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Swarm Intelligence-Based Performance Optimization for Mobile Wireless Sensor Networks: Survey, Challenges, and Future Directions

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ABSTRACT Network performance optimization has always been one of the important research subjects in mobile wireless sensor networks. With the expansion of the application field of MWSNs and the complexity of the working environment, traditional network performance optimization algorithms have become difficult to meet people's requirements due to their own limitations. The traditional swarm intelligence algorithms have some shortcomings in solving complex practical multi-objective optimization problems. In recent years, scholars have proposed many novel swarm intelligence optimization algorithms, which have strong applicability and achieved good experimental results in solving complex practical problems. These algorithms, like their natural systems of inspiration, show the desirable properties of being adaptive, scalable, and robust. Therefore, the swarm intelligent algorithms (PSO, ACO, ASFA, ABC, SFLA) are widely used in the performance optimization of mobile wireless sensor networks due to its cluster intelligence and biological preference characteristics. In this paper, the main contributions is to comprehensively analyze and summarize the current swarm intelligence optimization algorithm and key technologies of mobile wireless sensor networks, as well as the application of swarm intelligence algorithm in MWSNs. Then, the concept, classification and architecture of Internet of things and MWSNs are described in detail. Meanwhile, the latest research results of the swarm intelligence algorithms in performance optimization of MWSNs are systematically described. The problems and solutions in the performance optimization process of MWSNs are summarized, and the performance of the algorithms in the performance optimization of MWSNs is compared and analyzed. Finally, combined with the current research status in this field, the issues that need to be paid attention to in the research of swarm intelligence algorithm optimization for MWSNs are put forward, and the development trend and prospect of this research direction in the future are prospected.

INDEX TERMS Internet of things, mobile wireless sensor networks, swarm intelligent optimization algorithm, performance optimization, multi-objective optimization, energy efficiency, reliability.

I. INTRODUCTION

As an extension and extension of the Internet, the Internet of Things (IoT) is another major change in the field of information technology. The basic characteristics of the Internet of Things are the comprehensive perception, reliable transmission and intelligent processing of information [1], [2]. The entity information is obtained through the sensing device, and transmitted to the relevant service node through the network, thereby realizing human-object, object-object interconnection, and realizing intelligent identification, positioning, tracking, monitoring and management of the physical world [3], [4]. Internet of Things is a heterogeneous architecture composed of various supporting technologies, such as physical-oriented RFID and wireless communication technology, the intelligent terminal-oriented mobile computing technology, the wireless sensor network technology for sensing nodes, user the data sharing and application services

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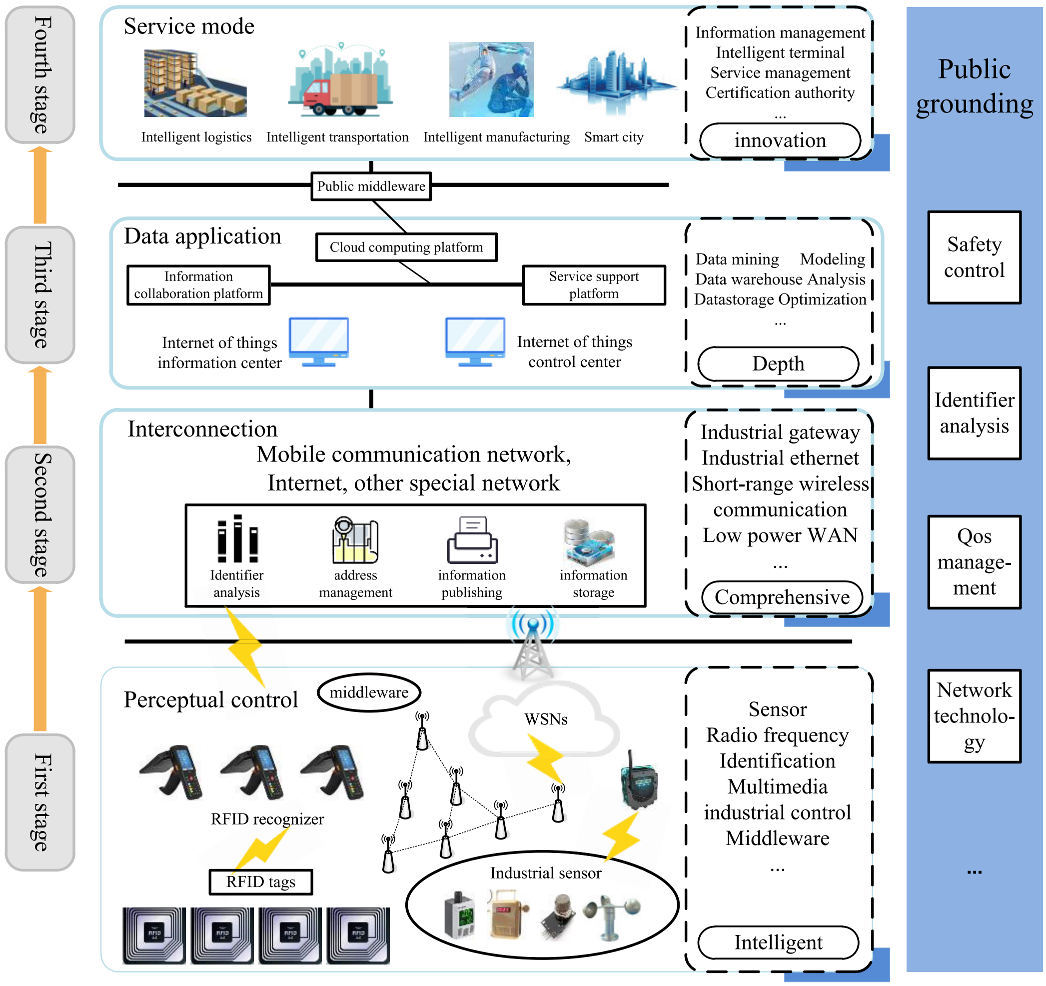

FIGURE 1. Architecture of the industrial Internet of Things.

for the Internet [5]. With the development and deepening of the application of Internet of Things technology in various fields of economy and society, and the change of access mode of Internet and energy supply mode of nodes in the future, a large-scale, low-power wireless sensor network, which integrates information sensing, data transmission and processing capabilities, will surely appear in all aspects of our lives [6], [7].

At the same time, with the deep integration of industrialization and informatization, the interconnection of various aspects of industrial production has gradually become possible, and the industrial Internet of Things (IIoT) came into being [8]. The development of the industrial Internet of Things is one of the important symbols of the industry entering the era of 4.0, that is, the era in which the physical and physical worlds merge with each other [9], [10]. As a product of the deep integration of industrialization and informatization, the industrial Internet of Things monitors, analyses and adjusts the industrial production through key technologies such as automation [11], sensors, communication, large data storage and analysis, so as to achieve the goals of improving production efficiency and optimizing the resource allocation. Industrial Internet of Things can greatly improve the efficiency and reliability of industrial production, and is an important trend in the future development of manufacturing [12]. As one of the key technologies of the industrial Internet of Things, the wireless communication technology provides a solution for building an information-based, intelligent production management and control network [13]. Industrial Internet of Things has the characteristics of comprehensive sensing, interconnected transmission, intelligent processing, self-organization and self-maintenance [14]. It is widely used in many fields such as intelligent transportation, intelligent factory, smart grid, intelligent environment detection, etc [15]. In the process of industrial production, the real-time collection, transmission, processing of the industrial data and monitoring and control of the industrial field equipment are realized by using the monitoring system composed of the Internet of Things technology [16]. It is of great significance to reduce the overall production cost of enterprises, improve the level of management decision-making and enhance production efficiency.

Wireless sensor networks (WSNs) are multi-hop self-organizing network systems formed by a large number of sensor nodes deployed in the monitoring area [17], [18]. They are an important technical form of the underlying network of the Internet of Things. With the maturity of wireless communication, sensor technology, embedded applications and microelectronics technology, WSNs can obtain the information people need at any time, any place, any environmental conditions, and lay the foundation for the development of industrial Internet of Things [19]. The application of WSNs mainly focuses on military, environmental monitoring, security monitoring, smart home, disaster site search and rescue, etc., especially in the harsh environment where humans can't reach or can't work, it can replace humans to collect, transmit and process the required information. As a medium for the seamless connection between human society and nature, wireless sensor networks are widely used in all aspects of life, changing the way people travel and communicate with nature [20].

Mobile wireless sensor networks (MWSNs), as the most important part of the branch of wireless sensor networks, have extremely wide application value in many aspects [21]. At the same time, with the rapid development and application of mobile terminal technology and mobile internet technology, mobile wireless sensor networks have become a new trend in the evolution of wireless sensor networks, and become a hot research field of WSNs [22]. The difference between mobile wireless sensor networks and wireless sensor networks lies in the inclusion of mobility, the use of node mobility to improve the coverage and connectivity of the network, improve the scalability and reliability of the network, balance the network energy consumption, and prolong the network's lifetime [23]. The difference between MWSNs and WSNs is to the mobility of the nodes, which improves the coverage, efficiency, and the reliability of the network. Due to the complexity of the industrial environment and the dynamic changes in the topological structure, specially during data acquisition and data transmission, the performance of the MWSNs is easily affected and may lead to failure of network. MWSNs are highly flexible and low-energy networks formed by a number of self-organizing wireless sensor nodes that are randomly scattered in the surveillance area [24]. Its main features are the limited energy resources of the sensor nodes in the network, the limited storage space and the dynamic changes of the topology of the network. MWSNs are mainly used to collect data of the monitoring objects, so as to achieve the purpose of research and control of monitoring objects [25]. In recent years, with the continuous development and maturity of swarm intelligence optimization algorithm and artificial intelligence theory, the swarm intelligent optimization algorithm has been widely used in the coverage optimization strategy, location algorithm, dynamic deployment of the network, node scheduling, data fusion, reliability and other aspects of mobile wireless sensor networks. MWSNs have been applied in many areas such as biological species migration research, urban environmental monitoring and control, and medical health. With the promotion of in-vehicle communication technology, the new application scenarios are emerging, and mobile wireless sensor networks will become the key technology for the development of smart cities in the future [26].

