Chapter 7
Bio-inspired Routing Strategies for Wireless Sensor Networks

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Abstract Successful behavioural and communication strategies of biotic communities can serve as an inspiration for algorithms used to design, manage, and control real-world networks. Many natural systems exhibit complex yet efficient behaviours. Some animal communities display sophisticated behavioural patterns arising from fairly simple activities of their members. The behaviours of ant colonies, swarms of bees, schools of fish, and even some human communities, can be seen as properties of distributed systems consisting of individual agents performing straightforward actions and communicating using simple strategies. Formally, the behaviour of such communities can be modelled as a massive yet intuitive multiagent system. The ensuing models can be applied to a variety of networking problems. This chapter looks at routing in wireless sensor networks and mobile ad-hoc networks as tasks that bear similarities to communication in biotic societies and swarms, and underlines the role of propagation phenomena in routing. It summarizes the basic principles of swarm intelligence and evolutionary computing and reviews recent advances in biologically-inspired network routing.

7.1 Introduction

There is a growing need for intelligent protocols and algorithms to design, manage, and control complex cyber-physical systems such as wireless sensor networks (WSN), sensor-actuator networks, mobile ad-hoc networks (MANET) and vehicular ad-hoc networks (VANET). In some applications, such as environmental monitoring [12, 42, 53], these networks are faced with many requirements and challenges

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D. Król et al. (eds.), *Propagation Phenomena in Real World Networks*,
Intelligent Systems Reference Library 85, DOI 10.1007/978-3-319-15916-4_7

that include autonomous operation, strict energy constraints, low computing power, multi-hop communication, robustness, reliability, adaptability, the ability to operate under harsh environmental conditions, etc. Routing protocols define the strategies and patterns that determine how such distributed networks communicate, and how data propagates [31] from one node to another and eventually outside the network. During the last decade, bio-inspired routing protocols have emerged as a group of methods suitable to address the complex multi-faceted nature of the problem, and specifically to contribute to the energy efficient network routing.

WSN share several properties with MANET and VANET. They are composed of a potentially large number of wireless nodes that perform prescribed tasks and exchange data [12, 17, 35]. Due to their limited transmission range, they communicate in a multi-hop fashion [35, 42]. In MANET, nodes are typically mobile, more powerful and homogeneous, i.e. without distinct roles. WSN nodes, on the other hand, usually have lower computing power, constrained memory, and limited energy available for their operation. Individual WSN nodes have often different roles and utilize diverse hardware (e.g. various types of sensors or energy storage devices). The roles of WSN nodes can be predefined and static, or dynamically assigned in response to the current state of the network or the environment [35, 38, 42]:

- *sensor nodes* collect, store, and eventually communicate data to other nodes. These nodes are the most common, low-power, low-cost devices. They have limited energy available for their operation, consisting in the simple tasks of sampling and transmitting data.
- *relay nodes* play an important role in long distance multi-hop communication. They maintain the connections between WSN segments. Typically, they have more powerful hardware and consume more energy compared to the sensor nodes.
- *sink nodes* are responsible for transmission of data outside the WSN to where it is required. A network can feature one or more sink nodes, sometimes referred to as *base station(s)*.

Individual wireless sensor nodes sometimes have relatively low-precision sensors, but the large number of nodes usually found in sensor networks allows the system as a whole to maintain high spatio-temporal resolution. With the rising complexity of WSN, self-organization and optimization becomes an integral part of their operation [42].

WSN can be used, for example, to monitor indoor or outdoor environments [12, 42]. Typical applications inside buildings include monitoring of temperature, light, humidity, air quality, and a number of safety-related detection tasks (e.g. of smoke or structural deformations). Outdoor applications include monitoring of habitats, environments, agriculture, disaster warning systems, traffic oversight, pollution and water quality assessment, etc. [7].

Most WSN operate according to two main paradigms [12]: *sample and send*, where sensor nodes collect measurements and send them to a sink, and *in-network processing*, where nodes perform additional tasks, such as data aggregation, event detection, or actuation.

Sensing is usually performed by wireless sensor nodes independently. They periodically activate their sensors (e.g. strain, vibration, temperature, or gas sensing devices) and record the measurements characterizing the environment where are they located. This operation is driven by a particular static or dynamic schedule, sometimes called *sensing rate* [46].

A multi-hop wireless transmission is performed to deliver data from wireless sensor nodes to one or more network sinks. Routing algorithms are essential for determining the way data is propagated from one node to another. They have a major influence on important network properties such as communication overhead, data availability (immediacy), network lifetime, and so on. The general objective of WSN routing is to maximize system performance. Performance of a WSN is, however, a broad and rather vaguely defined concept that comprises many sensor/network aspects such as reliability, measurement accuracy, sensor calibration, and error detection [12]. Other routing metrics include communication latency (time needed for a packet to get from its source to a destination), route length, and network energy efficiency. Energy efficiency can be defined, for example, as the ratio of received data and consumed energy [17].

The growth of WSN that can easily scale up to multiple thousands of nodes and the variety of deployment conditions make efficient WSN routing a complex optimization problem. In many cases, this is further exacerbated by the strict energy constraints.

The main traditional routing approaches are [45]:

- *hierarchical routing* that is based on node clustering and role assignments (e.g. Low Energy Adaptive Clustering Hierarchy (LEACH) [24], or Power-efficient Gathering in Sensor Information Systems (PEGASIS) [34]),
- *QoS aware routing* that focuses on achieving quality of service (QoS) requirements, and
- *location based routing* that employs location information for routing purposes.

From another perspective, WSN routing algorithms can be classified as [37]:

- *proactive algorithms* that construct data routes independently of the current communication requirements,
- *reactive algorithms* that respond to the communication needs of sensor nodes and construct routes on-demand, and
- *hybrid algorithms* that combine the proactive and reactive methods.

Proactive and reactive routing algorithms suffer from different types of problems. Proactive routing generates large overhead, whereas reactive routing yields high communication delays.

