On Swarm Intelligence Inspired Self-Organized Networking: Its Bionic Mechanisms, Designing Principles and Optimization Approaches

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***Abstract*—Inspired by swarm intelligence observed in social species, the artificial self-organized networking (SON) systems are expected to exhibit some intelligent features (e.g., flexibility, robustness, decentralized control, and self-evolution, etc.) that may have made social species so successful in the biosphere. Self-organized networks with swarm intelligence as one possible solution have attracted a lot of attention from both academia and industry. In this paper, we survey different aspects of bio-inspired mechanisms and examine various algorithms that have been applied to artificial SON systems. The existing well-known bio-inspired algorithms such as pulse-coupled oscillators (PCO)-based synchronization, ant- and/or bee-inspired cooperation and division of labor, immune systems inspired network security and Ant Colony Optimization (ACO)-based multipath routing have been surveyed and compared. The main contributions of this survey include 1) providing principles and optimization approaches of variant bio-inspired algorithms, 2) surveying and comparing critical SON issues from the perspective of physical-layer, Media Access Control (MAC)-layer and network-layer operations, and 3) discussing advantages, drawbacks, and further design challenges of variant algorithms, and then identifying their new directions and applications. In consideration of the development trends of communications networks (e.g., large-scale, heterogeneity, spectrum scarcity, etc.), some open research issues, including SON designing tradeoffs, Self-X capabilities in the 3^{rd} Generation Partnership Project (3GPP) Long Term Evolution (LTE)/LTE-Advanced systems, cognitive machine-to-machine (M2M) self-optimization, cross-layer design, resource scheduling, and power control, etc., are also discussed in this survey.**

***Index Terms*—Self-Organized Networking, Bio-Inspired, Swarm Intelligence, Synchronization, Load Balancing, Cooperation, Adaptive Routing, Network Security, Heterogeneous, Machine-to-Machine, Cognitive Radio.**

Manuscript received January 12, 2013; revised April 21, 2013. This work was supported by the National Natural Science Foundation of China (No. 61172050), the Program for New Century Excellent Talents in University (NECT-12-0774), the National Basic Research Program of China (2012CB315905), Beijing Science and Technology Program (Z111100054011078), the Foundation of Beijing Engineering and Technology Center for Convergence Networks and Ubiquitous Services, and National Key Projects (2012ZX03001029-005 and 2012ZX03001032-003).

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Digital Object Identifier 10.1109/SURV.2013.062613.00014

I. INTRODUCTION TO SELF-ORGANIZATION

SINCE modern communications networks must deliver ever increasing data rates at an ever decreasing cost per bit, the spatial reuse of the spectrum must be increased by deploying large number of pico-cells and femtocells. A combination of macro-cells and small cells consequently leads to the development of heterogeneous networks [1], resulting in the increasing complexity in the configuration and management of large-scale networks, the upgrading capital expenditures (CAPEX) and Operating Expenditures (OPEX), and the intensifying difficulties of centralized control, etc. The aforementioned challenges have inspired the studies on the appealing self-organization capabilities (e.g., self-configuration, self-optimization, self-healing, adaptivity to varying environment conditions, anti-failure, etc.) of future networks [2], [3].

Self-organization, existing in many branches of science such as biology, economic, telecommunications, etc., is essentially an interdisciplinary and heterogenous research field [2]. In [4], self-organization was defined as "the emergence of system-wide adaptive structure and functionality from simple local interactions between individual entities". In [5], [6], some appealing self-organization characteristics, such as "ability to self-organize in a fully distributed fashion, collaboratively achieving efficient equilibrium", have been generalized from biological systems and processes. For more self-organized networking (SON) features, please refer to Section II.

Since self-organization is expected to bring us remarkable benefits in terms of cost reduction in network configuration, management, operation and optimization, substantial research has been carried out to address the challenges brought by the ever increasing complexity, heterogeneity, and dynamics in complex communications systems [2], [7]. The study of collective behavior (or in other words, swarm intelligence) of social species can help humans manage complex systems, and bio-inspired algorithms have already given us some illumination on designing, maintaining and optimizing artificial SON systems. Note that one common ambiguity between the definitions of "self-organization" and "bio-inspired" is usually observed, as indicated by F. Dressler [2]: basically, only examples of self-organization being observed in nature and finding their roots in biological mechanisms can be named bio-inspired. In this paper, bio-inspired algorithms related to swarm intelligence will be our main focus, and we would like to use "bio-inspired" to represent "self-organization" in the following sections.

Some pioneering works on summarizing the essential and universal designing mechanisms of artificial SON systems have been carried out. In [4], four paradigms of designing artificial systems have been derived by looking at different SON protocols and extracting their common features as general principles. In [2], bio-inspired self-organization for artificial systems has been studied from an interdisciplinary point of view. Although [2] mainly focusing on wireless sensor and actor networks, adapting the proposed paradigms (e.g., local behavior rules, positive and negative feedback, massively distributed control without human intervention, etc.) to the other SON systems is possible. Enormous bio-inspired SON algorithms have been proposed and are proven to be effective in application fields such as communications networks, scheduling, medical science, etc. [2], [8]. Among them, the probably best known one is the Ant Colony Optimization (ACO) algorithm (as proposed by Marco Dorigo et al. [9]), which has already been applied to develop high-performance routing protocols for SON systems such as Wireless Sensor Networks (WSN) [10] and Delay tolerant networks (DTN) [11].

Compared to the conventional SON techniques, bio-inspired SON algorithms may lead to a more effective system in terms of networking, maintenance, control and optimization. For instance, in the reference broadcast synchronization (RBS) scheme [12], it requires each node to broadcast the physical-layer reference beacons to its neighbors, and the nodes that receive the beacon will exchange with each other the arrival time of the beacon relative to the local clock and thus obtain a time synchronization [12]. Different from it, bio-inspired algorithms (e.g., the firefly-inspired algorithm [13]) may obtain a cost-effective physical-layer synchronization by simply depending on the local pulse interactions among individuals, i.e., based on the pulse-coupled oscillators (PCO) theory [14]. Besides, the capability of adapting to environmental changes in bio-inspired SON systems comes from the inheritance of biological species, and this capability is much higher than the conventional solutions. More advantages of bio-inspired solutions over conventional SON algorithms are summarized in Table I.

In this paper, we survey and compare different aspects of swarm intelligence and introduce various bio-inspired algorithms that have been proposed to improve the performance of artificial SON systems (note that the reference list in this survey is by no means complete). Selected techniques in terms of physical-layer (i.e., network synchronization), Media Access Control (MAC)-layer (including cooperation, division of labor, and load balancing) and network-layer (including network security and adaptive routing) functionalities are discussed. We first introduce the biological principles of various algorithms, and then analyze their advantages, drawbacks and further design challenges, followed by identifying their new directions and open problems. Furthermore, some advanced issues and applications of bio-inspired SON techniques, including SON designing tradeoffs, Self-X capabilities in the 3rd Generation Partnership Project (3GPP) Long Term Evolution (LTE)/LTE-Advanced systems, cognitive machine-to-machine (M2M) self-optimization, cross-layer design, resource scheduling, and power control, etc., will also be discussed in this survey.

The remainder of this paper is organized as follows. The fundamental features of SON systems are first introduced in Section II. After that, the main categories of bio-inspired self-organization technologies will be sketched out in III. The physical-layer synchronization mechanisms, including firefly-inspired and singing cricket-inspired algorithms, are surveyed and compared in Section IV. Some critical MAC-layer issues, including bio-inspired spectrum sensing, cooperation and division of labor, and load balancing, are surveyed and discussed in Section V, followed by the critical network-layer issues of security and adaptive routing being surveyed and compared in Section VI. Discussions on practical applications and open research issues for bio-inspired SON techniques are given out by Section VII. Finally, conclusions are drawn in Section VIII.

II. FUNDAMENTAL FEATURES OF SELF-ORGANIZATION

In existing literatures, the essential properties that are regarded as fundamental SON mechanisms and principles have been summarized, such as [2].

1) ***Systematism**: Self-organization is a system-wide activity happened in a coherent system that has parts, interactions, structural relationships, behavior, state, and a border that delimits it from its environment [15].*
2) ***Complexity**: SON systems are complex systems, and "complexity" implies: i) there is self-organization and emergence in complex systems; ii) complex systems are organized in a distributed manner without centralized control; iii) even if one knows to a large extent the parts of self-organized systems as well as the connections between those parts, it is still difficult to model the systems and to predict their behavior [16].*
3) ***Cohesion**: The closure of the causal relations among the parts of a dynamic system that resistant to internal or external fluctuations, which might disrupt the system's integrity [17].*
4) ***Non-linearity**: Self-organization is a process in which the higher-level functionality of the system emerges solely from numerous interactions among the lower-level components and without an internal or external control/intervention. The overall system can perform more powerful and complex tasks than can be participated by summing up the actions of the individuals.*
5) ***Distributed control**: A distributed control mechanism is applied to the SON systems to enable their fulfilling global tasks. Nobody inside or outside of the SON systems is responsible for guiding, directing or controlling the system. Each individual one works on its own intention to collaborate on the global tasks.*
6) ***Sub-optimum**: One of the most fundamental principles in designing SON systems is to reduce global state information by achieving the needed effects based on local information or probabilistic approaches only. However, this may not necessarily lead to the desired global optimization of the systems.*
7) ***Adaptivity**: SON systems are capable of adapting to changing environments and being resilient to failures and damages. A small change in environmental pa-*

TABLE I
ADVANTAGES OF BIO-INSPIRED TECHNIQUES OVER CONVENTIONAL SON SOLUTIONS

Technical Content	Conventional SON Solutions	Bio-Inspired Techniques
Control Information Exchange	Requires control information exchanges among individuals	Without control information exchange
Controlling Mechanisms	Local information exchange with a relatively higher complexity	A lower complexity enabled by using local interactions
Resource Utilization	Relatively low	High
Adaptivity to Changes	Relatively low	High
Network Scalability	Relatively low	High
Network Synchronization Performance	Local synchronization obtained by transmitting synchronization packets	Low-complexity and global PHY-layer synchronization by transmitting pulses
MAC-Layer Delay	Relatively high	Low
Communications Overhead	Relatively high	Low
Routing Information Flooding	Yes	Avoided
Protocol Processing	Higher complexity	Lower complexity
Hardware Complexity	Relatively high	Low

rameters may result in a big change in the systematic behavior.

By exploiting the properties aforementioned, some well-known SON systems such as wireless ad hoc [18] and WSN [19] have been developed. Besides, the SON properties have also been investigated in wireless cellular networks with an ultimate goal of improving their robustness, reliability, scalability and power efficiency [7]. Regarded as a critical and main feature of the 3GPP LTE/LTE-Advanced systems, the capabilities of Evolved Node B (eNodeB) have already been incorporated with the SON properties of self-configuration, self-optimization, self-healing, and plug-and-play, etc. [3]. Besides, SON functionalities, such as self-maintenance, self-optimization, and adaptive coverage coordination, etc., may be implemented in Home eNodeB (HeNodeB) to reduce the OPEX cost and improve the femtocell coverage simultaneously [20]. The Self-X capabilities can be summarized as follows.

- **Self-Configuration**: Self-configuration is a process with the newly deployed eNodeBs being configured by automatic installation procedures to get basic parameters and download necessary software for operation [21]. The self-configuration capability, which could integrate the newly added eNodeBs in a plug-and-play approach, significantly reduces the network deployment time and human involvement. Several self-configuration mechanisms have been proposed in wireless cellular networks [22]. Different from self-optimization, which optimizes parameters during network operating phase, self-configuration is usually assumed to execute during the installation/power-up/recovery phase of user equipments (UEs) or eNodeBs.
- **Self-Optimization**: Self-optimization techniques, which enable a mobile network to adaptively optimize their algorithms and system parameters to achieve optimal system performance (in terms of, e.g., capacity, service coverage, etc.) in the presence of environment changes, are crucial for the operation and maintenance of mobile networks [23]. Various self-optimization functionalities, such as traffic steering and mobility load balancing (MLB), coverage/capacity optimization, and random access channel (RACH) optimization, etc., have been considerably studied [23]. Some other self-optimization functionalities, such as radio resource management (RRM), Inter-Cell Interference Coordination (ICIC), and power control, can also be realized in a dynamic and self-organization manner [3].
- **Self-Healing**: Self-healing, an event-driven process which aims to resolve the loss of coverage or capacity when a cell/site failure happens, is necessary to assist operators in recovering a collapsed network [23]. Several 3GPP LTE use cases are related to functionalities of self-healing (e.g., self-recovery of NE software, self-healing of board faults, cell outage detection/recovery/compensation, and return from cell outage compensation, etc.) and have been considerably studied [3].

Furthermore, some advanced features of the fourth generation (4G) mobile communications networks will also benefit from SON coordination and control of Multi-Input Multi-Output (MIMO) mode selection [24]. Other self-organization properties, including autonomous capabilities of individual NEs, high scalability of network, fault tolerance and distributed control paradigm, etc., have also been observed in Internet [25].

III. CATEGORIES OF BIO-INSPIRED RESEARCH

Bio-inspired techniques have been considerably studied in the past decades. As indicated by [2], the following three application domains of bio-inspired solutions to problems related to computing and communications can be distinguished:

- **Bio-inspired computing**, which represents a class of algorithms focusing on efficient computing, can be effectively used for a great number of problem spaces, such as optimization problems, exploration and mapping, and pattern recognition, etc.
- **Bio-inspired systems**, which rely on system architectures for massively distributed and collaborative systems, enable functionalities of, e.g., distributed sensing and exploration.

- **Bio-inspired networking** is a class of strategies for efficient and scalable networking under uncertain conditions.

In recent years, a great number of bio-inspired approaches have been proposed for improved efficiency. The primary concepts of some of the well-known bio-inspired research fields (not necessarily concentrating on domains of communications and networks, as illustrated in Fig. 1) will be outlined in the following subsections.

A. Evolutionary Algorithms

Evolutionary algorithms (EAs), which are rooted on the Darwinian theory of evolution, can be categorized into the following classes, Genetic Algorithms (GAs), evolution strategies, evolutionary programming, generic programming, and classifier systems [26]. EAs represent a set of search techniques used to find an optimal or approximate solution to optimization problems. Besides, EAs can also be utilized in wireless networks by solving problems of the location management and channel-assignment procedure [27].

B. Artificial Neural Networks

A neural network traditionally refers to a network of biological neurons, and the term is now used to refer to an Artificial Neural Network (ANN), whose primary objective is to acquire knowledge from the environment (i.e., a process of self-learning is performed). In most cases, an ANN is an adaptive system that is capable of changing its structure based on external or internal information that flows through the network, hence complex relationships between inputs and outputs can be modelled [28].

C. Artificial Immune Systems

Artificial Immune System (AIS) is a type of optimization and pattern-recognition algorithm inspired by the principles and processes of the mammalian immune system, and the immune system's characteristics of self-learning and memorization are typically exploited by the AIS algorithms to facilitate the development of communications networks with the capability of misbehavior- and intrusion-detection [29]. The identification of computational viruses and network intrusions has been considered as one of the most important anomaly-detection tasks in the domain of communication networks [2].

D. Cellular Signalling Pathways

In view of the fact that the functionality of a eukaryotic cell relies on the complex network of biochemical processes, which must be highly regulated and controlled, two kinds of signalling pathways, i.e., intracellular signalling and intercellular signalling, are emphasized in cellular processes. Basically, two communications paradigms can be differentiated, with the regulation of the concentrations allowing diffuse message transmission, and specific reactions being triggered by exchanging particles such as proteins. This behavior can be directly applied to different aspects of computer communications [30].

E. Molecular Computing

The basic idea of molecular computing is to apply operations to a set of molecules, and problem solving using molecular computing is executed in the form of brute-force search strategies in which the operations are simultaneously applied to all molecules. The capability of high-speed information processing and storage has been emphasized in molecular computing, and this technique can thus be successfully used for solving NP-complete problems, graph coloring, and integer factorization, etc. [2].

F. Swarm Intelligence

Swarm Intelligence is an Artificial Intelligence (AI) technique, which is studied based on the observations of the collective behavior in biological activities such as ant/bee foraging, division of labor, larval sorting, nest building, and cooperative transport, etc. [8]. The number of applications of swarm intelligence is exponentially growing in fields of, e.g., communications networks, combinatorial optimization and robotics. Self-organized networks with swarm intelligence as one possible solution have already exhibited their advantages over conventional SON techniques in terms of adaptive routing, load balancing, etc.

One of the most famous Swarm Intelligence inspired algorithms is ACO algorithm [9]. Deneubourg et al. studied the ability of ants collectively finding the shortest path to the best food source, and it was observed that the shortest path between two candidates will finally be chosen due to a denser pheromone being laid on it [31]. ACO algorithms have already been applied to solve the routing algorithms in artificial SON systems such as mobile ad hoc networks [32], Wireless Sensor Networks (WSN) [33], or Delay tolerant networks (DTN) [11], with a better scalability or the other performance metrics being emphasized. Besides, the honey bee colony can also be modelled as a population-based multi-agent system, with many features, such as efficient allocation of foraging force to multiple food sources without central control, decision-making without any global knowledge of the environment, etc., being observed and desirable in designing and optimizing the performance of artificial SON systems [34]. A considerable number of studies have been carried out in swarm intelligence to solve practical problems of adaptive routing, resource allocation, and robot cooperation, etc. [8], and the typical bio-inspired algorithms related to swarm intelligence will be surveyed in the following sections.

