Intelligent Computing for Wireless Sensor Networks : A Survey

Meenu[1], Deepti Sharan[2],Priya Tripathi[3]
[1,3]Computer Science Department, IINTM ,Janakpuri New Delhi, [2]Computer Science Department, AUM Education Society,USA
[1]drmeenu.knsl@gmail.com, [2]deepti.sharan@gmail.com, [3] priyatripathi.iitm@gmail.com

Abstract: Wireless sensor networks (WSNs) consist of distributed, autonomous devices that collaboratively monitor and sense physical or environmental conditions. WSNs encounter several challenges, primarily due to communication failures, computational and storage limitations, and constrained power resources. In recent years, computational intelligence (CI) paradigms have been successfully employed to address various issues such as data aggregation and fusion, energy-efficient routing, task scheduling, security, optimal deployment, and localization. CI offers adaptive mechanisms that demonstrate intelligent behavior in complex and dynamic WSN environments, providing flexibility, autonomy, and robustness against topology changes, communication disruptions, and evolving scenarios.

However, WSN developers often lack awareness or a comprehensive understanding of the potential of CI algorithms. Conversely, CI researchers may not be fully familiar with the practical challenges and specific requirements of WSNs. This disconnects hampers collaboration and innovation. To bridge this gap, this paper provides an in-depth introduction to WSNs and their characteristics. It also presents an extensive review of CI applications across various WSN-related challenges, drawing insights from diverse research fields and publication sources. Additionally, the paper discusses the advantages and limitations of CI algorithms compared to traditional WSN approaches and offers a general evaluation of CI algorithms as a guide for their application in WSNs.

Keywords: Wireless Sensor Network, Computational Intelligence, Clustering Algorithms

1. Introduction

A wireless sensor network (WSN) comprises distributed, autonomous devices that cooperatively sense or monitor physical and environmental conditions [1]. WSNs are utilized in diverse applications, including environmental monitoring, habitat tracking, natural disaster prediction and detection, medical monitoring, and structural health assessment [2]. These networks consist of numerous small, low-cost, disposable, and self-sufficient sensor nodes, typically deployed ad hoc across large geographical areas for remote operations.

Sensor nodes face significant constraints, such as limited storage, computational power, communication bandwidth, and energy supply. Generally, sensor nodes are organized into clusters, with each cluster having a designated cluster head. The cluster head aggregates data from the nodes and forwards it to a specialized node, known as a sink node or base station, via multi-hop wireless communication, as illustrated in Figure 1. However, some WSNs may be simpler, consisting of a single cluster with one base station [3]–[5]. Other configurations, such as networks with multiple base stations or mobile nodes, are also possible. Article [6] provides a classification of WSNs based on communication functions, data delivery models, and network dynamics.

Resource limitations and dynamic topologies introduce challenges in areas such as network discovery, control and routing, collaborative data processing, querying, and task assignment [2]. Computational intelligence (CI) incorporates principles of learning, adaptation, evolution, and fuzzy logic to create intelligent systems. Beyond paradigms like neural networks, reinforcement learning, evolutionary algorithms, and fuzzy systems, CI also includes approaches such as swarm intelligence, artificial immune systems, and hybrid methodologies.

CI paradigms have found practical applications in fields like product design, robotics, intelligent control, biometrics, and WSNs. Researchers have successfully applied CI techniques to address numerous challenges in WSNs. However, these applications are being developed across various research communities, with no unified overview of the work. Most of the contributions are scattered across journals and conferences that do not primarily focus on WSNs.

The objective of this survey is to bridge this gap by providing a concise yet comprehensive overview of various CI approaches and their applications, offering WSN researchers fresh perspectives and inspiration. Additionally, the survey highlights unresolved challenges in WSNs and explores potential CI applications, aiming to motivate researchers to integrate CI techniques into WSN-related studies and developments.

2. Literature Review

This survey aims to provide a comprehensive overview of the application of computational intelligence (CI) techniques to address challenges inherent in wireless sensor and actuator networks (WSANs). Despite both CI and WSANs being active research domains, they are seldom explored together in a unified context. To the best of our knowledge, this is the first systematic review that categorizes, analyzes, and compiles CI applications within the WSAN field, effectively bridging the gap between these two complementary paradigms.

While some existing works delve deeply into specific niche areas relevant to our survey, research explicitly linking CI to WSANs remains limited. Survey papers and books focusing on WSANs [11–15] are relatively scarce compared to those addressing WSNs as a whole [16–18] or targeting specific WSN problems [19–24]. Even in studies where CI methods are used, they are often not the primary focus.