A. PROBLEM STATEMENT AND MOTIVATE

Optimization, especially bio-mimetic strategy-based optimization in MWSNs, is one of the important research subjects in MWSNs [27]. Some manuscripts published in this area are highly diverse in their approaches and implementations. However, some related work has been done addressing the various issues individually (e.g., energy efficiency, data fusion, QoS, reliability and security) and they tend to overlook the whole scenario of collective optimization approach which encompasses these two or three MWSNs issues. Applying these definitions to MWSNs, more specifically, the swarm intelligence optimization algorithms are important in MWSNs applications for the following main reasons [28]:

(1) MWSNs usually monitor the dynamic environments that change rapidly over time. For example, the communication capability of the sensor nodes may change due to the disturbance and change of the external environment. It is desirable to develop wireless sensor networks that can adapt and operate efficiently in such a harsh environments [29].

(2) MWSNs may be used for collecting the information of the sensor nodes about unreachable, dangerous locations (e.g., underwater monitoring, waste water monitoring and environmental monitoring in nuclear industry) in exploratory applications. Due to the unexpected behavior patterns that may arise in such scenarios, the system designers may develop the new solutions that initially may not operate as expected. The sensor system designers would rather have robust the swarm intelligence optimization algorithms that are able to calibrate itself to newly acquired knowledge [30].

(3) MWSNs are usually deployed in complicated industrial environments where researchers cannot build accurate mathematical models to describe the system behavior. Meanwhile, some complex tasks in MWSNs can be prescribed using simple mathematical models but may still need complex algorithms to solve them, meanwhile, the problem of latency needs to be considered. (e.g., the reliability problem, the routing problem [31], [32]). Under similar circumstances, the swarm intelligence optimization algorithms provide the best performance for the system model of MWSNs.

(4) New uses and integrations of MWSNs, such as in the multiple-input multiple-output technologies (MIMO) [33], machine-to-machine (M2M) communications [34], and industrial Internet of things (IIoT) technologies, have been introduced with a motivation of supporting more intelligent decision-making and autonomous control [35].

B. CONTRIBUTION

In this paper, aiming at the performance optimization of the key technologies of MWSNs, first, we provide a review of the key technology of MWSNs and a detailed classification of the swarm intelligence algorithms based on various metrics. In addition, we present a comprehensive review of the existing performance optimization methods of MWSNs with the aim to represent the state-of-the-art technology by including the most recent approaches and routing proposals. We also believe that the classification of the MWSNs presented in this paper introduces the most detailed and accurate perspective on the subject to date.

Generally, these early surveys of the performance optimization for MWSNs concentrated on the expert system, neural networks and decision trees which were popular due to their efficiency in both the theory and practice. In this paper, we decided instead to include a wide variety of important *up-to-date* swarm intelligent algorithms for a comparison of their strengths and weaknesses. Another distinction between our survey and earlier works is the way that the swarm intelligent algorithms are presented. Our work discusses the swarm intelligent algorithm based on their target of the challenges for MWSNs, so as to encourage the adoption of existing swarm intelligent solutions in MWSNs applications. Finally, we build on existing surveys and go beyond classifying and comparing previous efforts, by providing useful and practical guidelines for MWSNs researchers and engineers who are interested in exploring the novel swarm intelligent optimization algorithm for future research. In comparison with the current general selection approaches, the following contributions are made in this paper:

- A comprehensive survey of the system architecture of industrial Internet of Things and an overview of the application area and the key technology for industrial IoT are provided. Moreover, we explore the relation between the industrial IoT and MWSNs.
- A review of the characteristics of swarm intelligence algorithms and a detailed classification of the reviewed algorithms are provided.
- Compared to other survey papers in the field, this survey provides a deeper summary of the most relevant of the swarm intelligence algorithms in MWSNs.
- Some research challenges and open research issues in MWSNs are also discussed, and the performance comparison of the reviewed algorithms in MWSNs are described

The remainder of this paper is organized as follows: Section 2 provides an overview of the characteristics of MWSNs and compares with the advantages and disadvantages of WSNs. Section 3 describes the classification methods and the characteristics for the intelligent optimization algorithms in detail. Section 4 provides an overview of the application of swarm intelligence optimization algorithm in various fields of MWSNs. In Section 5, we compare the performance of different swarm intelligence optimization algorithms in MWSNs. And we systematically analyze the prominent MWSNs routing protocols with discussion on their respective merits and demerits. Section 6 discusses the open research issues and the future directions of MWSNs. Section 7 summarizes and concludes this paper.

II. OVERVIEW OF MOBILE WIRELESS SENSOR NETWORKS

In the traditional wireless sensor network, whether it is a planar structure or a layered structure, the sensing nodes are generally fixed, and the multi-hop routing method is used to forward the data packets to the sensor nodes [36]. The sensor nodes close to Sink consume energy faster by forwarding a large number of packets from the distant nodes, and these nodes form the bottleneck nodes of the network. However, when the bottleneck node is exhausted, there is still residual energy left by the sensor nodes away from the sink node [37]. The introduction of mobile nodes for data collection can not only avoid the ‘‘energy hole’’ problem, but also balance the energy consumption of network [38]. Therefore, energy-saving design based on mobility has become a new research field in wireless sensor networks. Utilizing the mobility characteristics of nodes, the network connectivity, coverage and energy distribution of MWSNs are used for dynamic node deployment or location adjustment to fill the routing holes of the network and the detection dead zones of the sensing nodes [22]. Meanwhile, it is convenient to manage the network topology, achieve targeted detection, and dynamically adjust the network structure when the network load is unbalanced. MWSNs have the characteristics of flexibility, low power consumption and fast networking. They can be applied in many fields, such as field environment, detection of harsh industrial sites, etc. MWSNs can be divided into three categories according to the type of movement of nodes: 1) Sink node move, the ordinary nodes are stationary; 2) Sink node is stationary, the ordinary nodes move; 3) Both the Sink node and the ordinary node move [39].

As a centerless, node-movable, topology dynamic change, wireless multi-hop and highly autonomous network, MWSNs have the characteristics of short communication distance, small coverage and strong mobility of nodes [40]. At the same time, due to the limited energy, calculation and storage capacity of mobile sensor nodes, it is difficult, energy-intensive and low-efficiency for a single node to complete complex tasks. The nodes of mobile sensor networks need to cooperate to complete complex tasks [41]. The Sink node often has much higher initial energy, computing power, storage capacity and communication distance than the ordinary sensor nodes. Usually, the task of data collection, data processing, storage, transmission and access to the host computer monitoring center in MWSNs work is handed over to it, which can save the energy consumption of sensor nodes, and improve the efficiency of the network and prolong the network's lifetime [42].

Compared with the traditional static wireless sensor networks, mobile wireless sensor networks have several advantages [43]:

First, the mobility of MWSNs expands the coverage of wireless sensor networks. The traditional static wireless

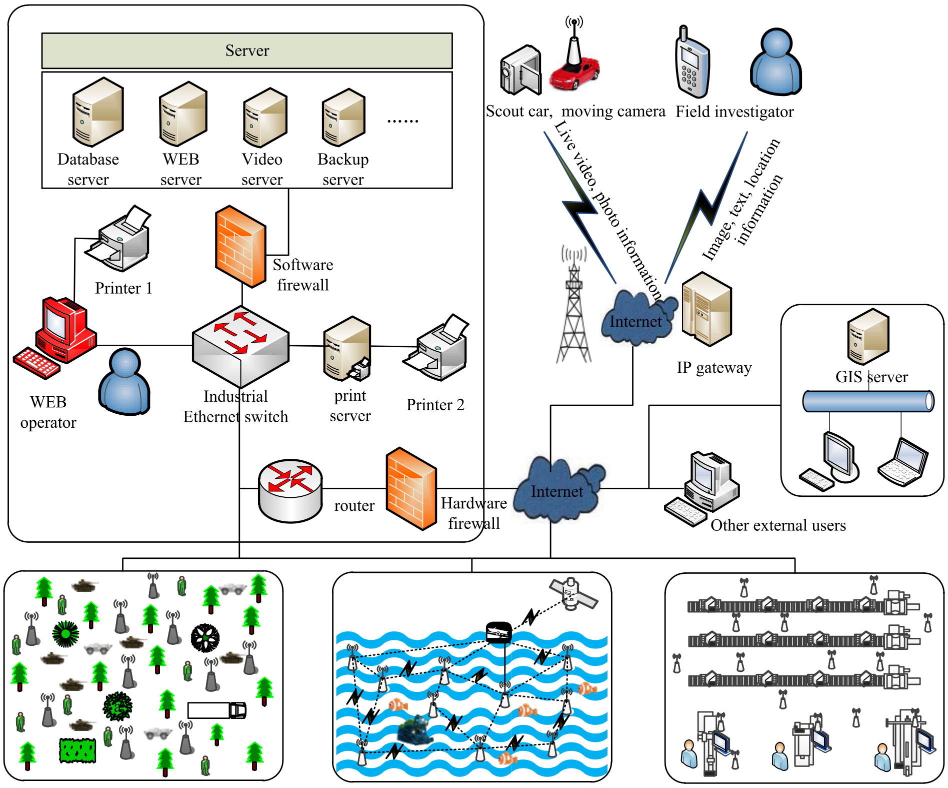

FIGURE 2. The architecture of Mobile Wireless Sensor Networks.

sensor network needs to rely on the layout of a large number of sensor nodes to complete the coverage of the area, and the mobility characteristics of mobile wireless sensor network greatly reduce the number and difficulty of the deployment of the sensor nodes.

Second, the mobility of MWSNs reduces the data communication delays and increases the network throughput. The static sensors use the multi-hop method to transmit data only for small-scale wireless networks, once the size of wireless sensor network increases, the multi-hop transmission method will bring huge delay and increase the unpredictability of data transmission [44]. Introducing the mobile node characteristics, MWSNs can use mobility to transmit data and adopt a delay-delay routing strategy to complete the data forwarding, thereby improving the data transmission speed in the network, improving the data throughput and reducing the latency of the network. The research shows that the number of mobile nodes increases linearly with the number of static sensors, and the throughput of mobile wireless sensor networks is 3-5 times that of static wireless sensor networks. At the same time, reducing multi-hop transmission of data can effectively reduce errors and packet loss during data transmission, and improve communication quality of the network [45].

