Bio-inspired Algorithms in the Optimisation of Wireless Sensor Networks: State of the Art Review

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Abstract: This work presents a metadata review of the current state of the art in the optimisation of Wireless Sensor Networks. WSN are a growing technology in industrial and personal use fields. The Quality of Service (QoS) of WSN is associated to the architecture of WSN nodes and network design. In this work, the composition of the nodes and network is analysed. The success of WSN is related to the maximisation of the lifetime and coverage of the device, allied to the minimisation of energy consumption and number of nodes, guaranteeing a good network connectivity and high transmission. The most common WSN issues are presented and reviewed. The most suitable optimisation technique is Multi-objective (MOO) which is exemplified in this work from complex multi-objective functions which include several WSN problems. The second part of this review focus on bio-inspired algorithms in WSN optimisation: Genetic Algorithms (GA), Particles Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO). Other less common methods are also presented and related to WSN issues.

Keywords: Wireless Sensor Networks; Multi-objective Optimisation; Bio-inspired Algorithms; WSN Architecture; WSN Optimisation

1. Introduction

Wireless Sensor Networks (WSN) are a promising technology to assist in monitoring, control and supervision. In fact, WSN are composed of nodes which communicate wirelessly between each other, sending data to a central processing unit; the rearrangement and communication of the nodes are set for specific applications, making these devices versatile. A typical WSN network architecture is represented in Figure 1.
Figure 1. WSN architecture.

The small size of the nodes makes the cost of the equipment low and enables the communication of the nodes with low energy consumption [1,2]. In this way, WSN are advantageous in industrial environments, including pipeline monitoring, production line control and energy management, and in public services, such as healthcare, environment, safety and transportation systems. In healthcare, WNS are used for vital status monitoring and rehabilitation supervision. In the past few years, agriculture has been automatized, namely for irrigation control, animal localisation, water control and air quality monitoring. Safety and traffic systems have benefited from WSN for traffic-light control, accident signalisation and parking space assistance, among others [3]. The increase of popularity of WSN, which goes hand in hand with the technological development of the society, is represented in Figure 2. It is visible the increase in the scientific production, especially in the recent years.

Figure 2. Scientific production in the WSN field.

The performance of WSN relies on the design of the device, which is intrinsically related to the architecture of WSN nodes. The composition of the nodes will be analysed in the first part of this work. In most cases, it is desirable to maximise the lifetime and coverage of the device, allied to the minimisation of energy consumption and number of nodes, guaranteeing a good network connectivity and high transmission. Since several parameters are at stake, the use of Multi-Objective Optimisation (MOO) is the most suitable approach for WSN. In MOO, multi-objective functions are used, including constraints. For cases in which the optimal values are not achieved at the same time for all the objectives, the system has multiple optimal solutions instead of a single global optimum. These multiple optima are found through Pareto Fronts (PF) [4].
Bio-inspired algorithms are based on the behaviour and characteristics of living beings. *Evolutionary Computation* has been studied since the 60’s [5, 6] and is based on evolution features, such as selection, reproduction, recombination and mutation. Nowadays, a wide range of bio-inspired algorithms are available, such as Genetic Algorithms (GA), Particles Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) [6]. The second part of this work will be dedicated to the analyses of bio-inspired algorithms applied to WSN problems.

2. WSN Composition

In this section, the composition of WSN is going to be reviewed. The components of the sensor nodes will be assessed, as well as the architecture of the network.

2.1. Sensor Node Components

The sensor nodes comprise, not only, the sensing function, but also other relevant features of the system, such as power supply, storage, processing and communication. In this way, a sensor node has four main units: the power unit, the sensing unit, the processing unit and the communication unit [2, 7]. A schematic representation is shown in Figure 3. If the data is collected by the sensor in analog format, an ADC converter is then used to convert into digital. In the processing unit, the data is processed by a microcontroller or microprocessor, and stored (memory). The communication is performed through a radio system. All the units are supplied by the power unit (battery).

![Figure 3. Sensor node components.]

2.2. Network Architecture

As stated in the Introduction, a crucial aspect of WSN is the communication of the nodes. As shown in Figure 1, the nodes communicate between them and also with the Base Station. The base station sends information to the nodes, where the information is processed, once the received amount of data is sufficient to perform the required processing by the user. The processed data is then sent back to the Base Station. The zone within the reach of the nodes is the *Sensing Region* or *Sensor Field*.