G. Main Focus of This Paper

The well-known bio-inspired techniques are categorized in Fig. 1, and among those techniques, swarm intelligence inspired SON algorithms will be emphasized. Although conventional self-organized networks (such as ad hoc, sensor networks) have already been considerably studied, swarm intelligence may pave a new way toward building an intelligent SON system. For instance, ACO algorithms enable an adaptive routing with a higher scalability and load balancing capability than conventional algorithms such as Ad-hoc On demand Distance Vector routing (AODV), and firefly-inspired

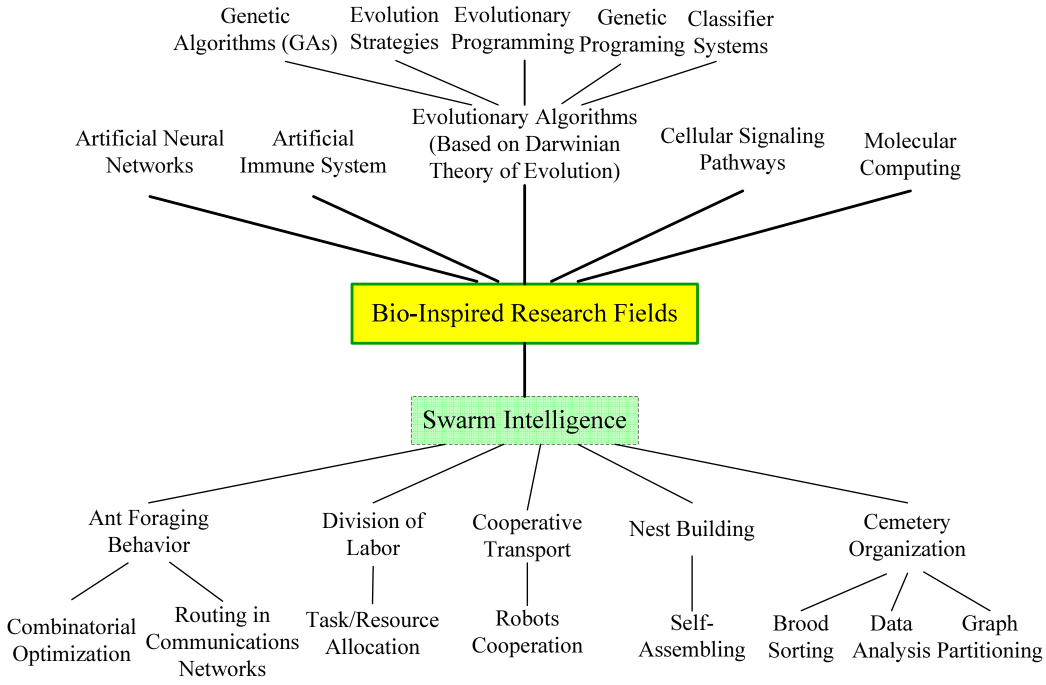

Fig. 1. The well-known bio-inspired research fields.

algorithm may lead to a scalable network synchronization in self-organized networks with a high convergence speed.

In the following sections, SON techniques with swarm intelligence as one possible solution will be surveyed. In order to make the readers specialized in communications easy to understand, the following three sections are organized based on the Open System Interconnect (OSI) layers, i.e., the physical layer (focuses on network synchronization), MAC layer (focuses on cooperation, division of labor, and load balancing) and network layer (focuses on network security and adaptive routing). The technical contents of this survey are illustrated in Fig. 2.

IV. PHYSICAL-LAYER SYNCHRONIZATION IN SON SYSTEMS

Time synchronization plays an important role in communications systems in that it allows the entire system to cooperate and function as a cohesive group. For instance, timing synchronization may be critical in wide-area networks (WAN) due to an ambiguity problem induced by propagation delays [35]. In WSNs, on the other hand, time synchronization has proven to be critical in sensor fusion applications. The existing synchronization schemes for wireless networks can be categorized into either centralized or decentralized solution, as shown in Fig. 3.

A. Centralized Synchronization

Communication systems with a cluster structure may achieve its synchronization in a centralized manner. Cluster head, acting as the critical node, provides a standard synchronization parameter for the whole cluster by utilizing an external reference (e.g., the Global Positioning System (GPS) [36]). Mill's Network Time Protocol (NTP) [37] as well as its extended protocol (i.e., extended NTP [38]) is a typical centralized synchronization protocol and has been widely used in the Internet.

B. Decentralized Synchronization

Although a centralized method achieves an accurate synchronization with a high reliability, it is expensive in terms of energy consumption and the hardware cost. Moreover, the network scalability is also limited in the centralized scheme. On the other hand, decentralized synchronization, which does not rely on a global time clock, can improve both the synchronization reliability and network scalability simultaneously.

Some protocols have been proposed for time synchronization by exchanging time information explicitly among nodes at the packet-level, requiring the processing of these messages to calibrate the time difference between nodes. The majority of those protocols use point-to-point transmissions instead of capitalizing on the broadcast nature of wireless channels, with physical-layer algorithms (e.g., [39]–[42]) being operated. RBS scheme [12], on the other hand, obtains a mutual synchronization among the nodes in the network instead of locking to a global time clock. Since the RBS scheme requires a large amount of data exchange among the co-broadcast-domain nodes so as to share each node's timing information with all the other nodes, this scheme still suffers a performance degradation in terms of scalability. In a different way, bio-inspired approaches enable a massively distributed and cost-effective physical-layer synchronization in a large-scale network.

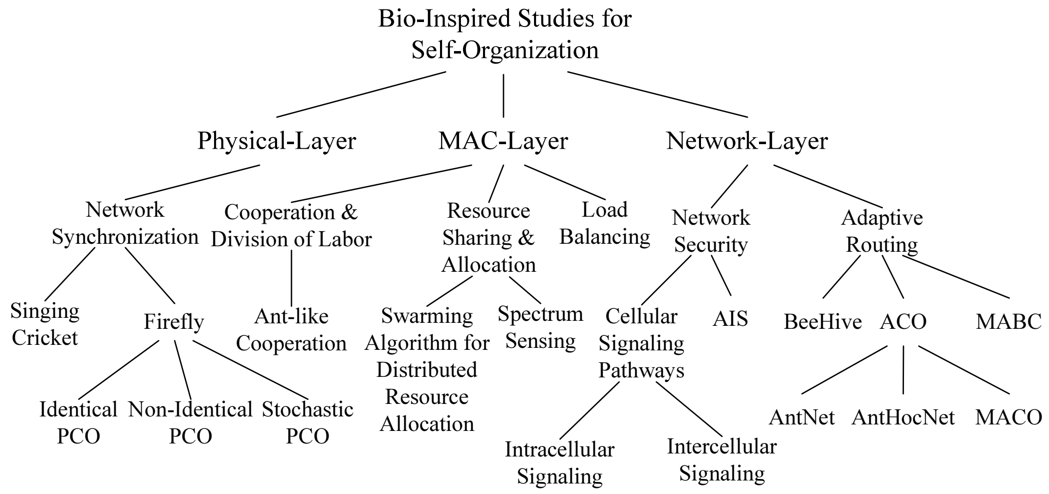

Fig. 2. Technical contents as well as specific bio-inspired algorithms of this survey. Acronyms: MAC-Media Access Control; ACO-Ant Colony Optimization; PCO-pulse-coupled oscillators; AIS-Artificial Immune System; MABC-Multiple Ant-Bee Colony; MACO-Multiple Ant Colony Optimization.

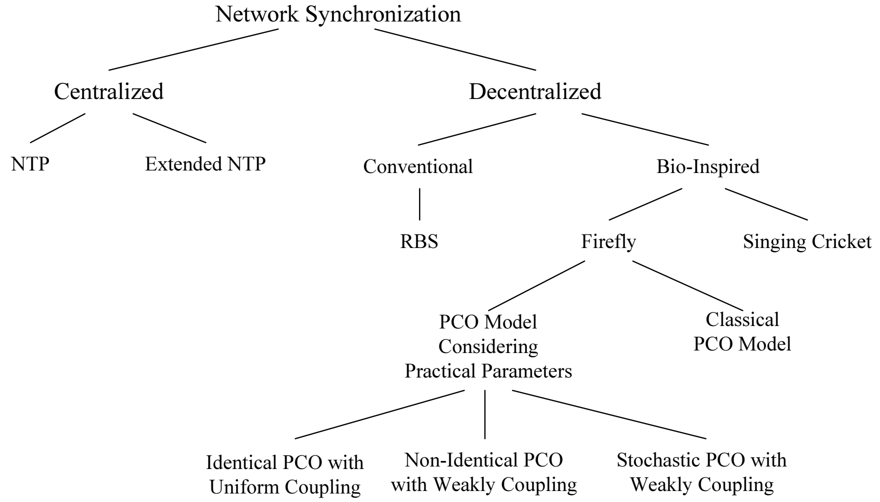

Fig. 3. Classification of the works on physical-layer synchronization. Acronyms: NTP-Network Time Protocol; RBS-reference broadcast synchronization; PCO-pulse-coupled oscillators.

*1) **Firefly-inspired Synchronization Principle**:* The phenomenon of self-synchronization can commonly be observed in natural species such as firefly [13] and modelled using the theory of coupled oscillators [43], in which each individual oscillator interacts through periodically emitted pulses. An oscillator represents the internal clock dictating when to flash, and this clock is adjusted upon reception of a pulse from other oscillators. The pulses received at each node will cause an increase to the state variable and thus create an offset in the phase of each receiving node. Over time, synchronization emerges and pulses of different oscillators are transmitted simultaneously. This effect on the state variable is called the *coupling* between the transmit and receiver nodes. Based on the PCO theory, self-synchronization of a large-scale SON system can be realized by employing the well-known Peskin's model [44], which has modelled the pacemarker as a network of N "integrate-and-fire" oscillators [45], with each being characterized by a voltage-like state variable x_i. The state variable x_i usually monotonically increases between transmissions. When $x_i = 1$, the i-th oscillator fires and x_i jumps back to zero.

The major advantage of the PCO synchronization strategy comes from the fact that it operates exclusively at the physical layer by transmitting pulses instead of packet messages. Therefore, the following four advantages are obtained: i) the imprecision due to MAC-layer delays, protocol processing or the other software implementation does not exist, and ii) the messages exchanged in the PCO scheme (i.e., the periodic pulsing signals) are independent of the origin of the signals since each received pulse is treated identically, and iii) no memory is required to store time information of other nodes, and iv) the procedure adopted at each node is independent of the node identity and remains the same regardless of the number of nodes in the network (i.e., the scalability is significantly improved).

Convergence toward synchrony for the PCO model in fully-meshed networks has been proven with an assumption of uniform coupling, noise-free environment and no delays between the firing and receiving of pulses. However, before applying the PCO model in practical systems, several practical assumptions on the delays and the coupling strength must be taken into account. It has been proven by [46] that a PCO system may become unstable and is never able to synchronize when a delay occurs. PCO models considering all those practical parameters will be surveyed in follows.

2) ***Identical PCO Models:*** In [47], realistic parameters such as the path-loss effect on the coupling strength, the presence of noise, and the propagation delay, have been imposed upon existing PCO model. The goal of this distributed synchronization procedure is to allow all the nodes in the network to agree on a common phase so that the transmission of pulses at each node can be maximally aligned. Although it is impossible to perfectly align the pulses relative to all the receivers due to the delay differences among nodes, the propagation delay will still be much smaller than both the pulse transmission period and the pulse duration, if the network of interest is located within a small area.

In [48], a scalable PCO synchronization protocol for large-scale WSNs is proposed, and the optimum operating point for achieving the best tradeoff between network convergence speed and the energy spent to reach synchrony is exploited. Two network scenarios are considered: i) the case of a single broadcast domain, where the nodes are located within the broadcast range of one another (i.e., all-to-all coupling is enabled), and ii) the case of multiple broadcast domains (i.e., synchronization over multiple hops, and nodes are subject only to local coupling). Besides, the pulse detection and refractory period, which is a duration of time right after a node's own firing and during which the node is not supposed to receive any signal, is incorporated into the mechanics of PCO to adapt to the non-ideal synchronization conditions such as path loss attenuation, the propagation delay and noise. It's shown that the synchronization time increases as $O(\log N)$ in the case of local coupling, while in the all-to-all coupling case, the synchronization time decreases as the number of nodes N increases.

To reflect more realistic effects of delay and packet loss, synchronization using a low-level MAC-layer timestamp is proposed [49], with each node being able to adjust its clock when receiving a timestamp. Since the ideal case of Mirollo and Strogatz model (where all nodes transmit simultaneously) is avoided in this method, too many collisions happen in the timestamps exchange and consequently prevail nodes from synchronizing. In view of the difference between synchronization process and data transmission, all nodes transmitting synchronously a common synchronization sequence (e.g., it can correspond to a Pseudo-Noise (PN) sequence or the IEEE 802.11a preamble) can be beneficial to the signal detection in a faraway receiver due to the power superposition from all transmitters [50]. Since the random backoff observed in asynchronous transmissions can be effectively mitigated in the synchronous transmission, a quicker network synchronization can be obtained by taking advantage of a common synchronization sequence from a physical-layer perspective.

3) ***Non-identical PCO Models:*** Non-uniform coupling among oscillators in the PCO model has also been studied, with the effect of propagation delays either being considered [51] or not [52]. Ernst et al. perform a complete mathematical analysis of two-oscillator model with delay and concluded that synchronization can still be achieved if inhibitory couplings are adopted [51]. Konishi and Kokame analyzed the stability of non-identical PCOs with a refractory period and a given frequency distribution [53]. Under the assumption of weak coupling, PCO networks using the phase model have been studied for neural networks [54], which considered only two assumptions: i) each isolated neuron fires periodically, and ii) the neurons are weakly connected.

In [55], linear non-identical PCOs model is proposed and used to analyze PCO synchronization with different frequencies. Since each oscillator has a unique frequency and leads to a different phase value in a different oscillator for a certain time, the relationship among the phase variables of different oscillators should be determined. An identical coupling strength is assumed in [55] for ease of analysis. If phases of two oscillators always return to zero at the same time, those oscillators are assumed to be synchronized, otherwise they are assumed to be instantaneously synchronized if their phases return to zero simultaneously at some point in time. Since two synchronized oscillators are clumped together as a group that fires in synchronization and interacts with other oscillators as one single entity, the two-oscillator model can be straightforwardly extended to multi-oscillator models. It is also proven that a higher coupling strength implies a higher convergence speed, and coupling more oscillators in a system will make the oscillators easier to clump into the synchronous firing group (i.e., it is equivalent to increasing the coupling strength of the oscillator).

Hu and Servetto [56] proposed a stochastic PCO model and proved synchronization using the law of large numbers for dense networks. By using spatial averaging, the errors inherent in each node can be averaged out in the proposed cooperative time synchronization. Since an average of the information from a large number of surrounding nodes is observed, synchronization performance can be improved due to the higher quality observations. However, the results only hold for dense wireless networks with a large number of nodes. Besides forming dense clusters, the synchronization process is also proven to be accelerated by increasing node mobility in a mobile ad hoc network [57].

The successful synchronization strategies taken from biology has also been combined with modern control techniques to improve the performance of the PCO model [58]. In [59], an acoustic event detection system is designed to locate the source (such as a gunfire) using a sensor network, with a PCO-based algorithm being introduced to tackle the synchronization of the acoustic event detection system. It is proven that the PCO-based algorithms provide SON systems with desirable synchronization properties, and a higher local coupling strength implies a less time to reach the synchrony.

4) *Cricket-Inspired Synchronization*:

It was observed that the snowy tree crickets are capable of synchronizing their chirps by responding to the preceding chirp of their neighbors [60]. It has been proven that a cricket is able to adjust its song to any other song like its own very quickly, and the insect can achieve synchrony within two cycles by either lengthening or shortening its own period in response to the preceding chirp. If a neighbor's chirp precedes his own, a cricket will shorten his chirp as well as the following intervals. If, on the other hand, a cricket follows his own, it will lengthen its chirp interval and sometimes the following chirp, as schematically shown in Fig. 4. Different from the firefly-inspired algorithms, which are mainly focused on addressing problems of time synchronization, the cricket singing mechanism can be employed to address the frequency synchronization issues in the wireless networks. However, until now, there are still very few technical papers focusing on this topic, which is interesting and needed for further investigation.