During the last decade, many challenges of MANET and WSN routing have been addressed using various bio-inspired approaches [22, 29, 37, 49, 52]. Bio-inspired methods are often based on a combination of proactive and reactive approaches, allowing them to accomplish adaptive routing, improve network load balancing, and contribute to network topology discovery [37]. As a result, so called *bio-inspired routing* has become a first class WSN routing paradigm [45]. This chapter provides

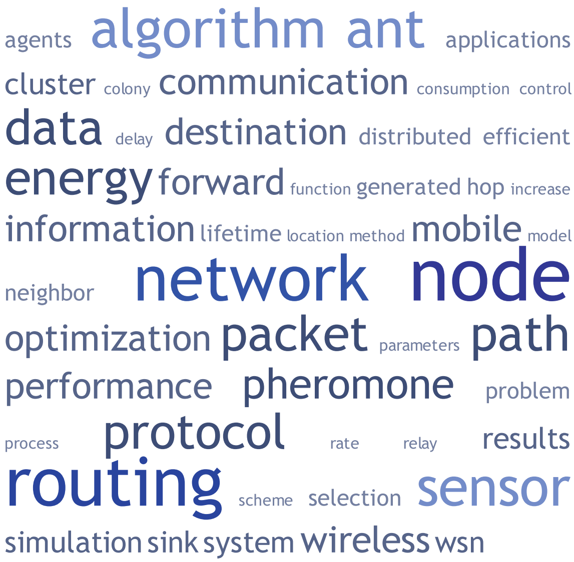

Fig. 7.1 Tag cloud formed from the surveyed articles

an up-to-date survey of the latest developments in the area of bio-inspired routing in WSN. It complements previous surveys on this and similar topics [37, 42, 49, 61], by considering new application opportunities, new challenges of massive monitoring networks, as well as the emergence of new bio-inspired algorithms. A tag cloud composed of the most frequent, non-trivial terms from surveyed research articles is shown in Fig. 7.1. It clearly illustrates the emphasis on routing, performance, and energy efficiency and the dominance of ant-like algorithms in these papers.

The rest of this chapter is organized into four sections. The bio-inspired methods that are applied in the area of WSN routing most often are reviewed in Sect. 7.2. This includes the description of several methods of swarm intelligence and evolutionary computing, and a short summary of several other bio-inspired methods. Section 7.3 provides an up-to-date, detailed, annotated survey of bio-inspired routing methods. Section 7.4 summarizes the contents of the chapter, brings major conclusions, and outlines future prospects of this exciting research area.

7.2 Biologically-Inspired Methods

There are two main groups of bio-inspired methods used to solve WSN routing problems: *swarm intelligence* and *evolutionary computing*. The algorithms based on swarm intelligence [17, 21, 29, 52] include methods inspired by Ant Colony Optimization, Particle Swarm Optimization, and Honey Bee Mating Optimization. Evolutionary methods for WSN routing are mostly based on Genetic Algorithms [2, 17, 37, 49]. The benefits of combining traditional and bio-inspired routing algorithms have been recognized as well [29]. This section provides a brief overview of the principles of swarm intelligence and evolutionary computing, and the description of several selected algorithms.

7.2.1 Swarm Intelligence

Swarm intelligence [9] is a collection of methods to solve complex, real-world problems using the paradigm of collective behaviour of distributed agents. This paradigm has been inspired by the intelligent behaviour of systems composed of many simple individuals, such as ants, bees, bats, etc. Similarly, an artificial swarm system consists of many unsophisticated agents that cooperate in order to achieve desired behaviour [8]. This approach is concerned with exploiting global behavioural patterns emerging from local interactions, rather than with the design of sophisticated central controllers governing the entire system.

7.2.1.1 Ant Colony Optimization

Ant Colony Optimization (ACO) [18] is a meta-heuristic approach based on certain behavioural patterns of foraging ants. Ants have shown the ability to find optimal paths between their nests and sources of food. This intelligent path-finding activity is based on stigmergy—indirect communication through modification of the environment. Ants travel randomly to find food, and when returning to their nest, they lay down pheromones. When other foraging ants encounter a pheromone trail, they are likely to follow it. The more ants travel on the same trail, the more intensive the pheromone trace is, and the more attractive it is for other ants.

Emulation of this behaviour can be used as a probabilistic computational technique for solving complex problems that can be cast as finding optimal paths [18]. An artificial ant, k, placed on vertex, i, moves to node, j, with probability

$$p_{ij}^{k} = \frac{\tau_{ij}^{\alpha} \eta_{ij}^{\beta}}{\sum_{l \in N_i^k} (\tau_{il}^{\alpha} \eta_{il}^{\beta})}, \tag{7.1}$$

where N_{ik} represents the neighbourhood of node i for ant k (i.e. a set of nodes that are available for the ant to move to), τ_{ij} represents the amount of pheromones placed on arc a_{ij}, and η_{ij} corresponds to a-priori information reflecting the cost of passing the arc a_{ij}. After ants finish their forward movement, they return to the nest with food. The tour of ant k is denoted T^k. Its length, C^k, is used to specify the amount of pheromones, $\Delta\tau_{ij}^{k}$, to be placed by the ant on each arc, ij, on the trail that led to the food source

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{1}{C^k} & \text{if arc } (i, j) \text{ belongs to } T^k \\ 0 & \text{otherwise} \end{cases}, \tag{7.2}$$

$$\tau_{ij} = \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}. \tag{7.3}$$

Alternatively, $\Delta\tau_{ij}^{k}$ can be derived from the solution quality expressed as the amount of food collected, L_k.

After all ants finish one round of their movement, the amount of pheromones on each arc is reduced through evaporation

$$\tau_{ij} = (1 - \rho)\tau_{ij}. \tag{7.4}$$

The coefficients α, β and ρ are general parameters of the algorithm that control the ratio between exploitation of known solutions and exploration of new areas of the search space. This canonical form of the ACO algorithm is called Ant System (AS). A pseudocode describing an AS with n ants is shown in Algorithm 7.1.

Algorithm 7.1 Ant System

```
Generate initial pheromone matrix P with respect to graph topology
0 → generation
while Termination criteria not met do
    Place n ants randomly on graph vertices.
    Set the amount of collected food for each ant to 0
    foreach ant do
        Move forward on the graph; follow the probabilistic (7.1)
        Compute the amount of collected food corresponding to ants trail
    end
    Find ant with the largest amount of collected food; let the ant lay pheromones in P on its trail
    according to (7.3)
    Evaporate pheromones in P according to (7.4)
    generation + 1 → generation
end
```

There are numerous variants of the ant algorithm. Modifications of the original ant system, such as elitist ant system and ant colony system [18], max-min ant system, fast ant system, ant-Q, and antabu, have been designed and applied in various problem domains, including bioinformatics, scheduling, data clustering, text mining, and robotics [20]. They have also been successfully used for finding optimal paths in complex networks. They perform best when the problem to be solved has suitable a priori heuristic information, and especially when some sort of local search algorithm is employed [18].

Among bio-inspired routing methods, ACO has been used most often. This can be attributed to their mutual similarity. Multi-hop data transmission is similar to stigmergy in ant communities, a form of communication in massive multiagent systems. Such natural communication strategies have evolved over millions of years and are effective in coordinating colonies of up to several millions of individuals. Emulation of these principles represents a natural choice for the management and control of massive artificial multiagent systems. There are ant-like routing methods for MANET and VANET that focus on improving communication overhead [22], reliability [3], scale [16, 25], and communication cost distribution [28]. Ant-inspired WSN routing methods are primarily motivated by optimization of energy consumption [4, 10, 15, 50]. However, many other objectives have been pursued, including network security [5], self-organization [15], dealing with multiple sinks [38], etc.

