimize IoT networks, since it allows better distribution of energy consumption and can support very large numbers of sensors. When data routing is direct, the more distant sensors run out of energy sooner, possibly subjecting other nodes to intermittent transmission and causing them to exhaust their power supply by relaying additional messages from other nodes. One solution is to prioritize exchanges by dividing data collection into clusters or partitioned areas and thereby reducing interference and improving radio link quality, thus reducing the number of retransmissions. By frequently changing the cluster-head, battery power can be maintained for longer and nearly equal times for all sensors. The focus of the present study is a clustering model based on the p-median problem where p represents the number of cluster-heads in a static wireless sensor network. The problem is formulated above in section 2.1.

3.2. Mathematical model

3.2.1. Initialization assumptions

- The network contains a single base station.
- The nodes and base station are not mobile.
- The nodes know their geographical location.
- The base station has an unlimited power supply.
- Each data packet is transmitted fully.

3.2.1. Contraints

- Distance between nodes
- Distance between nodes and the base station
- Residual energy of the nodes

3.2.1. Objectives

- To minimize energy consumption

To minimize data loss by transmitting data packets in single hops from the node to the cluster-head (no intervening nodes)

Since the energy cost of communication between two sensor nodes depends on the distance between them, we are attempting to minimize the total distance between nodes and cluster-heads and between cluster-heads and the base station.

The objective of minimizing data loss does not appear as an objective function in the mathematical model but is achieved by considering single-hop routing between nodes of different levels of responsibility. That is, a member node sends its data directly (in one hop) to a cluster-head, and the cluster-head sends the data directly (in one hop) to the base station.

Mathematical Model: The classical p-median formulation (IP) given above in 3.1 is modified for the present purpose to give the following p-median clustering model

(PMC):

$$(PMC)\begin{cases} Min \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} + \sum_{j=1}^{n} d_j y_j & \\ \sum_{j=1}^{n} y_j = p & (4.1) \\ \sum_{j=1}^{n} x_{ij} = 1 & ,i=\overline{1,n} \quad (4.2) \\ \sum_{i=1}^{n} x_{ij}\left(ERX(L_i)+ETX(L_i,d_j)\right) \le y_j\left(E_j - ETX(L_j,d_j)\right) & ,j=\overline{1,n} \quad (4.3) \\ x_{ij} \le y_j & ,i,j=\overline{1,n} \quad (4.4) \\ x_{ij}, y_j \in \{0,1\} & ,i,j=\overline{1,n} \quad (4.5) \end{cases} \quad (4)$$

Where:

- $y_j = 1$ if and only if node j is selected to be a cluster-head,
- $x_{ij} = 1$ if and only if node i will transmit data to cluster-head j,
- d_{ij} is the distance between node i and node j,
- d_j is the distance between node j and the base station,
- E_j is the energy available at node j.
- Constraints 4.1 limit the number of cluster-head s to "p",
- Constraints 4.2 ensure that each node i is connected to only one cluster-head,
- Constraints 4.3 ensure that each cluster-head j has sufficient energy to receive and transmit its data and the data of all client nodes connected to it,
- Constraints 4.4 ensure that the nodes are affiliated with a cluster-head node (and not with a client node).

4. Results and discussion

3.1. Simulation setup

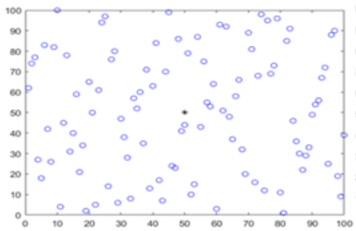
Table 1. Simulation parameters

Parameter	Value
Area	100 x 100 m^2
Network size	100
Base station location	(50, 50) or (50, 125)
Data packet length (L)	500 bits
Initial energy (E_0)	2 J
Consumption of energy by the electronic components (E_{elec})	50 nJ/bit
Free space dissipated energy in amplifier (E_{fs})	10 pJ/bit/m^2
Multipath dissipated energy in the amplifier (E_{amp})	0.0013 pJ/bit/m^4
Data aggregation energy consumption (E_{AD})	5 nJ/bit
Distance threshold d_0	87 m