C. Comparison among Variant Synchronization Mechanisms

Although many systems utilize centralized synchronization methods in consideration of their high accuracy and low convergence time, they are often vulnerable to the failure of the cluster head and non-scalability. Besides, the synchronization accuracy of the low-level nodes in a hierarchical network will inevitably degrade due to their distances with the root node. As compared to the centralized methods, decentralized techniques have been proven to enable an accurate synchronization for a large-scale network. By mitigating the drawbacks (e.g., large amount of data exchange, and synchronization performance degradation in the low-level nodes) observed in conventional decentralized algorithms, bio-inspired algorithms can be operated exclusively at the physical-layer and obtain a massively distributed synchronization at a low cost of hardware/software complexity. The main advantages of PCO-based algorithms including i) a high scalability with respect to the number of participants in the network, and ii) the robustness to the network topology changes. However, the performance of the bio-inspired algorithms may be impacted by various factors such as the node density, the coupling strength in PCO model, and the modulation schemes. Different from the PCO models, the cricket singing mechanism enables an adaptive rhythm synchronization and can be utilized to address the frequency self-synchronization issues in SON systems. A comparison among variant synchronization algorithms is given by Table II.

D. Remaining Challenges in Bio-Inspired Synchronization

Although bio-inspired algorithms can deliver substantial benefits to achieving a self-synchronization with high scalability, there still exist some challenges to address.

- Tradeoff between Network scalability and synchronization performance: Since a higher coupling strength in PCO models usually leads to a higher synchronization accuracy and convergence speed, a network with a denser node-concentration in a limited geographical area may easily achieve synchrony within a smaller number of cycle periods, however, at the cost of degrading the network scalability. Thus, proposing new PCO models (with either identical or non-identical coupling) to enable an accurate/quick synchronization with a weak coupling strength and/or low pulse power is still a challenging task.
- Improving the adaptivity of PCO models by adaptively adjusting the coupling strength according to changing network topology and radio environment would be a promising way to realizing a smart self-synchronization for large-scale mobile networks.
- In consideration of the network heterogeneity in the future, different types of nodes may require different levels of synchronization quality. Thus, a distinguishing synchronization solution, which adopts non-uniform PCOs and non-identical coupling models in variant types of nodes, may play a critical role in optimizing both the network scalability and the overall synchronization performance.
- Proposing a cost-effective frequency control mechanism to facilitate a high-performance frequency synchronization will also be a challenging topic in large-scale wireless SON systems. As inspired by singing cricket, a sophisticated frequency control mechanism is needed to enable an adaptive frequency self-synchronization in each node.

V. MAC-LAYER ISSUES IN SON SYSTEMS

Since modern communication networks must deliver ever increasing data rates at an ever decreasing cost per bit, the spectral efficiency of the networks has to be further improved. For instance, wireless mesh networks, regarded as a cost-effective technology for providing broadband connectivity, require higher capacity to provide a higher throughput as the network density increases [61]. However, the current static spectrum allocation policy faces spectrum scarcity due to a large portion of the assigned spectrum being used sporadically [62]. Sophisticated spectrum sharing techniques such as Cognitive Radio [63] must be employed to significantly improve the spectrum utilization. Besides spectrum sharing, another critical MAC-layer functionality, cooperation, is also widely exploited to improve the network's capacity, robustness and scalability [64]. Moreover, the division of labor among individuals by performing different tasks simultaneously is proven to be more efficient than if tasks were performed sequentially by unspecialized individuals [8].

In the following subsections, bio-inspired approaches are investigated to address critical MAC-layer issues (including cooperation, division of labor, resource sharing & allocation, and load balancing) in SON systems, as illustrated in Fig. 5.

A. Cooperation and Division of Labor

Cooperation is commonly observed in social species, where a worker usually does not perform all tasks but rather specializes in a set of tasks [65]. For instance, some honey bees exhibit cooperative or collaborative behaviors in the activities of foraging, taking care of larva, and attacking the intruder, etc. Mechanisms of cooperation and adaptive division of labor have already been used to address some complicated problems such as travelling salesman problem, scheduling problems, and vehicle routing problems [8], etc.

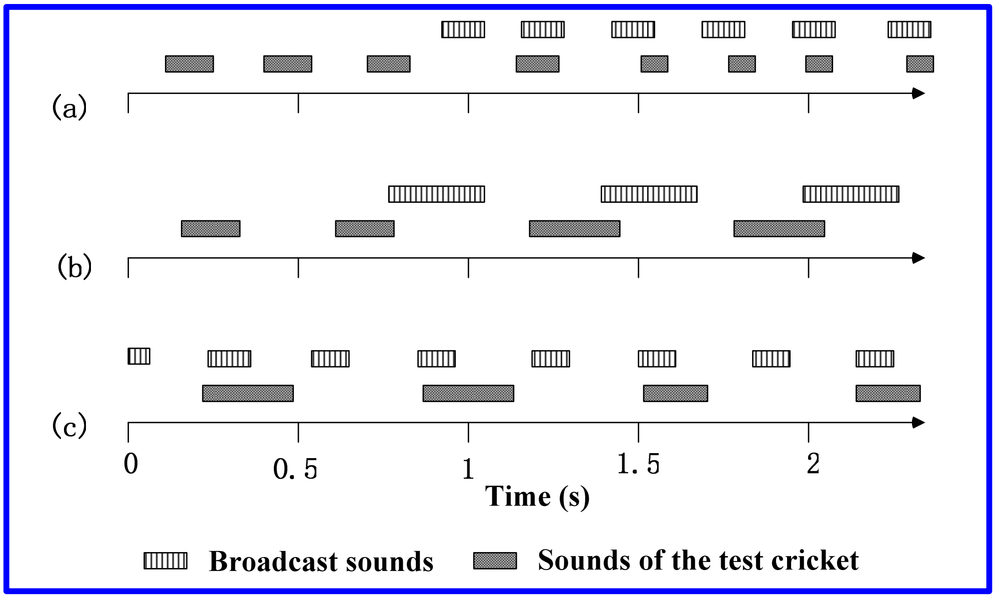

Fig. 4. Synchronization of the songs of a snowy tree cricket: (a) the sounds of the test cricket is entrained by a faster artificial rhythm; (b) the sounds of the test cricket is entrained by a slower artificial rhythm; (c) an example of 1:2 locking [60].

TABLE II
COMPARISON OF VARIANT SYNCHRONIZATION ALGORITHMS: CENTRALIZED, DECENTRALIZED RBS, BIO-INSPIRED FIREFLY (I.E., PCO MODELS) AND CRICKET SYNCHRONIZATION ALGORITHMS

Category	Algorithm	PCO & Coupling	Advantages	Disadvantages
Centralized	NTP [37]	N/A	1) High accuracy 2) High scalability	1) High Complexity; 2) Accuracy degradation in the low-level nodes
Decentralized	RBS [12]	N/A	Without relying on global clocks	Requires a large amount of data exchange
Bio-Inspired PCO-Model	Mirollo [14]	Identical PCO Uniform Coupling	PHY-layer sync. with high scalability	Unable to sync. when delay occurs
	Hong [47]	Identical PCO Uniform Coupling	Sync. obtained with delays	Ultra-Wideband (UWB) pulses are hard to detect
	Allen [49]	Identical PCO Uniform Coupling	MAC timestamps are easy to detect	Collisions happen in timestamps exchange
	Tyrrell [50]	Identical PCO Uniform Coupling	A quicker sync. is obtained	A common sync. sequence is required
	Hong [48]	Identical PCO Uniform Coupling	Sync. precision doesn't degrade over multi-hop	UWB pulses are used for sync.
	An [55]	Non-identical PCO Weakly Coupling	Easy for massively distributed sync.	Weaker coupling strength degrades sync. speed
	Hu [56]	Stochastic PCO Weakly Coupling	Sync. improves as node-density grows	Works well only in dense-node scenarios
Bio-Inspired Cricket	Walker [60]	N/A	Adaptive rhythm synchronization	A sophisticated frequency control is required

In the division of labor, the ratios of workers performing the different tasks can also vary in response to internal perturbations or external challenges to maintain the colony's viability and reproductive success. Task/resource allocation has been studied in the context of complex problem solution by performing multiple tasks in parallel [2], and the developed algorithms are directly applicable to any multi-system architectures that need to distribute workload among a number of available systems.

Focusing on the task-allocation problems, the solutions can basically be attributed to the following two categories:

- *Intentional Cooperation*: The model of intentional cooperation enforces agents to explicitly cooperate with purpose through task-related communication. Typically, auction-based task allocation mechanisms are used in this context, with an auctioneer or centralized coordinator being used to enable cooperation of different systems.
- *Emergent Cooperation*: Agents do not explicitly work together under emergent cooperation. Instead, group-level cooperative behavior emerges from the interactions

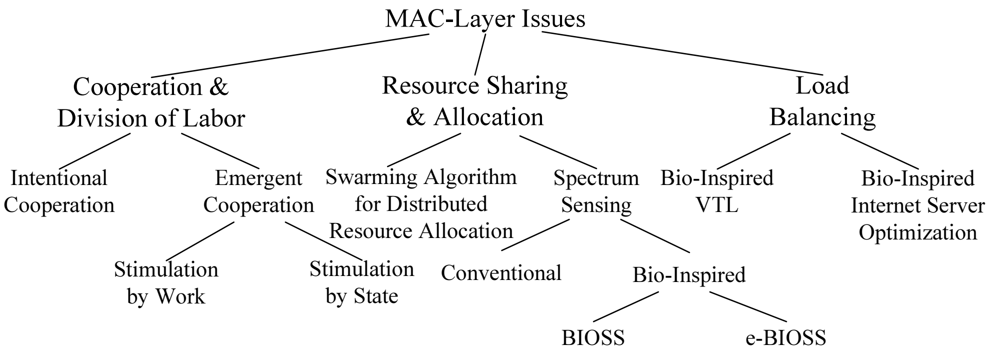

Fig. 5. Classification of the works on MAC-layer issues. Acronyms: MAC-Media Access Control; VTL-Virtual Traffic Lights; BIOSS-BIOlogically-inspired Spectrum Sharing.

among the systems and with the local environment. An emergent systems is usually able to perform a specific task efficiently rather than a general-purpose functionality.

The main advantage of the intentional cooperation comes from its capability of supporting heterogeneous agents and tasks. Basically, all solutions in intentional cooperation represent an optimization process, with reallocation of tasks being possible. However, the most challenging problem inherent to all intentional cooperation techniques is the communications overhead, because all systems need to periodically report their local state to a central system. The emergent cooperation, on the other hand, is motivated by biological analogies in many cases (especially focusing on swarm intelligence), and therefore the term *ant-like* cooperation has been used to describe the emergent cooperation techniques. The emergent cooperation can be further categorized into two classes, i.e., *Stimulation by Work* [66] and *Stimulation by State* [67]. A comparison between the intentional cooperation and the emergent cooperation is given by Table III. Although the existing bio-inspired methods related to division of labor are primarily proposed for optimizing cooperation of multi-agent systems (e.g., multi-robot systems [2], [8]), those approaches have a significant potential to be applied to the self-organized communications networks.

B. Bio-Inspired Spectrum Sharing

Contention control protocols such as Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) and slotted Aloha have already been proposed in IEEE 802.11 Wireless Local Area Network (WLAN) standards as effective MAC methods to share wireless medium among multiple mobile stations [68]. To optimize the resource utilization, some improvements on these protocols have also been studied [69]. Besides wireless networks, distributed resource optimization methods may also be applied in a wider fields such as optical networks [70]–[73], optical-wireless broadband access [74] and wireless cellular networks [75].

CR technology aims to detect and utilize the temporally unused spectrum bands by sensing the radio environment so as to enhance the spectrum utilization. New challenges arise in spectrum sharing in SON systems due to the lack of centralized control in dynamic spectrum management. Bio-inspired algorithms may be investigated to provide a new way toward achieving efficient and decentralized spectrum sharing. Spectrum sharing in Cognitive Radio Networks (CRNs) has great similarities with task allocation in insect colony: CR users sense the environment for the available spectrum bands and then, transmit their packets to available spectrum bands simultaneously. According to this analogy, the channel selection probability can be determined to enable each CR user to effectively share the best available spectrum bands in a distributed manner. Each individual computes the channel selection probability for every available channel to effectively capture the available spectrum band [76].

In [77], the existing swarming algorithm has been extended to the case of inter-nodes communications affected by random link failures and quantization noise. The extended algorithm can be applied to the distributed resource allocation on the time-frequency plane, where the activity of the primary users is modelled as set of continuous-time Markov processes. Remarkable benefits in terms of minimizing the interference produced by the CR users, taking advantage of cooperative sensing, avoiding collisions among the users and limiting the spread of resources in the time-frequency domain, etc., can be brought.

In [76], a BIOlogically-inspired Spectrum Sharing (BIOSS) algorithm, which is based on the adaptive task allocation model in insect colonies, is proposed. The main principle of BIOSS is summarized as follows [76]. *Similar to CR, individuals in insect colonies sense the environment to detect the tasks and then, the detected tasks are performed simultaneously by individuals which are suitable for performing that task. Every individual has a response threshold for each task, and the individuals perform the task when the level of the task-associated stimuli* s *exceeds their threshold.* Efficient spectrum sharing over multiple spectrum bands is enabled by BIOSS, which performs a decentralized spectrum sharing and without the need for any inter-user coordination. However, a high probability of conflicts between CR users in BIOSS may degrade its spectrum utilization. In order to mitigate this drawback, an enhanced BIOSS algorithm (i.e., e-BIOSS [78]) is proposed to enable CR users to select the appropriate

TABLE III
COMPARISON BETWEEN THE INTENTIONAL COOPERATION AND THE EMERGENT COOPERATION

	Advantage	Disadvantage
Intentional	1) Supports heterogeneous task allocation; 2) Optimization process is achievable.	Additional communications overhead is required due to centralized task allocation
Emergent	1) Simplicity in performing local algorithms; 2) Very low communications overhead	1) Only works for distributed operations; 2) A global optimization is unavailable; 3) Limited support for heterogeneous environment

channels to transmit while at the same time avoid interference to the incumbent users. The channel selection probability function in e-BIOSS algorithm is modified to enable a CR user to be gravitated towards the channel with a minimum excess power. Besides, a binary learning factor, which leads to a direct decision being made on whether to adopt or abandon a certain channel, is also applied in e-BIOSS to enable a rapid reaction to the dynamic wireless environment in each CR user.

As compared to the conventional spectrum sharing methods, which are usually based on centralized control, bio-inspired methods enable a distributed spectrum sharing and thus have a high adaptivity to the heterogeneous and dynamic radio environment. A comparison among variant spectrum sharing algorithms is given by Table IV.

C. Load Balancing

The phenomenon of load balancing can be widely observed in the collective behaviors of social species [79]. For instance, honey bees in their foraging activity exhibit a property of load balancing, and inspired by this activity, an algorithm was developed to perform Internet server optimization [80]. Although load balancing is usually regarded as a main feature of multipath routing protocol (left for study in Section VI), it will be analyzed in this subsection from the perspective of MAC-layer optimization.

In [81], a biologically inspired approach, as illuminated by the smart method of how the ant colony captures a freshwater crab, is employed to solve the traffic congestion problems via a self-organized paradigm. A leader car at each intersection is elected in a distributed manner and acts as Virtual Traffic Lights (VTL), which is responsible to manage the flow of vehicles at that intersection. After the leader passing the intersection, it will then dynamically hand its responsibility over to another leader. The election of VTL is described as follows. When a car approaching an intersection, it should check whether there is already an established VTL or not. If a VTL has already been elected, the other cars should obey this existing VTL and decide their actions under direction of this VTL. If not, the cluster leaders in each leg of the intersection must negotiate and elect a leader who will contemporarily act as VTL and manage the traffic at the intersection. The elected VTL in each section will announce the traffic condition to its neighboring cars, and a car approaching this intersection can switch to another light-congestion intersection based on the traffic congestion information as well as location messages obtained from the inter-vehicle communications.

It's proven that the bio-inspired traffic control without using of infrastructure-based traffic lights increases the traffic flow rates by about 60% during rush hours [81]. In addition, some other advantages, such as reducing the number of accidents at intersections without traffic lights, increasing the energy efficiency of urban transportation, and mitigating congestion, etc., can also be brought.

D. Remaining Challenges in MAC-Layer Issues

Although bio-inspired algorithms have exhibited their advantages in efficiently addressing problems such as resource sharing, cooperation and load balancing, etc., in artificial SON systems, there still exist several challenges to be treated.

- In order to reduce the communications overhead in large-scale SON systems, bio-inspired solutions, which require none or limited communications overhead due to their localized behaviors, are promising. However, improving the heterogeneous-supporting capability of bio-inspired solutions would still be a challenging task.
- The energy consumption of cooperation might become another challenging issue in wireless SON systems, which are usually battery-driven and have limited capabilities for energy harvesting.
- Bio-inspired spectrum sharing techniques raise a new challenge: since the implementation of a static or fixed common control channel (CCC) is infeasible in CRNs, CCC-mitigation techniques must be devised for clusters of CR users [82]. For instance, localized CCC mechanism can be performed to enable CR users to select/maintain/change the CCC in a self-organization manner. Moreover, additional dynamic strategies should also be enabled to facilitate a reliable exchange of signalling information in cooperative spectrum sensing.
- Since dynamic task allocations involving optimal but long-lasting decision processes may not be feasible in real-time environments, the convergence speed of bio-inspired solutions must be greatly improved to satisfy the time constraints of real-time task allocations.