The network can be classified from the way the nodes communicate with the Base Station. If each node communicates with the Base, the system is *Single-Hop*. This type of architecture enables long distance communication; however, the energy consumption is higher when compared to the data collection and processing. In contrast, if a *Multi-hop* architecture is used, not all the nodes are connected to the Base. In fact, the information is transmitted through intermediate nodes, *Cluster Heads*, which decreases the energy...
consumption [8]. Figure 4 shows a schematic representation of the two types of communication.

![Single-hop](image1.png) ![Multi-hop](image2.png)

**Figure 4.** Nodes communication.

In the network, the single and/or multi communication between the nodes can be performed in two forms: Flat Network and Hierarchical Network. In a Flat Network, there are no cluster heads, the Base sends information to all the nodes, which respond through a multi-hop path. In a Hierarchical Network, the communication is performed through the cluster heads [9]. The difference between the type of network is represented in Figure 5.

![Flat Network](image3.png) ![Hierarchical Network](image4.png)

**Figure 5.** Network classification.

3. Design and Optimisation of WSN

The performance of WSN relies on the design and optimisation of the device. It is desirable to maximise the lifetime and coverage, allied to the minimisation of energy consumption and number of nodes, guaranteeing a good network connectivity and high transmission. Multi-Objective Optimisation (MOO) techniques have been developed to relate the architecture of WSN with their performance, proposing solutions to the potential problems of WSN. In this section, the optimisation fields in WSN will be reviewed.
In Figure 6 are shown the most optimised WSN problems in the literature. It is visible that the energy is a crucial topic, present in a large number of papers. The coverage, clustering and network lifetime are also widely assessed. Other frequent topics are the reliability, throughput, latency, security, load balancing and network connectivity. Each of these problems will be reviewed next.

Energy

The energy supply of WSN is provided by the power unit, which is composed of a limited battery. In this way, energy saving is a crucial issue in WSN. In fact, energy related optimisations are the most common topic of WSN MOO optimisation, as visible in Figure 6 [10-19]. Two main fields are used, Energy Consumption and Energy Efficiency. The nodes consume energy for data acquisition, processing and transmission, which is the task that que consumes a larger amount of energy. The Energy Consumption is given by the sum of the energy involved in each nodes path, and the objective is to minimise that value, \( \min \left( \sum_{n=1}^{N} E_{n}^{a} + E_{n}^{p} + E_{n}^{t} \right) \), in which \( E_{n}^{a} \) is the energy consumed in the data acquisition, \( a \), of each node, \( n \), which \( E_{n}^{p} \) is the energy consumed in the data processing, \( p \), of each node, \( n \), and which \( E_{n}^{t} \) is the energy consumed in the data transmission, \( t \), of each node, \( n \). N is the total number of nodes. The Energy Efficiency is related with the network lifetime. The objective is to efficiently use the energy, maximising the device lifetime. This can be done, for example, by scheduling the active and dead nodes, or by programming cycles in which the equipment is only activated when necessary. A common form to express the energy efficiency is by the ratio between the transmission rate and the power dissipation [2,7,20].

Coverage

The second issue most implicated in WSN studies with MOO techniques is coverage, as visible in Figure 6 [21-30]. Coverage refers to the sensing range, i.e., the area in within the reach of the sensors. Coverage can be studied through three topics: area coverage, point coverage and barrier coverage. Area coverage concerns the space area that is at reach of at least one sensor. If Point coverage is used, the objective is to ensure that a certain and defined number of points (with known coordinates) are included in the reach of at least one sensor. Barrier coverage is related to the sensing across the barrier that is established by the coverage area of the nodes. Usually, coverage is analysed by comparing the distance between the nodes and the space points, either individually or as a cluster which belongs to the same area, which must be smaller than the sensing range of at least one node. In some analyses, the network coverage is evaluated by the percentage of covered points, in relation to the total points of the system [1, 2, 31].

Clustering

Clustering is an important issue of WSN, used in a large number of WSN papers, as visible in Figure 6 [32-41]. In fact, clustering is crucial for prolonging the network lifetime and energy saving. In clustering, the cluster heads and connections between the nodes are defined. With optimisation techniques, the number of active and dead nodes are selected and clustered in function of the maximisation of the network lifetime and minimisation of energy consumption [1, 42].

