

Coverage, Deployment and Localization Challenges in Wireless Sensor Networks Based on Artificial Intelligence Techniques: A Review

WALID OSAMY^{1,2}, AHMED M. KHEDR^{3,4}, AHMED SALIM^{4,5},
AMAL IBRAHIM AL ALI⁶, AND AHMED A. EL-SAWY¹

¹Computer Science Department, Faculty of Computers and Artificial Intelligence, Benha University, Benha 13518, Egypt

²Department of Applied Natural Science, Applied College in Unaizah, Qassim University, Unaizah 56452, Saudi Arabia

³Computer Science Department, University of Sharjah, Sharjah, United Arab Emirates

⁴Mathematics Department, College of Sciences, Zagazig University, Zagazig 44516, Egypt

⁵Department of Computer Science, College of Sciences and Arts, Qassim University, Buridah, Al-Mithnab 51931, Saudi Arabia

⁶Information Systems Department, University of Sharjah, Sharjah, United Arab Emirates

Corresponding author: Ahmed M. Khedr (akhedr@sharjah.ac.ae)

ABSTRACT The growing importance and widespread adoption of Wireless Sensor Network (WSN) technologies have helped the enhancement of smart environments in various fields such as manufacturing, smart city, transport, health and the Internet of Things, by providing pervasive real-time applications. In this paper, we analyze the existing research trends of Coverage, Deployment and Localization challenges in WSN concerning Artificial Intelligence (AI) methods for WSN enhancement. We present a comprehensive discussion on the recent studies that utilized various AI methods to meet specific objectives of WSN, from 2010 to 2021. This would guide the reader towards an understanding of up-to-date applications of AI methods with respect to different WSN challenges. Then, we provide a general evaluation and comparison of different AI methods used in WSNs, which will be a guide for for research community in identifying the most adapted methods and the benefits of using various AI methods for solving the Coverage, Deployment and Localization challenges related to WSNs. Finally, we conclude the paper by stating the open research issues and new directions for future research.

INDEX TERMS Artificial intelligence, coverage, deployment, Internet of Things, localization, wireless sensor networks.

I. INTRODUCTION

The field of Ad-hoc network technology is experiencing remarkable research attention over the years [1]. The two main categories of Ad-hoc networks are Mobile Ad-hoc Network (MANET) and Wireless Sensor Networks (WSNs). WSNs have limited power consumption and comprises of low cost devices when compared to MANETs [2]. MANETs are designed for mobile devices that are capable of moving freely in any direction independently, while WSN nodes with embedded CPU and smart sensors are generally deployed and used for data sensing and monitoring of surrounding environmental factors such as wind, air, humidity, pressure, vibration, detecting gases and chemicals, earthquake and

so on [3], [4]. The increasing benefits of IoT applications in daily life have revolutionized people's lifestyle choices. For effective communication of data among nodes, many such IoT-based applications demand exact identification of node position and location [5]. WSN is regarded as the core component of IoT and enables a wide range of applications [6]–[12]. The integration of WSN into the IoT allows the dynamic connection of sensor devices to the Internet and achieve the tasks assigned. WSN provides valuable capabilities to applications such as in science, military, health care, engineering, environment, home applications, area monitoring, detection of forest fire, landslide detection, and disaster prediction, but at the same time faces different challenges due to its constrained resources such as restricted computing and processing, energy, memory, storage, and communication capability [13], [14].

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The key focus of this survey is to provide a comprehensive discussion on the recent studies of Coverage, Deployment and Localization challenges that utilized various Artificial Intelligence (AI) methods to meet specific objectives of WSN, during the span of 2010 to 2021. Then, we provide a general evaluation and comparison of using different AI methods to solve Coverage, Deployment and Localization challenges in WSNs, which will be a guide for research community in identifying the mostly adapted methods to address these challenges and the benefits of using various AI methods.

We primarily present an overview of Coverage, Deployment and Localization challenges in WSNs and the utilized AI techniques. Then, we briefly summarize the utilized AI techniques for solving these challenges and enhancing WSN performance in terms of packet transfer rate, energy efficiency and WSN lifetime etc. This study will provide the reader with adequate understanding about the Coverage, Deployment and Localization challenging concerns of WSN and the power of AI techniques in solving these WSN challenges.

While survey papers exist on analyzing various challenges facing WSNs, most of them focused on applying AI methods to solve a particular problem, such as routing, data gathering, data aggregation, or energy usage, while others focused on solving some of the challenges faced by WSN. There has been related work that discussed or partially surveyed the literature related to AI based protocols and algorithms solving different WSN challenges. The work in this survey is different from others as our intention is to provide a contemporary survey of the more recent literature. Our focus is to cover and compare several solutions of Coverage, Deployment and Localization challenges using different AI techniques which allow to explore new strategies for resolving existing WSN problems and to enhance the WSN performance.

Moreover, we have reviewed the papers published from 2010 to 2021 to carry out a systematic analysis and comparison. The paper provides a comprehensive survey of 72 relevant papers across different academic disciplines from reliable database sources. Among the papers examined, the solutions of three challenges in WSNs using different AI techniques have been identified and classified. This classification of the solutions according to the AI techniques is then employed during the discussion of these challenges in WSN to show how AI techniques handled each challenge. Some papers may cover multiple aspects and will be surveyed for each category. In addition, the paper identifies challenges, promising research directions in applying AI-based solutions to various WSN challenges, with the aim to promote and facilitate further research.

In summary, the major contributions of this paper are as follows:

- 1) We present a brief summary of the utilized AI techniques to overcome the Coverage, Deployment and Localization challenges in WSNs.
- 2) A comprehensive discussion on the recent studies of Coverage, Deployment and Localization challenges

that utilized various AI methods to meet specific objectives of WSN during the span of 2010 to 2021 is given.

- 3) We present a solid comparison between the utilized AI techniques for solving each challenge.
- 4) We identify promising research directions in applying AI-based solutions to Coverage, Deployment, and Localization challenges in WSN, with the aim to promote and facilitate further research.

The abbreviations of the main used terms are summarized in Table 1.

TABLE 1. Table of main abbreviations.

Abbreviation	Description
AI	Artificial Intelligence.
WSN	Wireless Sensor Network.
IoT	Internet of Things.
ANN	Artificial Neural Network.
ACO	Ant Colony Optimization.
ABC	Artificial Bee Colony.
BA	Bat Algorithm.
CI	Computational Intelligence.
DC	Data Collection.
DL	Deep Learning.
DNN	Deep Neural Network.
GA	Genetic Algorithm.
PSO	Particle Swarm Optimization.
RL	Reinforcement Learning.
SI	Swarm Intelligence.
WOA	Whale Optimization Algorithm.
CSO	Cuckoo Search Optimization.

Article Organization: The rest of the article is structured as follows: In section II, the methodology used to conduct this survey is discussed. A brief background, definitions of the solved challenges in WSN, and the summary of the utilized AI techniques are given in Section III. Coverage challenge and the associated AI solutions are presented in Section V. Deployment and localization challenges and their respective AI solutions are discussed in Section VI. For each of the above sections, we have included the respective open research issues that can guide the research immunity for future innovations. Section VII provides the conclusion.

II. RESEARCH METHODOLOGY

The research methodology adopted here is divided into four phases: Phase 1 is the articles selection phase which includes database sources selection step and articles selection and filtering step. Phase 2 includes articles classifications. Phase 3 includes articles analysis which is covered later in sections V and VI along with discussions on open research challenges. Finally, Phase 4 includes the discussion and future scope which is covered later in the section VII where we conclude the paper.

A. ARTICLES SELECTION PHASE

- **Database sources selection step:** The quality of research can be affected by paper sources and the key search criteria. For that, the papers covered in this review are selected from reliable databases, Scopus

(<https://www.scopus.com/>), Web of Science (<https://clarivate.com/webofsciencegroup/solutions/web-of-science/>), IEEE Explorer (<https://ieeexplore.ieee.org/>), and ACM digital library (<https://dl.acm.org/>). Moreover, only indexed journals are considered. In order to execute a good search to cover the most relevant work, query search string and search keywords related to the research topic are selected in a good manner.

- **Articles selection and filtering step:** Research topic-related terms, short phrases along with Boolean operators (ANDs and ORs) are used to form the search queries. The diagram in Fig. 1 shows the whole processes of generating the query strings.

To find the primary relevant papers; query search strings are executed on the selected databases in abstracts, keywords, and titles from 2010 to 2021. Moreover, journal articles are included and other types are excluded.

The resulting search results are combined and filtered to select the primary papers, where, papers that are not directly related to our subject, duplicated or have not enough quality are not considered. Moreover, in order to determine the eligibility of the filtered articles to our targets first abstract is read and if it doesn't contain an indicator of its eligibility then the content of the article is investigated. Otherwise, the article is selected. Using this, 72 relevant papers are elected as primary papers.

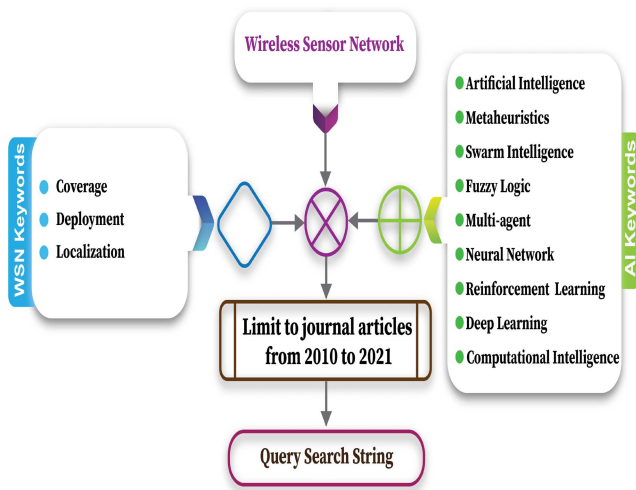


FIGURE 1. Query search string formation diagram.

B. ARTICLES CLASSIFICATIONS PHASE

Among 72 papers examined, different AI techniques in WSNs have been identified and classified from primary database sources as shown in Fig. 3. These techniques include Fuzzy Logic, Artificial Neural Network, Evolutionary Computation, Nature-inspired, Multi-Agent Systems, Trajectory based, Physical computation, Reinforcement Learning and Hybrid. An overview of these techniques is presented later in section III-B, besides, this classification of AI techniques

is employed during the discussion of each challenge in WSN to show how AI techniques handled each challenge.

Fig. 2 shows the number of selected journal research articles per year.

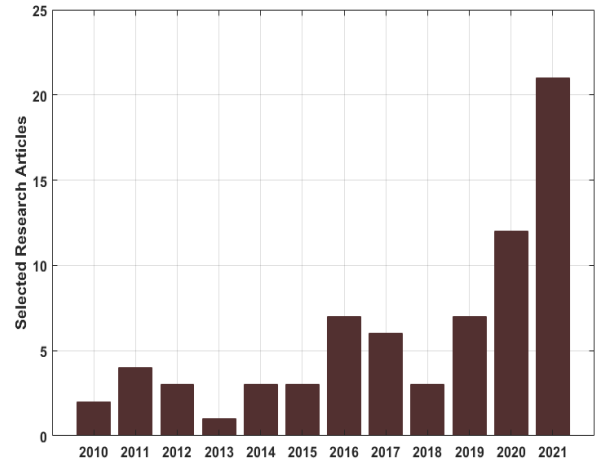


FIGURE 2. Number of selected research articles per year from 2010 to 2021.

III. SURVEY BACKGROUND

This section provides a brief background information on the focus of our survey. Here, we will first define the Coverage, Deployment and Localization challenges in WSNs, followed by the definitions of the different utilized AI techniques to solve WSN challenges.

A. THE HANDLED WIRELESS SENSOR NETWORKS CHALLENGES

1) COVERAGE

In deployment, according to the function of a network, two terms are discussed. One is coverage and other is connectivity. Coverage is the most important performance metric for WSN which determines how well a sensor field is monitored [15]. It is categorized into two types, one is target coverage which is based on the largest count of targets that can be covered depending upon some target assumptions. While the other one, called area coverage, is related to the area covered by the whole sensing field [16], [17]. Connectivity is a performance measure which indicates how well the active sensor nodes remain connected with each other and represents the communication capability of the WSN [18].