VI. NETWORK-LAYER ISSUES IN SON SYSTEMS

With the growing importance of communication techniques, more complicated communication networks are being designed and developed. The challenges of dealing with the vast complexity of networking problems (e.g., adaptive routing, congestion control, and load balancing) accentuate the need for more sophisticated/intelligent network-layer techniques. As inspired by social insects such as ants [83] and honey bee [84], several mobile agent-based paradigms have been designed to solve the control, routing and load balancing problems in communications networks. In this section, critical network-layer issues, including network security and adaptive routing, will be investigated, as depicted in Fig. 6.

TABLE IV
COMPARISON OF VARIANT SPECTRUM SHARING ALGORITHMS: CONVENTIONAL AND BIO-INSPIRED ALGORITHMS

Algorithm	Control Paradigm	Advantages	Disadvantages
Conventional	Centralized Control	1) Reliability 2) Fast spectrum handoff	1) Needs common control channel; 2) Lacks adaptivity to dynamic and heterogeneous environment
BIOSS [76]	Distributed Control	1) Adaptivity to dynamic radio environment; 2) Simplicity due to a distributed coordination	High probability of conflicts among CR users
e-BIOSS [78]	Distributed Control	1) Utilization of low-power channel is improved; 2) Binary learning factor enables a direct decision; 3) Conflicts among CR users is mitigated	Since channels with a minimum power excess are selected, the best available channel is likely to be wasted

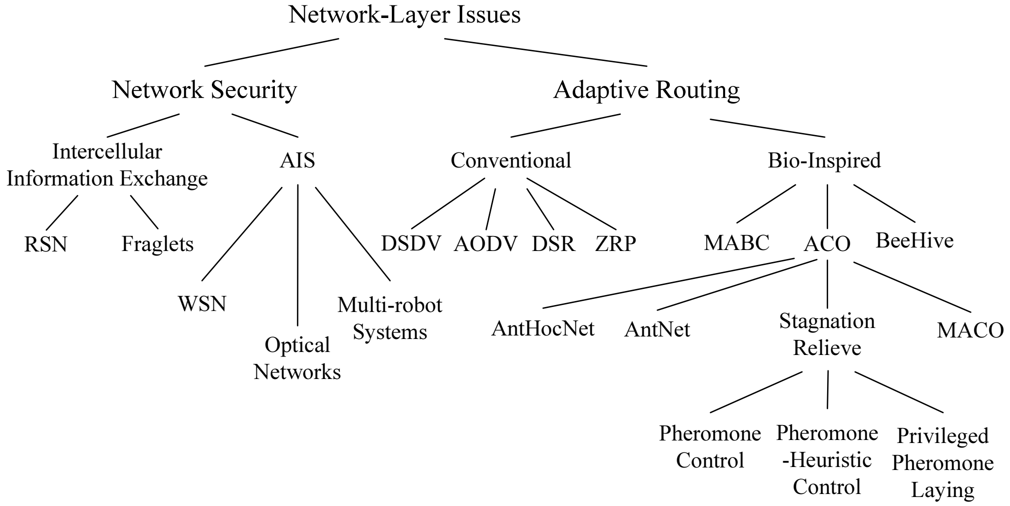

Fig. 6. Classification of the works on Network-layer issues. Acronyms: AIS-Artificial Immune System; RSN-Rule-based Sensor Network; WSN-Wireless Sensor Network; ACO-Ant Colony Optimization; MACO-Multiple Ant Colony Optimization; MABC-Multiple Ant-Bee Colony; DSDV-Destination-Sequenced Distance-Vector; AODV-Ad-hoc On demand Distance Vector; DSR-Dynamic Source Routing; ZRP-Zone Routing Protocol.

A. Network Security

Security mechanisms are critical to operating and maintaining artificial SON systems, in which the massively distributed operations and decentralized control paradigms are essentially performed [85]. Enormous security mechanisms have already been studied in various systems to combat malicious attack, node failure, and other kinds of threats [86]. Among those techniques, the most well-known bio-inspired approaches are AIS and intercellular information exchange (e.g., Molecular biology) [87].

1) AIS: The primary goal of an AIS, which is inspired by the principles and processes of the mammalian immune system, is to efficiently detect changes in the environment or deviations (non-self) from the normal system behavior in complex problems domains, and to automatically memorize these characteristics [88]. According to the given shape-space and the affinity measure, an AIS can be used efficiently for general-purpose anomaly detection. The normal behavior of a system is often characterized by a series of observations over time, and the problem of detecting novelties or anomalies can thus be viewed as finding deviations in a characteristic property in the system. The underlying concepts are outlined in Fig. 7. This feature can be applied to the domain of communications networks to perform the identification of computational viruses and network intrusions.

One of the first AISs is developed by Kephart for adaptive virus detection [89]. Based on this work, misbehavior detection and attack- or intrusion-detection systems are developed [90]. Meanwhile, a similar AIS conceptual frameworks for generic application in networking has been presented in [91]. A misbehavior detection in nature-inspired Mobile ad hoc Network (MANET) protocol called “BeeAdHoc” is proposed in [92]. An application of AIS based distributed node and rate selection in sensor networks has been proposed in [93], in which sensor networks and their capabilities (e.g., their transmission rate) are modelled as antigens and antibodies. AIS has also shown brilliant results for misbehavior detection and helps in designing and implementing the security framework in WSNs [87]. Furthermore, a bio-inspired secure autonomous routing mechanism called “BIOSARP”, which is based on

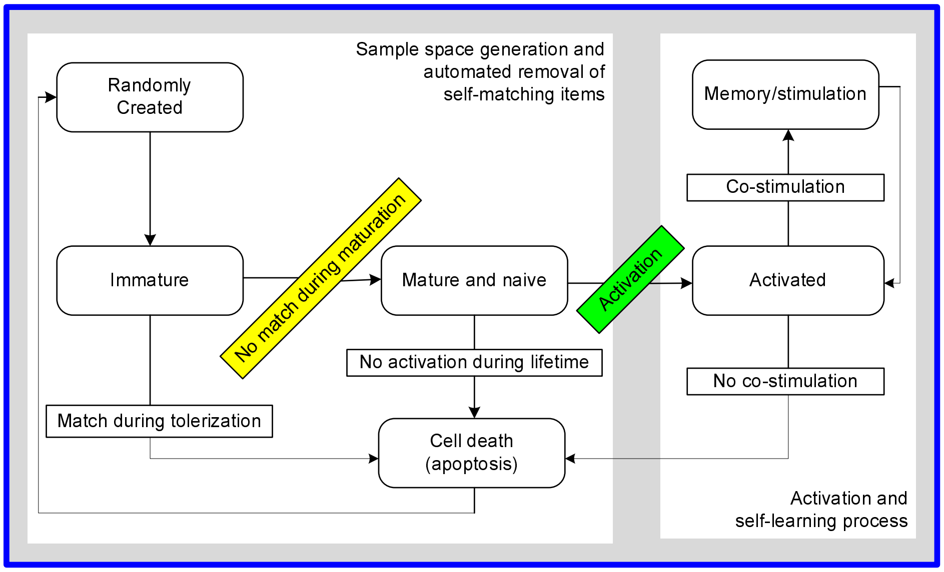

Fig. 7. Conceptual model of AIS properties, including processes of (a) sample space generation and automated removal of self-matching items, and (b) activation and self-learning [2].

ACO routing algorithm, has also been proposed for WSNs to treat the attack issues successfully [94].

Besides wireless networks, designing scalable security mechanisms is particularly critical in transparent optical networks (TONs) due to the high speeds and transparency inherent in them [95], [96]. The basic idea of TONs' security mechanism is: the desired global goals (e.g., the efficient failure management, detection and location, etc.) are first defined, followed by some local interactions and processes being developed to achieve those system-wide goals [95]. In [96], intelligence is embedded into the optical network to enable it continuously learn from different faults and attacks in a self-organized manner. In [97], a new self-organized method, as analogous to the human immunization system's primary defense mechanism, is proposed to enable the network autonomously and persistently adapt to network changes by learning newly observed vulnerabilities, while at the same time obviate the effort to exploiting already discovered ones. Furthermore, the immune-network theory can also be used to suppress or encourage multi-agent behavior [98] and for approaches such as collaborative mine detection [99]. For more AIS-based security methods, the interested readers may refer to [100], [101] for an in-depth reading.

2) Intercellular Information Exchange: Many similar structures are observed in the domain of biology and in computer networking [30], and the investigation of structure and organization of intercellular communication seems to be valuable with regard to efficient networking strategies. Signaling in biological systems occurs at multiple levels and in many shapes. Two cellular signaling techniques can be distinguished [2]: i) *Intracellular signaling* that refers to the information processing capabilities of a single cell, and ii) *Intercellular signaling*, in which communications among multiple cells is performed by intercellular signaling pathways. This subsection will mainly focus on the latter technique.

A number of approaches have been discussed using artificial signaling networks for networking applications, and most of them is targeting programming schemes for massively distributed systems such as sensor networks. For instance, the same communications mechanisms can be emulated using the Rule-based Sensor Network (RSN) approach [102], which defines the following three basic concepts: i) *data-centric operation*, i.e., each message carries all necessary information to allow this specific handling, ii) *specific reaction on received data*, i.e., a rule-based programming scheme is used to describe specific actions to be taken after the reception of particular information fragments, and iii) *simple local behavior control*, i.e., simple state machines control each node. Another approach for a metabolic execution model for communications protocols is Fraglets [103]. Similar to RSN, this model is also based on the concept of data-centric communications. Furthermore, the execution relies on the unification of code and data, featuring a single unit called fraglet that are operands as well as operators. Using the fraglet system, network-centric operations can be executed by participating nodes after reception of a specific fraglet. A simple example of a fraglets program can be found in protocols such as the confirmed-delivery protocol (CDP) [103].

3) Comparison between AIS and Intercellular Information Exchange: Investigation of AIS not only allows the development of more sophisticated technical solutions but also helps to improve the underlying theoretical models of the immune system. The scope of AIS spans a wide area of application domains such as fault and anomaly detection, data manning, agent-based systems, autonomous control, and security of information systems, etc. As compared to it, the intercellular information exchange mechanism can be exploited to perform diffuse (probabilistic) communications with specific encoding of the destination receptors for intercellular communications [2].

B. Adaptive Routing

Adaptive routing, regarded as a critical functionality of wireless self-organized networks, has already been considerably studied in the past decades. A typical scenario of building SON systems using multi-hop routing is in the wireless ad hoc network, which poses two challenges either due to its constantly changing topology or because its routing database is insufficient to support a trusted data storage [104]. Several well-known routing algorithms have been proposed to address those challenges. The existing algorithms are traditionally classified as either proactive or reactive, where in the former (e.g., Destination-Sequenced Distance-Vector routing (DSDV) [105]), nodes try to maintain at all times routes to all other nodes, but in the latter (e.g., AODV [106] or Dynamic Source Routing (DSR) [107]), nodes only gather routing information on demand. Hybrid algorithms such as Zone Routing Protocol (ZRP) [108] combine the advantages of both the proactive and reactive approaches. Besides the single-path algorithms aforementioned, some multipath routing algorithms (e.g., [109]) have also been proposed to offer an interesting alternative in terms of link robustness and load balancing capability.

However, one challenge may arise in developing routing protocols for dynamic networks: transmitting large routing table (e.g., in Routing Information Protocol - RIP) or flooding multiple copies of link-state-packets (LSPs) in Open Shortest Path First (OSPF) in short or regular intervals may incur large routing overhead, while flooding LSPs and transmitting routing table in longer intervals may result in slower responses to changes in network topology. As compared to that, using ACO algorithms for routing in dynamic network seems to be appropriate. The concentration of pheromone in ACO is used as an indicator to replace the distance or number of hops to indicate the route's preference. Since the exchange of pheromone is implicit without directly transmitting routing entries, routing overhead can thus be significantly reduced. Moreover, ant's pheromone laying can also reflect network configuration or topology changes, and this capability makes ACO more adaptive and decentralized.

A number of desirable properties, such as highly adaptive to environment changes, working in a distributed way with a high robustness, and having a capability of providing automatic load balancing, etc., are thus exhibited in the ACO algorithms to improve the quality of service (QoS) in dynamic network environments. The performance comparison between traditional routing algorithms and ACO algorithms in terms of routing information, routing overhead, adaptivity and load balancing is summarized in Table V. Variant bio-inspired routing protocols will be surveyed in follows.

1) ***ACO Mechanism****:* Following the ant-foraging principle, the ACO algorithm can be mathematically described [2], [110]. An artificial ant is typically realized as a simple program consisting of procedures that simulate the laying and sensing of pheromone, and data structures that record trip times and the nodes that it passes. Migrating from node to node, the laying of pheromone is simulated by recording in a counter the number of ants that pass a node, and by this way, the decision of an ant is influent by a function of pheromone concentration.

By employing ACO algorithm, ant based control (ABC) system was designed to solve the load balancing problem in circuit-switched networks [111], with approaches of aging, delaying and noise being adopted to mitigate stagnation. After that, some ramifications of ABC system, such as [112], were also proposed, where Subramanian et al. focused on routing in packet-switched networks, and Heusse et al. proposed a cooperative asymmetric forward (CAF) for routing in packet-switched networks with asymmetric path costs. Besides, several famous algorithms such as AntNet [113] and AntHocNet [114], have been developed for use in packet-switched networks, and the ACO-based algorithm is proven to outperform the AODV routing algorithm in terms of either packet delivery ratio or average end-to-end packet delay. Furthermore, some advanced ACO algorithms that employ multiple colonies of agents have also been proposed to further improve the network load balancing performance, as surveyed in follows.

2) ***Stagnation Relieve in ACO****:* In ACO, once an optimal path is chosen by all ants, this will consequently increase an ant's preference for choosing that optimal path. However, this strategy may also lead to *Stagnation*: i) congestion is prone to happen in this optimal path, and ii) the probability of ants selecting other paths is dramatically reduced (i.e., load balancing is degraded). In consideration of the fact that network topology and/or radio environment will always be changing, the current optimal path may become non-optimal after a while either due to congestion and/or network failure, whereas the other non-optimal paths may also become optimal due to network environment changes. Therefore, the adaptiveness of ACO must be promoted to effectively address the stagnation issues.

Several stagnation-alleviate approaches such as pheromone control, pheromone-heuristic control and privileged pheromone laying, have been proposed:

- ***Pheromone Control***: This method reduces the influences from past experience and encourages the exploration of new (or previously non-optimal) paths. For example, i) *Evaporation*, which prevents pheromone concentration in optimal paths from being excessively high and preventing ants from exploring other (new or better) alternatives [115]; and ii) *Aging*, which controls the amount of pheromone deposited for each ant, and an ant will deposit lesser and lesser pheromone as it moves from node to node [116]; and iii) *Limiting and Smoothing Pheromone*, which mitigates stagnation by limiting the amount of pheromone in every path. By placing an upper bound on the amount of pheromone for every link, the preference of an ant for optimal paths over non-optimal paths is thus reduced [117].
- ***Pheromone-Heuristic Control***: This method configures ants to make them do not solely rely on sensing pheromone for their routing preferences. This can be accomplished by configuring the probability function for an ant to choose a link using a combination of both pheromone concentration and heuristic function of parameters such as distance [117] or queue length [118].
- ***Privileged Pheromone Laying***: This method permits a selected subset of ants to have the privilege to deposit extra or more pheromone. Two issues are of interest:

TABLE V
COMPARISON BETWEEN TRADITIONAL ROUTING ALGORITHMS AND ACO ALGORITHMS

Issues	Traditional Algorithms	ACO Algorithms
Building Routing Preference	Based on Transmission time/delay	Based on Pheromone Concentration
Routing Information Exchange	Routing information and data packet are transmitted separately	Ants can be piggybacked in data packets
Adapting to Topology Changes	Low: Transmit routing table or Flood LSPs at regular intervals	High: Frequent transmission of ants
Load Balancing Capability	Low	High
Routing Overhead	High	Low
Routing Update	Update entire routing table	Update a pheromone table entry independently
Routing Control	Centralized	Decentralized
Network Scalability	Low	High
Entire Network Optimization?	No	Yes

i) the assessment of the quality of the solution of ants, ii) the number of ants to be selected to deposit extra pheromone and the amount of pheromone that ants are permitted to deposit. One of the simplest approaches to assess the quality of the solutions of ants is to compare their forward-trip times by employing a fitness-landscape (FDC) approach [117]. The other methods, such as *only a sub-set of ants deposits pheromone* [119] or *only the best ant deposits pheromone on its return trip* [117], can also be used to address the stagnation issues.