Network Lifetime

The available battery for each node is limited. Thus, the network lifetime is dependent on the energy saving. Once the energy of one node ends, the node fails which might compromise the whole network. In fact, if portions of the system are at reach of only one sensor, the coverage area changes when those sensors are out of battery. In this way, the lifetime of the network is maximised by optimising the clustering and the energy saving [1, 2, 43-52].
Reliability
Fault Tolerance or Reliability are a crucial element for a safe and trustable network [53-62]. As previously stated in the most addressed issues of WSN, the network is affected by several parameters, such as energy and clustering. Fails in the network can occur and it might not be easy, or even possible, to replace one node, for example, if the battery is down. In this way, the reliability establishes a probability of the network to be working properly. Commonly, a Poisson distribution is used to assess the probability of failure, \( P = e^{-\lambda t} \), in which \( \lambda \) is the failure rate of each node and \( t \) is the time [2, 63].

Throughput
Throughput is a way to evaluate the success of the information transmission. In fact, it measures the amount of data that the network can process in a certain amount of time, \( T = \sum_{n=1}^{N} Dp_{n} \bar{D}p^{3}/t \), in which \( Dp_{n} \) is the number of data packets successfully transmitted through each node, \( n \), \( \bar{D}p^{3} \) is the average size of the data packets, and \( t \) is the transmission time. In general, a larger number of nodes is related with a higher throughput [1]. As visible in Figure 6, the maximisation of \( T \) is common in WSN optimisation problems [64-73].

Latency
Latency is the delay between the instructions and the data transmission [74-80]. A larger number of nodes contributes to dissemble latency since a larger number of paths are available. However, a larger number of nodes is associated to a larger delay. In most WSN, a fixed bandwidth, i.e., the amount of data transmitted per unit of time, is used. A higher bandwidth increases the speed of the data transmission which makes the latency more noticeable [2].

Network Security
Network security consists in the protection of the network against traffic attacks which compromise the privacy and confidentiality of the data packets. There are two main types of network security: data related, which deals with the protection of the data itself, and network related, which concerns the network features, such as location and transmission flow [2]. The minimisation of the loss of privacy is a common way to ensure the network security in WSN MOO problems, as shown by [81-91].

Load balancing
Load balancing is an important step to optimise the WSN lifetime. In fact, load balancing is used to balance the energy consumption of each node to avoid large discrepancies [92-101]. As previously reviewed, the network is compromised from the first node failure. By balancing the load, all the nodes will run out of energy at a similar time which increases the reliability of the system, since the lifetime depends on the whole network and not on weak nodes [1, 102].

Network connectivity
As previously mentioned, the rearrangement of the nodes and the definition of the network paths (Clustering and Coverage) are main issues that affect the energy saving and lifetime of WSN. Another aspect that must be considered for the network design is the connectivity [103-112]. In fact, each node should be in the sensing range of at least one of the other nodes in order to enable the communication, \( R_{i-j} < S_{j} \), which \( R_{i-j} \) is the distance between nodes \( i \) and \( j \), and \( S_{j} \) is the sensing range of node \( j \) [2].
As previously shown in the review of the WSN problems, the different factors are related and linked. In this way, to ensure the Quality of Service (QoS) of WSN, the objective functions need to include different parameters. In Figure 7 are represent the WSN problems that are most used in MOO papers. It is visible that the issues are intersected, showing the power of MOO techniques in the achievement of multiple objectives.

Different multi-objective functions in WSN have been extensively reviewed, previously [1, 7].

Singh et al. (2018) [113] proposed a multi-objective function to optimise the congestion control in WSN. The multi-objective function included: the arrival rate, i.e., the rate at which new data packets arrive at the nodes (\(\min(f_{\text{arate}})\)), the bandwidth (\(\max(f_{\text{band}})\)), the transmission rate (\(\max(f_{\text{band}})\)), the congestion (\(\min(f_{\text{congestion}})\)), the queue length, which measures the availability of a node to receive new data packets, (\(\min(f_{\text{queue}})\)) and the energy consumption, (\(\min(f_{\text{energy}})\)). The objective functions of each parameter were designed in order to build a global function, including six objectives.