2) DEPLOYMENT AND LOCALIZATION

The term deployment refers to the positioning of operational wireless nodes in the monitoring area to form the desired WSN. It is a very challenging issue in WSN and the performance of a network can also be affected by this. Nodes are deployed either by placing one after the other or by dropping randomly [15]. The key purpose of deployment is to determine node locations, and to identify problems with coverage

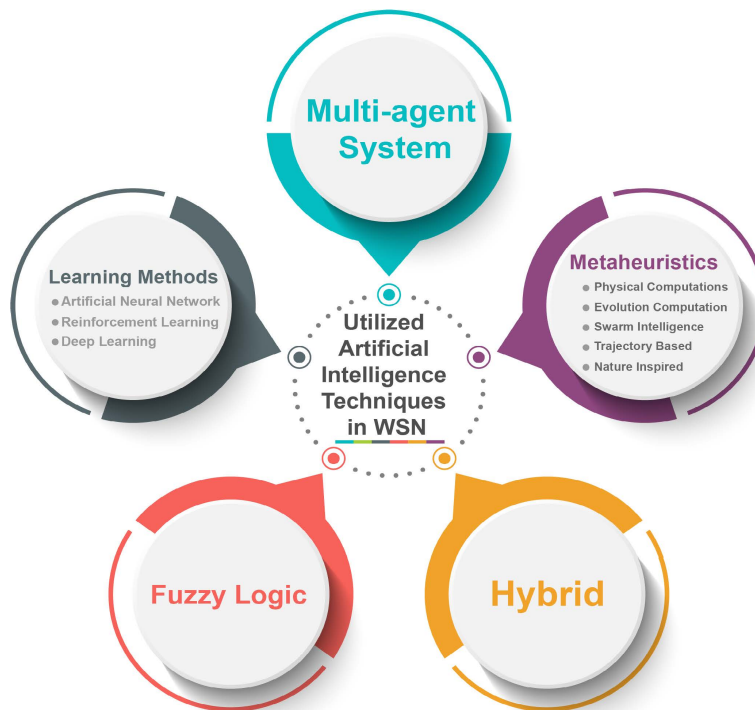


FIGURE 3. AI methods applied to address WSN challenges.

and connectivity [19]. As WSN nodes are deployed with limited capacity batteries and their replacement is difficult once deployed, energy conservation is the major challenge in WSN.

The other term, called localization, refers to the way of determining the physical location of nodes in a WSN. This is a primary concern as the nodes in WSN are generally distributed in an ad-hoc manner and the knowledge about their positions is essential for effective communication between the nodes [6], [20], [21]. There is no infrastructure available to estimate the location of the deployed nodes. Hence, localization plays a key role in various WSN applications, as without location information we cannot predict the source of events and other factors such as wind, air, humidity etc.

B. THE UTILIZED ARTIFICIAL INTELLIGENCE TECHNIQUES

AI is the ability of a computer system to perform tasks which require human intelligence and mimics human brains or human thoughts. It is considered as one of the important area of computer science that tries to make machine “smart.” The most widely used techniques of AI include: search methods, learning methods, fuzzy system, knowledge based and reasoning. AI is applicable to resolve many complex concerns in various sectors such as security, finance, health care, transportation and so on, through its ability in handling deficient and noisy data, dealing with non-linear problems, and are suitable for use in prediction and generalization at high speed once trained [22]. AI techniques for WSN is the main focus of this survey. We have studied and classified various AI techniques used in WSN as

depicted in Fig. 3. Different AI techniques used in addressing WSN challenges include Fuzzy Logic, Artificial Neural Network, Evolutionary Computation, Nature-inspired, Multi-Agent Systems, Trajectory based, Physical Computation, Swarm Intelligence, Deep Learning, Reinforcement Learning and Hybrid. An overview of these techniques is presented as follows.

- 1) **Metaheuristics:** Metaheuristics are the most common type of algorithms that use a degree of randomness to achieve optimal solutions to hard problems (or as optimal as possible). [23]. Metaheuristics are applied to a large number of areas. Metaheuristic algorithms can be categorized in various ways. For example, one scheme of classification is: trajectory-based and population-based approaches [24]. Trajectory-based schemes typically aim to locate a single optimal solution through piecewise style movement in the design (search) space (e.g., simulated annealing). While population-based schemes use multiple solution through search space and cooperate with each other to reach the final solution (e.g., evolutionary computation, physical inspired computation and nature inspired computation). Evolutionary computation is inspired by biological evolution and natural selection, crossover or recombination and mutation (e.g., Genetic Algorithm, Differential Evolution and Memetic Algorithm). Physical inspired computation is inspired by physical areas such as classical and quantum mechanics, thermodynamics, electromagnetism, relativity, and optics [25] (e.g., Central Force Optimization,

Gravitational Search Algorithm, Intelligent Water Drops and so on). Nature inspired computations imitate colonies, birds, flocks, insects in their living method or individuals communication (e.g., harmony, bat algorithm, cuckoo search etc.). The collective behavior that arises from a group of social insects has been called Swarm Intelligence (SI). SI deals with the cooperation of numerous homogeneous individuals in the environment [26]. Such techniques involve strategies and share information among the individuals for self-organization, learning and co-evolution during iterations to provide high efficiency. The individuals follow very simple rules and as there is no central infrastructure available to show how individuals behave, interaction can take place between individuals and these individuals as a population can exchange related data using any message-carrier [27]. Multiple interacting intelligent agents can solve a problem that is hard to solve by an individual agent or monolithic system, by searching and interacting with environment. Agents search for other neighboring agents and interact with them or with the environment to learn new things and to make decisions. Agents use their knowledge for making decision and take an action on the environment to solve their allocated task [28].

- 2) **Learning Methods:** One of the most important feature in the human (or animals) is learning. Learning is the ability to automatically acquire new information and improve it from experience without being explicitly programmed. So, learning is a part of AI like Artificial Neural Network (ANN), Reinforcement Learning (RL) and Deep Learning (DL).

With the ability to mimic biological neural network and human attributes, ANNs have been successful in solving complex challenging problems. ANN consists of small interconnected devices known as nodes inspired from the biological neurons in a brain. Information is passed from these interconnected devices using links which is represented by an arrow. Input and weight are the two values associated with an incoming connection, whose summation will generate the unit's output. After training an ANN using training data sets, new data sets can be introduced so that the trained ANN can be used further for prediction and classification purposes. The key advantage of using ANNs over other methods lies in its ability to model non-linear and complex processes without much interruption between input and output variables. It is used to solve many problems related to prediction and validation, optimization, function approximation, clustering, time series analysis and pattern recognition. Several architectures of ANN are present in literature which include: Radial Basis Function network, Multi-Layer Perception (MLP), Back-Propagation and Recurrent Neural Network (RNN) [22].

Another area of AI concerned with how intelligent agents ought to take actions in an environment in order to maximize the notion of cumulative reward is termed as RL. In RL process, learning is achieved using interaction between learning objects and its related environment. Objects tries to learn using trial and error method. RL consists of three components: value function, environment and reinforcement function. The environment for RL is often dynamic, with a set of probable states. For each state, there exists a set of possible actions at each time [29].

With the ability to learn without human supervision, drawing from data that is both unstructured and unlabeled, DL is an attractive AI function based on representation learning. DL mimics the human brain in processing data and creates patterns that are used in decision making. The architecture of DL includes several layers in between input and output layer and non-linear information processing units. DL is considered as a universal learning scheme and it is used to find solution to all kinds of problems in various application areas [30]. DL is also used to solve problems of big data analytics which include determining the volume of input information necessary to represent DL algorithms and obtaining good data abstractions and representations [31]. Feature extraction is represented in multiple hierarchical levels, which distinguishes DL from other machine learning approaches. DL is used in various situations where machine intelligence is useful:

- People can't explain their expertise (sound and speech recognition, language understanding and vision).
- The solution needs adaptation to a particular case (e.g. personalization, biometrics).
- If the solution to a problem changes over time (e.g. stock and price prediction, tracking, weather prediction).
- Human expert is absent (e.g. navigation on Mars).
- The problem size is huge for limited reasoning capabilities (e.g. finding matching ADs to Facebook, calculating webpage ranks, sentiment analysis).

Currently, DL is practically used in almost every field. Hence, this technique is often termed as Universal Learning Technique [30].

- 3) **Fuzzy Logic (FL):** FL is another AI technique that imitates the way of human decision making. It is used for uncertain reasoning or managing incomplete information [22]. The possibilities are either True (T) or False (F). FL works on the basis of 'truth-value' between 0 and 1 [32]. Fuzzy set membership can take any value between 0 and 1. Examples include centroid defuzzification, maximum and mean-of-maxima [29].
- 4) **Multi-Agent System (MAS):** Some complex problems are difficult or impossible for an individual agent or a monolithic system to solve. In such cases,

multi-agent based systems play a crucial role. MAS is a self-organized intelligent system that models some real-world domain involving many different components, interacting in diverse and complex ways and where the system-level properties are not readily inferred from the properties of the components. MAS is composed of multiple autonomous intelligent entities known as agents, which are typically capable of cooperating to solve problems that are beyond the abilities of any individual member. MAS are a part of Distributed AI. Agents solve their tasks and offer more flexibility due to their inherent ability to learn and make autonomous decisions. Agents use their interactions with neighboring agents or with the environment to learn new contexts and actions. Subsequently, agents use their knowledge to decide and perform an action on the environment to solve their allocated task. MASs are important primarily because they have been found to have a wide range of applicability [28].

These are some of the recent AI techniques that have been popularly used in addressing the WSN challenges. In the upcoming sections, we present an up-to-date survey of existing research trends with respect to AI methods applied in WSN for handling Coverage, Deployment and Localization challenges. Then, we go through each of these challenges and identify the different methods to address these challenges through the use of different AI techniques along with open research issues in each of these categories. We further present a comprehensive discussion on the recent studies regarding these techniques. Moreover, we compare them to determine suitable technique(s) in overcoming various challenging concerns of WSN and state the open research issues and future research directions.

IV. RELATED WORKS

Over the years, the research in the field of WSN is becoming more active and numerous works have been done for WSN enhancement. To address the challenges of WSN, different surveys are conducted based on various factors. Some of the recent research in solving challenges of WSN using AI techniques are presented here. Kulkarni *et al.* [33] conducted a survey of solving various WSN challenges using Computational Intelligence (CI) techniques. The authors showed that many CI algorithms have outperformed under severe and uncertain environment conditions and limited power supply, however, some solutions are not the best as no real time evaluations of these solutions are done on practical WSN scenarios. According to their findings, design and deployment challenges are usually centralized issues and for this, Artificial Neural Networks (ANN), Genetic Algorithm and Particle Swarm Optimization are very much suited. While SI is considered as a good paradigm for routing in MANETS, the large communication overhead makes it necessary that the SI models have to be modified to suit the properties and requirements of WSN.

In [34], Sarobin *et al.* provided some recent analysis and showed that energy efficiency can be enhanced by considering the following challenges of WSN which include: node localization, scheduling, design and deployment, clustering and data aggregation. The survey briefly explains how SI techniques are used to solve these challenges and improve WSN lifetime, coverage and connectivity. They also illustrate that most of the works are on stationary WSNs, so mobile WSNs must be encouraged in future. Most of the existing techniques based on SI are only simulation based. They should be implemented and tested in real-time environment.

A discussion on Intelligent Optimization of WSN using bio-inspired computing can be found in the survey conducted by Jabbar *et al.* [35]. The authors presented the solutions for non-biological systems using bio-inspired algorithms. Also, the authors presented that some of the issues of WSN can be solved using hybrid approaches of CI.

In [36], Maksimovi *et al.* presented a survey related to the use of FL in WSN. FL is considered as a promising approach to evaluate diverse parameters in an efficient manner. It improves decision making, reduces resource consumption and is suitable for resolving WSN issues such as routing, data aggregation, security, localization as well as deployment. FL can tolerate unreliable or imprecise readings easily. The authors presented it to be an easier and efficient technique. The disadvantage of using this technique is that the rules count grows exponentially with the variables count and storage requires much extra memory. They showed that the FL approach can solve the shortcomings of most of the algorithms. As this is a rule based approach and due to constant traversal of rules, it may slow down the event detection and decision making process. To solve this problem they also presented rule based reduction techniques which are efficient, but none of them can be considered as a general solution. A key property that must be kept in mind is that the reduction techniques employed should not affect the application accuracy. So, selection of the best reduction technique is very challenging. Future work that needs to be done is to implement a software based FL to enhance the speed of the system

Discussions on metaheuristics and how to employ them to solve the deployment problem are addressed in [37], and how to use them to solve lifetime problems of WSN are covered in [38]. Multi-Objective Optimization techniques in the context of WSNs are presented in [39] to introduce the development efforts for surveillance and monitoring. The requirements of different optimization approaches like mathematical programming and heuristics/meta-heuristics based optimization were discussed with other advanced optimization techniques.

The study discussed in [18] categorizes different coverage approaches into four major groups: computational geometry-based, grid-based, force-based and techniques based on metaheuristics. And, in terms of their advantages and disadvantages, make some distinctions between these systems. Their discussion is mainly about the

coverage classification, sensing models, practical difficulties in deploying WSNs, and research problems in WSNs.

As seen above, the related work discussed or partially surveyed the literature related to AI based protocols and algorithms solving different WSN challenges. Even though there exist survey papers to address the coverage, deployment and localization challenges, most of them focused traditional techniques and only few relatively are working with the application of AI methods to solve WSNs challenges e.g, routing or energy consumption. The work in this survey is different from existing surveys as our intention is to provide a contemporary survey to compare different AI techniques which allow to explore new strategies for resolving existing WSN problems and to enhance the WSN performance by overcoming the Coverage, Deployment and Localization challenges of WSNs, and we cover several optimization techniques with different challenges in WSNs. The core content of this survey is the use of AI schemes for WSN while we cover all aspects of it in addressing multiple WSN challenges. In order to carry out systematic review and comparison, we have reviewed the papers published from 2010 to 2021.