3) ***AntNet:*** Routing techniques in communications networks inspired by the foraging behavior of ants have been addressed by the AntNet approach [113], which was carried out with the aim of optimizing the performance of the entire network. The way through the network in AntNet is determined by a greedy stochastic policy according to the following steps: i) ants randomly search for food. ii) After locating the destination, the agents travel backwards on the same path used for exploration. iii) Finally, all traversed nodes are updated with the most current information about the destination node. Since the goodness of a path is reinforced according to the trip times of forward ants, the selection probabilities updated by backward ants can influence ants travelling in the forward rather than backward direction. AntNet is proven to be not restricted to routing application in networks with symmetric costs only [120]. Some enhancements of AntNet by considering real-time statistics have also been devised [121]. In [122], another ramification of AntNet is proposed, with some benefits, such as a saving of network resources, a higher anti-failure capability, and a reduction in both overhead and congestion, being brought. In addition, AntNet has also been augmented by using genetic algorithm (GA) [123], and the ant system with genetic algorithm (ASGA) [124] as well as its generalized algorithm (i.e., synthetic ecology of chemical agents (SynthECA) [125]) has been proposed to solve problems of point-to-point routing, point-to-multipoint and multipath routing, and fault location detection [126] in circuit-switched networks.

4) ***AntHocNet:*** Since AntNet may have a significant overhead due to its relying on repeated path sampling, AntHocNet [114] as an improvement of AntNet has been proposed to relieve this overhead. Both reactive and proactive components are included in AntHocNet: In a path setup phase, AntHocNet represents a reactive routing approach by setting up paths when they are needed at the start of a session, with routing paths being represented as pheromone trails to indicate their respective quality. After setting up a path, data packets are stochastically routed as datagrams over the different paths using the pheromone information. While a data session is active (i.e., during the course of the communication session), paths are proactively probed, maintained and improved. The source node will send out proactive forward ants, which follow the pheromone values in the same way as the data but have a small probability at each node of being broadcasted, according to the data sending rate. The probabilities in the routing tables of AntHocNet are calculated in a similar way to the maths presented for AntNet. Moreover, the *Hello Messages* are used to enable nodes to know about their immediate neighbors and have pheromone information about them in their routing table. A number of studies have been carried out in order to investigate the network behavior of AntHocNet. For instance, the performance comparison of AntHocNet and AODV is performed for various speed values in an ad hoc network, and shows the performance advantage of AntHocNet over AODV in terms of both the delivery ratio and the average packet delay.

5) ***BeeHive:*** Inspired by the bee colony, a well-known routing algorithm called *BeeHive* [84], which was developed by Farooq et al., has been applied in telecommunications networks with a property of load balancing being emphasized in it. The *BeeHive* algorithm not only reduces the overhead of collecting the routing information, but also helps in maintaining smaller/local routing tables, to which all the agents provide the information about the quality of the paths they traversed. All the agents launched by the same node but exploring different paths will exchange their information via the routing table, and this information exchange helps in evaluating the overall quality of paths that the launching node involves in. Similar to the observation in foraging activities of a honey bee colony [34], the node quality in the proposed algorithm is formulated as a function of proportional quality of only those neighbors that possibly lie in the path toward the destination. Once data packets arrive at a node, the routing information about the quality of that node's different neighbors for reaching their destinations is accessed, and the packets will select the next neighbor toward the destination in a stochastic manner depending upon its quality. Following this rule, not all packets follow the best paths in *BeeHive* algorithm, and this will help in improving the load balancing in the future complex networks such as 3GPP LTE [127] or heterogeneous wireless networks [128].

6) ***MACO:*** Different from the single-colony ACO algorithms aforementioned, Multiple Ant Colony Optimization (MACO) technique employs more than one colony of ants to search the optimal paths [129]. Each ant colony deposits a different type of pheromone in MACO, and one type of pheromone can only be detected by the ants lay it [129]. SynthECA [125], which enables communications and cooperation among different types of ants through the interaction of different pheromone types, can be regarded as a kind of MACO technology. MACO has also been augmented with a repulsion mechanism [130] that prevents ants from different colonies to choose the same optimal path: ants are not only attracted by the pheromones of other ants in their own colonies, but they are also repelled by the pheromones of other colonies. When only pheromone from its own colony is present, there is a higher probability that an ant will choose the path with the higher concentration of its own pheromone type. However, an ant is less likely to prefer paths with higher concentration of pheromone from other colonies due to repulsion mechanism. Since MACO enhances the adaptiveness of optimal path creation and increases the probabilities of allowing new or better paths to be exploited in a dynamic network, the load balancing in packet-switched networks can be significantly improved.

7) ***MABC:*** By combining MACO with bee colony algorithm, an improved version of MACO algorithm, i.e., Multiple Ant-Bee Colony (MABC) Optimization, is thus proposed to improve the load balancing and avoid congestion in the most optimal path at the same time [131]. The main purpose of MABC algorithm is to improve the convergence time in MACO algorithm using more accurate pheromone laying strategy. At the beginning, the algorithm uses forward ants to find a suitable solution from one node to another, and then bees are used to update the routing tables based on data collected by ants. More information must be stored in the routing tables: an $L \times N$ routing table is reserved in each node, with L representing all the outgoing links and N standing for the number of nodes minus one (the node itself). In each table entry, P_{ij} is used to denote the chance of node i to be selected as the next node on the way to node j, and T_{ij}^{k} represents the k-th dancer bee's recorded trip time. Since MABC uses several ant-bee colonies with different types of pheromone, an effort has been made to distribute the network traffic in several optimal local paths by creating several pheromone tables in each node and routing the data packets using these tables. It has been proven that the MABC outperforms MACO in terms of fault-tolerance [131].

8) ***Comparison among Variant Routing Algorithms:*** The comparison among variant bio-inspired routing algorithms is given by Table VI. As compared to the ACO-based algorithms, routing information such as propagation delay and queuing delay of the exploited paths in *BeeHive* are required to be exchanged between the launching and visited nodes so as to explore multiple paths with quality guarantee. However, this requirement will inevitably impose a heavier load burden on the routing protocol when refreshing the routing table. Evidently, MABC outperforms the other algorithms in terms of both load balancing and fault-tolerance capabilities. This fault-tolerance capability may become more critical in the future CRNs, where an ever worsening situation of spectrum scarceness may be met to worsen the dynamic of network [132]. Furthermore, new challenges may also arise in designing cognitive routing algorithms in the future complex network environments such as heterogeneous networks [133] and cognitive wireless mesh networks [134], in which the ACO algorithms with multiple colonies will exhibit big advantages over the single-colony algorithms in terms of both adaptiveness and robustness.

C. ***Remaining Challenges in Network-layer Issues***

Although bio-inspired algorithms have already exhibited enormous advantages in improving the network security, robustness, adaptiveness and load balancing capabilities, there still exist some challenges to address in the future.

- In bio-inspired security, the challenge may lie in the following issues: i) The mapping between the natural systems and the artificial representation. ii) Architectural design, whose goal is to create a system that uses a natural system as an inspiration and exhibits a type of emergent behavior, while at the same time identifies the various components of a class of models that share a common functionality. iii) New framework and theory need to be developed to help us reason about the system we create.
- Although bio-inspired security algorithms such as AIS have spanned a wide area of applications, investigating more theories and frameworks to ensure a massively distributed security will be a rather challenging topic in the future.
- Stagnation mitigation: As indicated by [135], the shortest path created by ACO is only statistical, and if by chance, many of the ants initially choose a non-optimal path, other ants are more likely to select it, leading to further reinforcement of the pheromone concentration along this non-optimal path. Even if an optimal path is created, congestion may happen in the optimal path to degrade its quality.
- Although MACO improves the load balancing capability of a dynamic network by employing more than one colony of ants, the final convergence state of MACO heavily depends on the initial path selection of each type of ants, especially if the types (and number) of ants in MACO are too few.
- In consideration of the worsening spectrum environment and an ever increasing complexity in network, developing a robust routing algorithm for heterogeneous CRNs with high capabilities of fault-tolerance, adaptiveness, load balancing and convergence will be another challenging task. Moreover, further exploiting the intelligences of variant natural colonies (e.g., that beyond ants and honey bees) and utilizing them to optimizing the routing protocols for large-scale SON systems would also be a promising topic in the future.

TABLE VI
COMPARISON AMONG ACO-BASED ROUTING ALGORITHMS

Algorithm	Category	Advantages	Disadvantages
AntNet [113]	Proactive & Multipath & One Ant Colony	1) Robust multipath routing; 2) Automatic load balancing; 3) Adaptivity	Significant overload due to repeated path sampling
AntHocNet [114]	Proactive & Reactive & Multipath & One Ant Colony	1) Overload in AntHoc due to repeat path sampling is avoided; 2) Better delivery ratio	A high average delay is observed in the simple scenarios
MACO [129]	Multiple Ant Colony	1) Congestion in the optimal path is relieved; 2) High load balancing	Initial path selection may impact its convergence
BeeHive [84]	Honey Bee Colony	1) Load balancing enabled; 2) Quality paths being created	Routing information exchange imposes an additional traffic burden
MABC [131]	Multiple Ant-Bee Colonies	1) A better Fault-tolerance capability than MACO; 2) High load balancing	Delay caused by using multiple colonies at the beginning of failure

VII. PRACTICAL APPLICATIONS AND OPEN RESEARCH ISSUES OF BIO-INSPIRED TECHNIQUES

Bio-inspired approaches are currently emerging from early research into universally applicable and carefully investigated solutions. Although the related technologies have already attracted more and more attention, their application to the artificial SON systems is still a rather new research subject. There are still very few studies that focused on systems other than wireless networks, if there were some (e.g., bio-inspired algorithms for security in optical networks [95], [96]). Although the concept of self-organization has already been extended to some heterogeneous environment (e.g., the integrated cellular and ad hoc relay (iCAR) network [136]), a solution of being universally applicable to variant SON systems is still unavailable yet. Thus, studying bio-inspired SON technologies and applying them to the future heterogeneous networks must be highlighted. The following questions are necessarily answered: what kind of bio-inspired algorithms are applicable to network control/optimization, what kind of networking problems can be addressed by using bio-inspired algorithms, and how to apply a bio-inspired algorithm to a networking problem. In the following subsections, we will summarize the presented concepts of bio-inspired networking and discuss some practical bio-inspired applications as well as open research challenges.

A. Fundamental Tradeoffs in Bio-Inspired Paradigms

As already known from surveys aforementioned, three tradeoffs may be met in designing bio-inspired algorithms: i) *Tradeoff between local rule and global optimization*: although complex behaviors can also be achieved in artificial SON systems on the basis of local rules, they may not necessarily lead to an optimum solution to the systems [2]. ii) *Tradeoff between the scalability and controllability of an artificial system*: predictability of the system behavior must be reduced for a self-organized system, and a fundamental tradeoff arises between the system's controllability and scalability [2]. A new theory of distributed self-control and self-management is therefore required to pave the way toward the controllable self-organized system with a high scalability. iii) *Tradeoff among availability, consistency and reliability of control information*: in order to minimize human intervention, the control decisions as well as data measurement/probing/processing should be operated autonomously and with a high reliability [137]. Therefore, a tradeoff between the optimality of SON methods and the signaling cost in performing data processing should be addressed.

Besides the aforementioned tradeoff, conflicting objectives may be pursued by different bio-inspired solutions. For instance, in a cellular system, having a small number of base stations operating near full capacity is more beneficial than the even-load solution from the perspective of total power saving [138], but that paradigm is obviously against the principle of load balancing. In view of the fact that self-organized solutions for the future heterogeneous networks are usually multi-objective problems, effectively mitigating the conflicts is critical to propel the practical applications of bio-inspired approaches.

B. Self-X Capabilities in Cellular Systems

1) SON Capabilities in 3GPP LTE: As the rapid development of SON technologies, their applications in cellular mobile networks have been promoted by 3GPP [139] and Next Generation Mobile Networks (NGMN) [140]. Many research projects, such as the SOCRATES project [141], 4WARD project [142], E3 project [143], and FUTON [144] in Europe, have been founded to develop critical SON technologies. Three main SON capabilities, including self-configuration, self-optimization and self-healing, have been emphasized in 3GPP LTE systems [3]. Self-configuration is a process with the newly deployed eNodeBs being configured by automatic installation procedures to get basic parameters and download necessary software for operation. Self-optimization techniques, which enable a mobile network to adaptively optimize their algorithms and system parameters to achieve optimal system performance (in terms of, e.g., capacity, service coverage, etc.) in the presence of environment changes, are crucial for the operation and maintenance of mobile networks. Self-healing, regarded as an event-driven process and aiming to resolve the loss of coverage or capacity once a cell/site failure happens, is necessary to assist operators in recovering a collapsed network.

2) Bio-Inspired Techniques for Self-Organization and Self-Healing: Bio-inspired techniques can be applied to reconfigurable hardware cell architecture, with capabilities of self-organization and self-healing being supported [145]. Those capabilities come from two fundamental biological processes, i.e., fertilization-to-birth and cell self-healing, as enabled by Deoxyribonucleic acid (DNA). In the former process, a new organism is created through cell replication and differentiation, and in the latter, a dead cell is replaced with a new one of the same kind. By employing those self-organizing processes to hardware design, it allows individual components of the system to configure and repair themselves. A new platform based on the electronic DNA (eDNA) can thus be developed to enable a reconfigurable hardware cell architecture. The mechanism aforementioned may play an important role in improving the SON capabilities of 3GPP LTE, with some concrete performance measures, such as a fast self-configuration, a hardware-level self-healing, and a high fault-tolerance capability, etc., being obtained [145].

C. Applications of Bio-inspired Techniques in Heterogeneous Network

Since multiple types of cells (including macro, micro, pico, femto, etc.) will coexist in the future heterogeneous networks (HetNets), an ever increasing number of parameters need to be managed and optimized. Besides, in consideration of the spectrum scarceness we meet today [82], proposing cost-efficient SON methods to improve the spectral efficiency and reduce the operational cost at the same time would be a critical but challenging topic for future cognitive HetNets. Bio-inspired techniques are promising to improve performance of HetNets in terms of radio coverage, channel capacity, throughput, CAPEX/OPEX, etc., via methods such as radio range extension and dynamic resource reservation/load balancing across base stations [146].

1) Link Quality Estimation: In order to develop an efficient SON system, link qualities of next-hop relays must be estimated with a high reliability to facilitate a robust multi-hop routing. In order to mitigate the poor performances observed in conventional static link-quality aware routing metrics that adopt simple estimators based on moving average filters, bio-inspired estimator based on the neural network paradigm can be utilized to improve the link-quality estimation [147]. The neural network paradigm assures the ability to learn from the environments in unsupervised mode, and thus exhibits an effectiveness in applying to heterogeneous SON systems such as wireless mesh networks, with low-power devices being implemented. It has been proven that the proposed bio-inspired method outperforms the conventional algorithms such as the Simple Moving Average (SMA) and the Exponentially Weighted Moving Average (EWMA) in terms of both packet delivery ratio and routing hop count.

2) Distributed Beamforming: In order to address the challenges raised in the conventional beamforming techniques such as requiring a priori channel knowledge at transmitters, high-complexity in distributed beamforming with a single bit feedback, and limited adaptivity to the environmental variations, etc., bio-inspired approaches have been proposed to achieve some breakthrough. A bio-inspired robust adaptive random search algorithm (BioRARSA) is proposed to enable a convergence time scales linearly with the number of distributed transmitters, as inspired by a heuristic random search mechanism that mimics the foraging behavior of E. Coli bacteria [148]. Since the convergence time of BioRARSA is insensitive to the initial sampling step-size of the algorithm, it exhibits a robustness against all initial parameters and the dynamic nature of distributed HetNets. It has been proven that the proposed BioRARSA outperforms existing adaptive distributed beamforming schemes by 29.8% on average [149].

3) Relay Placement: In view of the fact that the wireless network may sometimes suffer a large-scale damage and would thus create multiple disjoint partitions, this kind of damage can be recovered by placing relay nodes at proper geographical position to reestablish wireless connectivity between isolated nodes. For instance, in a hierarchical cooperative relay-based heterogeneous network such as 3GPP LTE, cooperative relay nodes are usually deployed to provide a coverage extension based on the convergence of heterogeneous radio networks [136]. Besides, some advanced cooperative technologies such as Coordinated Multipoint Transmission/reception (CoMP) have been chosen as one of the candidate techniques for 3GPP LTE-Advanced to increase the average cell throughput and cell edge users' spectral efficiency in both the uplink and downlink transmissions [150].

Although a plethora of studies on cooperative relay has been carried out, obtaining a cost-effective solution in HetNet is still not an easy job. As inspired by a spider web, a new bio-inspired approach is proposed to establish a spider-web-like topology to enable the segments to be situated at the perimeter [151]. Compared to the approaches using a minimum spanning tree, the proposed spider-web-like topology exhibits a stronger connectivity and enables a better load balancing capability among relays simultaneously. As the requirement of green communications, emerging technologies such as small cells will play an important role than ever, and a specific relay-placement solution must be provided to facilitate a better spectrum utilization and against the ever increasing interference due to a denser relay deployment. Bio-inspired approaches, featuring adaptivity, low complexity, robustness and load balancing, etc., can thus be utilized to optimize the problem of dense relay placement.