\[
 f \rightarrow \max (f_{\text{arate}} + f_{\text{band}} + f_{\text{band}} + f_{\text{congestion}} + f_{\text{queue}} + f_{\text{energy}}) 
\]  

(1)

Rachedi and Benslimane (2016) [114] proposed a MOO case in which the Pareto front was used, instead of a global function comprising all the objectives. The functions included five different objectives: the security level of WSN (\(\max(f_{\text{security}})\)), the throughput
\[ \text{max}(f_{\text{thr}}), \text{delivery ratio (max}(f_{\text{delivery}}), \text{delay (min}(f_{\text{delay}}), \text{and the energy consumption (min}(f_{\text{energy}})). \]

Another example which shows the capacity of MOO to ensure QoS of WSN was proposed by Yang et al. (2011) [115] to optimise a space based reconfigurable network. The objective function included the most common WSN problems, energy consumption (\( \text{min}(f_{\text{energy}}) \)), system lifetime (\( \text{max}(f_{\text{life}}) \)), and coverage (\( \text{max}(f_{\text{coverage}}) \)), which were manipulated and constrained to build an overall function

\[ f \rightarrow \text{min} \left( f_{\text{energy}} + f_{\text{life}} + f_{\text{coverage}} \right) \quad (2) \]

4. Bio-inspired Algorithms in WSN Optimisation

As previously mentioned, MOO techniques are the most suited method for WSN optimisation. This review will focus on Biological Inspired Algorithms. These methods are part of a main group called Evolutionary Computation which is based on biological evolution features, such as selection, reproduction, recombination and mutation. The development of Evolutionary Programming occurred mainly in the 60s [5, 6], based on neo-Darwinian theory of evolution. The most known and used bio-inspired algorithms are Evolutionary Algorithms (EA) and Genetic Algorithms (GA). A subgroup of these methods is Swarm Intelligence, which is inspired by the community behaviour and schooling of populations, such as Particles Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO), which do not use a fitting function (operator) to classify the solutions that are generated at each iteration (these algorithms will be further described in this section).

In WSN problems, Multi Objective Evolutionary Algorithms (MOEA) are frequently used. In Multi Objective Optimisation (MOO), since several objectives are at stake, it might not be possible to find a single optimum. Instead, a set of optimal solutions are proposed, called Pareto Optimal Solutions, which are a compromise between the objectives of the multi optimisation, i.e., the limits of the Pareto fronts represent the optimum for one of the equations of the multi objective function, without compromising the others [4]. Since evolutionary algorithms are population-based, it is possible to approximate the Pareto Front in a single run. The most common algorithm in MOEA optimisation of WSN is Non-dominated Sorting Genetic Algorithm II (NSGA-II), in which the selection and reproduction steps are iterative. A modification of the original MOEA was already proposed, called Multi Objective Evolutionary Algorithm based on Decomposition (MOEA/D), in which only one solution is kept by each population member, i.e., at each iteration, the value that each element keeps is updated if its fitting is better than the previous value. Different versions of MOEA/D are nowadays available. Hybrid MOEAs are also commonly used. These techniques are hybrid since they use features of different algorithms. For example, a PSO algorithm can be used with the addition of using a fitting function at each iteration to evaluate the populations [116]. Other popular approaches of MOEA are the Particles Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) algorithms.

In Figure 8 are represented the three most common main groups (a large amount of papers use a modified version of the original methods) of bio-inspired algorithm in WSN papers: Genetic Algorithms (GA), Particles Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO). It is visible that GA is the most used method, with a total of 175 papers. PSO is used in 92, and ACO is the less used, with 30 papers. Concerning each WSN domain, it is possible to conclude that for energy, coverage, reliability and network connectivity, GA is more used that PSO and ACO. In contrast, in clustering, network lifetime, throughput and security, PSO is more common. Latency and load balancing are similarly weighted in relation to the use of PSO and GA. In general, ACO is less used than GA and PSO.
The choice between Genetic Algorithms (GA), Particles Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) in the optimisation of WSN, depends on the algorithms structure which is more or less suitable for each WSN problem. The basics of the original GA, PSO and ACO will be assessed and associated to examples of WSN issues. Other bio-inspired algorithms that have already been used in WSN are also reviewed.