Third, the introduction of mobile nodes by MWSNs can reduce the energy consumption of the network and prolong the network's lifetime. In a static wireless sensor network, the energy consumption of each node is unbalanced [19]. The sensor node that hops from the Sink node needs to bear the multi-hop forwarding task of data from the other sensor nodes to the base station, which consumes a lot of energy, which will seriously affect the stability and service life of the network. Because of the mobility of nodes, MWSNs can often provide the charging power or larger batteries. The energy consumption will no longer be a problem to be considered in network optimization design [46]. After the mobile node is introduced, the static node does not need to wait for the data forwarding at the moment of waking up, but only needs to wake up for a short time when the mobile node is close, and transmits the data to be forwarded to the mobile node, thereby reducing the energy consumption and prolonging the network's lifetime through long-term dormancy. In addition, after the introduction of the mobile node, the sensor nodes in the network may communicate with the mobile node through one hop without transferring the data to the fixed data center through multiple hops, thereby reduces the burden of one hop node around the data center and balances the energy consumption of the sensor nodes in the entire network [47].

III. OVERVIEW OF SWARM INTELLIGENCE OPTIMIZATION ALGORITHMS

The intelligent optimization algorithm [48] is an algorithm that solves the problem according to the bionics principle by the law of behavioral habits in nature and biology. It solves the optimal solution of the optimization problem under complex constraints through certain rules or a certain mechanism and thought search process to meet the needs of users.

TABLE 1. Classification methods for intelligent optimization algorithm.

Type	Common algorithms
Simulate evolutionary process	Genetic algorithm(GA) [52] Differential evolution algorithms (DE) [53] Genetic programming algorithm (GP) [54] Evolutionary programming algorithms (EP) [55] Memetic algorithm (MA) [56] Multi-objective evolutionary algorithm (MOEA) [57] Gene expression programming (GEP) [58]
Simulate animals or plants or insects behavior	Ant colony optimization (ACO) [59] Particle swarm optimization (PSO) [60] Artificial fish swarm algorithm (AFSA) [61] Artificial bee colony algorithm (ABC) [62] Bat algorithm (BA) [63] Firefly algorithm (FA) [64] Cuckoo search algorithm (CSA) [65] Shuffled frog leaping algorithm (SFLA) [66] Fruit fly optimization algorithm (FOA) [67] bacterial foraging optimization (BFO) [68] Artificial plant optimization algorithm (APOA) [69] Chicken swarm optimization algorithm (CSO) [70] wolf pack algorithm (WPA) [71]
Simulate human social behavior	Harmony search algorithm (HS) [72] Teaching-learning-based optimization (TLBO) [73] Social emotion optimization algorithm (SEOA) [74] Social cognitive optimization algorithm (SCO) [75]

The classification of common typical intelligent optimization algorithm is shown in Table 1. The intelligent optimization algorithm uses the determined rule order to search the optimal solution of the problem, and gradually moves to the optimal solution of the objective function [49]. While the swarm intelligent optimization algorithm uses the probability transfer rule, which can select different initial points to start searching for the optimal solution, and can also search the search space of the optimal solution in parallel [50]. In addition, the intelligent optimization algorithm uses the gradient information of the search space to search for the optimal solution of the objective function. However, the swarm intelligent optimization algorithm does not need the gradient information of the search space, and uses the fitness value of the individual to guide the search [51].

The swarm intelligent optimization algorithm is a very important branch of the intelligent optimization algorithm [76]. The difference between swarm intelligence optimization algorithm and classical intelligent optimization algorithm is that a probabilistic search algorithm of swarm intelligence optimization algorithm does not need prior knowledge enlightenment, does not depend on the mathematical nature of solving the problem itself, does not need to derive and continue solving the problem, does not need to establish the data calculation model related to the problem itself, and directly solves the optimal solution of the objective function [77]. It only needs the input information of the data layer, and can effectively construct a formal model to solve the problem that the traditional intelligent optimization algorithm is difficult to solve or cannot solve [78].

The intelligent optimization algorithm mainly includes genetic algorithm, simulated annealing algorithm,

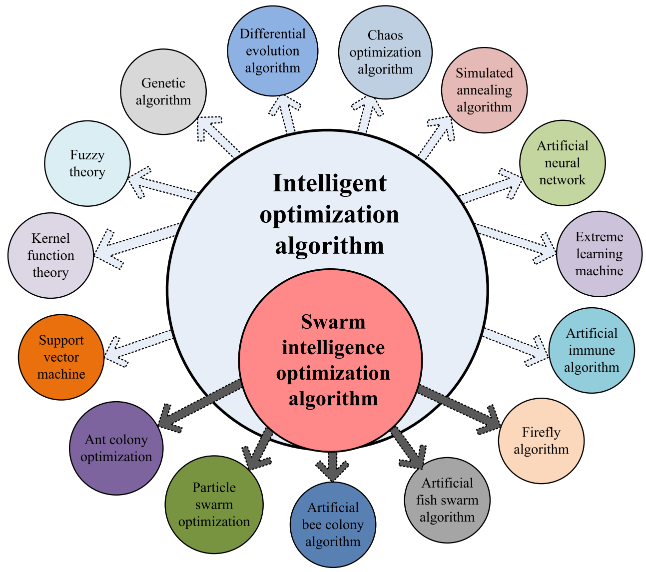

FIGURE 3. The relationship between the intelligent optimization algorithm and the swarm intelligence optimization algorithm.

artificial immune algorithm, artificial neural network, extreme learning machine, differential evolution algorithm, mixed pure optimization algorithm, fuzzy theory, kernel function theory, support vector machine, ant colony algorithm, particle swarm optimization, artificial bee colony algorithm, firefly algorithm, shuffled frog leaping algorithm and artificial fish swarm algorithm [79]–[83]. Among them, the swarm intelligent optimization algorithm is inspired by the living habits of animal groups, and based on these living habits combined with intelligent heuristic algorithms generated by artificial intelligence. The relationship between the intelligent optimization algorithm and the swarm intelligence optimization algorithm is shown in Figure 3.

The swarm intelligent optimization algorithm is a random search algorithm established by simulating group behaviors such as mutual cooperation and sharing information in nature. Compared with the classical optimization algorithm, it has the advantages of simple structure and easy implementation. The swarm intelligent optimization algorithm is an effective method for solving complex engineering optimization problems with high dimension and multi-extremum. It has strong robustness, wide application, parallel computing, and can be effectively solved in most cases. It has become a research hotspot in recent years. Taking advantage of the self-organization and feedback of biological populations, the special point is that when the global model is unclear, the swarm intelligent optimization algorithm can quickly find the optimal solution of complex combinatorial optimization problems. Especially in the field of bioinformatics, in the face of the search of massive data information, and without optimizing the target global model, the swarm intelligent algorithm can obtain satisfactory results, and has unique advantages compared with other optimization methods. The swarm intelligent optimization algorithm opens up a new way for the system optimization, the NP-hard problem and combination optimization with its advantages of distributed computing, simple implementation, parallelism, flexibility and robustness. It provides a new solution for practical engineering applications such as power system, communication network, workshop production scheduling, transportation, etc. The research of swarm intelligent algorithm has important significance and broad application prospects.

The swarm intelligent optimization algorithm is an emerging intelligent optimization method. It is a meta heuristic search algorithm based on the swarm behavior for multiple iterations of a given target. At the core of swarm intelligence is a group of many individual individuals that work together to achieve goal optimization. Among them, a single individual in a population has only simple search ability or intelligence, and communication and cooperation are individuals who communicate with their neighbors or communicate with other individuals indirectly by changing the environment, so that they can interact and cooperate. The swarm intelligence algorithm has the following characteristics:

(1) Simple and easy to implement. The individual behavior of the population is simple, and it follows the rules formulated within the population. The unity of action and behavior are consistent, and the realization of swarm intelligence is simple, so it is simple and easy to perform.

(2) Good scalability. The amount of information that each individual in the group can perceive is limited, but the data transmission between them is realized in a non-contact form (dance, pheromone, etc.), and the individual individuals cooperate with each other and have better scalability.

(3) Self-organizing. In order for a population group to complete a complex task, it must cooperate with each other through individuals.

(4) Strong robustness. When the population searches for the optimal solution of the combinatorial problem, the individual search method is distributed and there is no centralized control. Even if the individual searches for the optimal solution, it will not make the whole population lose the solution of the optimal problem, and will not affect the global optimal solution, so it has strong robustness [84].

In the intelligent algorithm studied in this paper, we mainly elaborate on particle swarm optimization algorithm, ant colony optimization algorithm, artificial fish swarm algorithm, artificial bee colony algorithm and shuffled frog leaping algorithm.

A. PARTICLE SWARM OPTIMIZATION ALGORITHM

The particle swarm optimization algorithm (PSO) simulates the foraging behavior of birds in flight mainly through biological principles [85]. According to the experience of searching for food and previous information sharing, the birds search for the best food source through individual collaboration [86]. In order to realize the complex characteristics of the whole particle group behavior and reduce the complexity of the algorithm technology, the individual birds are represented by the volumeless and massless particles, and the simple behavior rules are formulated for the particles [87]. To improve the performance of the PSO algorithm, the certain information exchange and information sharing mechanisms are adopted between individual individuals. The PSO algorithm is called a typical swarm intelligence optimization algorithm as a distributed optimization algorithm. The search process of the particle swarm optimization algorithm simulates the predation behavior of the bird population, and the individual individuals move according to the set rules [88]. The predation behavior of a large number of individual individuals reflects the swarm intelligence behavior. The algorithm has broad application prospects in the fields of polynomial function optimization, traveling salesman problem solving and shop scheduling [89].

Suppose that in the D-dimensional data space, there are M particles forming a particle population, and the position of the i-th particle is assumed to be $x_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]^T$, The speed of the particles is $v_i = [v_{i1}, v_{i2}, \ldots, v_{iD}]^T$, where $i = 1,2,\ldots,M$. The historical optimal position searched by the particles i in the population is p_i, and the global optimal position searched by the entire particle population is p_g. Then the parameter x_i is substituted into the objective function, and the fitness value is calculated to find the optimal solution. For the $k+1$th iteration, each particle in the PSO updates its own velocity and the position data calculation formula as follows:

$$v_{i,d}^{k+1} = w\,v_{i,d}^{k} + c_1 r_1 (p_{i,d} - x_{i,d}^{k}) + c_2 r_2 (p_{g,d} - x_{i,d}^{k}) \quad (1)$$

$$x_{i,d}^{k+1} = x_{i,d}^{k} + v_{i,d}^{k+1} \quad (2)$$

In the formula (1) and (2), $= 1,2,\ldots,D$, ω are inertia weights, c_1 and c_2 are the cognitive and social parameters, r_1 and r_2 are the random numbers between [0,1].