We have outlined a number of open research questions that need to be addressed in the future. We hope that this article, with its rich bibliography content, will provide valuable insight into recent trends in research on the WSN and encourage new research.

V. COVERAGE SOLUTIONS BASED AI TECHNIQUES IN WSNs

WSNs collect data from surrounding environment and transmit it to the BS for further analysis and processing. A major problem while deploying the sensors is that its area coverage should be maximized. The coverage maximization problem is however considered as NP-hard [49]–[51]. Table 3 summarizes the AI based solutions for coverage problems in WSN.

Several AI techniques are applied to handle the coverage issues in WSN. We discuss them as follows: In WSN applications, such as surveillance and security, extending the lifetime over which a WSN can cover and track all targets is a key problem. In [52], the authors proposed a memetic algorithm (MA) for enhancing WSN lifetime and to solve SET K-COVER problem. This is one of the effective technique to partition a given set of nodes into various covers, each of which must include all targets, and then to activate these covers one by one. The SET K-COVER problem is to find the maximum number of covers associated with the longest lifetime extension, which is analogous to partitioning the set of sensors into maximum possible count of covers. Therefore, more covers enable longer lifetime of a network. This problem of determining the maximum count of covers is treated as SET K-COVER problem. This is an NP-complete problem, so MA is proposed to solve this problem. The proposed MA outperforms other approaches in terms of count of covers obtained and hit rate. This proposed scheme may be applied with other constraints and objectives to extend lifetime of network.

Network coverage being one of the most important challenges in the deployment of WSN, the researchers always aim to have intelligent algorithms to solve this problem. To cover all points of interest, it is required to determine a sensor set with maximum residual energy. The work in [53] proposed a scheme based on PSO and ACO to solve the problem of minimum weight sensor coverage (MWSCP), based on the boolean disk model and the probabilistic sensor model, i.e. to locate a sensor with maximum residual energy to cover all points of interest.

Three Pheromones ACO (TPACO) is developed to answer the Efficient-Energy Coverage (EEC) problem in [54]. TPACO has a special feature that traditional ACO Algorithms do not have. It applies three types of pheromones to find a solution effectively, whereas traditional ACO algorithms applies only a single pheromone type. Local pheromone is one of the three pheromones, allowing an ant to manage its coverage area with reduced nodes. The latter two pheromones are global, one of which is used per points of interest to optimize the number of active nodes required, and the other is used to create a node collection that has as many sensors as an ant has selected the number of active nodes by applying the former pheromone. Moreover, another advantage of this scheme is that two user parameters of ACO techniques are not used. The alternative method proposed by [54] solve the EEC challenge by an ACO method different from the ACO approach presented in [53] where the ACO merely followed the lead of the preceding entity and is thus not tailored for optimized results. Swarm knowledge is the basis of the ACO algorithm, where complex group action arises from the behavior of several basic agents. In comparison, unlike [53], [54] uses a probabilistic sensor detection model that represents the particular characteristics of the sensors, such as the sensing range of sensors and the heterogeneous nodes collection.

In deterministic deployment, sensors can be placed exactly according to the need. To solve deterministic coverage problems of WSN, an approach based on Immune-Swarm Intelligence (ISI) is presented in [55]. This approach makes use of the benefits of both SI and immune system, and combines them to get better optimization results and better coverage speed. Communication of information between particles, effect of sensing and communication radii, diversity maintenance in antibodies and nodes coverage probability are considered in this. PSO picks the best particle from all generations to quickly reach the optimum solution. Size of swarm, evolving generations, gene exchange proportion and gene exchange individual order influence the performance and proper calculation of these parameters have contributed to the improved performance of the algorithm.

A Centralized Immune Voronoi deployment Algorithm (CIVA) is presented in [56] to maximize coverage and energy problems using binary and probabilistic models. In this proposed approach, a Multi-Objective Immune Algorithm (MOIA) that utilizes the features of Voronoi diagram is introduced to improve coverage and lifetime of the network.

TABLE 2. Summary of the existing surveys.

Approach	Focus	Coverage	Deployment and Localization	Others	Limitations
[33](2010)	Survey of computational intelligence applications to some problems in WSNs	×	✓	QoS	Relatively old
[40](2012)	A Survey of Localization in Wireless Sensor Network	×	✓	QoS	Relatively old and general
[41](2012)	A survey on coverage and connectivity issues in wireless sensor networks	✓	✓	Connectivity	Relatively old and No AI techniques
[35](2013)	Discussion on Intelligent Optimization of WSNs through Bio-Inspired Computing	×	✓	QoS and Scheduling	Focus to an ACO-based scheme to solve some issues in WSNs and Relatively old
[34](2015)	Exploiting SI techniques in WSN	×	✓	QoS and Scheduling	Consider SI only and Relatively old
[42](2017)	Localization in Wireless Sensor Networks: A Survey on Algorithms, Measurement Techniques, Applications and Challenges	×	Localization	×	No AI techniques
[18](2020)	Review of coverage and connectivity concerns in WSNs and their solutions	✓	Deployment	×	Consider metaheuristic only and deployment with coverage only
[43](2020)	survey of fuzzy logic in wireless localization	×	Localization	×	Consider only fuzzy logic
[44](2018)	Review on Swarm Intelligence Optimization Techniques for Obstacle-Avoidance Localization in Wireless Sensor Networks	×	Localization	×	Consider only Swarm techniques
[45](2016)	Deployment schemes in wireless sensor network to achieve blanket coverage in large-scale open area: A review	×	Deployment	×	No AI techniques
[46](2020)	WSN Strategies Based on Sensors, Deployment, Sensing Models, Coverage and Energy Efficiency: Review, Approaches and Open Issues	✓	Deployment	Sensing Models	No AI techniques
[47](2021)	A survey on the characterization parameters and lifetime improvement techniques of wireless sensor network	✓	×	×	limited AI techniques
[48](2019)	Coverage Protocols for Wireless Sensor Networks: Review and Future Directions	✓	×	×	No AI techniques

It involves two phases: In the initial phase, MOIA is used for activating optimal count of nodes having minimum sensing ranges and in the second phase, sensing range is adjusted by using Voronoi diagram, to achieve coverage optimization with limited moving cost. These two phases help in controlling the positions, adjusting the mobile nodes sensing range, to improve the coverage and to minimize the energy drain in WSN. In this approach, both binary and probabilistic models are used with and without obstacles to improve coverage of WSN. The main feature of this algorithm is that, they consider dissipated energy in mobile WSN, sensing coverage and cover age redundancy simultaneously.

A sleep scheduling coverage algorithm based on RL for solar powered WSNs is proposed in [57]. It takes a two-stage sleep scheduling algorithm to direct the mode of operation of the sensors step-by-step, that merge the precedence operator based group construction scheme and the Q learning-based technique for active node selection. It considers the

precedence operator, the remaining energy, the frequency of nodes recharging and the environmental states.

A service coverage preserving sleep schedule scheme is proposed in [58] for multi-sense WSN architecture where different nodes support different set of services. Here, two issues are resolved i.e., redundancy degree evaluation and sleep factor estimation. Redundancy degree indicates the possibility of replacing a WSN node. In this approach, they consider the redundancy degree on both layers (node and service level) to design a sleep factor estimation scheme using FL to incorporate node’s residual energy, reliability and redundancy. Sensor nodes are heterogeneous in service oriented architecture of WSN. Bloom filters are used to store the supported services of specific sensor nodes. Fuzzy engine determines the sleep factor corresponding to each node. Higher redundancy degree will lead to higher sleep factor, and the sleep scheduling will avoid a lot of unnecessary energy consumption. The Counting Bloom Filter is responsible for

ensuring that the sleep procedure will not affect the services, and the proposed scheme guarantees the service coverage. The results demonstrate the efficiency of the method in terms of space and time costs. It also stabilizes the energy utilization and WSN lifetime.

A bio-inspired algorithm, known as Energy Efficient Multi-parameter Reverse Glowworm Swarm Optimization (EEMRGSO) is proposed in [59] to solve coverage and energy issues which are quite challenging to be attained at the same time. Movement of nodes are required to achieve high rate of coverage, however, the nodes consume more energy for motion. Hence coverage and energy can be regarded as correlated problems. Sensor nodes are moved on some pre-defined grid points to reduce redundant coverage. Each node is assumed to be an individual glowworm. The coverage area of two nodes can be same as a result of random node deployment. The energy utilization can be reduced by limiting the total traversed distance and the count of node movements. For this, they defined two purposes for the node movement to happen: one is to cover the lower energy target neighbor node and the other purpose is to reduce the overlapped coverage such that a node from dense region will move towards the closest grid points. Simulation results reveal that this method is more energy efficient than other approaches and also it achieves a maximum effective coverage.

Harmony search (HS) based algorithm proposed in [60] to optimize the coverage ratio with the optimum number of sensor nodes deployed. The HS based deployment algorithm will find the optimal number of sensor nodes as well as their optimum locations to optimize the network cost and maximize the network coverage. The capacity of HS is changed to automatically evolve the required number of sensor nodes as well as their optimal positions. This can be achieved by integrating the idea of adaptable length encoding for each solution vector to indicate a variable number of candidate sensor nodes. Coverage ratio of the network, sensor nodes count and minimum gap between sensor nodes are the key elements of a new objective function that has been given to validate the option of optimum number of sensor nodes and their locations. In [61], ACO is utilized for WSN implementation by seeking solutions to the combination optimization challenge of grid-based coverage with Low cost and Connectivity Guarantee (GCLC) using increased count of ant transitions. In [15], ACO Greedy is introduced, which applies a greedy migration approach to further boost performance. These ACO-based schemes face two big challenges. First, an ant suffers blindness in search process as it deviates away from points of interests (PoIs) at some stage during a output construction process. Second, there is a significant number of redundant sensor nodes in the final output that needlessly contribute to the coverage cost. The issue of blindness in search is discussed and resolved in the solution suggested by [62]. In this method, distant PoI clusters are first covered, and then the sensors deployed are linked to a minimal number of sensors. However, there is a question of redundant sensors around the PoIs that still have to be resolved. In order to

tackle this issue, the work in [63] suggests an ACO-based architecture for WSN implementation in a practical 3-D setting, by making improvements to the basic ACO algorithm. It provides solutions to the combination optimization issue of GCLC in a 3-D environment and runs in two stages. In first phase, basic ACO with a modified heuristic value is utilized to generate sparsely positioned nodes in the solution. In the second phase, an effective two ants technique is used to eliminate redundant sensors. The proposed solution outperforms the state of the art in terms of computational costs and reducing the number of nodes deployed. It greatly eliminates redundant sensors compared to standard ACO based algorithms [15], [61] and [62].

Two nature-based algorithms are proposed in [64] to maximize the area coverage. Most of the algorithms in previous works are facing issues like large computation time and solution instability. Hence, to overcome these issues, two nature based algorithms are implemented named Improved Cuckoo Search (ICS) and Chaotic Flower Pollination Algorithm (CFPA) which are developed from the concept of cuckoo search and flower pollination. The objective is to develop a model for area coverage maximization of WSNs using fixed count of heterogeneous sensors. The main idea of ICS is inspired from the breeding scheme of cuckoos where they lay their eggs in other host bird's nest. If the host bird recognizes this intrusion, it will either throw out the disguised eggs or desert the nest. It includes the same three phases as in cuckoo search. Updating is different in CFPA as compared to ICS. It involves two evolutionary steps; global pollination and local pollination. Only best solutions from every generation is selected to reproduce. Simulation results demonstrate that this scheme performs better than other approaches in terms of quality of solution and calculation time.

Bio-inspired multi-objective algorithms are presented in [17] to solve network lifetime and target coverage problems. Four bio-inspired multi-objective techniques are evaluated. The frameworks of MOEA/D, NSGA-II, MOPSO, NSPSO and two mutation operators are proposed as local search operators. The proposed approach solves the problem while ensuring connectivity condition. A self-adaptive heuristic operator is designed and the four methods are augmented with the aim to explore more cover sets and target coverage probability. The results demonstrate that the combination of multi-objective optimization algorithms and self-adaptive heuristic operators are the best for use and provide better results than other approaches.

To solve the problem of area coverage maximization in heterogeneous WSN, the authors of [65] proposed a meta-heuristic approach based on GA that incorporates heuristic method for initialization of population, fitness function for integral area calculation, and a mix of two distinct operators: 1) Laplace (LX) and 2) Arithmetic crossover (AMXO) for executing crossover operation. Number of sensors are fixed. The surveillance area considered is two dimensional with heterogeneous sensor nodes of count k deployed such that a

node i has a sensing range r_i . The key focus is to determine the optimal positioning of the nodes for maximizing the area coverage. The algorithm is analyzed in terms of efficiency, stability and accuracy and tested on 15 benchmark problem instances. The method exceeds the performance of other techniques in output quality, accuracy and stability, and has an acceptable computation time. Obstacle constrained area coverage maximization and area coverage issues associated with connectivity and WSN lifetime to accommodate realistic demands are not covered in this paper.