Genetic Algorithms

Genetic Algorithms were developed in the 60s and 70s. The studies in GA are mainly assigned to John Holland and his group which culminated with the publication of the book *Adaptation in Natural and Artificial Systems* (1975) [117]. Since GA are based on the evolution theory, the optimisation system is composed of chromosomes. The GA steps involve the *generation* of the first set of chromosomes, the *selection* of the chromosomes that will reproduce, the *crossover* for the production of new chromosomes, and the consideration of the occurrence of *random mutation* [6, 118]. The GA concept is illustrated in Figure 9.
The optimisation problem has $n_d$ dimensions, i.e., the number of optimisation variables, which defines the size of the chromosomes. Typically, the values of the optimisation variables are converted into a bit string of 0’s and 1’s to approach the DNA coding. In this example, the chromosomes will then be binary. The number of chromosomes, $n_c$, as well as the number of iterations, $n_{it}$, are defined by the user.

The GA optimisation starts with a random set of chromosomes. In a 4 dimensions problem with 3, for example: [0 1 0 1], [0 0 1 1], [0 0 0 1].

The chromosomes are then evaluated by a fitting function, $f$, chosen by the user. The probability of chromosome $c$ to reproduce is given by

$$P = \frac{f(x_{ci})}{\sum_{c=1}^{n_c} f(x_c)}$$

In the chromosomes that are selected to reproduce, crossover takes place at the selected bit, following the biological procedure of meiosis. For example, if [0 1 0 1] and [0 0 1 1] are crossed over after the second bit, the resulting chromosomes are: [0 1 1 1] and [0 0 0 1].

The mutation randomly switches 0 into 1 and vice versa. This step occurs with a probability that is set by the user, in general a low value, such as 0.001. Mutation can be implemented before or after the selection and crossover, or not used, depending on the optimisation objectives. The advantage of using mutation is the introduction of new genetic material, which might be important to enlarge the searching region.

After each iteration, the chromosome with the highest fitness, $C_{\text{best}}$, is recorded, as well as the best fitted chromosome so far, i.e., until the current iteration, $C_{\text{gbest}}$. These chromosomes are considered to the next iterations in order to lead the system to the optimum value.

The algorithm can be summarised in the following steps:

- Generate the first set of chromosomes;
- Evaluate each chromosome with the fitting function;
- Select the chromosomes that will reproduce;
- Crossover the selected chromosomes;
- Apply mutation (if considered);
- Store $C_{\text{best}}$ and $C_{\text{gbest}}$;
- Repeat the steps until $n_{it}$.

Nowadays, different variations of the original GA have already been developed, in which modifications to the equations were introduced [6, 118].

GA have been applied to the optimisation of various problems of WSN, such as security authentication [119], design and layout optimisation [120, 121], thermal comfort and energy saving in public buildings [122] and Unmanned Aerial Vehicles (UAVs) path planning [123, 124].

Particles Swarm Optimisation

Particles Swarm Optimisation (PSO) is an optimisation technique developed by Kennedy and Eberhart (1995) [125], based on the behaviour of organisms on a social milieu, such as a bird flock or a fish school. “In theory at least, individual members of the school can profit from the discoveries and previous experience of all other members of the school during the search of food” [126], contains the main idea of the particles swarm: the information of each particle, regarding the exploitation zone, is shared with the other particles which will lead the system to an optimal point. In this way, PSO is an iterative algorithm formed by a family of particles in which each particle keeps track of its coordinates and shares them with the other particles. The PSO concept is illustrated in Figure 10.
The key parameters of PSO are the number of particles, \( n_p \), the number of iterations, \( n_{it} \), and the number of dimensions, \( n_d \), (i.e., the number of optimisation parameters or variables). The system is initialised with a random family of particles,

\[
x_p = x_{\text{min}} + \text{rand}(1)(x_{\text{max}} - x_{\text{min}})
\]

where \( x_p \) represents the position of the particles and corresponds to a matrix with dimensions \( n_{it} \cdot n_p \cdot n_d \), \( x_{\text{min}} \) and \( x_{\text{max}} \) are the minimum and maximum values for each variable and \( \text{rand}(1) \) is a random number between 0 and 1.

At each iteration, the best position of each particle until the current iteration (\( x_{p_{\text{best}}} \)) and the best particle of all particles (\( x_{g_{\text{best}}} \)) are identified. The values of \( x_{p_{\text{best}}} \) and \( x_{g_{\text{best}}} \) are used to move the particles towards the optimal solution [127].