Some researchers have highlighted the use of specific CI methods in addressing particular WSN challenges [25, 26], while others have examined how a single CI technique applies to multiple WSN-related problems [27–34]. Although valuable, these studies are narrower in scope and do not emphasize WSANs. This survey builds upon these contributions to present a broader and more holistic perspective, specifically tailored to the WSAN domain.

3. Challenges In Sensor Networks

Real-world deployments of wireless sensor networks (WSNs) typically support one of three primary applications: periodic reporting, event detection, and database-like storage. **Periodic reporting**, the simplest and most common scenario, involves sensors sampling the environment at regular intervals, storing the data, and transmitting it to base stations. These networks often connect to actuators, such as automatic irrigation or alarm systems, and are widely used in monitoring applications like agriculture [7,8], microclimate [4,5,9], habitat surveillance [10–12], military operations [13], and disaster relief [14]. A key characteristic of periodic reporting is its predictable data traffic and volume.

In contrast, **event detection** applications [3,15] operate by sensing the environment and immediately evaluating the data for significance. If an event is detected, the data is sent to the base station, resulting in sporadic and unpredictable data traffic. Even when no events occur, nodes exchange minimal data for route management and status checks.

Database-like storage systems [16], similar to event-based systems, store all sensory data—whether periodic samples or event-triggered readings—locally on nodes. Base stations then query and retrieve the required data directly from the nodes. The main challenge here is implementing efficient data storage and retrieval mechanisms.

Challenges in WSN Deployments

WSNs face several deployment-specific challenges:

3.1 Wireless Ad Hoc Nature

➢ **Characteristics:** WSNs lack fixed communication infrastructure and rely on shared wireless media, which introduces issues like unreliable and asymmetric links. However, the broadcast advantage allows packets sent to one node to be received by all its neighbors.

3.2 Mobility and Topology Changes

➢ **Characteristics:** Nodes may join, leave, move, or fail, causing dynamic topology changes. Networks must remain robust to such disruptions.

3.3 Energy Constraints

➢ **Characteristics:** Nodes operate on limited energy, often with no possibility of battery replacement or recharging. Communication tasks consume the most power, necessitating energy-efficient protocols.

3.4 Physical Distribution

➢ **Characteristics:** Data is distributed across nodes, making global information gathering costly. Decentralized algorithms are essential to reduce communication overhead.

Key Challenges Addressed by CI Techniques

➢ **Design and Deployment**

WSNs serve varied applications, from tissue-implanted sensors to forest-fire monitoring. Deployment strategies vary, requiring tailored designs to optimize node type, quantity, and placement.

➢ **Localization**

Localization ensures nodes are aware of their positions, critical for event detection and geometric-aware routing [17,18]. Common methods involve time-of-arrival signals from multiple base stations [19,20].

➢ **Data Aggregation and Sensor Fusion**

Sensor fusion combines data from multiple nodes to enhance accuracy or reduce communication overhead. Techniques like Kalman filters and Bayesian networks are commonly used [21,22].

➢ **Energy-Aware Routing and Clustering**

Efficient energy use is crucial for extending network lifetime. Hybrid routing protocols and hierarchical clustering are effective strategies for managing densely deployed networks [23].

➢ **Scheduling**

Energy conservation requires nodes to operate on strict schedules, alternating between sleep and active modes. Scheduling ensures efficient sensing, transmission, and locomotion while maximizing network lifespan.

➢ **Security**

Wireless links are vulnerable to threats like eavesdropping, impersonation, and message tampering. Robust security measures, including encryption and intrusion detection, are critical for maintaining network integrity [24].

➢ **Quality of Service (QoS) Management**

QoS refers to ensuring application-specific service attributes like fairness, delay, bandwidth, and packet loss. Networks must balance QoS with resource optimization to meet user expectations [27].

These challenges and their solutions underscore the importance of integrating advanced techniques, including computational intelligence, to enhance WSN performance and reliability across diverse applications.

4. Computational Intelligence Techniques

Computational Intelligence (CI) is a smart computational approach that employs heuristic algorithms to efficiently derive approximate solutions for NP-hard problems. CI paradigms are well-suited for adapting to the dynamic and evolving nature of WSNs. The following subsections provide a brief overview of several CI paradigms applied to clustering in WSNs.