The PSO algorithm is a parallel, random intelligent optimization algorithm. It does not need to be optimized, has the characteristics of being divisible, steerable, continuous, etc. The algorithm converges faster, the algorithm is simpler, and the programming is easier to implement [90]. The PSO algorithm has the following advantages: The algorithm has good robustness and can adapt to the needs of different application environments; it has strong distributed processing capability and is easy to implement in parallel; it can quickly converge to good expected optimization values; it is easy to combine with other algorithms to improve algorithm optimization performance [91].

B. ANT COLONY OPTIMIZATION ALGORITHM

The ant colony optimization algorithm is a biomimetic optimization algorithm proposed by Dorigo and Stützle [92]. It is a random global optimization technique inspired by the ant colony foraging behavior. The algorithm is simple and convenient to combine with other algorithms [93]. When the ants are looking for food, they will leave a substance called pheromone in the passing place. The other ants will compare the size of the pheromone on different paths when advancing, choose the direction in which the pheromone concentration is the largest, and leave their own pheromone. In the same time, the better the path will be accessed by more ants, so that the chances of subsequent ants selecting the optimal path will increase, and finally all ants will take the optimal path to the food source [94].

At the beginning, the pheromones on every path of the ant are the same. $\tau_{ij}(0) = C$, the variable C is a constant. The ant k ($k = 1,2,\ldots,m$) selects the moving direction according to the pheromone on the ant motion path during the motion. At time t, the calculation P_{ij}^k of the transition probability that the ant k chooses from the position i to the position j is as follows:

$$P_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum\limits_{s \in allowed_k} \tau_{is}^{\alpha}(t)\eta_{is}^{\beta}(t)}, & j \in allowed_k \\ 0, & \end{cases} \tag{3}$$

$$allowed_k = [1, 2, \cdots, n-1] - tabu_k \tag{4}$$

wherein, the variable $allowed_k$ represents the node that the ant k can choose at the next step, the variable $tabu_k$ records the node through which the ant k is currently passing, the variable $tabu_k$ follows the evolution process for dynamic adjustment, the variable η_{ij} indicates the visibility factor. It is calculated by the heuristic algorithm that $\eta_{ij} = 1/d_{ij}$ is often taken, the variable α and the variable β are parameters, indicating the relative importance of the pheromone trajectory and visibility in the ant selection path. After the n-th time, each cycle of the ant ends, and the pheromone of each path is adjusted according to the following formula:

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} \tag{5}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^k \tag{6}$$

wherein, the variable $\Delta\tau_{ij}^k$ represents the amount of pheromone left by the k-th of the ant in the path (i, j). The value is determined according to the trait of the ant. The shorter of the path, the more pheromone is released. The variable $\Delta\tau_{ij}$ represents the increment of the pheromone quantity of the path (i, j) in this loop; the parameter ρ is the attenuation coefficient of the pheromone trajectory, generally the parameter ρ is set as $\rho < 1$, thereby preventing the infinite accumulation of pheromones on the path. The parameter $\Delta\tau_{ij}$, $\Delta\tau_{ij}^k$, and P_{ij}^k have different expressions for different specific algorithms, and should be specific to specific problems [95].

The ant colony algorithm has the following advantages [96]:

(1) In general, the ant colony algorithm is a kind of simulated evolutionary algorithm, which combines positive feedback mechanism, distributed computing and greedy search algorithm. Ant colony algorithm generally does not fall into local optimum in search.

(2) The ant colony algorithm is different from other algorithms in that it can express complicated phenomena through natural evolution mechanism. It can rely on pheromone cooperation instead of individual information exchange mechanism, which makes the algorithm more scalable and reliable, meanwhile, it can handle difficult and fast problems reliably and quickly [97].

(3) The ant colony algorithm has quite good computational parallelism, and is extremely suitable for computation on a computationally intensive parallel machine.

C. ARTIFICIAL FISH SWARM ALGORITHM

The artificial fish swarm algorithm is an intelligent optimization algorithm proposed by Dr. Li Xiaolei [98]. It is clustered by constructing artificial fish stocks and simulating the process of fish searching for food. There are three main behaviors of artificial fish: rear-end hunting, gathering, and foraging [99]. The ultimate goal of the three behaviors is to find the best individual. The artificial fish swarm algorithm is a kind of swarm artificial intelligence stochastic optimization algorithm. It has strong global search ability, is insensitive to initial value and parameter selection, robust, simple and easy to operate [100]. The control parameters of the whole process of the algorithm are as follows: the sample set of structural planes is n, the moving step of artificial fish is $Step$, the field of vision is V, and the number of iterations is t.

The fitness function of the artificial fish swarm algorithm is calculated as follows: it mainly uses the reciprocal of the squared sum of the structural plane coordinates to the convergence distance of the structural plane as the fitness function. Its fitness function $f(x)$ is calculated as

$$f(x) = \frac{1}{\sum\limits_{i=1}^{k}\sum\limits_{j=1}^{n} \left\| d(c_i - x_j) \right\|^2} \tag{7}$$

In the formula (7), the variable k is the number of clusters, the variable n is the total number of sample planes. $\left\| d(c_i - x_j) \right\|^2$. It is the distance of the sample x from the center of gravity c in the grouping plane. Its distance calculation formula is

$$d(c_i - x_j) = \sqrt{1 - (n_c \cdot n_j^T)^2} \tag{8}$$

In the formula (8), the variable n_c, n_j are the unit normal vector of the cluster structure plane and the unit normal vector of the j structure plane [101].

The mobile strategy of the artificial fish swarm algorithm mainly includes four steps: they are foraging behavior, cluster behavior, rear-end behavior and bulletin board [102].

(1) The foraging behavior. Under the assumption of initial aggregation, the artificial fish are randomly searched in the field of view of the structural sample set, and the search formula (9) is

$$X_j = X_i \times Step \times Rand() \tag{9}$$

In the formula (9), the parameter $Step$ is the moving step size, the function $Rand$ outputs a random number in (0∼1). The coordinate value of X_j can be obtained by moving randomly at the new position X_j according to formula (8). The new position fitness can be calculated according to the formula (6) and the formula (7). If the fitness of X_j is greater, the forward formula can be obtained as follows:

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\left\| X_j - X_i^t \right\|} \cdot Step \cdot Rand() \tag{10}$$

In the formula (10), the parameter X_i^{t+1} is the position of the new focus after performing the foraging behavior multiple times.

(2) The group behavior. The artificial fish X_i searches for the number of partners in the field of view. After the search is completed, the mean coordinate of the number of fish in the current field of view is calculated, which is the central coordinate value. If the center position is more adaptable, the center coordinate value is output and moved according to the formula (11) to obtain a new focus coordinate, which is compared with the central coordinate value, and the center position calculation method is shown in the formula (12).

$$X_i^{t+1} = X_i^t + \frac{X_{cen} - X_i^t}{\|X_{cen} - X_i^t\|} \cdot Step \cdot Rand() \tag{11}$$

$$X_{cen} = \sum_{i=1}^{g} X_j / g \tag{12}$$

wherein, the parameter X_j is the coordinate of a structural plane in the field of view; the variable g is the number of partners, and the parameter X_{cen} is the new gathering position of the structural plane obtained by the group of fish.

(3) The rear-end behavior. The artificial fish X_i searches for the partner X_{max} with the highest fitness in the current field of view. After finding the largest partner, the artificial fish moves to the fish within the field of view V of the fish group, and the movement mode is as shown in the formula (13). According to the formula (13), the coordinates of the new cluster center X_{next} can be obtained, and the better ones of X_{next} and X_{max} are recorded.

$$X_{next}^{t+1} = X_i^t + \frac{X_{\max} - X_i^t}{\|X_{\max} - X_i^t\|} \cdot Step \cdot Rand() \tag{13}$$

In the formula (13), the parameter X_{max} is the individual with the greatest fitness in the field of fish.

(4) The bulletin board. The bulletin board is used to record the individual state of the optimal artificial fish. After the artificial fish completes each iterative operation, it compares its state with the records in the bulletin board. If its own adaptation value is larger, the content in the bulletin board is replaced with its current state. Otherwise, the content in the bulletin board remains the same. When the algorithm iteration ends, the bulletin board records the optimal state [103].

D. ARTIFICIAL BEE COLONY ALGORITHM

The artificial bee colony algorithm is abbreviated as ABC algorithm, which is a combination optimization algorithm of non-numeric calculation, and also belongs to meta-heuristic intelligent algorithm [104]. In 2005, Dr. Karaboga of the University of Ergiyes in Turkey proposed a novel intelligent heuristic artificial bee colony algorithm by observing the foraging behavior of bee colonies [105]. The algorithm accomplishes the work of collecting honey through the division of labor and dance between the individual bees to transmit information, role transformation and unity and cooperation of the bee colony. In addition, the artificial bee colony algorithm does not need to know the prior knowledge of the solution problem. Through the local search and global search of the bee colony algorithm, the optimal solution of the optimization problem is quickly found, and the convergence speed of the algorithm is faster [106].