Target coverage issue is addressed in [16] through directional sensor nodes which are self-configurable with adjustable sensing ranges, with an objective of maximizing Directional Sensor Networks lifetime. However, the maximum network lifetime with adjustable ranges problem is NP-complete. So determining an optimal solution with less computational complexity is difficult. The authors proposed a target-oriented metaheuristic approach which is based on GA and incorporates two popular power conserving methods: scheduling and adjusting, for solving the coverage problem and maximizing the network lifetime. Scheduling technique has a main contribution in maximizing network lifetime. The proposed target-oriented GA based algorithm works in several rounds generating a cover set as output in each round that will monitor the targets present in the network. Each round consist of an initialization phase and a cover set formation phase. Then GA is applied to select appropriate cover sets from possible ones. Some changes are done in GA representation of chromosomes, introduces an effective fitness function, manages critical targets in chromosome production process, and presents a repair operator for checking and fixing the offspring validity. The proposed approach outperforms other greedy algorithms in terms of constructing the cover sets that consume relatively less energy with a considerable enhancement in lifetime of the network.

Another intelligent optimization algorithm, called Bat Algorithm (BA), inspired by the echolocation and foraging behavior of bats, is used to determine the optimal sensing sensor node and the corresponding path to minimize energy consumption in [66]. The work aims to enhance the lifetime of the network by extending the life of the operational sensors, and the data obtained by the super node will be sent to the sink as well. The simplicity and flexibility of the algorithm for different parameter values of the parameters show the superiority to other schemes. The results indicate that the algorithm is scalable and hence appropriate for different network states.

In [67], a Hybrid Coverage Hole Recovery Scheme for WSNs, which depends on both sensing power control and node relocation using a game theory based Q-learning algorithm, to recover coverage holes in a distributed fashion was suggested. Sensor nodes can restore Coverage Holes by using only local acquaintances through the formulated potential game. To reduce the coverage gaps, the combined action of node reposition and sensing range adjustment is chosen by each sensor node.

A major problem in designing WSNs is coverage maximization, in which a given number of sensor nodes must be deployed in a way that maximizes area coverage of a given network, without violating practical constraints. This is a known NP-hard problem and thus requires metaheuristic approaches for practical problem sizes. Two meta - heuristic algorithms, namely GA and PSO, are presented in [68] to solve this issue. The solution involves the partial use of heuristic initialization, the new fitness function, the modified virtual force algorithm, the inclusion of a uniform deceleration to the estimation of inertia weight and the addition of the impact of the subpopulation' head individuals.

The study in [69] proposed a Dynamic Reverse Glowworm Swarm Optimization (FIS-RGSO) based Dynamic Fuzzy Inference Method of energy and coverage in smart green mobile WSNs with the goal of achieving minimal energy utilization by the nodes through their optimal motions so that nodes can cover greater area and increase their lifespan. The proposed solution boosts the lifespan and energy-efficiency, and the performance of green WSN is enhanced by taking better and coordinated node movements based on the Fuzzy Inference method, resulting in minimum power consumption and less distance traversal.

The work [70] propose an algorithm called Heuristic Hole Healing (H3) that employs adjustable sensing ranges and exploits node mobility to repair emergent coverage holes. The algorithm selects suitable nodes by gauging the degree of overlap and the residual energy of each node in the vicinity of the coverage hole. H3 employ a Fuzzy Inference System (FIS) to rank the nodes from most eligible to least eligible. This ranking represents the order in which nodes will attempt to repair the detected coverage hole. The FIS considers two input criteria to make this decision: sensor nodes' energy stores and the total overlap in sensing ranges for each node. A Nash Q-Learning oriented node scheduling algorithm is implemented in [71] for coverage and link maintenance where each node autonomously learns its optimal behavior to enhance the coverage rate and sustain network connectivity. The learning algorithm is added to each sensor node. The main aim of this is to allow the nodes to identify their optimal action. This helps to minimize the total activated nodes in every scheduling round. Also, preserves the criteria of coverage and connectivity of the WSN. The comparative analysis with other schemes gives evidence of its reliability and accuracy.

Improved CSO algorithm proposed in [72] determines the sensor covers by optimizing the sensing range of the sensors to reduce the redundancy in the network. The proposed algorithm partitions the sensor set into non-disjoint subsets with varying sensing range such that each cover provides k -coverage in the network. In [73], the authors describe how these challenges can be resolved by designing an efficient WSN with the help of meta-heuristic algorithms. The authors have configured an optimized route/path using ACO algorithm and deployed static WSN nodes. After configuring an efficient network, if we can maximize the coverage area, then

we can ensure that the network is a reliable network. For coverage area optimization, the authors used a hybrid differential evolution-quantum behaved PSO (DE-QPSO) algorithm. An effective multi-objective connected coverage target based WSN algorithm is proposed in [74] namely Multi-Objective Binary Cuckoo Search algorithm. The proposed model also handles the critical targets in the given sensing region. The algorithms hold the potentiality to handle minimized sensor deployment, maximized coverage and connectivity cost simultaneously. The work in [75] focused on providing an efficient target coverage model for various real-time applications and developing a Termite Flow Optimization (TFO) algorithm to solve the eliminated obstacles' target coverage problem. TFO deploys the nodes efficiently by adjusting their location closer to the target node's location. The entire sensor nodes are classified into subgroups as cover sets, active cover sets, and non-active cover sets to reduce energy consumption. TFO also solves the obstacles like an n-coverage problem, area coverage, and barrier coverage during the process. Hence TFO becomes more efficient and right solution for target coverage problems for WSN. In [76], a novel approach for coverage hole detection in WSNs called FD-TL (Force-directed and Transfer-learning) is proposed. FD-TL is based on layout generation capability of Force-directed Algorithms and image recognition power of Convolutional ANN with transfer learning. In contrast to existing approaches, the proposed approach is a pure topology-based approach since FD-TL can detect both triangular and non-triangular coverage holes from a WSN based on the input network topology without relying on the physical locations of the anchor nodes. In FD-TL, a Force-directed Algorithm is used to generate a series of possible layouts from a given input topology. Next, a Convolutional ANN is used to recognize potential coverage holes from the generated layouts. During the training phase, a transfer learning method is used to aid the recognition process. WSN sensing coverage problems, which comprise a basic metric for popular IoT applications, cannot be solved by traditional methods, while nature-inspired meta-heuristics can usually provide reasonable solutions. Based on this approach an improved ABC algorithm with teaching strategy is proposed in [77]. ABC, which is good at exploration but poor at exploitation, is improved by introducing a teaching strategy in teaching-learning-based optimization (TLBO) that has a rapid convergence but is easily trapped in a local optima. Thus, the proposed algorithm combines the advantages of ABC strong global search ability and TLBO rapid convergence. In addition, to retain the diversity and eliminate the parameter limit in ABC, a dynamic search update strategy is introduced instead of the scout bee phase of ABC. The WOA is a SI based Search-Algorithm while browsing for an optimal solution, but, it suffers from the poor and inconsistent exploration problem and that causes trapping of local optima in randomly deployed nodes that fail to guarantee network coverage [78]. To resolve the issue, an innovative study has been researched which presents an embedded coverage optimization WSN and it is based on Levy Flight mechanism with

WOA (LWOA) [78]. This updates the current search of location for positioning the sensors in the field. This mechanism can enhance and balance the exploration ability of WOA, which allows trapping of the local optima. From the experimental results, it can be construed and proved that the performance of Levy WOA (LWOA) has significantly improved the global search capacity and increase the efficiency of convergence, which immensely enhances the efficacy of coverage of nodes in turn amplifying the overall performance of the network. Biogeography-based optimization (BBO) is widely used in the field of cluster intelligent optimization because its search method has a better incentive mechanism for population evolution. In [79], through the research and improvement of the BBO algorithm, it will make full use of the ability of the BBO algorithm to sense interactive data in multidimensional and high-dimensional problems to achieve the optimal construction of the WSN coverage path. The move-in and move-out operation and mutation operation of the BBO algorithm enable WSN to find an efficient coverage path.

A. OPEN RESEARCH ISSUES AND CHALLENGES

Existing works based on disk communication models can be investigated further to examine the impact of other more realistic models. In such case, three contradictory objectives could be considered to formulate an enhanced solution. These are maximizing network lifetime (number of set covers), maximizing coverage probability, and maximizing communication reliability. The signal-to-interference-plus-noise ratio model and the log-normal shadowing model can be adopted to capture shadowing effect and the environmental noises and interferences.

Moreover, we found that the research communities work in two ways, one using deterministic mathematical methods and other using bio-inspired meta-heuristics for solving different versions of disjoint set cover problem in WSNs. Thus, we recommend future research work to bridge the gap between these two methods in a better way, and coupling their desirable features into one hybrid and heuristic algorithm.

According to the work in [65], the combination of LX and AMXO crossover operators gives positive and promising results when implemented on the same sets of instances. It is also important to decide the rate of each operator being applied on the individuals. After extensive experiments, they observed that the combined operator achieves optimal results when LX is applied at a rate of 10% and AMXO at a rate of 90%. These conclusions are meaningful for future work on this problem and can pave the way for advancements in the deployment of WSNs and the field of evolutionary computing.

Different aspects of MA can be explored to provide a better solution, where MA can be applied to extend the WSN lifetime with additional constraints and objectives, such as network connectivity for the communication range smaller than twice the sensing range and for point coverage. Robustness and dynamic performance when certain sensors fail will also

be crucial future research issues. At the same time, improving the Evolutionary Algorithm or local improvement operators' search capability will increase the MA's performance in prolonging WSN lifespan.

In addition, studies focussing the maximization of obstacles constrained area coverage problems related to connectivity and lifetime of WSNs also require significant attention. The gained outcomes of existing works can be applied to agricultural fields or other domains, where sensing data is put to intermediate gateways before sending to clouds. The gateways thus play the role of blockchain data generation nodes in context of the testing application. Uniformity in sensor deployment and the energy consumption due to sensor movement in the presence of obstacles in the sensing region should be taken into account while calculating a lifetime when the existing works are extended for a three-dimensional workspace.

Neural computing and the Glowworm Swarm Optimization algorithm may also be combined together for optimizing these challenges in WSN. Adequate communication protocols have to be applied and analyzed to improve the existing ones. For better results, an efficient payoff function based on deep Q-learning can be devised and implemented for teaching the agents. The results can be analyzed by comparing the performance in terms of convergence time, rewards, and global optimality. Optimized algorithms are required to meet more of the network design objectives such as network with obstacles, network connectivity and network lifetime. Further investigations are desirable to analyze the extent of signal interference, the relationship between the communication range and the packet collision, choice of simulation methodology, etc.

As seen in the past researches, most of the studies consider or depend on two or three objectives, whilst considering four or more objectives have less likely occurred. Therefore, future researchers should encourage and consider multiple-objectives while studying the performance and add other indicators to evaluate the suggested algorithm(s).

VI. DEPLOYMENT AND LOCALIZATION SOLUTIONS BASED AI TECHNIQUES IN WSNs

Most of the WSN applications demand that the nodes must have awareness of their location. For this, node localization and determination of nodes position become important and is challenging in WSN. This is important for certain reasons. Primarily, the sensors often capture information about environmental parameters such as pressure, humidity, temperature, etc., and such data will become futile if not collected along with location information. Hence, localization plays a vital role. Traditional localization algorithms (eg., GPS) are not appropriate for use in WSN and hence the researchers make effort to design new localization schemes that are suitable for implementation in WSN. Table 4 summarizes the AI based solutions to deployment and localization problems in WSN.

Several AI techniques are applied to handle the deployment and localization issues in WSN. We discuss them as follows: ACO is used in [80] to solve multiple knapsack problem. Using this approach sensor deployment problem is solved to achieve complete coverage and maximize network lifetime. The node deployment problem is modeled using multiple knapsack problem. WSN lifetime can be enhanced by finding the subset of nodes that can maintain both coverage as well as connectivity, and then scheduling them to communicate data to the sink node. This helps to achieve a balance in power consumption. Simulation results indicate that this scheme can enhance network lifetime significantly better when compared to other approaches.

In another paper [15], glowworm swarm optimization (GSO) technique is used to maximize coverage after an initial deployment of nodes in WSN, while limiting the movement of nodes. In this approach, each node is considered as a glowworm individual with luminescence property and emits light (luciferin) which is used for communication with its neighbors. Intensity of luciferin (luminescence) depends on the communication distance between the node and its neighbor. A node gets attracted and move towards a neighbor node with lower luciferin intensity. This helps to maximize the coverage as the nodes move towards lower node density regions. The proposed approach is easily scalable and needs no centralized control. Simulation results show that this technique performs better in terms of achieving high coverage with limited sensor movement.