4.1 Genetic Algorithm

Inspired by Charles Darwin's theory of evolution, specifically the concept of "survival of the fittest," Genetic Algorithm (GA) was formally introduced by John Holland in the 1970s [30]. GA is an adaptive heuristic search algorithm that simulates the process of biological evolution. Renowned for its robustness, it operates by exploring a population of potential solutions and has demonstrated remarkable flexibility in addressing dynamic and NP-hard problems.

The primary challenge in applying GA lies in encoding the problem into a set of chromosomes, where each chromosome represents a potential solution. The quality of these chromosomes is assessed using a fitness function. Based on their fitness values, selected chromosomes undergo crossover and mutation processes.

The **crossover** process generates new solutions, or offspring, by combining segments of two parent chromosomes. The **mutation** process introduces changes to one or more genetic elements in the offspring to maintain diversity and avoid convergence to local minima. This combination of techniques allows GA to explore the solution space effectively and adapt to complex problem scenarios.

Algorithm 1 : Basic steps describing the GA [31]

1 begin GA

2 for all N chromosomes

3 Initialize the population,generation counter

```
Initialize the GA parameters.
Calculate the fitness of each chromosome.
end for
while (the convergence condition is not satisfied) or
(the maximum number of iterations is not reached)
{
for all created N offsprings
Probabilistically select a pair of chromosomes
from current population using the fitness value.
Produce a new offspring xi using crossover
and mutation operators,where i = 1, 2, . . . ,N.
Evaluate the population.
end for
Replace current population with newly created one.
Update the generation counter.
}
end while
end GA
```

4.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) was developed in 1995 by James Kennedy and Russell Eberhart [32]. PSO is a powerful stochastic nonlinear optimization technique inspired by the movement and intelligence of swarms. It draws from the social behavior of birds or fish, where a group of birds searches for food in an area by following the bird nearest to it. PSO combines local and global search strategies through social interactions among particles, helping them find the best positions achieved so far.

PSO and Genetic Algorithm (GA) share similarities [33], as both are population-based stochastic optimization methods that begin with a randomly generated population. Both methods use fitness values to evaluate and update the population in search of an optimal solution through random techniques. However, PSO differs from GA in several ways: it lacks crossover and mutation processes, and particles do not "die." Instead, they update their positions based on internal velocities. Additionally, the information-sharing mechanism in PSO is quite distinct.

In PSO, each particle represents a point in a multi-dimensional space and updates its position influenced by two components: the cognitive component, which reflects the particle's individual experience, and the social component, which is derived from communication with neighboring particles. The fundamental PSO equations are presented in Equations 1 and 2, with several enhancements to the standard PSO model outlined in [34].

Algorithm 2: Basic steps of the PSO algorithm

```
begin PSO
Randomly initialize the position and velocity of
the particles: Xi(0) and Vi(0)
while (While terminating condition is not reached) do
for for i = 1 to number of particles
Evaluate the fitness:= f(Xi)
Update pi and gi
Update velocity of the particle Vi
Update position of the particle Xi
Evaluate the population fitness
Next for
end while
end PSO
```

The steps of the PSO process are outlined in Algorithm 2. The selection of the communication neighborhood, known as the swarm topology, plays a crucial role in the model's implementation. In a Star topology, all particles in the swarm communicate with each other, while in a Ring topology, each particle interacts only with two neighboring particles. While the Star topology can lead to faster convergence, this can sometimes be misleading, as it may result in premature convergence. On the other hand, the Ring topology tends to exhibit slower convergence and is less prone to premature convergence, making it more effective for multimodal problems. Various topologies have been proposed and discussed in [35].

Table 1: Overview different type CI Technique

Type of CI Techniques	Computational Complexity	Application Scenario	Example
Fuzzy Logic	Low	Reasoning with vague and imprecise concepts	Fuzzy controller for a plant irrigation system [31]
Learning Systems	Medium	Learning relationships among objects	Learning foraging behaviors in a robotic swarm [32]
Evolutionary Algorithm	Medium	Finding approximate solutions to challenging optimization problems	Calculating near-optimal path for data collection by a mobile sink [33]
Swarm Intelligence Algorithm		Finding approximate solutions to challenging optimization problems	Minimizing localization error of the sensors via a mobile anchor node [34]
Hybrid Systems	High	Combining the strengths of complementary techniques	Improve QoS metrics in a WSAN [35]