During the initialization phase, the ABC algorithm generates the honey sources are S, the number of bees and honey sources is equal. The lead bee in the bee colony performs a $P(P = 1,2, \ldots, N)$ round search for the honey sources, and continuously replaces the old honey source position with a new honey source position during the search process, wherein, the number of nectar is the fitness Better than the previous honey source. Finally, when all the above search processes are completed, the honey source location information will be shared with the follower bees, which will be returned to the place called the dance area, and the following bees will select the best honey source according to the greedy mechanism [107]. After the bee chooses the honey source, a search will be carried out in the area near the honey source. If a better honey source is found, the honey source will be replaced, that is to say, the better solution will be retained. The formula (14) is the formula for the location of the honey source exchanged between the leading and the follower bees [108]:

$$V_{ij} = x_{ij} + v_{ij}(x_{ij} - x_{kj}) \tag{14}$$

wherein, the variable k is a honey source different from i, the variable k is not equal to the variable i, the variable j is a random number subscript, v_{ij} obeys a uniform distribution on $[-1, 1]$, it is a random number, and its function is to control the domain range of x_{ij}. The closer the optimal solution is, the smaller the scope of the field will be. The follower bee in the bee colony will select the honey source that the leader bee to choose. And it will search for more excellent honey sources in the field, the follower bee's honey source selection behavior is determined according to the yield of the honey source, and the rate of return is quantitatively expressed by the fitness value. The formula (15) is the selection probability P_i of the honey source, wherein, the parameter fit_i is the fitness value corresponding to the i-th solution, and the variable S is the number of connections [109].

$$P_i = fit_i \Bigg/ \sum_{i \neq 1}^{S} fit_i \tag{15}$$

Assuming that the honey source has not improved after a continuous number of cycles, the solution is trapped in local optimum by taking the position and turning the leading bee at that position into a scout bee. It can be seen that the above defined number of cycles is an important parameter of the ABC algorithm. If the abandoned solution is x_k, then the scouting bee finds a new location and performs the substitution as follows:

$$x_k^j = x_{\min}^j + rand(0, 1)(x_{\max}^j - x_{\min}^j) \tag{16}$$

E. SHUFFLED FROG LEAPING ALGORITHM

In 2003, Professor Eusuff et al. proposed a sub-heuristic shuffled frog leaping algorithm (SFLA) [66]. It is a new intelligent evolutionary search method that mimics the frog group's foraging behavior. This kind of algorithm is based on the idea of frog group classification for meme information transmission [110]. The SFLA algorithm, inspired by the frog's search for food, searches for targets based on synergies between populations [111]. First, search for different frog individuals, then exchange the information in a local scope, construct an information search strategy within the subgroup, and form internal evolution with the exchange of information within the subgroup, and then derive different subgroups. The information reanalysis and exchange among subgroups form the global information exchange. These two modes interact with each other and alternate to solve the combinatorial optimization problem. The algorithm has many advantages, such as fewer parameters to adjust, fast calculation speed, strong global search and optimization ability, easy realization, etc. It has been widely used in practical engineering problems such as multi-objective optimization, resource allocation and so on [112]. The shuffled frog leaping algorithm combines the characteristics of bird foraging method and meme algorithm of genetic bionics, which iteratively searches for the optimal solution of population behavior. It is widely used in the traveling salesman problem, function processing, power supply system optimization, machine vision and so on [113].

The mathematical model of the shuffled frog leaping algorithm and the specific calculation process, randomly generate D frog individuals in a d-dimensional target search space, that is, the number of solutions of the target optimization function, forming the initial population of frogs $S = \{X_1, X_2, \ldots, X_D\}$. The current position of the i-th frog population is the solution to the current combinatorial optimization problem. Assuming that $X_i = (x_{i1}, x_{i2}, \ldots, x_{id})$, the individual fitness function value $f(X_i)$ of each frog can be obtained by arithmetic calculation, and the obtained frog individual fitness values are arranged according from good to bad. At the same time, referring to the frog group division criterion, the whole frog group is divided into N population groups $Y^1, Y^2, \ldots, Y^{\mathrm{N}}$, and each subgroup group contains M frog individuals, wherein it is satisfied that $D = N \times M$. The frog division criterion is to divide the first frog into the first subgroup, the second one into the second group, and so on, and divide the entire frog group into the formula (17).

$$Y_j = \{X_{j+N(l-1)} \in S\}, 1 \le l \le M, 1 \le j \le N \tag{17}$$

A local optimal search is performed in each frog subgroup, and in each iteration, the following three parameters are obtained: The optimal individual position X_b, the worst individual position X_w and the global best individual position X_g from the group are then updated, and then the worst frog individual position is updated, and the update strategy is as shown in the frog step update in the formula (18).

$$Q_i = rand() \times (X_b - X_w), \quad -Q_{\max} \le Q_i \le Q_{\max} \tag{18}$$

The position of the individual frog subgroup is updated according to the formula (19).

$$X'_w = X_w + Q_i \tag{19}$$

The parameter *rand()* is a random number between 0 and 1, and Q_{max} is the maximum step size allowed in the frog subgroup. After executing the update strategy of the above the formulas (6) and (7), the new position X'_w is obtained. If the newly obtained position X'_w is better than the previous X_w, then the frog is replaced by the X_w from the group current position X'_w. Otherwise, update the policy change update the step size formula according to the formula (20).

$$Q_i = rand() \times (X_g - X_w), \quad -Q_{\max} \le Q_i \le Q_{\max} \tag{20}$$

$$X'_w = X_w + Q_i \tag{21}$$

After executing the new update the formulas (20) and (21), a new frog position can be obtained. The same comparison with the previous position, just replace the current position, if the frog position has not been changed, then randomly generate a new individual position (function solution) instead of the principle of the frog individual position, can get the formula (22).

$$X''_w = rand() \times (O_{\max} - O_{\min}) + O_{\min} \tag{22}$$

wherein, X''_w is the current latest position, O_{max} and O_{min} are the maximum and minimum values of the search range among the frog subgroups, respectively [114].

The iterative update step above is continuously repeated until the maximum number of iterations set in the previously set subgroup is satisfied. When all the frog subgroups perform the local best search and get the best position of the frog individual, the global information exchange is performed. The process of exchange includes mixing, sorting and dividing all frog individuals into subgroups, and then searching for the optimal solution in each new subgroup. The optimal solution is the best position, so it keeps repeating until the pre-set iteration conditions are satisfied.

In summary, after nearly 30 years of research and development, the swarm intelligent optimization algorithm is theoretically perfect, with the advantages of robustness, the self-organization and flexibility, especially the elephant herding optimization (EHO), wolf pack algorithm (WPA), the butterfly optimization algorithm(BOA) and so on. For example, in [121], the author proposed the elephant herding optimization algorithm adopted for solving localization problems in WSNs. In recent years, it has been widely used in various fields such as the chaotic systems, financial forecasting, image retrieval, and feature selection. In order to visually compare the characteristics and application scenarios between different swarm intelligent optimization algorithms, the advantages, disadvantages and applicable scenarios of different swarm intelligent optimization algorithms are summarized, as shown in Table 2.

TABLE 2. Comparison of advantages and disadvantages of the swarm intelligent optimization algorithm.

Algorithms	advantages	disadvantages	Applicable scenario
PSO [87]	Parallel computing, easy to implement, high precision, fast convergence	Poor search ability, easy to fall into local optimum	Function optimization, neural network training and resource scheduling problems
ACO [93]	Distributed calculation, positive feedback mechanism, diversity	Convergence rate is slow, easy to fall into local optimum	Resource scheduling problems and traveling salesman problems
AFSA [99]	Parallel computing, fewer parameters, faster convergence	Low optimization accuracy, slow convergence rate, easy to fall into local optimum	Power system planning, sensor network coverage optimization, path planning
ABC [105]	High-dimensional problems work well and get local convergence quickly	Convergence is slow, easy to fall into local optimum	Image signal processing, feature selection and resource scheduling issues
SFLA [114]	Simple concept, few parameters, fast parallel operation, easy to implement	Easy to fall into local optimum, slow convergence	Clustering problem, resource network optimization and image segmentation
FA [115]	Less parameters, simple evolution process, strong global search ability	Early convergence is slow, and late convergence is unstable	Image processing, clustering problem, combinatorial optimization problem
BFA [116]	Parallel search, easy to jump out of local minimum	Low optimization accuracy and slow convergence	Pattern recognition, engineering parameter optimization
CA [117]	Simple model, few parameters, strong versatility	Slow rate of convergence, easy to fall into local optimum	Facility layout, clustering problem
FFOA [118]	Less parameters, simple structure, easy to implement	Depends on the initial conditions, low optimization accuracy, easy to fall into local optimum	Structural engineering design optimization, the node deployment strategy, resource scheduling
CSO [119]	Less parameters, simple structure, fast operation, easy to implement	Low optimization accuracy, easy to fall into local optimum	Function optimization, engineering design optimization, cluster analysis
EHO[120]	Less parameters, simple structure, easy to implement	Slow convergence rate, easy to fall into local optimum	Function optimization,location problem

IV. SWARM INTELLIGENCE APPLICATIONS IN MOBILE WIRELESS SENSOR NETWORKS

In recent years, with the continuous development and maturity of swarm intelligence optimization algorithm and artificial intelligence theory, the swarm intelligent optimization algorithm has been widely used in the coverage optimization strategy, location algorithm, dynamic deployment of the network, node scheduling, data fusion, reliability and other aspects of mobile wireless sensor networks, bringing new ideas to solve problems [120]. Through comprehensive literature analysis, mathematical formula derivation and mathematical modeling, a series of key technical problems in mobile wireless sensor networks (node deployment, optimal coverage, routing protocol optimization, data collection, data fusion, optimal clustering, topology optimization, node location, network security and reliability) are combinatorial optimization problems and the NP-hard problems [121]. The application of swarm intelligence optimization algorithm in mobile wireless sensor networks is shown in Table 3.

As the scale of wireless sensor networks continues to increase, the structure and node types of networks become more complex, and the network exhibits dynamic changes. More and more researchers begin to pay attention to the application of complex network optimization theory in the field of mobile wireless sensor networks. There are many indicators reflecting the performance of mobile wireless sensor networks, such as the network energy consumption, network coverage, network quality of service, network lifetime, packet loss rate, throughput, network transmission delay, network cost, connectivity and reliability. These indicators may or may not conflict with each other and restrict each other [122]. The performance optimization of mobile wireless sensor networks is a multi-objective optimization problem, which is a complex problem that requires decision makers to choose a trade-off solution. The relationship between the performance indicators of mobile wireless sensor networks is shown in Fig. 4.

A. NODE DEPLOYMENT AND COVERAGE EFFICIENCY

The coverage control and the sensor node deployment determine the perception and monitoring capability of the network, which directly reflects the quality of service of mobile wireless sensors. In order to achieve the purpose of reducing the blind zone covered by MWSNs and improving the ability of sensor nodes to obtain information, it is necessary to deploy the network nodes reasonably and effectively [123]. The swarm intelligence algorithm is an optimization problem, and the dynamic deployment of sensor nodes is actually an optimization problem. Therefore, the introduction of swarm intelligence algorithm can optimize the layout of wireless sensor nodes and improve the service performance of the entire network [124]. Compared with the traditional

TABLE 3. Optimization and application in MWSNs' domain.