7.2.1.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a global, population-based search and optimization algorithm based on simulation of swarming behaviour of bird flocks, fish schools and even human social groups [11, 20, 30]. PSO uses a population of motile candidate particles characterized by their position, x_i, and velocity, v_i, inside an $n-$dimensional search space they collectively explore. Each particle remembers the best position (in terms of fitness function) it visited, y_i, and is aware of the best position discovered so far by the entire swarm $\bar{y}$. In each iteration, the velocity of particle i is updated [20] according to

$$v_i^{t+1} = v_i^t + c_1 r_1^t (y_i - x_i^t) + c_2 r_2^r (\bar{y}^t - x_i^t), \tag{7.5}$$

where c_1 and c_2 are positive acceleration constants that influence the tradeoff between exploration and exploitation. Vectors r_1 and r_2 contain random values sampled from a uniform distribution. The position of particle i is updated given its velocity [20] as follows

$$x_i^{t+1} = x_i^t + v_i^{t+1}. \tag{7.6}$$

A basic global PSO (*gbest*) according to [20, 30] is summarized in Algorithm 7.2.

PSO is useful for dealing with problems whose solution can be represented as a point or surface in an $n-$dimensional search space. Candidate solutions (particles) are placed in this space and provided with a random initial velocity. The particles then move through the search space and are periodically evaluated using a fitness function. Over time, particles are accelerated towards those locations in the problem space that have relatively better fitness values.

In addition to the basic model, there is a number of alternative versions of PSO algorithm including self-tuning PSO, niching PSO, and multiple-swarm PSO. These variants have been developed to improve the convergent properties of the algorithm, or to solve other specific problems [11, 20]. A new variant of PSO utilizing the ideas of immune algorithms [40] and orthogonal learning has been recently used to solve

Algorithm 7.2 *gbest* Particle Swarm Optimization

```
Create population of M particles with random position and velocity
Evaluate an objective function f ranking the particles in the population
while Termination criteria not satisfied do
    for i ∈ {1, ..., M} do
        Set personal and global best position:
        if f(x_i) < f(y_i) then
            y_i = x_i
        end
        if f(x_i) < f(ȳ) then
            ȳ = x_i
        end
        Update velocity of particle i by (7.5) and its position by (7.6)
    end
end
```

the challenging task of route recovery and maintenance in networks with mobile sinks [27].

7.2.1.3 Marriage in Honey Bees Optimization

Marriage in Honey Bees Optimization (MBO) [1] is a bio-inspired optimization algorithm that builds on the principles of division of roles and specialization, visual stigmergy, and reproduction strategies found in bee colonies. The principles governing bee colonies are significantly different from those of ant colonies [21]. As the name suggests, the main inspiration for MBO is the complex reproductive behaviour of honey bees.

A honey bee colony consists of a single queen and a number of other individuals that are morphologically uniform, but specialize in different tasks. The single purpose of male bees (drones) is to mate with the queen and contribute to the reproduction of the colony. The drone dies immediately after its role in the mating process has been accomplished [1].

The drones are males born from unfertilized eggs. They are haploid, i.e. they have only one set of chromosomes which is used to fertilize eggs. The mating process involves several mating flights in which the queen mates with several drones and stores their sperm in a special organ called spermatheca [1].

The algorithm considers the mating flight as a set of state-space transitions and probabilistic mating encounters. The queen is initialized with certain energy level and leaves for the mating flight. She returns to the hive when the energy is depleted or her spermatheca full. Drone d mates with queen q with the probability given by an annealing function

$$p_{qd} = e^{-\frac{|f_q - f_d|}{s(t)}}, \tag{7.7}$$

where p_{qd} represents the probability of successful mating (adding the sperm of d to the spermatheca of q), f_q and f_d stand for the fitnesses of the queen and drone respectively, and $s(t)$ represents the speed of the queen q at the time of the encounter.

After each transition, the speed, $s(t)$, and energy, $e(t)$, of the queen are decreased using

$$s(t+1) = \alpha s(t), \tag{7.8}$$

$$e(t+1) = e(t) - \Delta_e, \tag{7.9}$$

where $\alpha \in [0, 1]$ is a scaling factor and Δ_e is a fixed energy reduction step.

When the flight ends, the queen starts breeding by randomly selecting a sperm from the spermatheca and combining it with her genome. The new solution is then subject to random mutation. The algorithm also utilizes a set of worker bees that care of a number of broods [1]. They represent different heuristics that are applied to improve solutions generated by the algorithm. A new solution that has better quality than any of the existing queens replaces the queen in the next iteration. An outline of the generic MBO is shown in Algorithm 7.3.

Algorithm 7.3 Marriage in Honey Bees Optimization

```
Initialize workers; generate Q queens at random and evaluate them
Use local search to find a good queen
for flight f ∈ {1, ..., max_flights} do
    for queen q ∈ {1, ..., Q} do
        Initialize energy, speed, and position
        while energy(t) > threshold do
            Move q to the next state  Choose drone d according to (7.7)
            if d is selected then
                Add d's sperm to spermatheca
            end
            Update q's energy and speed using (7.8) and (7.9), respectively
        end
    end
    Generate broods by crossover and mutation
    Use workers to improve the broods
    Update fitness and replace low-fit queens by brood with better fitness
end
```

The MBO algorithm combines meta-heuristic and heuristic approaches in a coherent bio-inspired framework. In addition to reproductive behaviour, other aspects of bees' lives have been used as an inspiration for routing algorithms, such as foraging [55], division of labour, and stigmergy [59].

7.2.2 Evolutionary Algorithms

Evolutionary computing is a group of iterative stochastic search and optimization methods based on the programmatical emulation of successful optimization strategies observed in nature [39]. Evolutionary algorithms use Darwinian evolution and Mendelian inheritance to model the survival of the fittest using the processes of selection and heredity [20].

7.2.2.1 Genetic Algorithms

The Genetic Algorithm (GA) is a population-based, meta-heuristic, soft optimization method [39]. GAs can solve complex optimization problems by evolving a population of encoded candidate solutions. The solutions are ranked using a problem specific fitness function. Artificial evolution, implemented by iterative application of genetic and selection operators, leads to the discovery of solutions with above-average fitness. The basic workflow of the standard GA is shown in Algorithm 7.4.

Problem encoding is an important part of the genetic search. It translates candidate solutions from the problem domain (phenotype) to the encoded search space (genotype) of the algorithm. In other words, it defines the internal representation of the problem instances used during the optimization process. The representation specifies the chromosome data structure and the decoding function [13]. The data structure defines the actual size and shape of the search space.

Crossover is the main operator that distinguishes GAs from other population-based stochastic search methods [39]. Its role in GAs has been thoroughly investigated and it has been labeled the primarily creative force in the evolutionary search process. It propagates so called building blocks (solution patterns with above average fitness) from one generation to another, and creates new, better performing, building blocks through their recombination. It can introduce large changes in the population with small disruption of these building blocks [60]. In contrast, mutation is expected to insert new material into the population by random perturbation of chromosome structure. This way, new building blocks can be created or old disrupted [60].