Step, \( v \), defines the particles displacement in the system and represents the distance between \( x_p^i \) and \( x_p^{i+1} \), in which \( p \) represents the particle and \( i \) the iteration,

\[
v = v_{\text{max}}(2\text{rand}(1) - 1)
\]

\( v_{\text{max}} \) is used to limit the values that \( v \) can take during the optimisation, constraining the exploitation zone of a particle. Thus, \( v_{\text{max}} \) is set in order to let the particles explore well the searching zone so they can find optimal points, without compromising the time (iterations) that the system would need to converge [128]. \( v_{\text{max}} \) is given by

\[
v_{\text{max}} = \frac{x_{\text{max}} - x_{\text{min}}}{\text{factor}}
\]

in which the constant \( \text{factor} \) “decides” how big a particle’s step can be.

Since the PSO is an iterative method, new values of \( x_p \) and \( v \) for each particle dimension are updated at each iteration by

\[
x_p^{i+1} = x_p^i + v^{i+1}
\]

\[
v^{i+1} = v^i + c1\text{rand}(1)(x_{p_{\text{best}}}^i - x_p^i) + c2\text{rand}(1)(x_{g_{\text{best}}}^i - x_p^i)
\]

Where \( i \) is the iteration, \( x_{p_{\text{best}}} \) is the best position of each particle and \( x_{g_{\text{best}}} \) is the position of the best particle, \( g_{\text{best}} \), \( \text{rand}(1) \) represents a random value between 0 and 1, \( c1 \) and \( c2 \) are constants [125, 129].

The algorithm can be summarised in the following steps:

Initialise the system (\( x_p \) and \( v \));
• Evaluate the objective function for each value of $x_p$;
• Select $x_p^{\text{best}}$ and $x_g^{\text{best}}$;
• Update $x_p$ and $v$;
• Loop until the maximum number of iterations.

Nowadays, different variations of the original PSO have already been developed, in which modifications to the equations were introduced [6, 130].

PSO has been applied to the optimisation of various problems of WSN, such as energy scheduling and efficiency [131], Time Division Multiple Access (TDMA) [132, 133], localisation [134-136] and data aggregation [137].

Ant Colony Optimisation

Ant Colony algorithms were developed by Dorigo in the early 90’s [138, 139]. The Ant Colony algorithm is based on the release of pheromones by ants, which enables to trace relevant paths. In mathematics, the concentration of pheromones released by a set of $n_a$ artificial ants are used as an indicator of the quality of the solutions, which enable to lead the system to an optimum. The ACO concept is illustrated in Figure 11, in which is visible that the ants prefer a shorter path, where the concentration of pheromones is larger.

![Figure 11. Ant Colony Optimisation scheme.](image)

The algorithm is started by choosing a family of ants which can move is space composed by $n$ nodes. The ants travel from node to node, leaving pheromones. The larger the amount of pheromone in the path that links a certain node $j$ to $k$, the higher the probability of an ant $a$ to travel through that path [6, 140]. The probability of an ant $a$ to travel from node $j$ to $s$ is given by

$$P_a(j,s) = \frac{\tau(j,s)\alpha h(j,s)^{\beta}}{\sum_{k=1}^{n}\tau(j,k)\alpha h(j,k)^{\beta}}$$

in which $\tau$ is the concentration of pheromones in the path between nodes $j$ and $s$, $h$ is the visibility of the path $j$-$s$, which in inversely proportional to the distance between nodes $j$ and $s$, $n$ is the total number of nodes. $j$ and $k$ refer to the starting and ending node, respectively, of a certain path. $\alpha$ and $\beta$ are parameters.

When an ant $a$ pass through a segment $j$-$k$, pheromones are left, according to

$$\tau_{j,k} = \tau_{j,k} + \Delta \tau^a$$

with $\Delta \tau^a = \frac{cf_{\text{best}}}{f_{\text{worse}}}$, in wich $f_{\text{best}}$ is the best value of objective function $f$ evaluated for ant $a$ in the path $j$-$k$, and $f_{\text{worse}}$ is the worst value of objective function $f$ evaluated for ant $a$ in the path $j$-$k$. $c$ is a parameter which weights the amount of pheromone left in a certain
path. A simplification is usually made by considering $\Delta \tau^a = 1/d$, in which $d$ is the distance travelled by the ant from $j$ to $k$ after returning to the original node $j$.