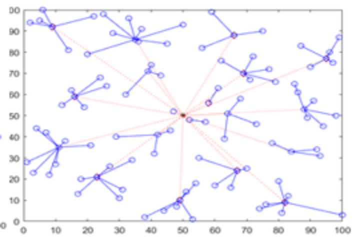
The proposed p-median-based method was implemented in Matlab R2021a for experiments. To test its performance, we consider a wireless IoT network in which 100 sensor nodes are distributed randomly over a 100 m by 100 m (10,000 m^2) area. The initial energy of all nodes is set to 2 J. Two base station locations are considered: at the center of the network, and outside of the network area. The simulation parameters are summarized in Table 1.

3.2. Simulation results

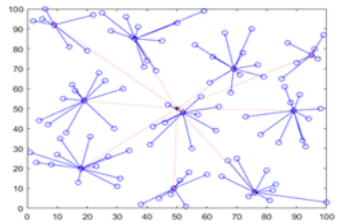
For the initial embodiment of the method, encoded 10-PMC, the number p of cluster-head s was preset, as in most of the works, at 10. In a second embodiment, called DV-PMC, the number was a decision variable determined by the program. Figures 4 and 6 illustrate the application of these embodiments using the two base station locations. The value of p determined by DV-PMC is 18. The corresponding energy consumptions are compared in Figures 5 and 7. Both embodiments were tested on 10 different wireless Iot networks having the characteristics listed in Table 1.



Network without clustering



Network clustered with 10-PMC



Network clustered with DV-PMC (18 CHs)

Figure 4 A wireless network node's clustering around a central base station (nodes located in a 100×100m² area *with the base station located inside the area)*

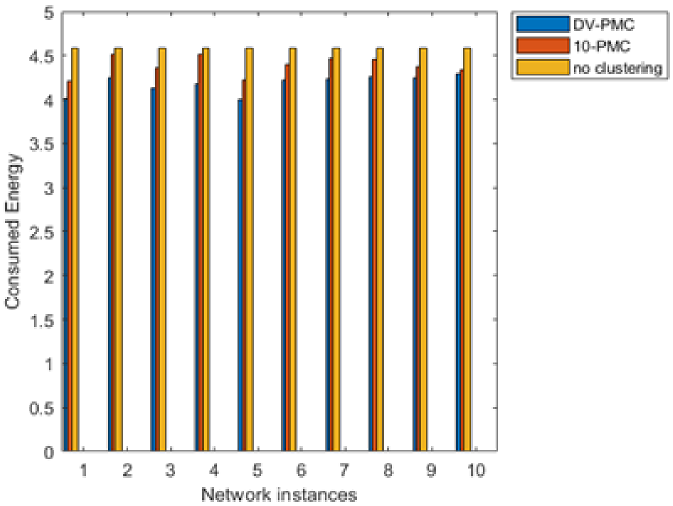
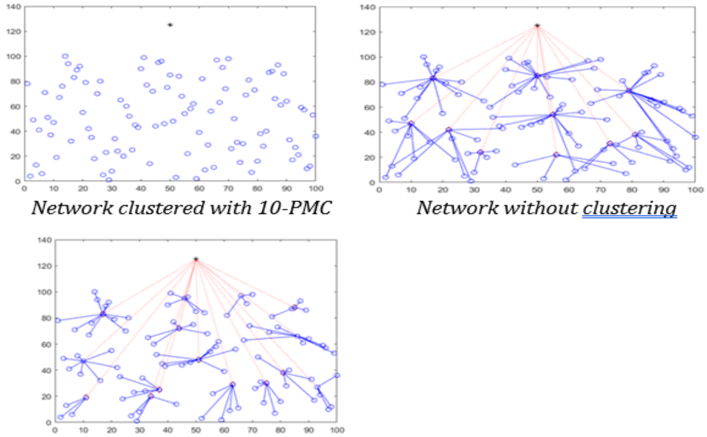


Figure 5 Energy consumed by the wireless IoT networks around a central base station.