GAs have been successfully used to solve a number of non-trivial multimodal optimization problems. They are capable of effectively searching large, potentially noisy solution spaces. Their clear principles, ease of interpretation, intuitive practical use, and significant results, have made GAs the method of choice for many applications. In the area of WSN routing, GAs have been used towards various objectives including improved energy efficiency [23, 48] and increased network lifetime [6].

Algorithm 7.4 Genetic Algorithm

Define objective (fitness) function and problem encoding
Encode initial population P of possible solutions as fixed length strings
Evaluate chromosomes in initial population using the objective function
while *Termination criteria not satisfied* **do**

Apply selection operator to select parent chromosomes for reproduction: $sel(P_i) \to parent1$, $sel(P_i) \to parent2$

Apply crossover operator on parents with respect to crossover probability to produce new chromosomes: $cross(p_C, parent1, parent2) \to \{offspring1, offspring2\}$

Apply mutation operator on offspring chromosomes with respect to mutation probability: $mut(p_M, offspring1) \to offspring1$, $mut(p_M, offspring2) \to offspring2$

Create new population from current population and offspring chromosomes: $migrate(offspring1, offsprig2, P_i) \to P_{i+1}$

end

7.2.3 Other Bio-inspired Algorithms

Swarm intelligence and evolutionary computation are the two major categories of bio-inspired algorithms. However, a number of other biological processes have served as an inspiration for various algorithms. Two interesting bio-inspired methods that have been recently used for WSN routing are based on cell biology and bacterial foraging.

7.2.3.1 Cell Biology

Different aspects of cell biology have inspired routing algorithms for WSN, for example consider the recently proposed attractor selection model based on the biology of *E. Coli* [33], and the pheromone protocol inspired by the life of unicellular organism *dictyostelium discoideum* [43].

The attractor selection model [33] provides a bio-inspired mechanism for adaptively selecting one of many possibilities. Each alternative is described by a system of stochastic differential equations modeled after messenger RNA (mRNA) synthesis and degradation. The algorithm converges to solutions that have high value of output probability for one alternative and low output probabilities for all other options.

The second WSN approach rooted in cell biology [43] uses a set of simple local rules describing the behavioural patterns of *dictyostelium discoideum* to implement a simple variant of the well-known swarm intelligence principle of following the path with the best fitness. The unicellular amoeboid *dictyostelium discoideum* produces a chemical signal (a type of pheromone) that attracts other individuals. Wandering *dictyostelia* are sensitive to the pheromone. An individual that detects the signal emits a pheromone itself and moves in the direction with highest pheromone density. This simple indirect communication strategy can be used to solve global optimization problems.

7.2.3.2 Bacterial Foraging Optimization Algorithm

Bacterial Foraging Optimization Algorithm (BFOA) is a recent bio-inspired method [14, 44]. It is a swarm-intelligent algorithm that implements the distinctive food searching strategy of the bacterium *E. Coli* as a type of parallel, nongradient optimization.

E. Coli is a simple and common microorganism that has developed a successful survival strategy combining collective and individual decision making. The foraging behaviour involves motility, swarming, reproduction, elimination and dispersal [14, 44]. Motility of the bacteria, called chemotaxis, involves two types of movements: swimming and tumbling. Swimming bacteria move in a fixed direction. Tumbling, on the other hand, is a movement that results in a change of the movement direction. The choice between swimming and tumbling depends on whether the bacteria perceives its environment as favorable. Swarming represents a social self-organization of a group of bacteria that influence each other. Reproduction leads to elimination of the least healthy bacteria and asexual reproduction of the most fit individuals. The best individuals produce clones that initially share their location. Elimination and dispersal serve as simulations of sudden changes in the environment and are implemented as the random removal of existing (healthy) bacteria and the random creation of new ones.

One particular part of the complex BFOA algorithm, the chemotaxis, has been recently used for WSN routing in [26]. It simulates the movement of the bacterium as a series of steps described as follows

$$\theta^i(j+1) = \theta^i(j) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}, \tag{7.10}$$

where $\theta^i(j)$ is the position of the i-th bacterium at chemotactic step j, $C(i)$ is the size of the step taken in the direction of the tumble, and $\Delta(i)$ is a random tumble vector subject to $\forall x \in \Delta(i) : x \in [-1, 1]$. The value of $C(i)$ is selected with respect to the quality of the solution represented by bacterium i located in chemotactic step j at position $\theta^i(j)$. The decision between swimming and tumbling is controlled by a simple logic. If the quality of the solution improves, swim in the current direction; otherwise, tumble. Chemotaxis has been successfully used as the main principle of a recent energy efficient WSN routing algorithm [26].

7.3 Bio-inspired WSN Routing Algorithms

This section provides a detailed overview of selected works on bio-inspired routing in the areas of WSN, MANET, and VANET. It is organized in a chronological way to capture the evolution of requirements, algorithms, and results in the field of bio-inspired routing methods.

The use of ACO for network routing can be traced back to 2002. The study by Sim and Sun [56] is an example of an early application of swarm intelligence in the field of general computer networking. It uses ACO to avoid network traffic congestion by continuously updating routing tables. To mitigate stagnation and improve optimization results, the authors use several distinct ant colonies—an approach called Multiple ACO. This study has confirmed that meta-heuristic, agent-based approaches can have different main objectives (e.g. load balancing, QoS). It has also shown that the problem of routing naturally matches the traditional application area of ant-like algorithms originally developed for optimal path finding.

Güneş et al. [22] proposed an ACO-based routing method called Ant Routing Algorithm (ARA) for use in MANETs. The algorithm is designed to achieve robust and reliable on-demand routing in the environment of dynamic wireless networks with mobile nodes. Its goal is to find a multi-hop route between two nodes interested in data exchange. The algorithm operates in two phases. During the *route discovery phase*, special agents called forward ant (FANT) and backward ant (BANT) are used to construct a routing table for the ensuing data exchange. The FANT agents are broadcast to the network by the sender node in a flood-like manner, while the BANT agents are returned by the recipient node. BANTs also mark their route by pheromones in routing tables of the nodes they visit. In the *route maintenance phase*, data packets are routed between the sender and recipient using probabilistic decision rules driven by pheromones in the local routing tables. Continuous updates of the pheromones either maintain or alternate the initial route depending on the actual state of the network. The algorithm operates in a distributed manner relying only on local information. As a result, it enables adaptive on-demand routing with a small overhead. Through software simulations, ARA was compared with traditional MANET routing algorithms such as the Ad-hoc On-Demand Distance Vector (AODV), Destination-Sequenced Distance Vector (DSDV), and Dynamic Source Routing (DSR). The bio-inspired algorithm performed on par with the traditional methods in terms of packet delivery rate and the number of lost packets, but with a lower overhead.