Key problem of MWSNs	Problem description	Optimization goal of MWSNs
Optimal deployment of nodes	Multi-objective optimization	Deals with the deployment/design problem of MWSNs
Optimal coverage of networks	Multi-objective optimization	Deals with the optimal coverage problem of MWSNs
Routing protocol optimization	Combinatorial optimization	Balances the power consumption, transmission delay and packet loss rate of MWSNs
Optimal data collection	Multi-objective optimization	Deals with the problem of maximizing data collection
Data fusion	Multi-dimension	Integrates the sensor data from multiple sources to get the best solution.
Optimal clustering	Multi-objective optimization	Deals with the clustering optimization problem of MWSNs
Topology optimization	Combinatorial optimization	Deals with the load balancing problem of MWSNs
Scheduling and MAC	Multi-objective optimization	Optimizes simultaneously or optimal tradeoff is required between objectives.
QoS management	Combinatorial optimization	Analytically plans and allocates resources for the best solution.
Localization	Multi-dimension	Deals with position estimation
Security	Combinatorial optimization	Searching for optimal solution from the possible inside threats, integrity, end-to-end data security, and key distribution for the best solution.
Reliability	Combinatorial optimization	Deals with the reliability problem of MWSNs

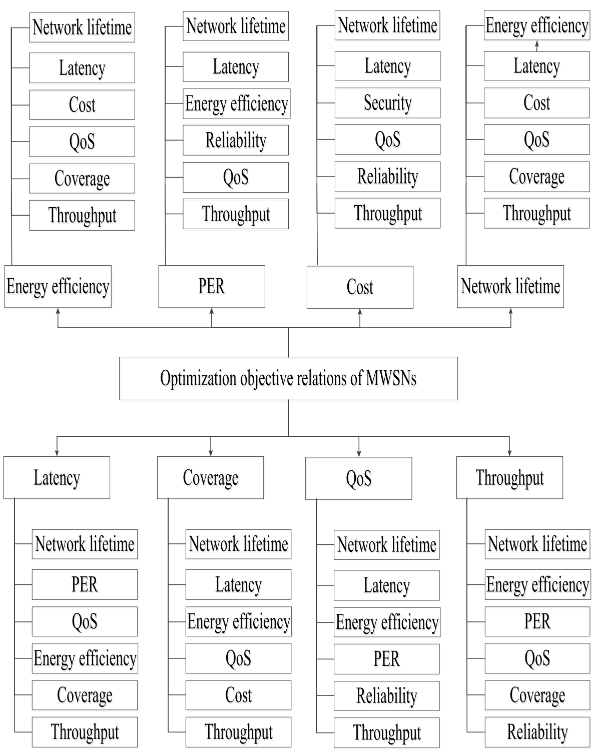

FIGURE 4. Relationship between the performance indicators of MWSNs.

coverage optimization methods, the swarm intelligence algorithm provides a lot of new effective deployment methods of the sensor nodes, and the energy of the sensor nodes is used more reasonably and effectively, which makes the MWSNs technology more exert its great application value. The application of swarm intelligence algorithm in the coverage optimization problem of MWSNs has attracted more and more scholars' attention and research. For MWSNs, the classification criteria are different and the coverage optimization algorithms are classified differently. We divide the coverage problem of MWSNs into virtual force-based algorithm node deployment algorithm, the computational geometry-based partitioning method, intelligent algorithm-based node deployment algorithm and heterogeneous hybrid network deployment algorithm, and then we introduce the research progress of each node deployment and optimal coverage algorithm from these four aspects.

1) OPTIMAL COVERAGE ALGORITHM BASED ON VIRTUAL FORCE

Umadevi *et al.* [125] used the virtual force and particle swarm optimization for effective node deployment, the virtual force algorithm is used for placement of nodes, and applied the particle swarm optimization to optimize the best fit between the neighbor nodes. The authors in [126] analyzed the convergence and deployment effect of the virtual spring force algorithm to derive our question, and then presented an optimized strategy that sensor deployment begins from the center of the target region by adding an external central force. In [127], the author used a voronoi diagram for the case of sensors with the same sensing ranges, and a multiplicatively weighted voronoi diagram for the case of sensors with different sensing ranges. The basic idea of this type of algorithm is to regard the sensor nodes in the deployment area as a positively charged charge, and then the nodes move and spread in the target area under the action of repulsive forces and boundary obstacles. Eventually all the nodes reach a relatively stable state. The virtual force algorithm is a widely used method in the node deployment of mobile wireless sensor network.

2) PARTITION METHOD BASED ON COMPUTATIONAL GEOMETRY

The basic idea of the grid-based algorithm is to divide the target monitoring area into several grids, and then approximate the area coverage by whether the grid is covered by the nodes. This kind of algorithms can reduce the number of nodes required by estimating the operation. In addition, the grid can also be used to estimate the nearsightedness of the grid position. In [128], the author proposed a novel coverage hole discovery algorithm for wireless sensor networks, VCHDA, and the proposed algorithm is based on the well-known Voronoi diagram. It can recognize coverage holes and label the border nodes of coverage holes effectively. The authors in [129] introduced the adaptive improved fish swarm optimization algorithm (AIFS) that extricated each node from the local optimum and reduced the overlap and overflow coverage. Drawing on the habits of fish, AFIS ensured the node mobility with respect to the food concentration at a certain point.

3) NODE DEPLOYMENT BASED ON INTELLIGENT ALGORITHMS

The intelligent algorithms have good global search ability and adaptability, and are widely used in the deployment of mobile auxiliary nodes in wireless sensor networks. For example in [130] the authors focused on optimizing the gateway deployment by minimizing the maximum distance, proposed an RPSO algorithm to search the optimal gateway deployment. In order to reduce the cost of sensor deployment, Su *et al.* [131] proposed an optimized strategy for mobile wireless sensor networks node deployment on the basis of dynamic ant colony algorithm. In order to overcome the shortcomings of weak local search ability and slow convergence speed for the standard artificial bee colony algorithm, Su *et al.* [132] proposed an improved multi-strategy artificial bee colony algorithm based on multiple populations. For example in [133] the authors focused on redundant network nodes, short life cycle and network effective coverage as optimization goals, and then introduced the inverse Gaussian mutation algorithms on AFSA, made the improved algorithm to solve the model, and got the optimal coverage scheme for mobile wireless sensor networks. In [134], the authors proposed a new improved discrete shuffled frog leaping algorithm (ID-SFLA) and its application in multi-type sensor network optimization for the condition monitoring of a gearbox, provided a new quick algorithm and thought for the solution of related integer NP-hard problem.

4) NODE DEPLOYMENT ALGORITHMS FOR HETEROGENEOUS MWSNS

In some applications of mobile wireless sensor networks, some of them are heterogeneous nodes, which have more and more powerful functions. For this type of network, the main idea is to take advantage of the mobility characteristics of heterogeneous nodes, move them to the appropriate location, and then improve the coverage of the entire network. For example in [135] the authors studied the barrier coverage problem in a mobile survivability-heterogeneous wireless sensor network, proposed a novel greedy barrier construction algorithm to solve the problem, the proposed algorithm efficiently solves the problem and outperforms other alternatives. In [136], the authors studied how to efficiently form barrier coverage by leveraging multiple types of mobile sensors to fill in gaps between pre-deployed stationary sensors in heterogeneous WSNs. Jameii *et al.* [137] proposed the adaptive multi-objective optimization framework based on non-dominated sorting genetic algorithm and learning automata for coverage and topology control in heterogeneous wireless sensor networks, the simulation results demonstrate the efficiency of the proposed multi-objective optimization approach in terms of lifetime, coverage and connectivity.

B. DATA COLLECTION

Data collection is one of the main tasks of mobile wireless sensor networks [138]. The sensor nodes transmit continuously perceived data to the base station in the form of wireless communication for further processing. Because of the limited energy, computing power and storage capacity of the sensor nodes, as well as the influence of the channel interference and the environment mutation, the data collection of MWSNs faces many challenges. The main task of data collection for MWSNs is to collect the sensory data from the sensor nodes [139]. The classification of data collection methods for mobile wireless sensor networks is shown in Fig. 5.

According to the driving method, the data collection of MWSNs can be divided into the time-driven and the event-driven [22]. The time-driven type means that the data collection is performed periodically, and the sensor node transmits its own perceived data in a certain manner in each cycle, and completes one cycle of data collection after receiving the data sent by all the nodes. The event-driven type refers to the sensor node monitoring an event of interest in the monitoring area. Once the event occurs, the sensor node reports the relevant information to the Sink node in time and then transmits it to the user [140].

For the time-driven data collection, a batch of collection points is determined according to the distribution of nodes, and then the intelligent optimization algorithm is used to solve the optimal loop through the collection points, and the data is periodically collected along the loop, which can effectively shorten the moving distance. For example in [141] the authors proposed optimal cluster-based mechanisms by a modified multi-hop layered model for load balancing with multiple mobile sinks for these problems, and analyzed the

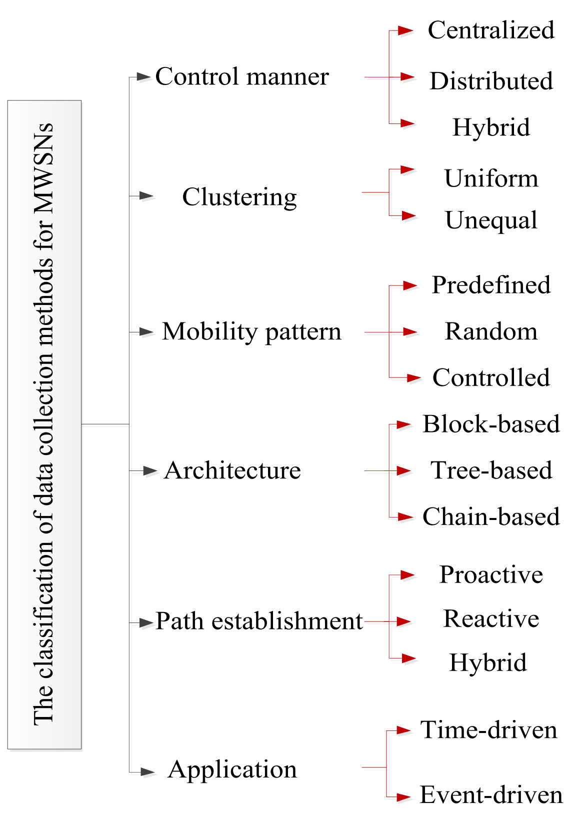

FIGURE 5. The classification of data collection methods for MWSNs.

cluster lifetimes in different situations and achieve balance to save significant energy. In [134] the authors proposed an ant-based routing protocol with QoS-effective data collection mechanism for MWSNs, the proposed routing protocol provides reliability by reducing the packet drop and end-to-end delay when compared to the existing protocols. A velocity energy-efficient and link-aware cluster-tree (VELCT) scheme for data collection in mobile WSNs is proposed which would effectively mitigate the problems of coverage distance in [143]. A three-layer framework is proposed for mobile data collection in wireless sensor networks, and a distributed load balanced clustering (LBC) algorithm is proposed for sensors to self-organize themselves into clusters in [144]. Wang *et al.* [145] applied the biogeography-based optimization to the dynamic deployment of mobile sensor networks, proposed the Homo-H-VFCPSO algorithm for the dynamic deployment, achieved better performance by trying to increase the coverage area of the network.