To solve the deployment problem in WSN, the work in [81] adopted potential field deployment algorithm (PDFDA) along with multi-objective deployment algorithm (MODA). These two approaches are developed using Tabu search meta-heuristic and artificial potential field to solve computational complexity while optimizing the cost of deployment. The event detection probability of a network must be greater than predefined threshold. After initializing deployment, virtual force is calculated that is exerted to move sensor nodes. This virtual force calculation which includes angle and magnitude is accounted for the deployment cost and decreases the deployed nodes count. In PDFDA, initial solution is refined iteratively by exploring the solution space until it reaches the predefined count of iterations. In each iteration, a certain number of candidate solutions are created from actual solution. Then a cost function is involved to select an appropriate solution from the generated candidate solutions, and all other solutions are placed in Tabu List that contains all those solutions which are already visited and could not be selected again as candidate solutions. After termination, algorithm returns best solution in Tabu List. PDFDA deployment strategy is tested on uniform as well as non-uniform event detection probabilities. This is a general algorithm to find optimal solution for various optimization problems. An extension of PDFDA, called MODA, to enhance the WSN lifetime while maintaining minimum deployment cost is also proposed. This is based on local neighborhood search algorithm. In this, each iteration generates a topology and we eliminate those

solutions that are present in Tabu List. Once MODA is terminated, the scheme selected one topology from non-dominated solutions. Simulations reveal that the proposed strategy is superior to existing strategies in terms of WSN lifetime, network connectivity and deployment cost.

The traditional schemes for environment monitoring suffer from the drawbacks of operation challenges, high costs, low stability and precision. It has been found that WSN along with mobile agent technology can effectively solve these problems. Motivated by this, the work in [82] utilized the mobile agent technology to solve these challenges and proposed a new scheme for environment monitoring. The authors developed an integrated framework based on mobile agent and WSN technology for intelligent monitoring of equipment room environment is proposed. Mobile agent is programmable and is capable of executing commands that could autonomously capture the real time sensor values, transmit messages, and migrate from one node to another. This system can monitor the equipment room environment, detect and locate equipment problems immediately, reduce manual operations, and enhance management efficiency. This system consists of three layers: WSN layer, control layer and application layer as provided in Fig. 4. In WSN layer, nodes are deployed in rooms to monitor and collect information such as electric power, water leakages and temperature. Such information gathered at the sink node is transmitted to the control layer. Application and database servers operate in the control layer. A control program is executed by the application server to process the information obtained from the sink node and stores the result in database server. If any abnormality is detected, control program immediately sends an alarm to management staff's telephone. Application layer is a platform which interacts with users. The users can monitor the real time data, request services and send orders to WSN (eg. requesting cabinet temperature value). The system is implemented in a company and the test results are evaluated for months. The results showed considerable improvement in management efficiency. It solves the deployment problems, reduces the cost, data flow in the network and latency of the system. It also improves node's life cycle and provides better load balancing.

To solve grid-based coverage issue with low-cost and connectivity-guarantee (GCLC), a deployment approach is presented in [83]. The authors adopted ACO with Greedy migration scheme (ACO-Greedy) and designed a non-uniform node distribution scheme in which dynamic tuning of the sensing or communication range is performed to overcome the energy hole problem and at the same time maximizes the WSN lifetime. For object point selection, ACO is used in which heuristic value and the rule for pheromone update is pre-defined which reduces the count of deployed nodes. Greedy migration scheme offers significant reduction in the deployment cost and contributes to full coverage.

A new deployment method is proposed in [15] to fill the coverage holes in sensing field. The presented scheme is based on Multi-objective Immune Algorithm (MIA) and uses

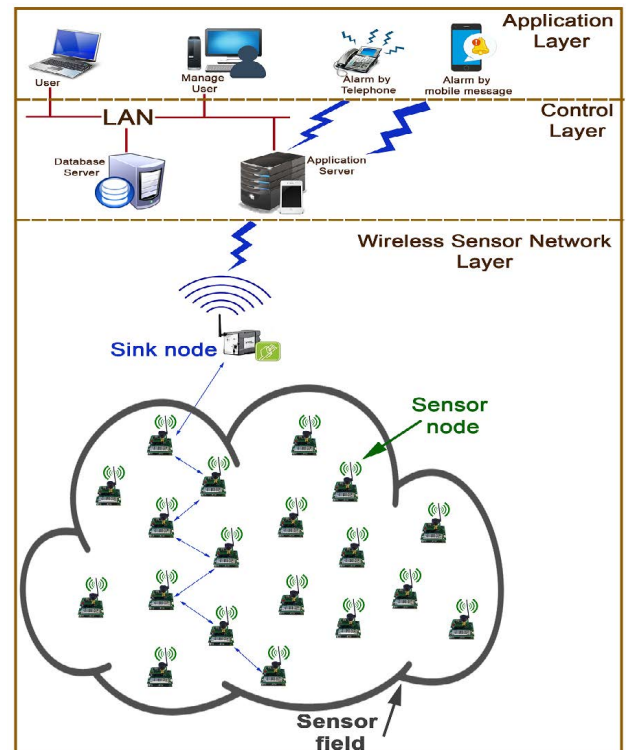


FIGURE 4. The scheme of environment monitoring system for equipment room [82].

binary sensing model to overcome the coverage hole problem caused by traditional deployment methods. The randomly deployed nodes are rearranged using MIA in such a way that it maximizes the coverage and minimizes the energy dissipated in mobility by limiting the movement distance of the nodes. This approach also ensures connectivity among nodes by limiting the movement distance of nodes within the communication range. MIA imitates the antibody-antigen reaction characteristics of biological immune system. The relationship between objective function and the feasible solution for the optimization problem resembles the antigen and antibody relationship in MIA. Initially, the BS broadcasts a short request enclosing its location to collect the ID and initial location of the mobile nodes in the network. Based on the received responses, BS determines the optimal position for those nodes using MIA by keeping coverage maximum and mobility cost minimum. Simulation results show that the proposed algorithm in different environmental setup i.e., with and without obstacles outperforms other existing techniques in terms of coverage as well as redundant area, convergence speed and cost of mobility.

The purpose of the work in [84] is to find a solution to relay node placement problem by optimizing the three conflicting objectives given by: average sensitivity area, average energy cost and reliability of the network. This is an NP-hard problem. They considered and applied various multi-objective meta-heuristics such as the trajectory

algorithm: MO-VNS, GAs: SPEA2 and NSGA-II, SI algorithms: MO-FA and MO-ABC, decomposition method based algorithm: MOEA/D, to optimize a freely available data-set.

Another approach to solve deployment problem of WSN using Metaheuristic algorithm is presented in [85]. The scheme is called Search Economics (SE). Metaheuristic algorithms have short-term memory and will fall into the local optimum easily. To overcome this problem, a search algorithm called Vision Search (VS) is presented in this paper. In search process, this approach uses the information of solution space and to achieve this, marketing research is done. SE uses two folds concept. In first fold, based on the solutions that are checked by the search algorithm, solution space capacity is computed and the second is to use the obtained knowledge known as “landscape of solution space.” Proposed algorithm provides better results for the deployment problem than other algorithms.

An improved Grey Wolf Optimizer (IGWO) is introduced in [86] to solve the optimal deployment challenge in WSN for better coverage in complex environments. A metaheuristic approach to solve localization problem in distributed WSN is proposed in [87] and is based on CSO. Localization issue in distributed WSN is considered as multidimensional in nature. CSO solves this problem in faster way with minimum localization error. This strategy is based on social behavior and hierarchical order of chickens. The work in [88] utilized GWO algorithm to solve the localization issue with the intention to figure out the geographical position of unknown nodes by utilizing anchor nodes in WSN.

The work in [89] developed a hybrid multi-objective optimization algorithm, which is based on a combination of multi-objective ABC and Levy Flight random walk. The aim of the algorithm is to solve the deployment issue in WSNs where coverage and connectivity have been regarded as objectives. This paper introduced a novel stochastic bee algorithm (MOLFB), a population-based optimization algorithm, inspired by the foraging behaviour of honey bees, and employed Levy Flight random walk distribution to enhance the random movement pattern of bees.

Another approach [90] addresses the relay node placement problem in WSNs from two multi-objective (MO) formulations with the aim of identifying robust scheme that solve the real time deployment challenge. Two goals, average sensitivity and energy cost, are included in the initial formulation, and three goals, the network stability along with the two previous goals, are included in the second formulation. Based on this, the authors examined how a wide variety of MO metaheuristics from the three major classes work. It includes evolutionary based (NSGA-II, MOEA/D and SPEA2), trajectory based (MO-VNS and MO-VNS*) and swarm intelligence (MO-ABC, MO-FA, and MO-GSA) schemes. In both optimization problems, the eight MO metaheuristics were used to find solutions to four implementation scenarios of increasing complexity, while considering a distinct count of relay nodes and communication constraints.

The work in [91] deals with the deployment challenge of WSNs with mobile robotic nodes for spatio-temporal surveillance applications. The scheme called deep reinforced learning tree (DRLT) that adopts deep RL (DRL) to enhance the ability to find most informative and suitable sampling locations. DRLT was introduced to scan a broad spatiotemporal region effectively with the aid of information gain. DRLT speeds up the exploration process and identify near-optimal sampling positions for a group of mobile robotic sensors within the area of interest. The robotic nodes are thought to be point sensors that only collect data at their location with Gaussian white noise. In addition, the robotic sensor location accuracy is measured by the field estimation error as estimated by the Kalman filter, and the field coverage is assessed by calculating the field monitoring uncertainty. Initially, to determine near-optimal sensor positions, the proposed algorithm is run offline. Then, to conduct insightful sampling and minimize the error in estimation, the robotic sensor nodes are deployed.

Another approach is presented in [92] in which location of sensor nodes can be determined with high precision by applying range-free method of localization named Mobile Anchor Positioning (MAP). Localization error can be further reduced in this approach by applying Modified Cuckoo Search (MCS), Bat Optimization Algorithm (BOA) and Firefly Optimization Algorithm (FOA) on the MAP result. Root Mean Square Error (RMSE) is taken as evaluation metric to compare these proposed approaches. Simulation results show that FOA-MAP outperforms other approaches and have minimum localization error.

A new multi-hop based solution to WSN localization problem is provided in [93]. In the primary phase, the distances from each node to the existing reference nodes are estimated using Sum-Dist algorithm. Then in the next phase, the initial node positions are determined using Min-Max technique. The final phase refines the estimated node positions through optimization, which is accomplished using the two proposed algorithms: PSO and BSA. This approach aims at optimizing the accuracy of inferred localization. Additionally, a confidence factor is computed for use in the final stage to assess the localization accuracy. Simulation results indicate that the BSA based strategy shows better results in performance when compared to PSO based strategy.

Another meta-heuristic approach is proposed in [94] named Butterfly Optimization Algorithm (BOA) to solve node localization problem. This approach mainly mimics the foraging behavior of butterflies. The main objective of this approach is to minimize localization error. BOA is used to estimate position of sensor nodes. BOA is compared with PSO and firefly algorithm in terms of localized nodes, localization error and computation time, using simulation. The results show that the BOA shows less localization error, while PSO estimates positions in less computing time but has high localization error.

Range-free localization algorithms use hop count values between anchor and sensor nodes and connectivity

information to locate the target nodes. A distributed algorithm for range-free localization of nodes for three dimensional WSNs is presented in [95]. The scheme is known as 3D-GA based improved distance vector hop (3D-GAIDV). The key objective of 3D-GAIDV algorithm is to improve localization accuracy over the DV-Hop algorithm [96]. Line Search Algorithm is utilized to calculate the optimal hop size of each anchor node. Precise distance estimation is done using this. Coplanarity concept is adopted to minimize the localization errors caused by the coplanar anchor nodes. The successfully localized nodes in the initial round are regarded as assistant anchor nodes which may assist the localization process in the upcoming rounds. Integration of GA with 3D-IDV contribute to fast convergence and enhanced accuracy in WSN localization. 3D-GAIDV algorithm shows better performance when evaluated under metrics such as location coverage, localization accuracy and scalability.

In [6], a fuzzy based technique for geographic routing is proposed, which is based on weighted centroid method of localization. The fuzzy localization algorithm utilizes the flow measurement through wireless channel in estimating the distance of separation between anchor nodes and sensor nodes. The centroid method is adopted for use to determine unknown node locations using the two fuzzy inference systems: Sugeno and Mamdani which contribute to enhanced accuracy in position estimation. Then, in order to minimize the energy expenditure and to prolong the network lifetime, another strategy is used which selects next CH hop based on location information detected by localization algorithm. After that, data transmission takes place. To increase the effectiveness of next hop CH selection, each CH uses Mamdani inference system and chooses the minimum cost next hop CH to transmit the data. This could promote considerable reduction in energy dissipation and improves lifetime of the WSN. The method is proved as effective in terms of metrics such as packets transmitted, dead nodes count, energy consumption and WSN lifetime.