The problem of routing in large scale MANETs was addressed by an ant-like approach in the work of Heissenbüttel and Braun [25]. The authors were interested in an efficient routing in wireless networks covering large geographical areas and comprising of large number of nodes. One of the research objectives was to avoid the flood-like broadcasting of forward agents (as in ARA) in order to scale to large networks. The proposed solution is based on the abstraction of physical network topology and creation of a logical topology employed for routing. Close nodes are grouped together to form *logical routers* (i.e. groups of nodes with identical routing tables), *logical links* between logical routers, and eventually *logical multi-hop paths*. The resulting routing algorithm, called Mobile Ants-based Routing (MABR), uses a single routing table and link cost table for each logical router. Otherwise, its operations are similar to those of ARA [22].

Another ant-based routing algorithm designed specifically for MANET is due to Hussein and Saadawi [28]. The algorithm, named Ant Routing Algorithm for Mobile Ad-hoc Networks (ARAMA), was designed as distributed, self-organizing, and multiobjective. It pays attention to node mobility, elevated error rates, energy constraints, and unbalanced energy distribution in the network. As in the previous cases, one of the main reasons to use a bio-inspired algorithm was the need for a robust procedure that would yield lower overhead than the traditional routing methods and therefore provide better performance and scalability. The basic operations of ARAMA are similar to those of ARA. Forward and backward ants are used to construct on-demand probabilistic routes between sender and receiver. However, the metrics for path evaluation, as well as the intensity of path discovery, are more sophisticated. Path evaluation considers the number of hops, communication delay, quality of service, and node battery state. Path discovery intensity (i.e. the intensity of sending forward and backward ants) is a function of network dynamics. Computer simulations have shown that ARAMA contributes to fair and balanced energy usage across the network.

A routing algorithm called Termite was developed by Roth and Wicker [51] as a robust, bio-inspired procedure for MANET routing. It uses route request and response packets to create and maintain adaptive routing tables. *Route request packets*, assuming the role of forward ants, are propagated through the network in a random walk-like manner until they reach their destination or die. *Route reply packets*, analogous to backward ants, are sent back to the source and update pheromones in routing tables of the nodes they visit. In addition, this algorithm uses two other types of packets: *hello packets* broadcast by nodes when they find themselves isolated, and special *seed packets* that spread the pheromones of each node in an attempt to reduce the need for route construction and to lower the number of route request packets. Stigmergy concepts of linear pheromone updates and exponential pheromone decay are used to keep routing tables up-to-date with changing network topology. However, rather than using a specific bio-inspired method, this algorithm uses a number of general ideas of swarm intelligence.

An adaptive hybrid algorithm designed for routing in networks spread across geographically disperse locations was proposed by Alena and Lee [3] in 2005. The routing strategy utilizes a combination of stigmergy-based probabilistic routing and a-priori information extracted from topographic and radio coverage maps. The ant-inspired portion of the algorithm uses an elitist approach with stronger pheromone updates on best routes found in each iteration. Route discovery and optimization is implemented by periodically sending forward ants to random destinations. Backward ants returning to senders update routing tables of all visited nodes according to the actual state of the network. The algorithm also addresses communication interruptions and performance problems. The goodness of a route is evaluated on the basis of *trip time* which reflects a number of metrics such as number of hops and communication congestion. The algorithm has been evaluated through complex simulations of a network of 50 mobile nodes in a realistic environment described by topographic maps. A comparison of the proposed algorithm with AODV and Ant-AODV has shown that the new algorithm performs best and can be considered for extremely demanding WSN applications such as planetary exploration [3].

Di Caro et al. [16] proposed a complex ant-based routing algorithm for MANETs. The algorithm was based upon another ant-based routing method developed for wired networks. However, it was extended to address the challenges of routing in WSN with dynamic topology and generic motile nodes without predefined roles. In contrast to previous ant-inspired routing methods (e.g. ARA [22]), the proposed *AntHocNet* algorithm aims to achieve a balance between proactive and reactive behaviour to establish a robust stochastic multi-path routing. AntHocNet's reactive *path setup* phase is triggered by data transmission. Forward ants are broadcast to the network with the goal of creating mesh-like (i.e. highly parallel) initial paths. During the *stochastic routing* phase, the packets are sent between the source and destination nodes according to the routing tables, which follow the stochastic path selection rules known from previous ant-inspired routing algorithms. The proactive *path maintenance and exploration* phase of AntHocNet includes periodically sending forward ants to explore new paths and routing configurations. The algorithm also uses several additional optimization techniques to maintain up-to-date routing information: hello messages are used for local communication, and link failure information is broadcast to the network. Computer simulations have shown that the algorithm yields low end-to-end delay and good packet delivery ratio, especially at higher node movement speeds [16]. However, the communication overhead of AntHocNet is higher than that of AODV.

The behaviour of honey bees inspired an energy-aware reactive routing algorithm for MANET introduced by Wedde et al. [59]. The main objective of the algorithm is to maximize network lifetime by distributing communication across multiple paths. This allows to achieve balanced energy consumption without compromising on performance. The algorithm successfully applied honey bee-inspired routing principles originally developed for wired networks in the environment of mobile ad-hoc networks. It is based on a complex and biologically well-described analogy between honey bee foraging strategies and network traffic patterns. In this analogy, every network node is modelled as a virtual *bee hive* with different compartments and different types of bees that travel across the network. Each hive contains bee *packers* who receive packets and transfer them to suitable bee foragers. The *foragers* act as transport agents sensitive to some optimization criteria, such as transport delay or node energy. Foragers also collect information about global network status. Finally, *scout* bees are broadcast to the network in order to discover new routes and share routing information with foragers.

The initial works on bio-inspired routing have shown that inspiration from nature can contribute to the improvement of efficiency and robustness of routing in wireless networks, and particularly in MANETs. They have, however, focused only on some aspects of the routing problem, such as network scaling, congestion elimination, and minimization of routing overhead, but ignored other aspects like energy efficiency and network lifetime.

An energy efficient WSN routing algorithm based on ACO was developed by Camilo et al. [10] in 2006. This study proposed and compared three ant-based routing strategies. *Simple ant routing* is a straightforward proactive routing algorithm utilizing forward and backward ants. The second algorithm, called *improved ant routing*, introduces energy awareness as a part of the route evaluation criteria. The third algorithm, named *energy efficient ant based routing* (EEABR), aims at reducing the amount of information saved in each routing packet (i.e. forward and backward ant). In contrast to previous approaches, each ant contains information about the average energy on the route up to the current node, rather than complete data on energy level for each visited node. The reduction of routing packet size contributes to lower data overhead and higher energy efficiency (ratio of consumed energy to transmitted data packets).

Rahmani et al. [48] developed an agent-based WSN routing strategy using a parallel GA. This approach combines stochastic, cost-based next-hop selection (the probability of sending packet to a neighbour is proportional to the cost of routing to the neighbour) with greedy selection of the neighbour with the highest remaining energy. This allows it to achieve a globally energy-efficient behaviour. A parallel GA is used to find the optimal parameters of the routing function. The search for optimal parameters for certain group of nodes is performed periodically by the base station.