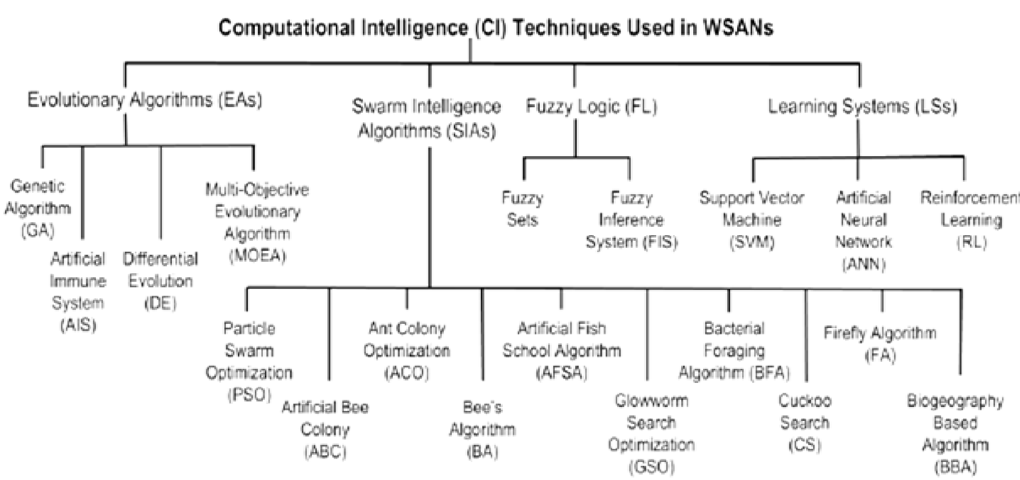

Fig 1: CI techniques used in the surveyed WSAN papers

5. Methodology (Ci Techniques Applied to Wsan Problems)

Wireless Sensor and Actuator Networks (WSAN) are collections of static sensor nodes and one or more sink nodes. The often-numerous sensor nodes are composed of one or more sensing modules, an energy source and a wireless communication device. The sensor nodes in these networks usually have limited computational power, thus requiring multihop chains to transmit their messages across the network to the sink nodes. WSNs are prone to node failure due to malfunction, energy depletion, malicious attacks or harsh environmental conditions. An extension of such networks is called Wireless Sensor and Actuator Networks (WSANs), which are made up of heterogeneous nodes capable of performing distributed computations and actuation tasks [25].

The WSAN Actuation problem category has been tackled from many standpoints using CI techniques. Those approaches that revolve around Task Allocation often resort to market-based allocation techniques optimized via EAs/SIAs to satisfy the overall system goal. There is plenty of room for the application
of MOO methods in this area. Another popular trend is to employ FIS/ANN to design control systems for these actuators that allow them to individually bid for certain tasks. Regarding the subset of Actuation approaches concerned with task execution via actuator coordination and event prediction,
FIS and FL are the main CI schemes employed to ensure a smooth coordination among the actuators, although we see an emerging interest in RL and MDP as LS representatives.

The optimization angle is still present via EAs/SIAs solving different manifestations of actuator coordination problems such as target tracking or path planning. A vast majority of the proposed approaches rely on a centralized computation architecture.

In the WSAN Communication category, the application of CI techniques to the routing subproblem is confined to solving optimization problems primarily via SIAs. The communication routes are mainly static (i.e., do not change over time) except that envisions dynamic communication backbones. Multiple aspects of these routes such as energy consumption, signal strength or message latency are taken into account during the optimization process. In the clustering subproblem, the suitability of a WSAN node to become a cluster head is modeled through an FIS and the selection of potential cluster heads network-wise is entrusted to EA-based optimizers. Finally, the QoS sub-problem is the least explored by CI techniques. The few available works are related to fuzzy control and genetic optimization at the node level to ensure reliable sensor-actuator communication.

Concerning the Sink Mobility category, CI optimization techniques have the upper hand as they try to derive the best path for the mobile sink. Some studies simultaneously identify the most suitable cluster heads in the WSAN. A few works depart from the traditional problem formulation by considering special cases such as multiple mobile sinks or a sparse network. Finally, an FIS to gauge the attractiveness
of the network regions for sink visitation was also put forth. MOO methods as well as LS/HS schemes would be a great addition to the repertoire of CI applications here.

The CI presence in the WSAN Topology Control category is largely dominated by EA/SIA-based optimization methods across all its subproblems, namely sensor deployment, relocation and replenishment. This is quite understandable since modifying the WSAN topology serves an ultimate goal, e.g., maximizing network lifetime or expanding/restoring network coverage. We do see increasing evidence of the successful synergy between FIS/DL and nature-inspired CI optimizers in the sensor relocation arena. Sensor replenishment by mobile actuators is an exciting and largely uncharted territory for new CI applications.