A hybrid approach (HVP-FELM) is introduced in [97] to improve the range-free localization (centroid) method by integrating FL system (FLS) with centroid and utilizes an Extreme Learning Machine (ELM) Optimization scheme to strengthen the features. First, FLS is used to adjust weight of centroid then, ELM is applied to optimize location estimate precision. Simulation results show that the performance of HVP-FELM is outstanding on irregular topology with comparatively low localization error.

A new optimization algorithm is proposed in [98] for localization of nodes in an outdoor environment. It is a range-based centralized algorithm used to solve non-linear optimization problem in which RSSI based ranging technique is applied to measure the distance from anchor nodes to unknown nodes. The estimated result is transferred to the sink for making final calculation. The four main stages involved are as follows: First stage measures the distance with the help of any ranging technique, based on any RSSI or time based technique. Next stage estimates the locations

of unknown nodes using any multilateration and angulation techniques. Third stage manipulates the available localization information using the localization algorithm to estimate the positions with high accuracy. Finally, the evolution stage examines the efficiency of the proposed algorithm. Intelligent water drops (IWDs) algorithm that mimics the flow of natural water drops in a river is modified and called IWD for continuous optimization (IWD-CO) for the optimization process. IWD-CO is used to enhance the accuracy in estimating the unknown nodes positions. Their evaluation results using metrics such as range, anchors density and noise prove that IWD-CO is a better choice for enhancing accuracy in localization.

In distance estimating methods or localization approaches, the ANN is adopted to determine the location of nodes or distances between WSN nodes. ANN delivers high performance, quick convergence, and low cost of computing [99].

The method of the ANN is suggested in [100] to reduce the noise impact on the localization of WSN. The application of the ANN on each node can make the node able to do localization by itself, or it can be done with the aid of the central controller. The authors considered the use of central controller in this work, however it can be extended to satisfy the other case with minor revisions. A central controller is equipped with an ANN based localization module to estimate the location of each node, and each anchor node is connected to central controller via the sink node. The anchor node is responsible for providing raw data to the sink. The nodes are fitted with ultrasonic transducers and, using the Time of Arrival (ToA) method, the time distance between the node and the anchor is measured and given to the ANN. The position of WSN nodes on the 2D-plane is the expected output. The 2D-plane neural network locate the WSN with five anchor nodes that provide ToA data to the ANN input layer and two corresponding output neurons represent the coordinate values x and y in the 2D-plane. Multi-layer perceptron (MLP) refers to a class of feed-forward ANN having multiple layers and are useful for mapping multiple inputs to a specified set of target outputs. MLP can be trained using supervised learning algorithms such as bayesian regularization and backpropagation. Two multi-layer perceptrons are built to resolve the localization problem: ANN1 (with a single hidden layer) and ANN2 (with two hidden layers). During the feed-forward process, each input neuron transmits the received input signal to the hidden layer. Each neuron in the hidden layer applies its activation function to the received signal from the input layer and the resulting signal is transferred to the output layer. Each neuron in the output layer uses its activation mechanism to generate the ultimate output. During training process, each output neuron compares the generated output with the target output to calculate the associated error and then backpropagates this error to the prior layers to update the weights of these neurons. Gradient descent technique is used for weights selection has a great impact on the convergence speed of ANN. It should not be too large or too small. Cricket motes produced by MIT and Crossbow are used for conducting experiments. The results

show the superiority of MLP with two hidden layers (ANN2) over other algorithms.

Authors in [99] introduced PSO-ANN which is a localization method for mobile WSN. The authors used ANN and PSO combination for better performance. PSO was applied to determine the optimal count of neurons required for accurate localization in WSNs. PSO-ANN technique showed improved performance and accuracy than other traditional schemes.

The location of the mobile node is estimated based on the RSSI by means of firefly algorithm based ANN (FA-ANN) technique in [101]. Mobile point RSSI data is calculated in advance and stored in the fingerprint database. To minimize the size of RSSI fingerprints, the discovery stage size estimation and principal component analysis is performed. To decrease the higher localization error and increase the efficacy of the location estimation, the affinity propagation clustering scheme is adopted. For accurate localization, the proposed FA neural network is trained based on the clustered RSSI value. Finally, a trained FA-ANN is used to determine the precise location of the mobile node with minimum mobile node energy consumption. The localization error is thereby minimized by the hybrid method and node prediction is performed at a faster rate. FA-ANN strategy uses less time for both the offline training phase and the online localization phase relative to PSO-ANN [99].

A WSN and a backpropagation-based ANN (BP-ANN) localization system are put into operation in [102] to detect and evaluate the location of an Alzheimer's patient in an indoor scenario. Kernel Extreme Learning Machines based on Hop-count quantization (KELM-HQ) is proposed in [103]. KELM-HQ uses the real number of hop-counts between anchors and uncertain nodes as training inputs and anchor positions as training goals for KELM training.

Another localization scheme based on multilayer perceptron (MLP) is proposed in [104]. The key focus of the work is to provide unknown nodes localization in unmanned aerial vehicles-aided WSNs. A range-free localization algorithm, called PCAL, is proposed in [105] using soft computing techniques. PCAL utilizes hop-count distances as the data to train and build a neural network. Before feeding the data into the neural network for the purpose of training, the dimensionality of data is reduced by principal component analysis algorithm.

In [106], a hybrid algorithm based on ABC and Grasshopper Optimization Algorithm (GOA) algorithm (BAGOA) is proposed to solve the problem of deployment optimization in WSNs. The proposed BAGOA algorithm utilizes the strength of the GOA to enhance the exploitative capability of the ABC by searching the neighborhood more efficiently instead of the blind random search of the basic ABC. By hybridizing the two algorithms, the BAGOA achieves a significant acceleration in the convergence and an increase in the search accuracy. Calculating the optimal deployment for a single WSN maintenance problem (WMP) scenario is NP-hard, and is intractable for large scale systems. Moreover, in WMP, a new deployment must be calculated following every failure.

In practical applications of WMP, mobile agents such as drones usually have limited computational resources, and must respond quickly to any failure [107]. This motivates the following search for tractable, heuristic solutions. The work in [107] study WSN maintenance problem (WMP) using a team of physical autonomous mobile agents. The agents are deployed in the area of the WSN in such a way that would minimize the time it takes to reach a failed sensor and repair it. The team must constantly optimize its collective deployment to account for occupied agents. The objective is to define the optimal deployment and task allocation strategy, that minimize the solution cost. The solution cost is a linear combination of the weighted sensors' downtime, the agents' traveling distance, and penalties incurred due to un-repaired sensors within a certain time limit. The proposed solution algorithms are inspired by research in the field of computational geometry and the design of the algorithms is based on state of the art approximation algorithms for the classical problem of facility location. The work in [108] proposes two algorithms for node deployment. One is an improved virtual force (VF) algorithm. The virtual forces of nodes include repulsive force between nodes and repulsive force at the boundary. The improved VF algorithm sets the virtual force threshold. The other is the re-sampling particle swarm optimization algorithm embedded with virtual force (RPSO-DV). The algorithm combines the advantages of three algorithms, including re-sampling particle swarm optimization (RPSO) algorithm, PSO algorithm based on coefficient adjustment (PSO-D) and improved VF algorithm. In the RPSO-DV algorithm, the virtual force of the node into the RPSO algorithm and the PSO-D algorithm is introduced. The RPSO-DV algorithm uses virtual forces to make the node distribution more uniform and improve the convergence speed. The RPSO-DV algorithm eliminates poor quality particles and introduces new particles to improve the diversity of the population. The algorithm adjusts the particle velocity and position update formulas, which improves the search ability of the population. It effectively solves the problem that traditional PSO algorithm is prone to fall into local optimal solution.

In [109] a novel algorithm called rotated black hole (RBH) is proposed, which introduces a rotated optimal path. RBH greatly improves the global search ability of the original black hole (BH) algorithm. Then, a new algorithm to optimize the position of the unknown node based on the DV-Hop positioning method, thereby reducing the error of the position estimation of the unknown node.

The work in [110] proposed an adaptive flower pollination algorithm (AFPA) with enhanced exploration and exploitation capabilities of conventional FPA for the localization of sensor nodes in WSN, where a single anchor is deployed to locate all unknown Target Nodes and by using the projection of the anchor nodes virtually in six directions using hexagonal projection for targeting the unknown nodes using AFPA.

In [111], the Cat Swarm Optimization (CSO) algorithm has been used by the parallel mode, encircling method, and mutation scheme, to speed up the convergence and improve

the accuracy and based on CSO, a new node localization method is proposed, which utilizes the coordinates of beacon nodes, the law of cosines, and the minimum hops. It not only retained the advantage of a range-free positioning algorithm but also improved the positioning precision compared with the DV-hop algorithm. In [112], the authors have introduced the concept of sensor node localization in a 2D dynamic environment using a single anchor node (static) along with virtual anchors to locate target nodes (dynamic) using hexagonal projection technique, and further, the estimated target node coordinates are optimized using novel naked mole-rat algorithm (NMRA).

The authors of [113] designed an effective metaheuristic-based Group Teaching Optimization Algorithm for Node Localization (GTOA-NL) technique for WSN. The goal of GTOA-NL technique is to determine the position of the unknown nodes by the use of anchor nodes in the WSN with minimum localization error and maximum localization accuracy. GTOA-NL technique derives a fitness function using Euclidean distance, which determines the location of the nodes in an iterative way.

In [114], the authors developed an intelligent model for developing localization pattern in WSN with a group of anchor nodes, rest nodes, and target nodes. The initial step of the proposed node localization model is the selection of the optimal location of anchor nodes towards the target nodes using the hybrid optimization algorithm. The second step is to optimally determine the location of the rest node by reference to the anchor nodes using the same hybrid optimization algorithm. Here, the weight has to be determined for each anchor sensor node based on its Received Signal Strength (RSS). The hybrid optimization algorithms check the direction to where the concerned node has to be moved by merging the beneficial concepts of two renowned optimization algorithms names as Rider Optimization Algorithm (ROA), and CSO to solve the localization problem in WSN. The newly developed hybrid algorithm is termed as Rooster Updated Attacker-based ROA (RUA-ROA).

The research in [115] aimed to develop a novel grey wolf ant lion recurrent (GWALR) localization model in WSN to find the location of each unknown node. Moreover, the fitness function of GWALR is utilized to track the location of each node. The key focus of this proposed model is to find the location of unknown nodes and to improve the RSS by reducing the localization error. In addition, the model that attained high RSS measure has better data broadcasting rate.

In [116], an improved localization method in WSNs called FOA-L (Fruit Fly Optimization Algorithm for node's Localization) is proposed. The proposed method applies the Fruit fly Optimization Algorithm (FOA) to minimize the error between estimated and real locations of the unknown sensors. In the proposed localization scheme, a group of flies in the search area initialized and they are given a random value of direction and distance. Then, find out the flies with the highest small value using fitness in order to estimate the location of the target node.

The work in [117] focuses on a swarm intelligence based Particle swarm optimization algorithm using velocity adaptation to minimize the localization error in WSNs.

[118] introduces an improved adaptive genetic algorithm (IAGA) to handle the aforementioned problem and uses a modified evaluation function to reduce the error of distance measurement in a topological structure. The experimental results prove that the IAGA algorithm based on DV-Hop has superior performance in comparison of original DV-Hop and other meta-heuristic algorithms. The conclusion can be drawn that metaheuristic algorithms have an better superiority over DV-Hop in locating nodes in WSN and the IAGA is more promising than other meta-heuristic algorithms.

A. OPEN RESEARCH ISSUES AND CHALLENGES

In future, the current works can be investigated further for evaluating the performance with respect to deployment and localization problems that involve obstacles and also node mobility. While applying meta-heuristic optimization algorithms such as CSO, improvement in the roosters behavior such as dynamic adjustment of the population of hens and chicks in each group or arranged behavior in roosters characteristics to update their velocity in a structured way could be implemented as an extension of existing works to achieve higher precision in localizing unknown nodes.

In addition, integrating one meta-heuristic algorithm like GWO with other variants of metaheuristic algorithms to form a hybrid algorithm for efficient move in convergence and diversity over the identification of maximum number of unknown node positions can be investigated further in multiple aspects for better results. The improved algorithm can then be tested in real life environments such as underwater WSNs. Moreover, the performance can be tested under different metrics for centralized and distributed solutions, to further reduce the localization error.

Hybridized versions (e.g., GA with Firefly Optimization Algorithm etc.) of meta-heuristic algorithms can be utilized to further minimize the location estimation error. The difficulty for future studies is the metric in localization which requires to be addressed to get the various application requirements to get optimal localization accuracy highlights. Therefore, in future work, an optimization technique such as PSO, GSA, Intelligent Water Drops, Backtracking Search Algorithm, or Slime Mould Algorithm could be used to select the number of hidden layers and neurons directly to examine the results without testing several ANN architectures.