A robust bio-inspired MANET routing algorithm focusing on QoS is due to Leibnitz et al. [33]. Unlike previous approaches, this method is inspired by the microscopic world of cell biology. In particular, it mimics the attractor selection process to adaptively select next-hop nodes. Routing operations of the *adaptive response by attractor selection* (ARAS) algorithm consist of two phases. The *route setup phase* finds a route with minimal number of broadcasts. The *route maintenance phase* follows this route through a probabilistic selection of next-hops, and piggybacks the information about route quality in a process similar to the forward and backward ant transmission in other ant-inspired methods. Software simulations have shown that ARAS has performance comparable to AODV, but with a lower overhead. However, this method has not been compared to other bio-inspired routing methods.

In 2009, Okdem and Karaboga [41] presented an algorithm and hardware platform for ACO-like WSN routing. The use of specialized hardware was motivated by the constrained energy and low processing power of wireless sensor nodes. The main routing objective is the maximization of network lifetime by spreading energy consumption across nodes through multi-path energy-aware routing. In the proposed algorithm, the sender node initializes communication with the base station, while the intermediate nodes are used to relay packets following an energy-aware probabilistic path-selection rule. Up-to-date information about the current status of transmission paths is propagated back to the nodes as a part of acknowledgement packets. Additionally, the nodes propagate their own energy level information to their neighbours. Matlab software simulations have shown that the proposed algorithm is more energy efficient than EEABR [10] when a hardware implementation of the routing chip is used.

A hybrid energy-aware WSN routing algorithm combining self-organized clustering and an improved ACO was presented in [47]. The algorithm uses self-organization to form clusters of nodes, select cluster heads, and establish a cluster head chain for communication between the base station and clusters. The routing algorithm operates in rounds. In each round, new clusters are formed on the basis of node location and energy level. Next, node chains are created by energy-aware ACO within each cluster. Finally, cluster heads representing the clusters are selected. All energy demanding operations are initialized and/or performed by the base station. The routing itself, however, is static and deterministic, following the configuration created by the process outlined above. Software simulations have shown that the proposed algorithm is more efficient than the traditional hierarchical routing algorithm (LEACH [24]).

Bari et al. [6] developed a WSN data gathering schedule that maximizes network lifetime; where lifetime is defined as the time when the first of fixed relay nodes stops operating due to depletion of its energy source. The scheduling task is cast as a global combinatorial optimization problem and solved using GA. To account for energy constraints, the algorithm considers energy dissipation of the sensor nodes. In addition, it can cope with energy depletion or the failure of critical nodes through dynamic rerouting. Compared to traditional techniques, such as integer linear programming, the GA-based scheduling approach can efficiently deal with very large networks.

The performance of two existing ant-based routing protocols under different application scenarios was studied by Domínguez-Medina and Cruz-Cortés [17]. They compared an *ACO-based location-aware routing* (ACLR) utilizing closeness of node neighbours, and the *energy efficient ant-based routing* EEABR [10]. This study simulated different WSN hardware and covered different network scenarios, including balanced versus imbalanced energy allocation, and fixed versus randomly selected source and destination nodes. The study has concluded that EEABR outperformed ACLR in terms of energy consumption, but the use of ACLR resulted in lower latency.

In 2010, Matsumoto et al. [38] proposed a bio-inspired data routing scheme designed to increase WSN lifetime by efficient data gathering, communication balancing, and quick adaptation to changes of network topology. The method was designed with special focus on networks with multiple sinks and large numbers of nodes. Each sink is assigned a distinct pheromone that is propagated to the network via a process called pheromone dispersion. Data transmissions are subsequently routed towards sinks following their pheromones. Software simulations have shown that the proposed algorithm outperforms several other ant-based routing algorithms, as well as a traditional multiple sink-aware routing protocol.

Another bio-inspired routing algorithm for WSN with multiple sinks was proposed by Paone et al. [43]. This protocol, inspired by the behaviour of unicellular organisms, operates in a highly distributed manner without global information about the network. The route construction phase of the protocol is called *signaling*. During signaling, each node spreads its *forwarding attitude* (i.e. information about its ability and willingness to route information towards sinks), and routing tables are created. In the *routing* phase, data packets are routed towards sinks following a probabilistic path selection principle. Computer simulations have shown that the proposed protocol performs better than directed fusion and yields good self-repairing capabilities.

A bio-inspired protocol for balanced packet routing, called BiO4SeL, was proposed in [50] and later extended in [15]. The main objective of the algorithm is to increase network lifetime by distributing data transmission paths between network nodes and base stations with respect to their remaining energy levels. The protocol operates in 3 stages. In the *bootstrap phase*, each node broadcasts information about its energy level. During the *initial route discovery phase*, the base station broadcasts special *iant* packets that discover optimal paths and construct routing tables. By design, BiO4SeL's iant packets avoid construction of long and invalid paths. In the probabilistic *data forwarding* phase, routing tables are used for data transmission and maintained by these packets. Simulations have shown that the method scales well, maintains good packet delivery rate, and achieves the best network lifetime when compared to other relevant routing algorithms such as AODV and ARAMA [28]. It also features low overhead, especially in scenarios with a few nodes producing data.

A routing algorithm for underwater WSN applications was presented by Vieira et al. [57]. The main goal of the protocol is to secure a reliable adaptive route towards mobile sinks in a swarm of mobile sensors monitoring local underwater events in space and time. The underwater environment is especially challenging due to the presence of water currents and because of the properties of underwater acoustic communication. Conventional routing protocols are not suitable for such conditions. One of the main aspects of the proposed protocol is the distribution of location information from sinks (special underwater vehicles or surface buoys) that are equipped by GPS and do not suffer from energy constraints. With the help of location information, the trajectory of mobile sinks on the 2D upper hull of the underwater swarm creates a pheromone trail capturing the position and direction of the underwater nodes. The routing has two principal stages: first, data packets are routed vertically towards the upper hull and then in a 3D cylinder to the location of mobile sinks using a geographic routing protocol.

Villalba et al. [58] proposed an extension to AntHocNet [16] to achieve autonomous operation and self-organization. Like AntHocNet, the new algorithm combines proactive and reactive aspects. However, it prefers routes that share neither nodes nor links (disjoint link/disjoint-node routes). This behaviour is implemented using two distinct types of pheromones called *real pheromones* and *virtual pheromones*. Simulation experiments concentrating on the number of hops in routes have shown that the modified bio-inspired algorithm performs better than AntHocNet in terms of data throughput, transmission success rate, average end-to-end delay, and communication overhead.

Ekbatanifard et al. [19] developed an energy-efficient QoS-routing algorithm using multiobjective GAs. The GA finds the least-cost energy-efficient path that satisfies delay constraints. The objectives optimized by the algorithm include communication reliability (expected number of transmissions for successful data forwarding), energy consumption (sum of energy costs of the routing tree), and the probability that end-to-end delay constraint is met. The algorithm utilizes a traditional multiobjective GA called NSGA2 to find a set of pareto-optimal routing trees.