4) Networking for Pervasive Communications: One of the major trends in the field of communication and computing is related to the arising of pervasive communication/computing environments characterized by an extremely large number of embedded devices, and conventional networking approaches seem unsuitable for scenarios of heterogeneity, scalability and complexity. A new framework needs to be defined to provide stable operations and service management functionalities in a fully distributed and decentralized way. A new bio-inspired approach called BIONETS is proposed to enhance the system performance in terms of scalability, robustness and efficiency [152]. In BIONETS, a network looks like a living ecosystem, where services play the role of organisms, evolving and combining themselves to successfully adapt to the dynamic environment. A new network architecture called service-oriented communication system (SOCS), which builds upon a disconnected topology and aims at achieving network scalability through the introduction of a communication paradigm based on localized opportunistic interactions among neighboring nodes, is also proposed. By exploiting the node mobility, information can be conveyed among the different islands of connected nodes. Numerical results show that the proposed model works well in a large-scale relaying network implementing IEEE 802.11b-compliant PHY and MAC-layer protocols.

D. Cognitive M2M Self-Optimization

1) Current Progress of M2M Technology: Different from human-to-human (H2H) communication, the objective of M2M communication is to increase the level of system automation in which devices and systems can exchange/share data with no or little human intervention. In the past years, the emergence of wireless communication systems, such as General Packet Radio Service (GPRS), in the Internet has become the premise for the advance of M2M communication [153]. Since M2M communication over cellular networks poses significant challenges as a result of the large number of devices, small data transmissions and a wide range of applications, the advanced cellular network technologies such as LTE/LTE-Advanced should efficiently cater to M2M communication. Besides, the increase in signaling overhead and diverse QoS requirements consequently calls for the development of high-performance scheduling algorithms in M2M LTE systems [154]. Moreover, hierarchical cooperative relay nodes can be deployed to provide a cost-effective coverage extension for heterogeneous radio networks, with some advanced technologies such as adaptive modulation and hierarchical RRM [155], mobility management and CR [156], being enabled in a self-organization manner [136].

2) Typical M2M Applications: M2M communication can be used in many applications. Smart grid, regarded as a typical M2M technology that enables utility providers to connect to their grid assets via wireless connections, improves the wireless monitoring capability of interactive utility networks with a property of more intelligent, resilient, reliable, and self-balancing [157]. Several M2M-enabled techniques have been proposed. In [153], the network architecture for home energy management system (HEMS) in the smart grid is introduced, with a dynamic programming algorithm being proposed to solve the problem of optimal HEMS traffic concentration. In [158], a new cognitive M2M (CM2M) communication paradigm is proposed to enhance the flexibility, efficiency and reliability of M2M communication, with the potentials of CM2M for the smart grid in variant networks being presented. CM2M system coexistence in TV White Spaces (TVWS) will become a new research challenge due to the requirements on fair and efficient spectrum sharing among heterogeneous users [158].

3) Bio-Inspired Resource Discovery/Scheduling mechanism for M2M: A bio-inspired resource discovery mechanism, in which information is provided by ant-based lightweight mobile agents travelling across a grid network and collecting data from each visited node, is proposed to address issues associated with grid scheduling upon dynamically discovered information [159]. Different policies, such as diverse ant colonies and different resource discovery approaches, are employed, and a more convenient and efficient resource discovery operation in the following time can be facilitated by utilizing already discovered and stored grid node's metadata snapshots in the past. Since the discovered information for each specific task is not simply discarded in the proposed scheme, an intelligent scheduling can be provided for the scope of serving the grid community as a whole rather than just for a single grid node. Ant-based resource discovery can thus be extended across diverse bounded grid communities in a manner which would enhance its current functionality and maintain its robustness, reliability and efficiency simultaneously [159].

Besides information discovery and grid scheduling, some other functionalities such as load balancing in the large-scale M2M networks can also be improved by using bio-inspired algorithms, with nodes self-organizing themselves as virtual clusters and efficiently balancing service requests among them [160]. Typical benefits of bio-inspired self-organization, such as high scalability, and the resilience to dynamism and unexpected system behavior, have been inherited by the proposed load-balancing scheme.

E. Cross-Layer Design for Multi-hop Routing, Network Security and Channel Access

Although swarm intelligence inspired algorithms can be largely categorized in terms OSI-layer functionalities (as discussed in Sections IV, V and VI), some functionalities may not necessarily specified by a single protocol layer. For instance, adaptive routing is usually regarded as a network-layer issue, however, physical- and MAC-layer parameters such as channel attenuation and interference may also play an important role in the routing optimization in a dynamic wireless environment. A cross-layer design may thus outperform the conventional single-layer solutions in terms of various parameters such as network lifetime, packet loss rate and load balancing capability.

1) Multi-hop Routing: As inspired by the organized and collaborative behavior of ants, a cross-layer routing protocol called LF-Ant is proposed for multi-hop WSNs [161]. At the network layer, the heuristic information is modelled by a fuzzy inference system to assist a cluster-head election and the routing process, with the fuzzy heuristic information dealing with measurements uncertainties of wireless channels to enhance the traditional ACO usage. At link and physical layers, a resultant relaying threshold is combined with an adaptive invoking of cooperative modulation diversity, and the vice cluster-head entity (i.e., the relay candidate) is proposed to support the cooperation of nodes, and to reduce the number of required retransmissions in the Automatic Repeat-reQuest (ARQ) system simultaneously. As compared to the conventional cross-layer protocols such as Low-Energy Adaptive Clustering Hierarchy (LEACH) [162], LF-Ant increases the network lifetime and decreases the packet loss rate simultaneously due to multiple parameters, such as residual energy, quality and consumption of previous transmissions, being taken into account by the functionality of bio-inspired cluster-head election.

2) Intrusion Detection: The cross-layer approach also suggests applying a bio-inspired evolutionary computational method to the functions of each protocol layer to improve the intrusion detection identification (IDID) performance of wireless networks. In [163], a cross-layer design, embedding genetic algorithms at the physical layer, anti-phase synchronization at the MAC layer, ant colony optimization at the network layer, and a trust model based on quantized data reputation at the application layer, is constructed. A two-stage algorithm, which detects network intrusions and then identifies the attack types, is implemented in IDID to overcome the problems of large sensor data loads and resource restrictions. Although IDID is primarily applied to intrusion attacks along WSN routes, this cross-layer approach does not rely on any particular protocol and can readily be extended to wider applications.

3) Next-Hop Selection and Channel Access in Sensor and Vehicular Actor Networks: Several challenges, including energy efficiency, timely channel access, reliable sensor-actor communication, autonomic operation, and cooperative control of actor nodes, are met in wireless sensor and actor networks (WSANs). Bio-inspired approaches may provide an ideal solution to the problems aforementioned. Inspired by the prey model in foraging theory, the BIO-inspired Cross-layer (BIOX) communication and coordination protocol is proposed for WSANs to permit each sensor node to autonomously determine its next-hop selection and channel access strategy [164]. The possible next-hop and available time slots of each sensor node are considered as prey in BIOX, and the available tasks are thus considered as prey types that are searched and performed by the actor nodes. Besides, the aim of channel access profitability is to allow each sensor node to obtain a sufficient level of packet transmission rate by regulating its channel access persistence. Since BIOX is a unified algorithm that incorporates MAC, routing, and transport layer functionalities to enable a energy-efficient channel access, this feature renders BIOX a robust and energy-efficient protocol for the realization of future WSANs applications. Besides the prey model, the marginal value theorem in behavioral ecology and biological division of labor phenomenon can also be employed to develop autonomous communication and coordination techniques for WSANs. The interested readers may refer to [165] for details.

F. Dynamic Resource Allocation

In a heterogeneous environment comprising cellular, Wireless Fidelity (wifi) and Worldwide Interoperability for Microwave Access (WiMax), etc., it is necessary for a node to dynamically choose a wireless network resource to support applications taking into account the channel condition, networking environment and QoS requirements of applications. In light of the inherent limitations in conventional centralized resource allocation approaches, which require nodes to frequently exchange messages to refresh information about the current network status, adaptive and autonomous resource allocation may play a more and more important role in future heterogeneous environment, with individual nodes behaving in a cooperative manner through local interactions (i.e., self-organization is characterized) [166].

1) Bio-Inspired OFDMA Subcarrier Allocation: One important challenge in management of Orthogonal Frequency Division Multiple Access(OFDMA) is to perform optimal subcarrier allocation without a centralized control. A distributed allocation technique inspired by swarm intelligence can allocate subcarriers between individual users in a cost-effective manner [167]. Particle Swarm Optimization (PSO) [168], regarded as an evolutionary algorithm concept and orients itself on the information exchange of a swarm of birds, fishes, or insects, may provide a possible solution of the optimal OFDMA subcarrier allocation problem. It has been proven that control parameters for learning and forgetting capabilities may have an impact on the performance of the proposed subcarrier allocation. In consideration of the fact that SON capabilities are more and more emphasized in wireless communications systems, bio-inspired approaches will consequently play a critical role in providing a cost-effective way to optimizing subcarrier allocation.

2) Bio-Inspired Dynamic Radio Access in Cognitive Networks: Based on a social foraging swarm model, the radio access and resource allocation mechanism in cognitive networks can emulate the motion of a swarm of birds searching for food, and thus enable the bio-inspired network cooperatively estimates the interference profile and allocates resources through purely decentralized mechanisms [169]. The main idea of the proposed bio-inspired algorithm is: *the occupied zones in the resource domain is regarded as dangerous regions that must be avoided by the swarm individuals as fast as possible, while idle bands represent regions rich of food that the agents have to occupy. The swarm mechanism includes an attraction force and a repulsion force, with the former being useful to minimize the spread over the resource domain, and the latter being useful to avoid collisions among swarm members.* The movement of the resources in the resource domain is guided by diffusion adaptation, which estimates and learns the interference profile through local cooperation, and the resultant network is thus able to learn and adapt its behavior to the varying environment in real-time and without the need for a centralized control. Since every node interacts only with a few neighbors without a full connectivity in the proposed bio-inspired model, the spatial reuse of radio resources can be significantly improved.

Bio-inspired mechanism aforementioned can be effectively employed in practical systems such as femtocells to optimize the resource allocation with QoS constraint. Besides, since the bio-inspired mechanism has already been endowed powerful learning and adaptation capabilities, its applications can be further extended to broader fields such as distributed power control, adaptive modulation and coding, etc., of the future communication networks.

G. Power Control and Energy Saving

Electricity consumers such as data centers, server farms, and telecommunication networks (especially wireless access networks) make up a large fraction of the total global energy demand today [170]. Bio-inspired approach may provide an ideal solution to power saving problems. As observed in termites' building-nest activity, individuals place building material probabilistically, initially at random. Through a process known as stigmergy, building material tends to pile up in regions where their density is already higher [171]. By making an analogy, i.e., the clients (such as mobile phones, wireless computers, etc.) are the building materials, and the servers (such as base stations, wireless access points, etc.) are the potential building sites, a client that finds itself covered by more than one server can become the object of a contest between them, and the process follows the "rich get richer" paradigm can thus result in some servers becoming redundant [138]. Evidently, having a small number of servers operating near full capacity while keeping other servers in idle with a lower power is more beneficial than distributing the load evenly over a larger population from the perspective of total power saving. For instance, in the scenarios of cellular or wifi networks, decreasing the number of transceivers actively involved in providing coverage for all mobile clients can reduce the network's aggregated power demand. This bio-inspired power-saving functionality has already been provided by most standards such as Universal Mobile Telecommunications System (UMTS) [172].

VIII. CONCLUSIONS

We have investigate the fundamental SON challenges and the current status of research efforts to address them from the perspective of bio-inspired solutions, including critical issues in terms of physical-layer (i.e., network synchronization), MAC-layer (including cooperation, division of labor, and load balancing) and network-layer (including network security and adaptive routing) functionalities. In each topic, we present survey and comparison of variant algorithms to exhibit their advantages and disadvantages. It shows that the bio-inspired mechanism is indeed a powerful source of innovative networking paradigm for artificial SON systems. Bio-inspired techniques have already been applied to several practical systems to address critical issues such as distributed beamforming, relay placement, dynamic resource scheduling and allocation, cross-layer design, and power control, etc. In spite of this, the bio-inspired study in artificial SON systems is still quite young, and there still remain significantly challenging tasks for the research community to address for the realization of many existing and most of the emerging heterogeneous network architectures. With this regard, some open research questions that need to be addressed were outlined. Being aware of the ever increasing complexity, heterogeneity, and dynamics of communications networks, proposing more bio-inspired methods that are universally applicable to variant network environments will still be a challenging task in the future.

ACKNOWLEDGMENT

The authors would like to acknowledge the editor and anonymous reviewers for their critical comments, which greatly improved this paper.

REFERENCES

[1] A. Khandekar, N. Bhushan, T. Ji, and V. Vanghi, "LTE-Advanced: Heterogeneous networks," in *Wireless Conference (EW), 2010 European*, 2010, pp. 978–982.

[2] F. Dressler, *Self-Organization in Sensor and Actor Networks*. Wiley, 2007.

[3] S. Hämäläinen, H. Sanneck, and C. Sartori, *LTE Self-organizing Networks (SON): Network Management Automation for Operational Efficiency*. Wiley-Blackwell, 2011.

[4] C. Prehofer and C. Bettstetter, "Self-Organization in Communication Networks: Principles and Design Paradigms," *IEEE Commun. Mag.*, vol. 43, no. 7, pp. 78–85, July 2005.

[5] F. Dressler and O. Akan, "Bio-inspired networking: from theory to practice," *IEEE Commun. Mag.*, vol. 48, no. 11, pp. 176–183, 2010.

[6] F. Dressler and O. Akan, "A Survey on Bio-inspired Networking," *Elsevier Computer Networks*, vol. 54, no. 6, pp. 881–900, 2010.

[7] S. Dixit, E. Yanmaz, and O. K. Tonguz, "On the Design of Self-Organized Cellular Wireless Networks," *IEEE Commun. Mag.*, vol. 43, no. 7, pp. 86–93, July 2005.

[8] E. Bonabeau, M. Dorigo, and G. Theraulaz, *Swarm Intelligence: From Natural to Artificial Systems*. Oxford University Press, 1999.

[9] M. Dorigo, M. Birattari, and T. Stutzle, "Ant Colony Optimization - Artificial Ants as a Computational Intelligence Technique," *IEEE Comput. Intell. Mag.*, vol. 1, no. 4, pp. 28–39, 2006.

[10] M. Goyal, W. Xie, H. Hosseini, and Y. Bashir, "AntSens: An Ant Routing Protocol for Large Scale Wireless Sensor Networks," in *2010 International Conference on Broadband, Wireless Computing, Communication and Applications (BWCCA)*, Nov. 2010, pp. 41–48.

[11] Z. Kuang, "An Multicast Routing Based on Ant Colony Optimization Algorithm for DTN," in *2010 Fourth International Conference on Genetic and Evolutionary Computing (ICGEC)*, Dec. 2010, pp. 354–357.

[12] J. Elson, L. Girod, , and D. Estrin, "Fine-grained network time synchronization using reference broadcasts," in *the 5th Symp. Operating Syst. Design, Implement. (OSDI)*, Dec. 2002.

[13] J. Buck and E. Buck, "Synchronous fireflies," *Scientific Amer.*, vol. 234, pp. 74–85, 1976.

[14] R. E. Mirollo and S. H. Strogatz, "Synchronization of pulse-coupled biological oscillators," *SIAM J. Appl. Math.*, vol. 50, no. 6, pp. 1645–1662, Dec. 1990.

[15] V. Arshinov and C. Fuchs, *Causality, Emergence, Self-Organisation*. NIA-Priroda, 2003.

[16] B. Edmonds, *What is Complexity? - The Philosophy of Complexity per se with Application to Some Examples in Evolution. In: Heylighen, F./Aerts, D. (Eds.) (1997) The Evolution of Complexity.* Dordrecht. Kluwer, 1999.

[17] J. Collier, *Self-Organisation, Individuation and Identity*, 2004.

[18] C. S. R. Murthy and B. S. Manoj, *Ad Hoc Wireless Networks*. Upper Saddle River, NJ: Prentice Hall PTR, 2004.

[19] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," *Comp. Net.*, vol. 38, pp. 393–422, 2002.

[20] J. G. Andrews, H. Claussen, M. Dohler, S. Rangan, and M. C. Reed, "Femtocells: Past, Present, and Future," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 3, pp. 497–508, 2012.

[21] 3GPP, "Evolved Universal Terrestrial Radio Access (E-UTRA) and Evolved Universal Terrestrial Radio Access Network (E-UTRAN), Overall Description, Stage 2, Release 8," *TS 36.300 v.8.8.0*, 2009.

[22] A. Eisenblatter, U. Turke, and C. Schmelz, "Self-Configuration in LTE Radio Networks: Automatic Generation of eNodeB Parameters," in *Vehicular Technology Conference (VTC Spring), 2011 IEEE 73rd*, 2011, pp. 1–3.

[23] H. Hu, J. Zhang, X. Zheng, Y. Yang, and P. Wu, "Self-Configuration and Self-Optimization for LTE Networks," *IEEE Commun. Mag.*, vol. 48, no. 2, pp. 94–100, Feb. 2010.

[24] M. Dottling, A. Osseiran, and W. Mohr, *Radio Technologies and Concepts for IMT-Advanced*. Wiley & Sons, Chichester, UK, 2009.