As future lines of research, the existing solutions can be extended to the 3D and real environments. In addition to developing a better way to depict the solution space, the goal can be to apply schemes like Search Economics to other optimization problems in the future to demonstrate the performance of existing works. Future work can also be concentrated on the evaluation of the existing algorithms in the terrains causing multiple anisotropies due to holes, non-uniform distribution of nodes, sparsity in the network and irregular radio patterns.

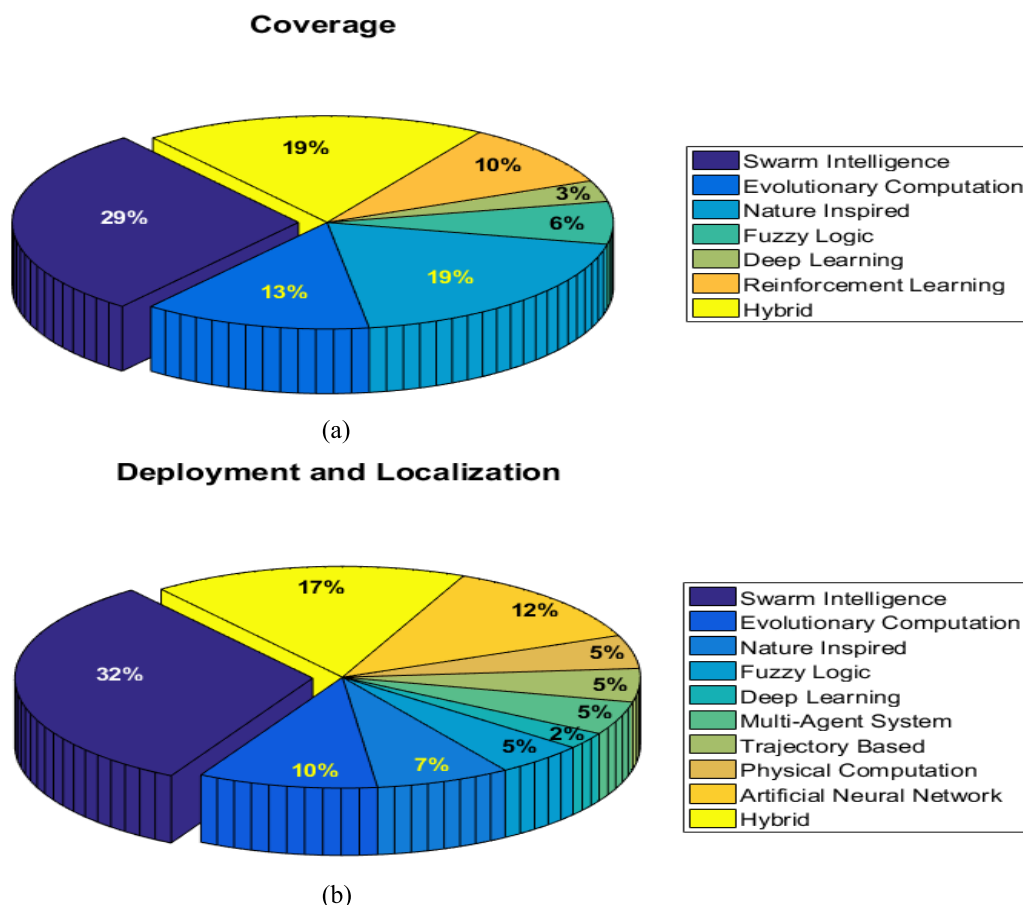


FIGURE 5. AI methods with respect to various challenges in WSN (a) The AI methods for coverage challenges in WSN. (b) The AI methods for deployment and localization challenges in WSN.

It would be interesting future extension to consider new meta-heuristics and a bigger data set while conducting real-world experiments to evaluate the performance. The factors to be studied include scalability in terms of the network density and diversity, network dimensions, and signal propagation as well as heterogeneous data traffic - all while considering the additional transmission protocol overhead. All these aspects are currently being addressed in ongoing research studies. Future studies can focus on more precise algorithms to localize the wireless sensors under the real-world conditions. Fuzzy control systems may be applied to diminish the noise and obtain a better positioning. The optimum location of the anchor nodes may help the anchor nodes to be placed into the areas that have lower chance of becoming obstructed by obstacles. Hence, a technique to find the optimum positions of the anchor nodes may be devised for a future study. Another focus can be on the security issues of such a system under different network models. Moreover, it could be interesting to try to extend the results obtained to a real WSN deployment.

VII. CONCLUSION

In this paper, we have provided a review of various challenges and problems in WSNs. Various AI methods in

WSNs are briefly introduced along with their classifications. AI techniques used by researchers to address the Coverage, Deployment and Localization challenges in WSNs are briefly explained for the span of 2010 to 2021. AI-based solutions to various problems in WSNs have been discussed and summarized. Moreover, the application of these methods in Coverage, Deployment and Localization summarized in Tables 3, 4, respectively.

From the findings depicted in Fig. 5, we can summarize the following:

- Coverage: 29% of articles for coverage in WSN applied swarm intelligence, 13% applied Evolutionary Computation, 19% applied Nature inspired, 6% applied FL, 10% applied Reinforcement learning and 19% applied hybrid algorithms.
- Deployment and Localization: AI methods used are Swarm Intelligence, Evolutionary Computation, Nature inspired, FL, Multi-Agent Systems, Trajectory based, Physical computation, Artificial neural network, and Hybrid. We can see that 29% articles applied Swarm Intelligence, 12% applied Artificial neural network, 17% applied Hybrid, 10% applied Evolutionary computation, 10% applied nature inspired, 5% applied FL, 5% applied Trajectory based and 12% applied other methods.

TABLE 3. Summary of AI based solutions to WSN coverage issues surveyed in section V.

AI paradigms	Algorithm	Ref.	Objective	Simulation/ deployment	Real-	Centralized/ Distributed	Mobility	Performance Parameters
Swarm Intelligence	EEMRGSO	[59]	Maximizing coverage and energy conservation	Simulation		Distributed	Mobile	Energy consumption and Total distance traversed.
Swarm Intelligence	TPACO	[54]	Efficient-Energy coverage	Simulation		Centralized	Static	Network lifetime and Time complexity.
Swarm Intelligence	ACO, PCO	[53]	Minimum weight sensor coverage	Simulation		Centralized	Static	Network lifetime, Average residual energy and Alive nodes.
Swarm Intelligence	MOSC	[17]	Maximizing coverage probability and network lifetime	Simulation		Distributed	Static	Coverage probability and Number of set covers.
Nature Inspired	CIVA	[56]	Optimizing coverage and energy	Simulation		Centralized	Mobile	Coverage area ratio and Energy consumption.
Nature Inspired	Immune-swarm Intelligence	[55]	Maximizing coverage probability	Real network deployment		Centralized	Static	Percentage area coverage.
Evolutionary computation	GA	[65]	Maximizing area coverage	Simulation		Distributed	Static	Average area coverage, Standard deviation, and Average computation time.
Evolutionary Computation	MA	[52]	Extending network lifetime	Real network deployment		Distributed	Static	Number of covers, Hit rate and Running time.
Evolutionary Computation	GA	[16]	Maximizing network lifetime	Simulation		Distributed	Static	Network lifetime and Energy consumption.
A hybrid of Cuckoo Search and Flower Pollination	ICS and CFPA	[64]	Maximizing area coverage	Simulation		Distributed	Static	Computation time and Stability.
A hybrid of PSO search and Genetic Algorithm	PSO and GA	[68]	Maximizing area coverage	Simulation		Centralized	Static	Percentage area coverage.
A hybrid of Fuzzy and Glowworm Swarm	GAFIS-RGSO	[69]	Maximizing area coverage and lifetime	Simulation		Distributed	Mobile	Total energy consumption and Total distance traversal.
FL	SOA	[58]	Achieving service coverage	Simulation		Distributed	Static	Time cost, Space usage and Energy efficiency.
FL	H3	[70]	Coverage hole repair	Simulation		Distributed	Mobile	Energy Consumption, Coverage ratio and Network lifetime.
RL	Qlearning	[57]	Maximizing network lifetime and area coverage	Simulation		Distributed	Static	Energy balance, Network lifetime, and Coverage ratio.
RL	Qlearning, Game Theory	[67]	Recover Coverage Holes	Simulation		Distributed	Static	Total coverage proportion, Energy related to sensing power and node motions, and Total energy consumption.
Reinforcement Learning	Nash Q-learning	[71]	Recover Coverage Holes	Simulation		Distributed	Static	Coverage rate, Number of cover set formation, and Average number of active sensor nodes.
Nature Inspired	Harmony Search	[60]	Maximizing area coverage	Simulation		Centralized	Static	Sensing Range, Cell Size, Coverage ratio, and Distance factor.
Nature Inspired	Bat Algorithm	[66]	Extend the network lifetime	Simulation		Centralized	Static	Live nodes, Energy consumption, and Network lifetime.
Swarm Intelligence	ACO	[61]	Minimum weight sensor coverage	Simulation		Centralized	Static	Computational Complexity and Deployment cost.
Swarm Intelligence	ACO	[19]	Minimum weight sensor coverage	Simulation		Centralized	Static	Average coverage cost, Energy consumption, and Ratio of surviving nodes.
Swarm Intelligence	ACO	[62]	Minimum weight sensor coverage	Simulation		Centralized	Static	Computational complexity, Deployment cost, and Network lifetime.
Swarm Intelligence	ACO	[63]	Minimum weight sensor coverage	Simulation		Centralized	Static	Deployment cost and Time overhead.
Nature Inspired	Improved cuckoo search algorithm	[72]	Determine the sensor covers by optimizing the sensing range of the sensors	Simulation		Centralized	Static	Network lifetime.

Continued on next page

TABLE 3. (Continued.) Summary of AI based solutions to WSN coverage issues surveyed in section V.

AI paradigms	Algorithm	Ref.	Objective	Real-deployment	Centralized/ Distributed	Mobility	Performance Parameters
Hybrid	aAnt colony optimization (ACO) and a hybrid differential evolution-quantum behaved particle swarm optimization (DE-QPSO) algorithm	[73]	optimized route/path and maximize the coverage area	simulation	Centralized	Static	Coverage Ratio
Nature Inspired	Multi-objective Binary Reinforced Cuckoo Search Algorithm	[74]	minimizing deployed sensors count, maximizing the connection and coverage cost of sensors.	Simulation	distributed	Static	F-Value, Computational Time, Overall Non-dominated Vector Generation and Spacing (SP).
Swarm Intelligence	Termite Flies Optimization Algorithm	[75]	Solve the eliminated obstacles' target coverage problem	Simulation	Centralized	Static	Network lifetime, Localization error accuracy, and Time complexity.
Deep Learning	Force-directed and Transfer-learning	[76]	coverage hole detection	Simulation	Centralized	Static	coverage hole detection performance in terms of Sensitivity and specificity.
Hybrid of ABC and teaching-learning-based optimization	ABC with the teaching strategy (TABC)	[77]	WSN coverage optimization	Simulation	Centralized	Static	Coverage Ratio
Hybrid of WOA and Levy Flight	Levy Flight with WOA (LWOA)	[78]	WSN coverage optimization	Simulation	Centralized	Static	Coverage Ratio
Evolutionary computation	Biogeography-based optimization (BBO)	[79]	optimize the WSN coverage path	Simulation	Centralized	Static	Success rate.

As we discussed above, population based meta-heuristic algorithms are used extensively because of their efficiency in providing best results. Their individuals don't use any symbolic reasoning and don't maintain a plan about the future, both of which are computationally expensive. Moreover, these techniques involve only limited memory requirements as they don't need to keep a lot of previous information. It can be robust, and maintain good quality performance in rapidly changing and diverse environments. Nowadays, we are witnessing a growth in the number of AI -based systems and solutions which facilitate the optimization of services in the field of WSN. The combination of both AI methods and WSNs have now become a reality, offering benefits to the area of Internet of Things, and allow systems to learn and to monitor activities and support the decision-making process. From analysis, we have noticed that the research community is focused highly on routing and clustering challenge. Moreover, the most appropriate AI methods used by the research community is swarm intelligence, while other AI methods gained less attention from research community, which is due to problem nature or method characteristics.

For enhancement of WSN, new AI algorithms as well as different strategies to embed these algorithms in WSNs have to be encouraged in future. At present, the majority of the solutions presented here applied AI methods to limited

problems in some areas. Most problems stem from incompatibility between layers and high human interaction. Self-Adaptivity is required for setting and adjustment of solutions. Hybrid approaches that optimize the resource utilization in WSN need to be developed [35]. Learning platforms and prototypes are needed rather than specialized solutions.