Network clustered with 10-PMC *Network without clustering*

(c) Network clustered with DV-PMC (15 CHs)

Figure 6 A wireless network node's clustering oriented towards a peripherally located base station (nodes located in a 100×100m² area with the base station located at a 25m outside the area)

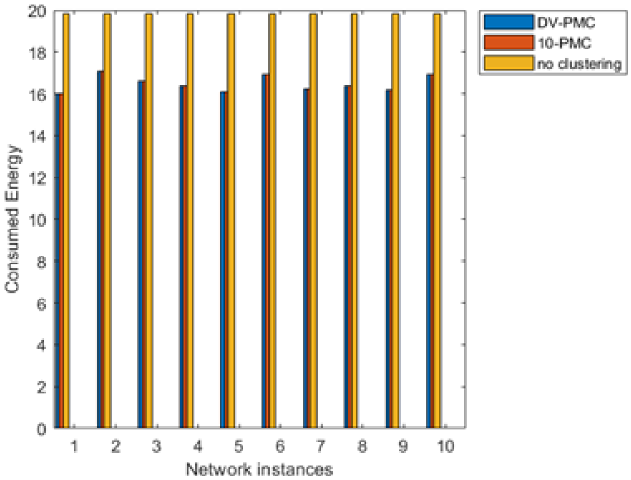


Figure 7 Energy consumed by the wireless IoT networks with its node clusters oriented a peripherical base station.

3.3. Discussion

Both embodiments of the p-median approach to node clustering reduced the total energy consumed by the wireless network when the base station was centrally located. The reduction was greater when the number of clusters decided by the program was used. The energy savings were thus 1.45–8.2% with 10-PMC and 6.49–12.52% with DV-PMC. When the base station was located peripherally, the savings ranged from 14.02% to 19.36% for both embodiments, since the program in this case chose 10 clusters for all iterations.

Most of the node clustering methods proposed to reduce energy use by wireless networks have been designed to work with base stations located within the node-covered area and perform poorly when the station is located outside this area. The present results are therefore encouraging and show that the simulation program can contribute significantly to increasing the energy efficiency of the wireless IoT network in either configuration.

5. Conclusion

This paper presents a new p-median formulation of the sensor node clustering problem for wireless IoT networks. In mathematical terms, the problem consists of minimizing the total distance function while considering a set of constraints, including node residual energy. The program is implemented in Matlab, all decision variables are natural numbers, and the solution yields the best number (p) of clusters and assigns all nodes to these. This approach was tested in two embodiments, one with p set at 10 and one in which p is determined by the program as a decision variable. Both embodiments showed that energy consumption by the nodes could be reduced and balanced by clustering the network optimally. However, in the case of a network configured with the base station located centrally, the energy saving was smaller when p was preset at 10 than when the program was allowed to choose p. This difference disappeared in the peripheral base station configuration since the program settled on p = 10. In this case, the energy saving reached 19.36%.

This dynamic partitioning of the network can provide improvements in energy efficiency, reduce interference, and thereby improve radio link quality and reduce data loss and retransmission.

The fact that the p-median problem can be solved for very large instances, using for example the method based on Lagrangian relaxation (Avella et al., 2012), makes it possible to compute good quality solutions for networks of up to 90,000 customers and potential facilities, allows the application of the proposed technique to large scale networks. Moreover, DV-PMC is suitable whether the base station is located inside or outside the network.

In future work, the proposed approach will be applied to a multi-objective hierarchical structure for wireless sensor networks combining clusters and multi-hop chains to maximize network performance and lifetime.

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