In 2010, Luo [36] proposed another QoS-based routing algorithm using a GA. It uses a probabilistic q-bit based representation of a set of routes connecting nodes to sinks, mutation and rotation operators, and a fitness function sensitive to communication bandwidth and energy costs. Simulations performed by the author have showed that the proposed approach achieved better throughput, lower delay, and longer network lifetime than hierarchical routing when the number of network nodes was large.

Apparently, energy efficiency became a major topic for the second generation of bio-inspired routing algorithms. Two algorithms, EEABR and AntHocNet, became the de-facto baseline methods for the development of further bio-inspired routing methods. Advanced applications such as routing in networks with multiple sinks, and underwater routing, have also been addressed by bio-inspired algorithms. Advanced variants of bio-inspired algorithms, including parallel and multiobjective GAs and hybrid algorithms, have been used.

A security motivated bio-inspired routing algorithm based on ACO and principles of fuzzy logic was created by Sethi and Udgata [54]. The primary objective of this algorithm is to improve network security and to increase attack resilience. Each node is assigned a *trusted value* determined by a fuzzy inference system from packet drop rate and the ratio between route reply time and time-to-live. This value also becomes part of a probabilistic next-hop selection rule used by an ACO-inspired routing procedure.

Zungeru et al. [61, 62] developed an ACO-based routing protocol for visual sensor networks. It addresses the specific requirements of video and image streaming applications (e.g. high bandwidth). The improved algorithm extending the original EEABR was developed to address the challenges of video surveillance, traffic monitoring, and environmental applications. It improves energy efficiency by intelligent initialization of routing tables, smart route maintenance strategy, prioritization of neighbouring nodes, and reduced frequency of network flooding. The simulations have shown that the new algorithm achieved in visual sensor network applications 30 % lower energy consumption than EEABR. It's performance in other metrics was comparable to that of EEABR.

A hybrid ant-inspired WSN routing algorithm combining the elements of proactive and on-demand routing strategies was presented by Almshreqi et al. [4]. It uses information about average and minimum route energy to find transmission path patterns and to spread out the energy cost of the communication. A simulation has showed that the proposed algorithm performs better than EEABR in terms of total energy consumption and energy efficiency.

Da Silva et al. [55] introduced a new bee-inspired algorithm for data dissemination and propagation. The algorithm extends the traditional hierarchical cluster-based protocols LEACH and LEACH-C with bee-inspired concepts. It is designed for WSN with continuous data flow. Such networks generate and process data continuously rather than in an event-driven manner. Using a realistic energy consumption model, the proposed method applies bee strategies to form clusters and select cluster heads. The algorithm preferably selects nodes located near data sources that have high levels of remaining energy and require very little energy to communicate with the base station. Simulation experiments have shown that this bio-inspired algorithm performs better than both LEACH and LEACH-C in terms of the number of packets sent to the base station, network lifetime, and the time until the first node in the network dies (i.e. the full network coverage time).

In 2012, Hoa and Kim [26] proposed a WSN routing algorithm based on the behaviour of the bacteria *E. Coli*. The algorithm constructs an in-network gradient field with maximum gradient concentration in and around the sink. The gradient of each node is based on its location relative to the sink. When the gradient field is formed, packets are routed using biased random walk. Directional bias of each node is based on its past efficiency as a relay for communication with sink. During the transmission, packets observe the gradient field and *tumble* in case they detect a decrease of the gradient on their route. The advantages of the algorithm include locality (no global information is needed), implicit load-balancing, and energy efficiency. It has been shown that the algorithm performs better than the shortest-path strategy, and yields relatively less mean communication delay and average energy consumption.

A secure ACO-inspired WSN routing algorithm was developed by Alrajeh et al. [5]. The use of a bio-inspired approach was motivated mainly by the need to strengthen the security of the network against network-layer attacks and WSN-specific attacks (such as sinkhole attack, false routing, and so on). The proposed reactive multi-path routing algorithm associates a special *trust value* with each node. The trust value is later used as a part of a decision rule for next-hop selection to route packets along paths that are both efficient and secure. Simulation experiments have demonstrated that the algorithm is performance-wise worse compared to LEACH, but better in terms of security.

Bitam et al. [7] proposed another security-oriented bio-inspired routing algorithm. The hybrid routing algorithm termed HyBR is designed specially for VANET. It incorporates communication patterns inspired by bee swarms applied to vehicle-to-vehicle and roadside-to-vehicle communication. It also utilizes principles of geographic and topology-based routing and employs a GA to find optimum routes. The algorithm has been evaluated by simulations of a realistic road network modelled after the city of Biskra in Algeria. It has been found superior to AODV and the greedy perimeter stateless routing (GPSR) protocols.

A fishing spider-inspired clustering method was used as a part of hierarchical routing algorithm in the work of K. Lee and H. Lee [32]. This algorithm is based on the analogy between water surface waves sensed by the fishing spider and concentric radio signals detected by wireless sensor nodes. The main aim of the algorithm is to form node clusters and select cluster heads on the basis of node neighbourhood degree and remaining energy levels. Such strategy is local and inexpensive, but it reflects the state of the entire network and changes with the environment in order to improve self-organization. Simulations have shown that the algorithm achieved longer network lifetime, higher remaining energy levels, and better scalability than LEACH.

A new genetic approach to energy efficient WSN routing was proposed by Gupta et al. [23]. This new scheme called Genetic Algorithm-based Routing (GAR) applies a GA to find efficient routes in a 2-level WSN. It conducts periodical search for a set of suitable next-hop nodes for each node in the network. The generic GA has been extended with modified crossover and mutation operators. The performance of this routing algorithm has been compared to traditional hierarchical routing and to the algorithm presented in [6]. The GAR algorithm has been found better in terms of achieved network lifetime.

In 2014, Hu et al. [27] proposed a bio-inspired algorithm for efficient routing in WSN with multiple mobile sinks. The method utilizes a multiple-swarm cooperative PSO to quickly recover routes damaged by the movements of the sink. The study introduced a new variant of PSO based on orthogonal immune learning to embrace the problem. The proposed algorithm, in combination with AODV, achieved lower packet loss, lower latency, and higher energy efficiency than three other AODV-based protocols.

The recent years have confirmed the trends observed in the field of bio-inspired routing algorithms. Energy efficiency has become the top optimization goal, especially for routing in an energy constrained WSN. Moreover, network security has emerged as a new aspect of bio-inspired routing. Traditional bio-inspired algorithms including ant colony optimization, genetic algorithms, and particle swarm optimization, as well as hybrid algorithms and new bio-inspired algorithms, have been used to address the routing problems with success.

A mind map created from a citation graph of all surveyed research articles is shown in Fig. 7.2. The elliptical nodes represent bio-inspired approaches, and each rectangular node indicates an article. Each link represents implementation and/or a direct reference between the article and the bio-inspired approach it connects.