Finally, in the WSAN Localization problem, we notice that range-based methods have been slightly more studied through CI techniques than their range-free counterparts. The need to reason under imprecise information (coming from unreliable distance estimates of the nodes) makes it an appealing choice for the application of FL/FIS and LS (ANN/SVM) techniques,

with some genetic and swarm-inspired optimizers in the background to produce an accurate solution. The latter category (range-free localization methods) hinges more heavily on EA/SIA-based optimization given the rather reliable estimates of the anchor nodes' position that are broadcast to the rest of the WSAN.

6. Conclusions And Future Applications Of Ci In Wsns

Recent literature shows that researchers have focused their attention on innovative use of CI techniques to address WSN issues such as design and deployment, localization, security, optimal routing and clustering, scheduling, data aggregation and fusion, and QoS management. Recent implementations of CI methods in various dynamical and heterogeneous networks are presented in this survey paper. CI paradigms and numerous challenges in sensor networks are briefly introduced, and the CI approaches used by researchers to address the challenges are briefly explained. In addition, a general evaluation of CI algorithms is presented, which will serve as a guide for using CI algorithms for WSNs.

An advanced CI approach called adaptive critic design holds promise to generate practical optimal/sub-optimal solutions to the distributed sensor scheduling problem. There are successful applications of adaptive critic designs in power systems, which show that the technique provides guaranteed stable optimal solutions under uncertainties and noise. The potential of adaptive critic designs remains to be exploited in the field of WSN scheduling

References

1. I. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Commun. Mag.*, vol. 40, no. 8, pp. 102–114, Aug. 2002.
2. C. Y. Chong and S. Kumar, "Sensor networks: Evolution, opportunities,and challenges," *Proc. IEEE*, vol. 91, no. 8, pp. 1247–1256, Aug. 2003.
3. G. Werner-Allen, K. Lorincz, M. Ruiz, O. Marcillo, J. Johnson, J. Lees,and M. Welsh, "Deploying a wireless sensor network on an active volcano," *IEEE Internet Comput.*, vol. 10, no. 2, pp. 18–25, 2006.
4. K. Martinez, P. Padhy, A. Riddoch, R. Ong, and J. Hart, "GlacialEnvironment Monitoring using Sensor Networks," in *Proc. 1st Workshop Real-World Wireless Sensor Netw. (REALWSN)*, Stockholm, Sweden, 2005, p. 5.
5. I. Talzi, A. Hasler, S. Gruber, and C. Tschudin, "Permasense:Investigating permafrost with a WSN in the swiss alps," in *Proc. 4th Workshop Embedded Netw. Sensors (EmNets)*, Cork, Ireland, 2007, pp.8–12.
6. S. Tilak, N. B. Abu-Ghazaleh, and W. Heinzelman, "A taxonomy of wireless micro-sensor network models," *SIGMOBILE Mob. Comput.Commun. Rev.*, vol. 6, no. 2, pp. 28–36, 2002.
7. A. Nayak and I. Stojmenovic, Wireless sensor and actuator networks:algorithms and protocols for scalable coordination and data communication.Wiley, 2010.
8. R. Verdone, D. Dardari, G. Mazzini, and A. Conti, Wireless sensorand actuator networks: technologies, analysis and design. AcademicPress, 2010.
9. R. Falcon, "Towards fault reactiveness in wireless sensor networks with mobile carrier robots," Ph.D. dissertation, University of Ottawa, 2012.
10. N. Mitton and D. Simplot-Ryl, Wireless sensor and robot networks:from topology control to communication aspects. World Scientific,2013.
11. D.-I. Curiac, "Towards wireless sensor, actuator and robot networks:conceptual framework, challenges and perspectives," ournal of Networkand Computer Applications, vol. 63, pp. 14–23, 2016.
12. I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," Computer networks, vol. 38, no. 4, pp.393–422, 2002.
13. P. Baronti, P. Pillai, V. W. Chook, S. Chessa, A. Gotta, and Y. F. Hu,"Wireless sensor networks: A survey on the state of the art and the 802.15. 4 and zigbee standards," Computer communications, vol. 30,no. 7, pp. 1655–1695, 2007.
14. Y.-G. Yue and P. He, "A comprehensive survey on the reliability of mobile wireless sensor networks: Taxonomy, challenges, and futuredirections," Information Fusion, 2018.
15. J. N. Al-Karaki and A. E. Kamal, "Routing techniques in wireless sensor networks: a survey," IEEE wireless communications, vol. 11,no. 6, pp. 6–28, 2004.