In the event-driven mobile scheme based on mobile Sink, the mobile strategy of Sink is determined by the events received. When the sensor node collects the sensing data, it sends a short event message to the node, and the mobile Sink formulates a corresponding mobile policy according to the event message, and then moves to a specific location to collect the node data. For example in [146] the authors studied the problem of controlling sink mobility in event-driven applications to achieve maximum network lifetime, and proposed a convex optimization model inspired by the support vector regression technique to determine an optimal trajectory of an MS without considering predefined structures. Gao *et al.* [147] adopted a hybrid method called HM-ACOPSO which combines ant colony optimization (ACO) and particle swarm optimization (PSO) to schedule an efficient moving path for the mobile agent, and the presented method outperforms some similar works in terms of energy consumption and data gathering efficiency. A fish-swarm based algorithm is designed requiring local information at each fish node and maximizing the joint detection probabilities of distress signals. Optimization of formation is also considered for the searching control approach and is optimized by fish-swarm algorithm in [148]. To minimize the energy consumption on the traveling of the mobile robot, In [149] the authors applied the concept of artificial bee colony (ABC) and design an ABC-based path planning algorithm, and validated the correctness and high efficiency of our proposal. In order to address the energy consumption problem, in [150] the authors proposed the shuffled frog leaping algorithm (SFLA) by suitably modifying the frog's population generation and off-spring generation phases in SFLA and by introducing a transfer phase. The experimental results are encouraging and demonstrated the efficiency of the proposed algorithm.

C. DATA FUSION

Data fusion methods can improve the accuracy of information acquisition, the power of energy conservation, and the efficiency of data collection [151]. The ultimate goal is to take advantage of multi-sensor joint operation to improve the effectiveness of the system. Data fusion is to remove redundant nodes, the fusion and other operations in the data collected by the multiple sensor nodes, so that the data is more concise and accurate. At the same time, the amount of packet transmission in the network is reduced, and the power consumption is reduced, the collection efficiency is improved, and the fault tolerance is strong [152]. Clustering-based data fusion for MWSNs is shown in Fig. 6.

In order to achieve efficient data fusion, data fusion is done through layer-based routing based on the hierarchical structure of sensor nodes in the network. The data fusion methods of MWSNs mainly include four types: the cluster-based data fusion, the chain-based data fusion, the tree-based data fusion and the grid-based data fusion [153].

1) CLUSTER-BASED DATA FUSION

In the application of large-scale mobile wireless sensor networks, if the sensor nodes transmit data directly to the base station directly, the sensor nodes near the base station will soon exhaust their energy. For this reason, the entire network is organized into different clusters, and the cluster heads fuse the data collected by the sensor nodes in the cluster, and then directly or indirectly communicate with the base station through the other cluster heads in a multi-hop manner. For example in [154] the authors proposed the sink mobility and nodes heterogeneity aware cluster-based data

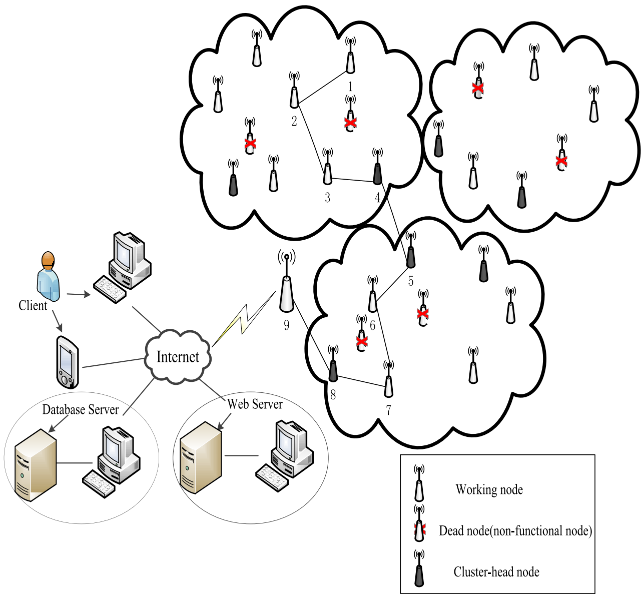

FIGURE 6. Data fusion in a clustered architecture for MWSNs.

aggregation algorithm (MHCDA) for efficient bandwidth utilization and an increase in network lifetime. Sung and Chung [155] proposed an improved particle swarm optimization (IPSO) approach to data integration optimization calculations, improved the efficiency of data fusion and prolonged the lifetime of network. In [134], the authors proposed a new improved discrete shuffled frog leaping algorithm (ID-SFLA) and its application in multi-type sensor network optimization for the condition monitoring of a gearbox, provided a new quick algorithm and thought for the solution of related integer NP-hard problem.

2) CHAIN-BASED DATA FUSION

In a cluster-structured mobile wireless sensor network, if the cluster head is far away from the members of the cluster, the data transmission will consume a large amount of energy. In response to this problem, the chain-based data fusion method advocates that the sensor node only sends data to the cluster head closest to itself. Before the data is collected, a node chain is generated to connect all the sensor nodes. Then select a node as the chain leader, and the choice of the chain leader is random. The data is transmitted from the two ends of the chain in the direction of the chain to the chain head. The intermediate node performs simple data fusion, and the chain first performs certain data fusion on the received information, and then transfers the merged data to the Sink node. In order to provide an improved performance amongst the existing, a routing algorithm called cluster-chain mobile agent routing was proposed in this work, it made full use of the advantages of both low energy adaptive clustering hierarchy and power-efficient gathering in sensor information systems [156].

In [157] the authors proposed an intelligent multi-sensor data fusion method using the relevance vector machine (RVM) based on an ant colony optimization algorithm (ACO-RVM) for the sensors' fault detection, the ACO-RVM algorithm has higher fault detection accuracy than the RVM with normal the cross-validation. In [158] the authors proposed the data collection and data fusion algorithm based on artificial bee colony for WSNs with mobile Sink, the proposed algorithm can effectively reduce data transmission, save energy, improve network data collection efficiency and reliability, and extend the network lifetime.

3) TREE-BASED DATA FUSION

In the tree network, the sensor nodes are organized into a tree with the Sink node as the root and the source node as the leaf node, and the non-leaf nodes perform data fusion in the process of data forwarding. The Sink node first floods the control message. The message consists of five parts: the ID, the parent node, its own remaining energy, the state, and the hops (the number of hops from the sink node). The node that receives the message will select the node with fewer hops and higher remaining energy as its parent node. This process continues and finally generates a data fusion tree with the aggregation node as the root node. For example in [159] the authors proposed a local-tree-reconstruction-based scheduling algorithm for the maximum lifetime data aggregation Tree Scheduling problem (LTRBSA), and used simulations to evaluate and demonstrate the performance of the LTRBSA algorithm when the sink node has 2-hop, 3-hop, and all information in the networks. In [160] the authors proposed the energy aware routing with ant colony optimization, and provided more feasible routing solutions in source node to sink node and provide significant enhancement on the lifetime of the sensor network.

4) GRID-BASED DATA FUSION

The data fusion method based on grid is that according to the location information and communication radius of nodes. The area monitored by the wireless sensor network is divided into a number of grids, each of which is assigned a node as a data fusion node. If a node has data to send, it can directly send the data to the data fusion node in the grid. For example in [161] the authors a virtual grid-based dynamic routes adjustment (VGDRA) scheme that aims to minimize the routes reconstruction cost of the sensor nodes while maintaining nearly optimal routes to the latest location of the mobile sink. A method is proposed to improve the quality of MWSNs data fusion by optimizing the weights and thresholds of neural networks, the BP neural network optimized by artificial fish swarm algorithm (AFSABP) neural network data fusion, the proposed algorithm has significant improvement in convergence speed and optimization accuracy [162]. In [134] the authors proposed a new improved discrete shuffled frog leaping algorithm (ID-SFLA) and its application in multi-type sensor network optimization for the condition monitoring of a gearbox. Abirami and Anandamurugan [163] proposed a shuffled frog meta-heuristic algorithm for cluster heads selection. The proposed method chooses the cluster head based on energy remaining in the

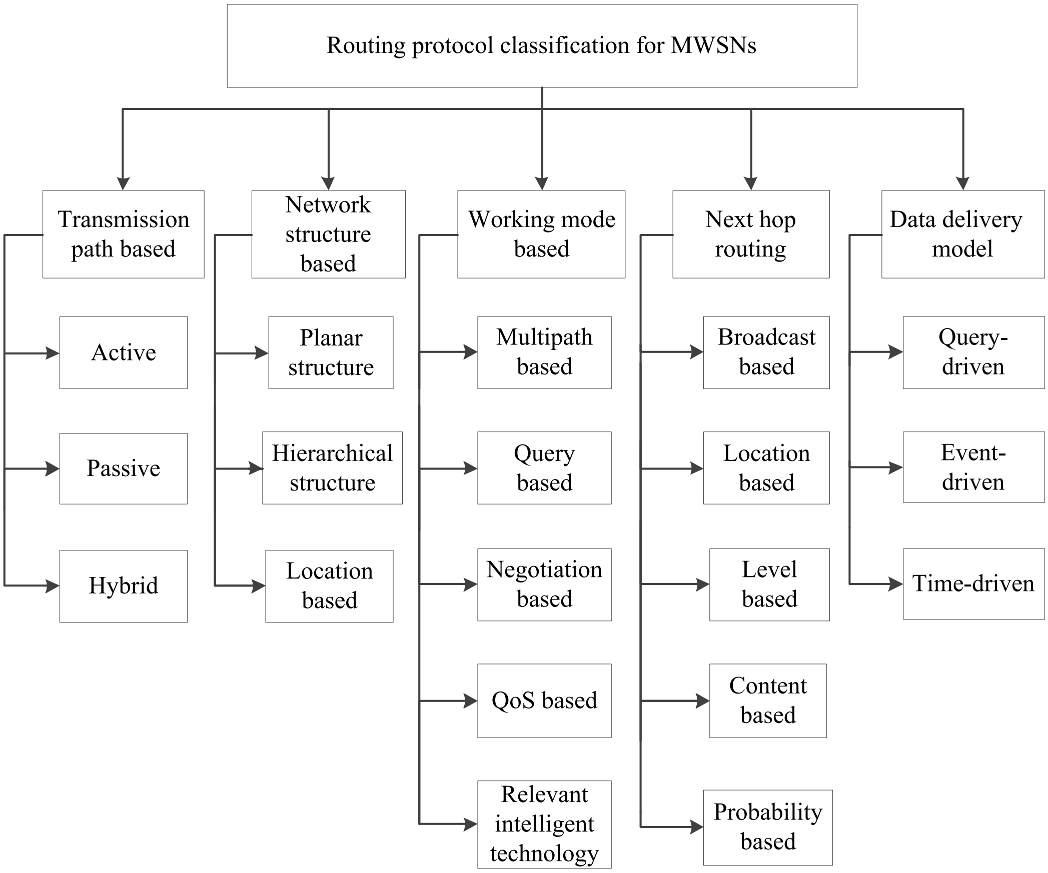

FIGURE 7. **Routing protocol classification for mobile wireless sensor networks.**

nodes, the proposed technique to outperform LEACH and the Genetic Algorithm based methods in terms of Quality of Service.