[25] A. S. Tanenbaum and M. V. Steen, *Distributed Systems: Principles and Paradigms (2nd Edition)*. Prentice Hall, 2006.

[26] L. N. D. Castro, *Fundamentals of Natural Computing: Basic Concepts, Algorithms, and Applications*. Chapman & Hall/CRC, 2006.

[27] S. K. Das, N. Banerjee, and A. Roy, *Solving Optimization Problems in Wireless Networks Using Genetic Algorithms In Handbook of Bioinspired Algorithms and Applications (ed. Olariu S, Zomaya AY and Olariu O)*. CRC Press, 2006.

[28] C. M. Bishop, *Neural Networks for Pattern Recognition, publisher=Oxford University Press, year=1996.*

[29] J.-Y. Le Boudec and S. Sarafijanovic, "An Artificial Immune System Approach to Misbehavior Detection in Mobile Ad-Hoc Networks," in *First International Workshop on Biologically Inspired Approaches to Advanced Information Technology (Bio-ADIT2004)*, Lausanne, Switzerland, pp. 96–111.

[30] F. Dressler and B. Kruger, "Cell Biology as a Key to Computer Networking," in *German Conference on Bioinformatics 2004 (GCB' 04)*, Poster Session, Bielefeld, Germany, 2004.

[31] J.-L. Deneubourg, S. Aron, S. Goss, and J. M. Pasteels, "The Self-Organizing Exploratory Pattern of the Argentine Ant," *J. lnsect Behav.*, vol. 3, no. 2, pp. 159–168, 1990.

[32] F. Ducatelle, G. D. Caro, and L. M. Gambardella, "Using ant agents to combine reactive and proactive strategies for routing in mobile ad hoc networks," *International Journal of Computational Intelligence and Applications*, vol. 5, no. 2, pp. 169–184, 2005.

[33] R. GhasemAghaei, A. Rahman, W. Gueaieb, and A. El Saddik, "Ant Colony-Based Reinforcement Learning Algorithm for Routing in Wireless Sensor Networks," in *2007 IEEE Instrumentation and Measurement Technology Conference Proceedings (IMTC 2007)*, May 2007, pp. 1–6.

[34] T. D. Seeley and W. F. Towne, "Tactics of dance choice in honey bees: Do foragers compare dances?" *Behav. Ecol. Sociobiol.*, vol. 30, pp. 59–69, 1992.

[35] S. Barbarossa, "Self-organizing sensor networks with information propagation based on mutual coupling of dynamic systems," in *Proc. IWWAN'05*, London, UK, May 2005, pp. 1–6.

[36] J. Mannermaa, K. Kalliomaki, T. Mansten, and S. Turunen, "Timing performance of various GPS receivers," in *Proc. Joint Meeting Eur. Freq. Time Forum and IEEE Int. Freq. Control Symp.*, Apr. 1999, pp. 287–290.

[37] D. L. Mills, "Internet time synchronization: The network time protocol," *IEEE Trans. Commun.*, vol. 39, no. 10, pp. 1482–1493, Oct. 1991.

[38] S. Ganeriwal, R. Kumar, S. Adlakha, and M. B. Srivastava, "Network-wide time synchronization in sensor networks," *NESL, Tech. Rep.*, 2003.

[39] Z. Zhang, W. Jiang, H. Zhou, Y. Liu, and J. Gao, "High accuracy frequency offset correction with adjustable acquisition range in OFDM systems," *IEEE Trans. Wireless Commun.*, vol. 4, no. 1, pp. 228–237, Jan. 2005.

[40] Z. Zhang, M. Zhao, H. Zhou, Y. Liu, and J. Gao, "Frequency offset estimation with fast acquisition in OFDM system," *IEEE Commun. Lett.*, vol. 8, no. 3, pp. 171–173, Mar. 2004.

[41] A. Laourine, A. Stephenne, and S. Affes, "A new OFDM synchronization symbol for carrier frequency offset estimation," *IEEE Signal Process. Lett.*, vol. 14, no. 5, pp. 321–324, May 2007.

[42] Z. Zhang, K. Long, M. Zhao, and Y. Liu, "Joint frame synchronization and frequency offset estimation in OFDM systems," *IEEE Trans. Broadcast.*, vol. 51, no. 3, pp. 389–394, Sept. 2005.

[43] A. Winfree, "Biological rhythms and the behavior of populations of coupled oscillators," *J. Theor Biol.*, vol. 16, no. 1, pp. 15–42, July 1967.

[44] C. S. Peskin, "Mathematical Aspects of Heart Physiology," *Courant Institute of mathematical Sciences, New York University*, pp. 268–278, 1975.

[45] L. Glass and M. C. Mackey, "A simple model for phase locking of biological oscillators," *J. Math. Biol.*, vol. 7, pp. 339–352, 1979.

[46] U. Ernst, K. Pawelzik, and T. Geisel, "Synchronization induced by temporal delays in pulse-coupled oscillators," *Phys. Rev. Lett.*, vol. 74, no. 9, pp. 1570–1573, Feb. 1995.

[47] Y.-W. Hong and A. Scaglione, "Time synchronization and reach-back communications with pulse-coupled oscillators for UWB wireless ad hoc networks," in *Proc. IEEE Conference on Ultra Wideband Systems and Technologies*, Nov. 2003, pp. 90–194.

[48] ——, "A Scalable Synchronization Protocol for Large Scale Sensor Networks and Its Applications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 5, pp. 1085–1099, May 2005.

[49] G. Werner-Allen, G. Tewari, A. Patel, M. Welsh, and R. Nagpal, "Firefly-inspired sensor network synchronicity with realistic radio effects," in *Proc. SenSys*, Nov. 2005.

[50] A. Tyrrell, G. Auer, and C. Bettstetter, "Fireflies as Role Models for Synchronization in Ad Hoc Networks," in *Proc. 1st Bio-Inspired Models of Network, Information and Computing Systems*, Dec. 2006, pp. 1–7.

[51] U. Ernst, K. Pawelzik, and T. Geisel, "Delay-induced multistable synchronization of biological oscillators," *Phy. Rev. E*, vol. 57, no. 2, pp. 2150–2162, Feb. 1998.

[52] L. F. Abbott, "A network of oscillators," *J. Phys. A, Math. Gen.*, vol. 23, pp. 3835–3859, 1990.

[53] K. Konishi and H. Kokame, "Synchronization of pulse-coupled oscillators with a refractory period and frequency distribution for a wireless sensor network," *Chaos*, vol. 18, no. 3, 2006.

[54] E. Izhikevich, "Weakly pulse-coupled oscillators, FM interactions, synchronization, and oscillatory associative memory," *IEEE Trans. Neural Netw.*, vol. 10, 1999.

[55] Z. An, H. Zhu, X. Li, C. Xu, Y. Xu, and X. Li, "Nonidentical linear pulse-coupled oscillators model with application to time synchronization in wireless sensor networks," *IEEE Trans. Ind. Electron.*, vol. 58, no. 6, pp. 2205–2215, 2011.

[56] A.-S. Hu and S. D. Servetto, "On the scalability of cooperative time synchronization in pulse-connected networks," *IEEE Trans. Ind. Electron.*, vol. 14, no. 6, pp. 2725–2748, 2006.

[57] G. A. Puerta, E. A. Aguirre, and M. A. Alzate, "Effects of topology and mobility in bio-inspired synchronization of mobile ad hoc networks," in *2010 IEEE Latin-American Conference on Communications (LATINCOM). Topic(s): Communication, Networking & Broadcasting; Computing & Processing (Hardware/Software)*, 2010, pp. 1–6.

[58] F. Nunez, Y. Wang, and F. J. D. III, "Bio-inspired hybrid control of pulse-coupled oscillators and application to synchronization of a wireless network," in *Proc. 2012 American Control Conference*, 2012, pp. 2818–2823.

[59] F. Nunez, Y. Wang, S. Desai, G. Cakiades, and F. Doyle, "Bio-inspired synchronization of wireless sensor networks for acoustic event detection systems," in *International IEEE Symposium on Precision Clock Synchronization for Measurement Control and Communication (ISPCS)*, 2012, pp. 1–6.

[60] T. J. Walker, "Acoustic Synchrony: Two Mechanisms in the Snowy Tree Cricket," *Science*, vol. 166, pp. 891–894, Nov. 1969.

[61] I. Akyildiz, X. Wang, and W. Wang, "Wireless mesh networks: a survey," *Comp. Net.*, vol. 47, no. 4, pp. 445–487, Mar. 2005.

[62] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "A Survey on Spectrum Management in Cognitive Radio Networks," *IEEE Commun. Mag.*, vol. 46, no. 4, pp. 40–48, Apr. 2008.

[63] Z. Zhang, K. Long, and J. Wang, "Self-Organization Paradigms and Optimization Approaches for Cognitive Radio Technologies: A Survey," *IEEE Wireless Commun. Mag.*, Apr. 2013.

[64] W. Zhuang and M. Ismail, "Cooperation in wireless communication networks," *IEEE Wireless Commun.*, vol. 19, no. 2, pp. 10–20, Apr. 2012.

[65] S. K. Robson and J. F. A. Traniello, "Resource Assesment, Recruitment Behavior, and Organization of Cooperative Prey Retrieval in the Ant *formica schaufussi* (Hymenoptera: Formicidae)," *J. Insect Behav.*, vol. 11, pp. 1–22, 1998.

[66] F. Mondada, E. Franzi, and P. lenne, "Mobile Robot Miniaturization: A Tool for Investigation in Control Algorithms," in *Proceedings of the Third International Symposium on Experimental Robotics (ISER'93)*, 1993, pp. 501–513.

[67] K. H. Low, W. K. Leow, and M. H. Ang, "Autonomic mobile sensor network with self-coordinated task allocation and execution ," *IEEE Trans. Syst. Man, Cybern. A, Sys. Humans*, vol. 36, no. 3, pp. 315–327, May 2006.

[68] A. M. Glass, R. L. Brewster, and N. K. Abdulaziz, "Modelling of CSMA/CA protocol by simulation," *Electr. Lett.*, vol. 24, no. 11, pp. 692–694, 1988.

[69] J. Barcelo, H. Inaltekin, and B. Bellalta, "Obey or Play: Asymptotic Equivalence of Slotted Aloha with a Game Theoretic Contention Model," *IEEE Commun. Lett.*, vol. 15, no. 6, pp. 623–625, June 2011.

[70] L. Guo, J. Cao, H. Yu, and L. Li, "Path-based routing provisioning with mixed shared protection in WDM mesh networks," *J. Lightwave Tech.*, vol. 24, no. 3, pp. 1129–1141, Mar. 2006.

[71] L. Guo, , and L. Li, "A novel survivable routing algorithm with partial shared-risk link groups (SRLG)-disjoint protection based on differentiated reliability constraints in WDM optical mesh networks," *J. Lightwave Tech.*, vol. 25, no. 6, pp. 1410–1415, June 2007.

[72] L. Guo, "Lssp: A novel local segment-shared protection for multi-domain optical mesh networks," *Comp. Commun.*, vol. 30, no. 8, pp. 1794–1801, June 2007.

[73] L. Guo, L. Li, H. Yu, and J. Cao, "Dynamic survivable routing heuristic for shared protected WDM optical networks," *IEEE Commun. Lett.*, vol. 10, no. 9, pp. 676–678, Sept. 2006.

[74] Y. Li, J. Wang, C. Qiao, A. Gumaste, Y. Xu, and Y. Xu, "Integrated Fiber-Wireless (FiWi) Access Networks Supporting Inter-ONU communications," *J. Lightwave Tech.*, vol. 28, no. 5, pp. 714–724, Mar. 2010.

[75] S. Sesia, I. Toufik, and M. Baker, *LTE - The UMTS Long Term Evolution: From Theory to Practice*. New York: John Wiley & Sons, 2009.

[76] B. Atakan and O. B. Akan, "BIOlogically-Inspired Spectrum Sharing in Cognitive Radio Networks," in *IEEE Wireless Commun. and Networking Conf. (WCNC)*, Hong Kong, China, Mar. 2007, pp. 43–48.

[77] P. D. Lorenzo, S. Barbarossa, and A. H. Sayed, "Decentralized Resource Assignment in Cognitive Networks Based on Swarming Mechanisms Over Random Graphs," *IEEE Trans. Signal Process.*, vol. 60, no. 7, pp. 3755–3769, July 2012.

[78] G. Li, S. W. Oh, K. C. Teh, and K. H. Li, "Enhanced BIOlogically-inspired Spectrum Sharing for cognitive radio networks," in *Communication Systems (ICCS), 2010 IEEE International Conference on*, Nov. 2010, pp. 767–771.

[79] S. Camazine, J. Deneubourg, N. Franks, J. Sneyd, G. Theraulaz, and E. Bonabeau, *Self-Organization in Biological Systems*. Princeton University Press, 2003.

[80] C. A. Tovey, "HONEY BEE Algorithm: A Biologically Inspired Approach to Internet Server Optimization," in *Engineering Enterprise, Spring*, 2004, pp. 13–15.

[81] O. Tonguz, "Biologically inspired solutions to fundamental transportation problems," *IEEE Commun. Mag.*, vol. 49, no. 11, pp. 106–115, Nov. 2011.

[82] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: a survey," *Comp. Net.*, vol. 50, no. 13, pp. 2127–2159, Sept. 2006.

[83] M. Dorigo and C. Blum, "Ant colony optimization theory: A survey," *Theoretical Computer Science*, vol. 344, pp. 243–278, 2005.

[84] M. Farooq, *From the Wisdom of the Hive to Intelligent Routing in Telecommunication Networks: A Step towards Intelligent Network Management through Natural Engineering*. PhD Thesis, University of Dortmund, Germany, 2006.

[85] K. Saleem, N. Fisal, M. S. Abdullah, A. B. Zulkarmwan, S. Hafizah, and S. Kamilah, "Proposed nature inspired self-organized secure autonomous mechanism for WSNs," in *Asian Conference on Intelligent Information and Database Systems, Quang Binh University*, Quang Binh Province, Vietnam, 2009, pp. 277–282.

[86] H. Yang, J. Shu, X. Meng, and S. Lu, "SCAN: Self-Organized Network-Layer Security in Mobile Ad Hoc Networks," *IEEE J. Sel. Areas Commun.*, vol. 24, no. 2, pp. 261–273, Feb. 2006.

[87] S. Balasubramaniam, D. Botvich, W. Donnelly, M. Foghluh, and J. Strassner, "Biologically inspired self-governance and self-organisation for autonomic networks," in *Proc. 1st International Conference on Bio Inspired Models of Network, Information and Computing Systems*, vol. 275, Cavalese, Italy: ACM, 2006, p. 30.

[88] L. N. D. Castro and J. Timmis, *Artificial Immune Systems: A New Computational Intelligence Approach*. Springer, 2002.

[89] J. Kephart, "A Biologically Inspired Immune System for Computers," in *4th International Workshop on Synthesis and Simulation of Living Systems*, MIT Press, Cambridge, Massachusetts, USA, 1994, pp. 130–139.

[90] J. Kim and P. Bentley, "An Evaluation of Negative Selection in an Artificial Immune System for Network Intrusion Detection," in *Genetic and Evolutionary Computation Conference (GECCO-2001)*, San Francisco, CA, 2001, pp. 1330–1337.

[91] S. Stepney, R. E. Smith, and J. Timmis, "Conceptual Frameworks for Artificial Immune Systems," *Int'l. J. Unconventional Comp.*, vol. 1, no. 3, pp. 315–338, July 2005.

[92] N. Mazhar and M. Farooq, "BeeAIS: Artificial immune system security for nature inspired," in *MANET routing protocol, BeeAdHoc, Springer-Verlag, Berlin Heidelberg, LNCS 4628*, 2007, pp. 370–381.

[93] B. Atakan and O. B. Akan, "Immune System Based Distributed Node and Rate Selection in Wireless Sensor Networks," in *1st IEEE/ACM BIONETICS'06*, Cavalese, Italy, Dec. 2006.

[94] A.-S. K. Pathan, *Security of Self-Organizing Networks: MANET, WSN, WMN, VANET*. CRC Press, Taylor & Francis Group, 2011.

[95] N. Skorin-Kapov, O. Tonguz, and N. Puech, "Self-Organization in Transparent Optical Networks: A New Approach to Security," in *9th International Conference on Telecommunications (ConTel'07)*, June 2007, pp. 7–14.

[96] J.-S. Yeom, O. Tonguz, and G. Castanon, "Security in All-Optical Networks: Self-Organization and Attack Avoidance," in *Proc. IEEE Int. Conf. Communications (ICC)*, June 2007, pp. 1329–1335.

[97] G. Castanon, I. Razo-Zapata, C. Mex, R. Ramirez-Velarde, and O. Tonguz, "Security in all-optical networks: Failure and attack avoidance using self-organization," in *2nd ICTON Mediterranean Winter (ICTON-MW'08)*, Dec. 2008, pp. 1–5.