Once the ant travels the path, the evaporation of pheromones occurs, decreasing its concentration by

$$\tau_{j,k} = (1 - E)\tau_{j,k}$$

in which $E$ is the evaporation rate between 0 and 1. An evaporation factor enables the ants to explore new paths, enlarging the searching area.

- The algorithm can be summarised in the following steps for each ant:
  - Place an ant at a random node;
  - Select a target node;
  - Calculate $d$ for each possible path;
  - Increase the release of pheromone $\tau_{j,k}$ for each path;
  - Decrease the pheromone $\tau_{j,k}$ for each path (evaporation);
  - Calculate $f$ and compare with already existent values to store $f_{\text{best}}$ and $f_{\text{worst}}$.

Modified versions of ACO algorithm are already available [141].

ACO has been applied to the optimisation of various problems of WSN, such as layout [142], secure routing protocol [143, 144], energy efficiency [145] and UAV planning [123].

Other Bio-inspired Algorithms

Other bio-inspired algorithms have also been developed and applied to WSN problems:

- Artificial Bee Colony (ABC) was applied to the optimisation of coverage and connectivity of WSN [146], lifetime [147], efficiency [148] and routing [149]. ABC algorithms have some similarities with GA and ACO; however, pheromones are not used and there is no crossover. In ABC, the bees are divided in employed bees, onlooker bees and scouts. Randomness (mutation) is introduced by scout and employed bees. The selection of paths is based on the amount of nectar [6].

- Firefly Algorithm (FA) has already been used for energy efficiency [150, 151], power management [152], routing [153] and self-organisation [154]. FA is based on flashing patterns and behaviour of fireflies, in which the brightness of fireflies is used to attract others. In optimisation, the brightness is proportional to the value of the objective function or can be used as a fitting function to guide the systems towards the brighter value, i.e., the optimum [6, 155].

- Cuckoo Search (CS) was applied to WSN problems such as clustering [156,157], energy efficiency [158] and location [159, 160]. CS is based on the brood parasitism of cuckoo species, cooperative breeding and nest takeover. Cuckoos chose other nests than their own to host the eggs which decreases the probability of abandoned eggs, increasing their reproductivity. In optimisation, the cuckoos lay one egg at a time in a chosen nest. The nests are evaluated based on the egg quality and have associated a probability of the foreign egg to be discovered. The best decision variables values will be associated to a high-quality nest, carrying the system towards an optimum [6,161].

- Lion Optimisation Algorithm (LOA) have been applied to WSN security [162], node deployment [163], pipeline monitoring [164] and energy efficiency [165]. LOA is based on the hunting behaviour of lions. Lions are divided in residents and nomads. Residents live together, and usually hunt in groups. Some lions and stay and rest, waiting for the hunter to return. The lions mark their territory with urine, to remember the best paths. In optimisation, the urine is related to the best paths (best values) and nomad lions introduce randomness, enlarging the searching area [166].

5. Conclusions
A review of the State of the Art of the WSN principal issues is presented, as well as the main bio-inspired algorithms that are applied to optimize WSN, including a bibliometric analysis from metadata research. WSN are practical and efficient for monitoring, control and supervision, which incites their development, optimisation and application over the years. The architecture of WSN as well as the composition of the nodes is presented and related to the WSN problems. Optimisation issues are reviewed: energy, coverage, clustering, network lifetime, reliability, throughput, latency, security, load balancing and network connectivity. It is shown that the most common topics in WSN papers are the energy, coverage and clustering, followed by the above-mentioned issues. Due to the large number of factors that influence the Quality of Service (QoS) of WSN, Multi-Objective Optimisation (MOO) is the most suitable method. Examples of multi-objective functions are presented and reviewed. Bio-inspired algorithms are commonly used in WSN optimisation. The three main methods are reviewed: Genetic Algorithms (GA), Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO), as well as less common methods, such as Artificial Bee Colony (ABC), Firefly Algorithm (FA), Cuckoo Search (CS) and Lion Optimisation Algorithm (LOA). The association of each method to the WSN problems is reviewed and examples of application are given.

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