16. J. Yick, B. Mukherjee, and D. Ghosal, “Wireless sensor network survey,” Computer Networks, vol. 52, no. 12, pp. 2292–2330, 2008.
17. M. Younis and K. Akkaya, “Strategies and techniques for node placement in wireless sensor networks: A survey,” Ad Hoc Networks, vol. 6 no. 4, pp. 621–655, 2008.
18. G. Anastasi, M. Conti, M. Di Francesco, and A. Passarella, “Energy conservation in wireless sensor networks: A survey,” Ad hoc networks,vol. 7, no. 3, pp. 537–568, 2009.
19. M. Xie, S. Han, B. Tian, and S. Parvin, “Anomaly detection in wireless sensor networks: A survey,” Journal of Network and Computer Applications, vol. 34, no. 4, pp. 1302–1325, 2011.
20. I. Khoufi, P. Minet, A. Laouiti, and S. Mahfoudh, “Survey of deployment algorithms in wireless sensor networks: coverage and connectivity issues and challenges,” International Journal of Autonomous and Adaptive Communications Systems, vol. 10, no. 4, pp. 341–390, 2017.
21. K. Langendoen, A. Baggio, and O. Visser, “Murphy loves potatoes:experiences from a pilot sensor network deployment in precision agriculture,” in Proc. 20th Int. Symp Parallel Distributed Proc. Symp.(IPDPS), Rhodes Island, Greece, 2006.
22. J. McCulloch, P. McCarthy, S. M. Guru, W. Peng, D. Hugo, and A. Terhorst, “Wireless sensor network deployment for water use efficiency in irrigation,” in Proc. Conf. Workshop Real-world Wireless Sensor Netw. (REALWSN), Glasgow, Scotland, 2008, pp. 46–50.
23. E. A. Basha, S. Ravela, and D. Rus, “Model-based monitoring for early warning flood detection,” in Proc. Conf. 6th ACM Conf. Embedded Netw. Sensor Syst. (SenSys), New York, NY, USA, 2008, pp. 295–308.
24. G. Barrenetxea, F. Ingelrest, G. Schaefer, and M. Vetterli, “The hitchhiker's guide to successful wireless sensor network deployments,” in Proc. 6th ACM Conf. Embedded Netw. Sensor Syst. (SenSys), New York, NY, USA, 2008, pp. 43–56.
25. T. Naumowicz, R. Freeman, A. Heil, M. Calsyn, E. Hellmich, A. Braendle, T. Guilford, and J. Schiller, “Autonomous monitoring of vulnerable habitats using a wireless sensor network,” in Proc. 3rdWorkshop Real-World Wireless Sensor Netw. (REALWSN), Glasgow, Scottland, 2008, pp. 51–55.
26. R. Szewczyk, J. Polastre, A. Mainwaring, and D. Culler, “Lessonsfrom a sensor network expedition,” in Proc. 1st European Workshop Sensor Netw. (EWSN), Berlin, Germany, 2004, pp. 307–322.
27. X. Peng, Z. Mo, L. Xiao, and G. Liu, “A water-saving irrigation system based on fuzzy control technology and wireless sensor network,” Proceedings of the International Conference on Wireless Communications, Networking and Mobile Computing, pp. 1–4, 2009.
28. J. Timmis, L. Murray, and M. Neal, “A neural-endocrine architecture for foraging in swarm robotic systems,” Studies in omputationalIntelligence, vol. 284, pp. 319–330, 2010.
29. J. S. Liu, S. Y. Wu, and K. M. Chiu, “Path planning of a data mule in wireless sensor network using an improved implementationof clustering-based genetic algorithm,” Proceedings of the IEEE Symposium on Computational Intelligence in Control and Automation, pp. 30–37, apr 2013.
30. S. Sivakumar and R. Venkatesan, “Error minimization in localizationof wireless sensor networks using modified cuckoo search with mobile anchor positioning (MCS-map) algorithm,” International Journal of Computer Applications, vol. 95, no. 6, 2014
31. M. Hamdy and H. El-Madbouly, “Improvement of QoS management in wireless sensor/actuator networks using fuzzy-genetic approach,”Proceedings of the International Conference on Networking and MediaConvergence, pp. 29–35, mar 2009.