Area coverage maximization and obstacle constrained area coverage problems along with connectivity and WSN lifetime to accommodate realistic demands is another future research direction [65]. At the same time, mobility-assisted localization involving obstacles requires further research. The challenge here is to optimize the path of location-aware multiple mobile anchors, and to reduce the localization error and maximize the count of nodes that are successfully localized. A multi-objective optimization model is desirable. More AI based researches have to be done to investigate the impact of irregular obstacle shapes on mobile anchors and to determine how they control their movements in such situations. The movement pattern of multiple mobile anchors in high-dimensional space may also be considered.

The application of AI optimization methods to overcome the challenges of Mobile WSNs (MWSNs) is a potential future direction. Some research challenges still remain relatively unresolved which include transmission delay, balancing the power consumption, reliability and safety of MWSNs.

TABLE 4. Summary of AI based solutions to deployment and localization problems in WSN surveyed in section VI.

AI paradigms	Algorithm	Ref.	Objective	Simulation/ Real-deployment	Centralized/ Distributed	Mobility	Performance Parameters
Swarm Intelligence	PSO and BSA	[93]	Determining node position	Simulation	Distributed	Static	Distance without errors and Distance with errors.
Swarm Intelligence	ACO	[80]	Maximizing network lifetime	Real network deployment	Distributed	Mobile	Network lifetime.
Swarm Intelligence	GSO	[19]	Maximizing coverage	Real network deployment	Distributed	Mobile	Distance and Coverage rate.
Swarm Intelligence	ACO-Greedy	[83]	Maximizing grid-base coverage with min cost and guaranteed connectivity(GCLC)	Simulation	Distributed	Static	Average coverage cost, Residual energy, and Average network lifetime.
Swarm Intelligence	IGWO	[86]	Optimize the node deployment for better coverage	Simulation	Distributed	Mobile	Coverage rate.
Swarm Intelligence	CSO	[87]	Improving localization accuracy	Simulation	Distributed	Static	Localization error.
Swarm Intelligence	GWO	[88]	Optimizing localization	Simulation	Distributed	Static	Mean localization error, Computational time, and Number of Localized nodes.
Swarm Intelligence	MOLFB	[89]	Optimizing connectivity and coverage	Real network deployment	Distributed	Static	Average running times, p - value in one-tailed test, and p -value in two-tailed test.
Nature Inspired	BOA	[94]	Minimizing localization error	Simulation	Distributed	Mobile	Percentage of localized nodes and Number of anchor nodes.
Nature inspired	MIA	[15]	Maximizing deployment area	Simulation	Centralized	Mobile	Redundant covered area, Coverage ratio, Coverage Ratio, and Maximum moved distance.
A Hybrid of Bat, Cuckoo Search and Firefly opt.	BOA, MCS and FOA	[92]	Minimizing localization error	Simulation	Distributed	Mobile	Root mean square error.
A Hybrid of Firefly Algorithm and Artificial Neural Network	FA-ANN	[101]	Minimizing localization error	Real network deployment	Distributed	Mobile	Localization accuracy.
A Hybrid of PSO and Artificial Neural Network	PSO-ANN	[99]	Minimizing localization error	Real network deployment	Centralized	Mobile	RSSI values, Data packet success, and Distance for outdoor and indoor environments.
Artificial Neural Network	BP-ANN	[102]	Minimizing localization error	Real network deployment	Distributed	Mobile	Mean localization error.
Artificial Neural Network	PCAL	[105]	Improve the localization process	Simulation	Distributed	Static	Localization error.
Physical Computations	IWDs	[98]	Enhancing localization accuracy	Simulation	Distributed	Static	Localization error.
Trajectory based	VS	[85]	Improving deployment problem	Simulation	Distributed	Static	Coverage rate.
Trajectory based	PFDA and MODA	[81]	Minimizing cost of deployment	Simulation	Distributed	Mobile	Network lifetime and Satisfaction rate.
Evolutionary Computation	3D-GAIDV	[95]	Improving localization accuracy	Simulation	Distributed	Static	Localization error, Communication cost, and Computational efficiency.
Evolutionary computation	GA	[84]	Real network deployment	Simulation	Centralized	Static	Hypervolume and set coverage.
FL	IMRL	[6]	Maximizing energy and network lifetime	Simulation	Distributed	Static	Localization accuracy and Energy dissipated.
FL	HVP-FELM	[97]	Improving localization	Simulation	Distributed	Mobile	Localization Error.
Artificial Neural Network	ANN1 and ANN2	[100]	Optimizing localization of WSN	Real network deployment	Distributed	Mobile	Localization Error.
Neural Network	KELM-HQ	[103]	Improve the accuracy of node localization	Simulation	Distributed	Static	Localization error.
Artificial Neural Network	MLP-ANN	[104]	Improve localization accuracy	Simulation	Distributed	Mobile	Localization error.
Deep Learning	DRLT	[91]	Optimizing localization of WSN	Simulation	Distributed	Mobile	Localization error.
Multi-Agent Systems	MA	[82]	Improving deployment	Real network deployment	Distributed	Mobile	Management efficiency.
Hybrid of EA and SL and Trajectory Algorithms	NSGA-II, SPEA2, MOEA/D, MO-FA, MO-GSA, MO-ABC, MO-VNS and MO-VNS*.	[90]	Relay Node Placement	Simulation	Centralized	Static	Median hypervolume and Average set coverage.
Hybrid of ABC and the Grasshopper Optimization Algorithm (GOA)	BAGOA	[96]	WSNs deployment optimization	Simulation	Distributed	Mobile	overlapping area.energy consumption

TABLE 4. (Continued.) Summary of AI based solutions to deployment and localization problems in WSN surveyed in section VI.

AI paradigms	Algorithm	Ref.	Objective	Simulation/ Real-deployment	Centralized/ Distributed	Mobility	Performance Parameters
Mobile Agent	WMP	[107]	Find a continuous deployment strategy and a task allocation scheme for the agents, which minimize the total cost, comprised of three objectives; minimize the sum of weighted sensor downtimes, the agents' travel distances, and the penalties.	Simulation	Distributed	Hybrid	Runtime analysis, T-Tests to validate the differences between the algorithms' performances.
Swarm Intelligence	RPSO-DV	[108]	Node deployment problem	Simulation	Distributed	Mobile	Coverage rate.
Physical computations	RBH algorithm	[109]	Enhances the localization accuracy of WSN in 3D terrain	Simulation	Distributed	Static	Localization error.
Nature inspired	PSO and HPSO	[110]	the determination of node location in 3D environment	Simulation	Distributed	mobile	convergence speed, localization error.
Swarm Intelligence	Improved Cat Swarm Optimization	[111]	Improve location accuracy	Simulation	Distributed	Static	average localization error.
Swarm Intelligence	mole-rat algorithm (NMRA)	[112]	location optimization	Simulation	Distributed	Mobile	average localization error.
Evolutionary algorithm	GTOA-NL	[113]	Node localization	Simulation	Distributed	Static	Localization rate analysis, Localization error analysis
Hybrid	RUA-ROA	[114]	develop an intelligent model for developing localization pattern in WSN	Simulation	Distributed	Static	Statistical Analysis
hybrid of Grey Wolf (GW) and Ant Lion (AL)	GWALR	[115]	find the location of each unknown node	Simulation	Distributed	Static	Energy Consumption, Throughput Ratio, Error Rate, Packet Broadcasting Ratio and the accuracy of location prediction.
Swarm Intelligence	FOA-L	[116]	minimize the error between estimated and real locations of the unknown sensors	Simulation	Distributed	Static	average location error and computation time.
Swarm intelligence	Velocity Adaptation PSO	[117]	minimize the localization error	Simulation	Distributed	Static	localization error
Evolutionary computation	IAGA	[118]	enhance the positioning accuracy	Simulation	Distributed	Static	convergence performance, Accuracy comparison

A combination of SI with other optimization techniques have to be encouraged in future. The cross-layer optimization model challenges must to be treated in a better way during the optimization of MWSNs. The results from the study of human-related biological features can be incorporated in future for further improvement of solutions to such problems. Distributed and real time application of algorithms in light weight form could be a future research direction to solve the challenges of dynamic MWSNs in future.

As the study shows, most of the existing solutions based on AI are only simulation based. The AI techniques should be implemented and analyzed in real-time environment [34], [119]. This should be encouraged in future. More

investigations are required to show how AI methods can be adapted. Cross-layer approaches using AI methods are rarely applied to challenges and is still a vital open research area. Also, hybrid AI methods are less applied and need to be discussed deeply. It can be expected that the future research will likely consider heterogeneity, dynamic environments and varying communication constraints during algorithms design. The application of AI techniques make the WSN cognitive towards managing and overcoming the challenges which arise during operation. We hope that the concepts provided in this paper direct the researchers for the use of AI in solving the challenging WSN issues by making the nodes more intelligent.

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WALID OSAMY received the B.Sc. (Hons.), M.S., and Ph.D. degrees in computer science from the Faculty of Science, Zagazig University, Egypt, in 2000, June 2006, and September 2010, respectively. He has been involved in the projects of network infrastructure and management information systems with the Communication Information Technology Center (CITC), Zagazig University. From 2010 to 2019, he was an Assistant Professor with the Department of Computer Science, Faculty of Computers and Informatics, Benha University, Egypt. Since 2015, he has been an Assistant Professor with Qassim University, Buridah, Saudi Arabia. Since 2019, he has been an Associate Professor with the Department of Computer Science, Faculty of Computers and Artificial Intelligence, Benha University. His research interests include computational intelligence and in the field of IoT [mobile computing and wireless sensor networks (WSNs)].



AHMED M. KHEDR received the B.Sc. degree in mathematics and the M.Sc. degree in optimal control from Zagazig University, Egypt, in June 1989 and July 1995, respectively, and the M.Sc. and Ph.D. degrees in computer science and engineering from the University of Cincinnati, OH, USA, in July 1999 and March 2003, respectively. From March 2003 to January 2004, he was a Research Assistant Professor at the ECECS Department, University of Cincinnati. From January 2004 to May 2009, he worked as an Assistant Professor at Zagazig University. From September 2009 to September 2010, he worked as an Associate Professor with the Department of Computer Science, College of Computers and Information Systems, Taif University, Saudi Arabia. Since December 2014, he has been a Professor at Zagazig University. From September 2010 till December 2019, he worked as an Associate Professor with the Department of Computer Science, College of Computing and Informatics, University of Sharjah, United Arab Emirates, where he has been a Professor, since January 2020. His research interests include wireless sensor networks, the Internet of Things, and distributing computing. He was awarded the State Prize of Distinction in advanced technology, Sharjah Islamic Bank Prize of Distinction in research, and the University of Sharjah Prize of Distinction in research, in June 2009, May 2013, and April 2014, respectively.



AHMED SALIM received the B.Sc. degree in computer science and the M.Sc. degree in distributed computing from Zagazig University, Egypt, in 2001 and 2006, respectively, and the Ph.D. degree in systems, network, and telecommunication devices from the Bonch-Bruvich University of Telecommunication, Saint Petersburg, Russia, in 2010. In 2012, he was a Consultant of the Information and Communication Technology Project (ICTP) at Zagazig University.

From 2011 to 2019, he was an Assistant Professor with the Department of Mathematics, Faculty of Science, Zagazig University, where he has been an Associate Professor, since 2019. Since 2014, he has been an Assistant Professor with the Department of Mathematics, Faculty of Science and Art, Qassim University, Al-Mithnab, Saudi Arabia. His research interests include decomposable algorithms, computing, the IoT, and wireless sensor networks.



AHMED A. EL-SAWY received the B.S. and M.S. degrees from Cairo University, in 2000 and 2003, respectively, and the Ph.D. degree in computer science from Suez Canal University, in 2011. From 2004 to until 2011, he served as a Lecturer with the Faculty of Computers and Information Systems, Taif University, Saudi Arabia. He has been a Lecturer at Benha University, Egypt, since 2012, where he has been an Associate Professor in computer science, since 2017, and the Head of computer science with the Faculty of Computers and Artificial Intelligence, since 2017. His research interests include using artificial intelligence in computer networks, bioinformatics, chimoinformatics, deep learning, and optimization.

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AMAL IBRAHIM AL ALI received the master's degree in computer science from Cardiff University, U.K., and the Ph.D. degree in IT from Glamorgan University, U.K. He is currently an Assistant Professor with the Information Systems Department, College of Computing and Informatics, University of Sharjah. He is a subject-matter-expert in AI and digital transformation, with a solid reputation in achieving corporate growth objectives through providing strategic directions, diverse perspectives, and positive leadership. He is an Alumnus of Stanford and MIT in innovation and AI strategies, and is an empaneled summits speaker. He revamped strategic plans to embed and provide for an integrated AI strategy in view of technological changes for prestigious government organizations in United Arab Emirates. He has expert knowledge in strategic development and digital transformation, fostered strong industrial connections that enhanced organizational performance and created competitive advantage which ultimately generated new revenues opportunities, leveraged strong leadership skills, communication skills, and networking capabilities. He chaired and participated in several high-profile committees both on the Emirate of Sharjah level and nationwide. He has maximized expertise in business and entrepreneurship, superior interpersonal skills, transparency, and flexibility.

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