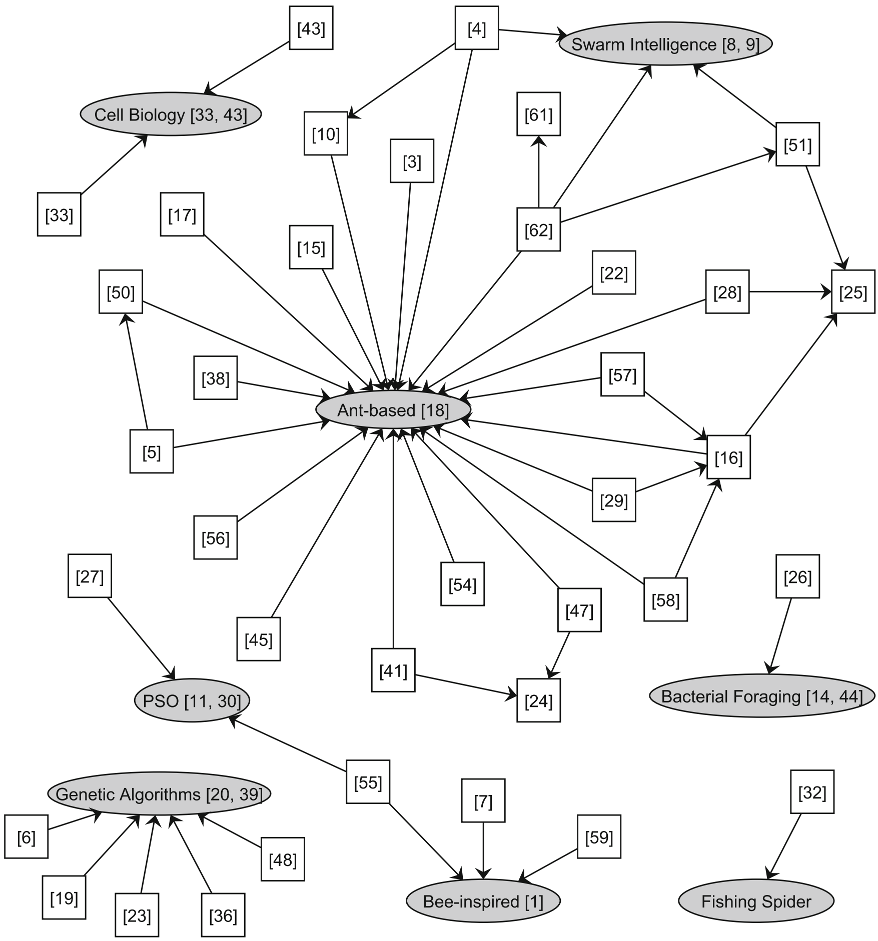

Fig. 7.2 Mind map illustrating the surveyed bio-inspired routing methods, individual research papers, and their mutual references

7.4 Conclusions

This chapter presents an up-to-date survey of recent studies dealing with bio-inspired approaches to routing in wireless sensor networks. Wireless communication is an essential part of WSN operations. Multi-hop data transmission strategies have to be adopted in order to deal with limited communication range of nodes' radios and energy constraints imposed by their limited power sources.

The traditional routing methods are challenged by the growing volume, extensive spatial coverage, and generally high complexity of contemporary WSN. Deterministic, global approaches can hardly address such complex tasks in an efficient way. On the other hand, bio-inspired methods draw their inspiration from natural systems that have properties similar to WSNs. For example, swarm-intelligent algorithms are essentially exchanging information in the way WSN should: in a local and computationally efficient, yet globally highly effective fashion. In contrast, evolutionary approaches can be used for global optimization, even of large scale networks. Various flavours of swarm and evolutionary algorithms, as well as other bio-inspired methods, introduce peculiar strategies that can be applied to achieve diverse routing goals.

In computer applications, bio-inspired methods were first used for optimization and search. As a result, they can be easily used to find communication patterns suitable to satisfy arbitrary objectives (communication latency, throughput, energy efficiency). Bio-inspired methods are also tightly linked to data mining and knowledge discovery. Often, they are used to extract hidden information from data or to uncover implicit patterns. That makes them sensitive to changes in network state and configuration, and thus capable of achieving adaptive routing behaviour.

The limited scope of this chapter could not possibly include all relevant studies. However, it provides a broad and logically structured overview of the most significant trends in bio-inspired routing strategies for wireless sensor networks. The works surveyed in this chapter can be informally classified according to the type of net-

Table 7.1 Classification of bio-inspired routing algorithms

Algorithm type	Network type	
	WSN	MANET/VANET
Ant-inspired	[4, 5, 10, 15, 17, 38, 41, 47, 50, 57, 61, 62]	[3, 16, 22, 25, 28, 54, 58]
Bee-inspired	[55]	[7, 59]
Swarm intelligence		[51]
Genetic algorithm	[6, 19, 23, 36, 48]	
Cell biology-inspired	[43]	[33]
Bacteria-inspired	[26]	
Particle swarm optimization	[27]	
Other bio-inspired (fishing spider)	[32]	

work and the nature of the routing algorithm, as shown in Table 7.1. However, many alternative classifications based on different criteria can be devised:

- the type of the algorithm (from the optimization point of view)—continuous optimization [27] versus discrete optimization (other)
- the type of the routing method—hierarchical routing [32, 47, 55] versus non-hierarchical routing (other)
- the number of sinks in the network—multiple [27, 38, 43, 57] versus single (other)
- the main objective—scalability [15, 16, 25, 32, 50], security [5, 7, 54], energy-efficiency (other)
- etc.

Such classifications are, however, necessarily inaccurate. Some algorithms combine two or more methods and some are suitable for multiple types of networks.

Efficient multi-hop routing is a challenging research problem whose solution is essential for practical operation of the future generation of massive wireless networks. A particular data transmission strategy defines:

- the way *data*, and eventually *information*, is shared among the nodes and propagated across the network, and
- the structure, amount, and propagation patterns of *meta-data* (such as routing tables, logs, or node role assignments), that is used to keep the network operational and its communication efficient.

Meta-data is created and propagated through the network with a single objective: to provide a framework for monitoring the environment and propagating the collected data to the user. From this perspective, the amount of meta-data should be minimized. However, it can be also perceived as a source of complementary information about the network and, indirectly, the monitored environment.

In the bio-inspired analogy, data corresponds to food or fitness, and meta-data is represented, for example, by pheromones, genes or coordinates. Each routing algorithm, mimicking certain biological communication and optimization strategy, affects the organization, scalability, sensitivity, adaptability, speed, and other properties of the network. Lessons learned from nature will undoubtedly be invaluable for attaining the objectives of the next-generation WSN: to facilitate autonomous, accurate, immediate, and cost-effective monitoring of vast heterogeneous environments, with adequate spatial and temporal resolution.

Acknowledgments This work has been been supported by the Natural Sciences and Engineering Research Council (NSERC) of Canada, Helmholtz-Alberta Initiative (HAI), and by TECTERRA project 1209-UNI-013

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