[98] D. Lee, H. Jun, and K. Sim, "Artificial Immune System for Realization of Cooperative Strategies and Group Behavior in Collective Autonomous Mobile Robots," in *4th International Symposium on Artificial Life and Robotics*, 1999, pp. 232–235.

[99] W. Opp and F. Sahin, "An Artificial Immune System Approach to Mobile Sensor Networks and Min Detection," in *IEEE International Conference on Systems, Man and Cybernetics*, vol. 1, The Hague, The Netherlands, 2004, pp. 947–952.

[100] R. de Lemos, J. Timmis, M. Ayara, and S. Forrest, "Immune-inspired adaptable error detection for automated teller machines," *IEEE Trans. Syst. Man Cybern. C, Appl. Rev.*, vol. 37, pp. 873–886, 2007.

[101] C. Lee and J. Suzuki, *SWAT: A decentralized self-healing mechanism for wormhole attacks in wireless sensor networks, in Y. Xiao, H. Chen and F. Li eds. Handbook on Sensor Networks*. World Scientific Publishing Co., 2010.

[102] F. Dressler, "Bio-inspired Network-centric Operation and Control for Sensor/Actuator Networks," *IEEE Trans. Comput. Syst. Biol. VIII*, vol. 4780, pp. 1–13, 2007.

[103] C. Tschudin, "Fraglets ł A Metabolistic Execution Model for Communication Protocols," in *2nd Symp. Autonomous Intelligent Net. & Sys.*, Menlo Park, CA, jun/jul 2003.

[104] J.-P. Hubaux, T. Gross, J.-Y. Le Boudec, and M. Vetterli, "Toward Self-Organized Mobile Ad Hoc Networks: The Terminodes Project," *IEEE Commun. Mag.*, vol. 39, no. 1, pp. 118–124, Jan. 2001.

[105] C. E. Perkins and P. Bhagwat, "Highly dynamic destination-sequenced distance-vector routing (dsdv) for mobile computers," *Comp. Commun. Rev*, pp. 234–244, 1994.

[106] C. Perkins and E. Royer, "Ad hoc on-demand distance vector routing," in *2nd IEEE Workshop on Mobile Computing Systems and Applications*, New Orleans, LA, Feb. 1999, pp. 90–100.

[107] D. B. Johnson and D. A. Maltz, *Mobile Computing, chapter Dynamic Source Routing in Ad Hoc Wireless Networks*. Kluwer, 1996.

[108] Z. J. Haas, "A new routing protocol for the reconfigurable wireless networks," in *Proc. IEEE Int. Conf. on Universal Personal Communications*, 1997.

[109] S. Mueller, R. Tsang, and D. Ghosal, *Multipath routing in mobile ad hoc networks: Issues and challenges, in Performance Tools and Applications to Networked Systems, volume 2965 of Lecture Notes in Computer Science*. Springer-Verlag, 2004.

[110] E. Bonabeau, M. Dorigo, and G. Theraulaz, *Swarm Intelligence: From Natural to Artificial Systems*. Oxford University Press, 1999.

[111] R. Schoonderwoerd, O. Holland, J. Bruten, and L. Rothkrantz, "Ant-based load balancing in telecommunications networks," *Adapt. Behav.*, vol. 5, no. 2, 1996.

[112] D. Subramanian, P. Druschel, and J. Chen, "Ants and reinforcement learning: A case study in routing in dynamic networks," in *Proc. Int. Joint Conf. Artificial Intelligence*, Palo Alto, CA, 1997, pp. 832–838.

[113] G. D. Caro and M. Dorigo, "AntNet: Distributed stigmergetic control for communications networks," *J. Artificial Intelligence Research*, vol. 9, pp. 317–365, 1998.

[114] G. D. Caro, F. Ducatelle, and L. Gambardella, "Anthocnet: an adaptive nature-inspired algorithm for routing in mobile ad hoc networks," *Euro. Trans. Telecommun.*, vol. 16, pp. 443–455, 2005.

[115] M. Dorigo and D. G. Caro, *The ant colony optimization metaheuristic, New Ideas in Optimization*. New York: McGraw-Hill: D. Corne, M. Dorigo, and F. Glover, Eds., 1999.

[116] R. Schoonderwoerd, O. Holland, J. Bruten, and L. Rothkrantz, "Ants for Load Balancing in Telecommunication Networks," *Hewlett Packard Lab., Bristol, U.K., Tech. Rep. HPL-96-35*, 1996.

[117] T. Stuzle and H. H. Hoos, "MAX-MIN ant system," *Future Gener. Comput. Syst. J.*, vol. 16, no. 8, pp. 889–914, 2009.

[118] M. Dorigo and T. Stutzle, *The ant colony optimization metaheuristic: Algorithms, applications, and advances, Handbook of Metaheuristics*. Norwell, MA: Kluwer: F. Glover and G. Kochenberger, Eds., 2002.

[119] B. Bullnheimer, R. F. Hartl, and C. Strauss, "A New Rank-Based Version of the Ant System: A Computational Study," *Institute Management Science, Univ. Vienna, Vienna, Austria, Tech. Rep. POM-03/97*, 1997.

[120] K. M. Sim and W. H. Sun, "Ant Colony Optimization for Routing and Load-Balancing: Survey and New Directions," *IEEE Trans. Syst. Man Cybern. A, Syst. Humans*, vol. 33, no. 5, pp. 560–572, Sept. 2003.

[121] D. G. Caro and M. Dorigo, "AntNet: Distributed stigmergetic control for communications networks," in *J. Artif. Intell. Res.*, vol. 9, 1998, pp. 317–365.

[122] B. Baran and R. Sosa, "A new approach for AntNet routing," in *Proc. 9th Int. Conf. Computer Communications Networks*, Las Vegas, NV, 2000.

[123] D. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*. Reading, MA: Addison-Wesley, 1989.

[124] T. White, B. Pagurek, and F. Oppacher, “ASGA: Improving the ant system by integration with genetic algorithms,” in *Proc. 3rd Genetic Programming Conf.*, July 1998, pp. 610–617.

[125] T. White, “SynthECA: A Society of Synthetic Chemical Agents,” *Ph.D dissertation, Carleton University, Northfield, MN*, 2000.

[126] T. White and B. Pagurek, “Distributed fault location in networks using learning mobile agents,” in *Lecture Notes in Computer Science. New York: Springer-Verlag*, vol. 1733, 1999.

[127] H. Zhang, X. Qiu, L. Meng, and X. Zhang, “Achieving distributed load balancing in self-organizing LTE radio access network with autonomic network management,” in *GLOBECOM Workshops (GC Wkshps), 2010 IEEE*, 2010, pp. 454–459.

[128] H. Son, S. Lee, S.-C. Kim, and Y.-S. Shin, “Soft Load Balancing Over Heterogeneous Wireless Networks,” *IEEE Trans. Veh. Technol.*, vol. 57, no. 4, pp. 2632–2638, July 2008.

[129] K. M. Sim and W. H. Sun, “Multiple ant-colony optimization for network routing,” in *Proc. 1st International Symposium on Cyberworld*, Tokyo, Japan, Nov. 2002, pp. 277–281.

[130] N. Varela and M. C. Sinclair, “Ant colony optimization for virtual-wavelength-path routing and wavelength allocation,” in *Proc. Congress Evolutionary Computation*, Washington, DC, July 1999, pp. 1809–1816.

[131] T. D. Seeley and P. K. Visscher, “MULTIPLE ANT-BEE COLONY OPTIMIZATION FOR LOAD BALANCING IN PACKET-SWITCHED NETWORKS,” *International J. Computer Networks & Communications (IJCNC)*, vol. 3, no. 5, pp. 107–117, Sept. 2011.

[132] H. Ma, L. Zheng, X. Ma, and Y. Luo, “Spectrum aware routing for multihop cognitive radio networks with a single transceiver,” in *Proc. IEEE CrownCom*, 2008, pp. 1–6.

[133] Y. Liu and D. Grace, “Cognitive routing metrics with adaptive weight for heterogeneous ad hoc networks,” in *Cognitive Radio and Software Defined Radios: Technologies and Techniques, 2008 IET Seminar on*, 2008, pp. 1–5.

[134] G. Zhang, C. Ding, J. Gu, and Z. Bao, “An Adaptive Multi-Path Routing Algorithm in Cognitive Wireless Mesh Networks,” in *Wireless Communications, Networking and Mobile Computing (WiCOM), 2011 7th International Conference on*, 2011, pp. 1–4.

[135] E. Bonabeau, M. Dorigo, and G. Theraulaz, “Inspiration for optimization from social insect behavior,” *Nature*, vol. 406, pp. 39–42, July 2000.

[136] M. Peng, Y. Liu, D. Wei, W. Wang, and H.-H. Chen, “Hierarchical cooperative relay based heterogeneous networks,” *IEEE Commun. Mag.*, vol. 18, no. 3, pp. 48–56, June 2011.

[137] N. Marchetti, N. Prasad, J. Johansson, and T. Cai, “Self-Organizing Networks: State-of-the-Art, Challenges and Perspectives,” in *Communications (COMM), 2010 8th International Conference on*, 2010, pp. 503–508.

[138] H. Hildmann, S. Nicolas, and F. Saffre, “A Bio-Inspired Resource-Saving Approach to Dynamic Client-Server Association,” *IEEE Intell. Syst.*, vol. 27, no. 6, pp. 17–25, 2012.

[139] 3GPP, “Self-Configuring and Self-Optimizing Network Use Cases and Solutions,” *Tech. Rep. TR 36.902 v.1.2.0*, May 2009.

[140] NGMN, “Use Cases Related to Self-Organising Network, Overall Description,” Apr. 2007.

[141] “SOCRATES Deliverable D5.9: Final Report on Self-Organisation and its Implications in Wireless Access Networks,” *EUSTREP SOCRATES (INFSO-ICT-216284)*, pp. 1–135, Jan. 2010.

[142] “4WARD,” *EU FP7 project.*

[143] “End-to-End Efficiency (E3),” *EU FP7 project.*

[144] “Fibre-Optic Networks for Distributed Extendible Heterogeneous Radio Architectures and Service Provisioning (FUTON),” *EU FP7 project.*

[145] M. R. Boesen and J. Madsen, “eDNA: A Bio-Inspired Reconfigurable Hardware Cell Architecture Supporting Self-organisation and Self-healing,” in *2009 NASA/ESA Conference on Adaptive Hardware and Systems*, 2009.

[146] G. de la Roche, A. Ladanyi, D. Lopez-Perez, C.-C. Chong, and J. Zhang, “Self-organization for LTE enterprise femtocells,” in *IEEE Global Telecommn. Conf. (GLOBECOM)*, 2010, pp. 674–678.

[147] M. Caleffi and L. Paura, “Bio-inspired Link Quality Estimation for-Wireless Mesh Networks,” in *IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks & Workshops, 2009 (WoWMoM 2009)*, June 2009, pp. 1–6.

[148] K. Passino, “Biomimicry of bacterial foraging for distributed optimization andcontrol,” *IEEE Control Syst. Mag.*, vol. 22, 2002.

[149] C.-S. Tseng, C.-C. Chen, and C. Lin, “A Bio-Inspired Robust Adaptive Random Search Algorithm for Distributed Beamforming,” in *Proc. IEEE Int. Conf. Communications (ICC)*, June 2011, pp. 1–6.

[150] M. Sawahashi, Y. Kishiyama, A. Morimoto, D. Nishikawa, and M. Tanno, “Coordinated Multipoint Transmission/Reception Techniques for LTE-Advanced,” *IEEE Wireless Commun.*, vol. 17, no. 3, pp. 26–34, June 2010.

[151] F. Senel, M. F. Younis, and K. Akkaya, “Bio-Inspired Relay Node Placement Heuristics for Repairing Damaged Wireless Sensor Networks,” *IEEE Trans. Veh. Technol.*, vol. 60, no. 4, pp. 1835–1848, May 2011.

[152] I. Carreras, I. Chlamtac, F. D. Pellegrini, and D. Miorandi, “BIONETS: Bio-Inspired Networking for Pervasive Communication Environments,” *IEEE Trans. Veh. Technol.*, vol. 56, no. 1, pp. 218–229, Jan. 2007.

[153] D. Niyato, L. Xiao, and P. Wang, “Machine-to-Machine Communications for Home Energy Management System in Smart Grid,” *IEEE Commun. Mag.*, vol. 49, no. 4, pp. 53–59, Apr. 2011.

[154] A. Gotsis, A. Lioumpas, and A. Alexiou, “M2M Scheduling over LTE: Challenges and New Perspectives,” *IEEE Veh. Technol. Mag.*, vol. 7, no. 3, pp. 34–39, Sept. 2012.

[155] D. Lopez-Perez, A. Ladanyi, A. Juttner, H. Rivano, and J. Zhang, “Optimization method for the joint allocation of modulation schemes, coding rates, resource blocks and power in self-organizing lte networks,” in *INFOCOM, 2011 Proc. IEEE*, 2011, pp. 111–115.

[156] S. Haykin, “Cognitive radio: brain-empowered wireless communications,” *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, pp. 201–220, Feb. 2005.

[157] Z. M. Fadlullah, M. M. Fouda, N. Kato, A. Takeuchi, N. Iwasaki, and Y. Nozaki, “Toward Intelligent Machine-to-Machine Communications in Smart Grid,” *IEEE Commun. Mag.*, vol. 49, no. 4, pp. 60–65, Apr. 2011.

[158] Y. Zhang, R. Yu, M. Nekovee, Y. Liu, S. Xie, and S. Gjessing, “Cognitive machine-to-machine communications: visions and potentials for the smart grid,” *IEEE Network*, vol. 26, no. 3, pp. 6–13, May 2012.

[159] Y. Huang, N. Bessis, A. Brocco, P. Kuonen, M. Courant, and B. Hirsbrunner, “Using Metadata Snapshots for Extending Ant-Based Resource Discovery Service in Inter-cooperative Grid Communities,” in *First International Conference on Evolving Internet (INTERNET’09)*, 2009, pp. 89–94.

[160] G. Valetto, P. Snyder, D. J. Dubois, E. di Nitto, and N. M. Calcavecchia, “A Self-Organized Load-Balancing Algorithm for Overlay-Based Decentralized Service Networks,” in *Self-Adaptive and Self-Organizing Systems (SASO), 2011 Fifth IEEE International Conference on*, 2011, pp. 168–177.

[161] M. P. Sousa, W. T. A. Lopes, and M. S. Alencar, “LF-Ant: A Bio-inspired Cooperative Cross-layer Design for Wireless Sensor Networks,” in *IEEE Int. Symposium on Personal, Indoor and Mobile Radio Commun. (PIMRC)*, Sept. 2011, pp. 289–293.

[162] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, “Energy-Efficient Communication Protocol for Wireless Microsensor Networks,” in *33rd Hawaii International Conference on System Sciences*, 2000.

[163] W. S. Hortos, “Bio-Inspired, Cross-Layer Protocol Design for Intrusion Detection and Identification in Wireless Sensor Networks,” in *7th IEEE Workshop on Security in Communication Networks 2012*, 2012, pp. 1030–1037.

[164] B. Atakan and O. B. Akan, “Bio-Inspired Cross-Layer Communication and Coordination in Sensor and Vehicular Actor Networks,” *IEEE Trans. Veh. Technol.*, vol. 61, no. 5, pp. 2185–2193, June 2012.

[165] T. H. Labella and F. Dressler, “A bio-inspired architecture for division of labour in SANETs,” *Adv. Biol. Inspired Inf. Syst.*, vol. 69, pp. 211–230, 2007.

[166] N. Wakamiya and M. Murata, “Autonomous and Adaptive Wireless Networking with Bio-inspired Algorithms,” in *Autonomous Decentralized Systems (ISADS), 2011 10th International Symposium on*, 2011, pp. 597–602.

[167] T. Renk, C. Kloeck, D. Burgkhardt, F. K. Jondral, D. Grandblaise, S. Gault, and J. C. Dunat, “Bio-Inspired Algorithms for Dynamic Resource Allocation in Cognitive Wireless Networks,” in *CROWNCOM’07*, 2007, pp. 351–356.

[168] J. Branke, *Evolutionary optimization in dynamic environments.* Kluwer Academic Publishers, 2002.

[169] P. D. Lorenzo, S. Barbarossa, and A. H. Sayed, “Bio-Inspired Decentralized Radio Access based on Swarming Mechanisms over Adaptive Networks,” *IEEE Trans. Signal Process.*, to appear.

[170] K. Dufkova, M. Bjelica, B. Moon, L. Kencl, and J.-Y. L. Boudec, “Energy savings for cellular network with evaluation of impact on data traffic performance,” in *2010 European Wireless Conference (EW)*, 2010, pp. 916–923.

[171] R. Beckers, O. Holland, and J.-L. Deneubourg, “From Local Actions

to Global Tasks: Stigmergy and Collective Robots," in *Proc. Workshop on Artificial Life, MIT Press*, 1994, pp. 181–189.

[172] S. Buzzi, D. Ciullo, M. Meo, and M. A. Marsan, "Energy-Efficient Management of UMTS Access Networks," in *Proc. 21st Int'l Teletraffic Congress (ITC 09), IEEE*, 2009, pp. 1–8.

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