The above are all data fusion methods based on the hierarchical structure of sensor nodes in mobile wireless sensor networks, which have advantages and disadvantages in terms of energy efficiency, scalability, communication bandwidth utilization, delay and throughput, and are suitable for different applications.

D. ROUTING PROTOCOL OPTIMIZATION

The energy of the sensor nodes in the mobile wireless sensor network is limited and cannot be supplemented. Therefore, the design of the routing protocols for MWSNs should achieve energy efficient utilization and prolong the node lifetime in the network. A mobile wireless sensor network is a multi-hop network in which each node in the network is both a transmitting node and a relay node [164]. If the sensor nodes are exhausted due to the energy exhaustion, the network topology will change dynamically, and the network needs to be rerouted and configured, which leads to instability of the topology of the network and the coverage of the network. In order to improve the energy consumption of the network, domestic and foreign scholars have proposed a number of advanced routing protocols. Depending on the partitioning criteria used, these routing protocols have different classification methods, as shown in Fig. 7.

1) PATH-BASED ROUTING PROTOCOL

According to the method of obtaining the destination node by the source node, the routing protocols of the mobile wireless sensor network are classified into active routing, passive routing, and hybrid routing. The active routing protocol periodically maintains a routing table for maintenance in the entire network, that is, a routing table containing the latest routing information to other sensor nodes. Once the node needs to send data, it can immediately get the route to the destination node. For example in [165] the authors proposed a fuzzy shuffled frog leaping algorithm (FSFLA), which employs the memetic shuffled frog leaping algorithm to optimize the mamdani fuzzy rule-base table based on the application specifications. Chatterjee and Das [166] proposed an enhanced version of the well-known dynamic source routing scheme based on the ant colony optimization algorithm, which could produce a high data packet delivery ratio in low end to end delay with low routing overhead and low energy consumption. In [167] the authors presented the fuzzy and ant colony optimization based combined MAC, routing, and unequal clustering cross-Layer protocol for MWSNs (FAMACROW) consisting of several nodes that sent the sensed data to a master station, the proposed algorithm improved the network's efficiency and prolongs the network's lifetime.

2) NETWORK-BASED ROUTING PROTOCOL

According to the topology of the network, the routing protocols of mobile wireless sensor network are classified into three types: plane routing protocol, cluster routing protocol and location routing protocol. The plane-based routing method requires the same function and status of each node, and the protocol uses a data-centric routing scheme. In this scheme, the sink node sends a query command to the sensing node in the selected area, waiting for the node to feedback information. For example in [168] the authors proposed a particle swarm optimization based clustering algorithm with mobile sink for wireless sensor network. In this algorithm, the virtual clustering technique is performed during routing process which makes use of the particle swarm optimization algorithm. In [169] the authors proposed an improved ACO algorithm approach for WSNs that use mobile sinks by considering the cluster heads distances. In [170] the authors proposed an energy-efficient network model that dynamically relocates a mobile BS within a cluster-based network infrastructure using a harmony search algorithm. Kumar and Kumar [171] proposed an energy efficient clustering mechanism, based on artificial bee colony algorithm and factional calculus to maximize the network energy and life time of nodes by optimally selecting cluster-head.

3) WORKING MODE-BASED ROUTING PROTOCOL

Mobile wireless sensor networks have a high degree of application relevance, and different routing protocols are used in different application environments. According to the working mode of the network, the routing protocol can be divided into multi-path based, query based, negotiation based, QoS based algorithms. In the multi-path routing protocol, the source node sends a message to the destination node to select multiple paths as routes, thereby reducing the transmission delay and improving network performance. However, due to the need to periodically send messages to keep the active state of the path, the communication overhead is increased. For example in [172] the authors proposed the ACOA-AFSA fusion routing algorithm, the proposed algorithm could reduce existing routing protocols' transmission delay, energy consumption and improve routing protocols' robustness. A swarm intelligence algorithm was introduced into the clustering algorithm of wireless sensor network, and an efficient and reliable clustering algorithm for wireless sensor networks based on quantum artificial bee colony algorithm was proposed in [173]. Tunca *et al.* [174] proposed Ring Routing, a novel, distributed, energy-efficient mobile sink routing protocol, suitable for time-sensitive applications, which aimed to minimize this overhead while preserving the advantages of mobile sinks.

4) NEXT HOP SELECTION BASED ROUTING PROTOCOL

Based on the next hop routing selection, the routing protocols of mobile wireless sensor networks are divided into broadcasting-based, location-based, hierarchical, content-based and probability-based routing protocols. In a broadcast-based routing protocol, each node independently decides whether to forward a message. If the forwarding is rejected, the message will be discarded. In [175] the authors proposed the sink mobility based energy balancing unequal clustering protocol (SMEBUC) for MWSNs with node distribution, which chose the nodes with more energy as cluster heads and divides all nodes into clusters of different size through the improved shuffled frog leaping algorithm (SFLA). In [176] the authors proposed an improved artificial bee colony (iABC) metaheuristic with an improved search equation to enhance its exploitation capabilities, the proposed clustering protocol outperforms other algorithms based protocols on the basis of packet delivery, throughput, energy consumption and prolong the network lifetime. A novel greedy discrete particle swarm optimization with memory (GMDPSO) is put forward to address the energy consumption problem [177]. In [178] the authors proposed a next hop selection mechanism for VANETs which takes the heterogeneous environment into consideration, the minimum hop count prediction method is firstly proposed to help the current packet-carrying vehicle node to estimate the minimum hop counts required from each neighbor to the destination.

E. ROUTING FAULT TOLERANCE OPTIMIZATION

The route fault tolerance strategy of MWSNs refers to the failure of the node or communication link in the mobile sensor network, causing the original data transmission path to be interrupted, and how to deal with the network faults adaptively, quickly and effectively, so as to ensure that the network runs reliably and accurately [179]. How to design an efficient routing fault-tolerant strategy, provide a stable and reliable data transmission path, ensure the robustness and anti-interference ability of data transmission, and improve network reliability and availability have become an urgent problem for mobile wireless sensor networks. The fault-tolerant design of MWSNs mainly focuses on node hardware fault tolerance, coverage fault tolerance and topology control fault tolerance, and routing fault tolerance [180]. At present, the fault tolerance methods proposed by researchers at home and abroad mainly focus on three aspects: link retransmission method, error correction code mechanism and multipath transmission method.

1) LINK RETRANSMITS METHOD

The failure rate of wireless communication links in MWSNs is much higher than that of limited networks, and increases as the number of hops transmitted by nodes increases. The link retransmission mechanism can transmit information to the required nodes with only one retransmission. Link retransmission is an effective method from the perspective of channel availability of MWSN. For example in [181], the real-time retransmission algorithm based on network coding (NCRR) was proposed to make the average number of transmissions as less as possible, the algorithm could effectively reduce the average number of transmissions and improve the transmission efficiency. In [182] the authors proposed a particle swarm optimization (PSO)-based unequal and fault tolerant clustering protocol, the proposed protocol addresses imbalanced clustering and fault tolerance issues in the existing energy-balanced unequal clustering protocol for the long-run operation of the network. For the problem of deploying a WSN with a specified minimum level of reliability at a minimum deployment cost is addressed. An ant colony optimization algorithm coupled with a local search heuristic is proposed, the experimental results demonstrate the effectiveness of the proposed approach in finding high-quality solutions to the problem [183].

2) ERROR CORRECTION CODE MECHANISM

It adopts the method of reconstructing the original data. The error correction code mechanism can obtain higher network reliability without link retransmission, but it needs to divide the data packet into diversified code words. This way, there is a defect and pride. The number of information and codewords must be chosen so that the number of messages cannot exceed the number of bits used to characterize the information [184], the number of codewords must be less than the capacity used to calculate the external storage space. In [185] the authors proposed an optimized cluster head selection using an improved artificial fish swarm algorithm (AFSA) metaheuristic, the proposed algorithm improved the network performance and lifetime. In [186] the authors proposed a reliable spanning tree construction algorithm, which is called reliable spanning tree construction in IoT (RST-IoT), the algorithm utilized the artificial bee colony algorithm to generate proper trees, the proposed algorithm improved the reliability of data gathering in emergency applications compared to the previous approaches.In [113] the authors proposed a new back propagation (BP) neural network based on an improved shuffled frog leaping algorithm (ISFLA), the ISFLA algorithm was developed on the basis of a chaotic operator and overcome the shortcomings of conventional shuffled frog leaping algorithm (SFLA).

3) MULTIPATH TRANSMISSION METHOD

The multipath approach is introduced in the fault tolerance of MWSN. The most important purpose is to achieve extended network lifetime and improve data transmission reliability and success rate. The fault-tolerant method of multipath routing is to establish multiple data transmission paths between the source node and the destination node. When the Sink node moves a certain distance away from the communication range of the node, interference from the external factors or the communication interruption occurs due to the failure of the node itself, the current transmission path will fail. This method can quickly switch to another transmission path, so as to obtain better fault tolerance and improve the reliability of data transmission. For example in [187] the authors proposed an energy optimized multipath routing protocol (EOMRP) to improve the packet delivery rate, load balancing and optimize the nodes energy based on the multipath routing and energy optimization model of the sensor nodes. In [188] the authors had developed a new algorithm called, exponential ant colony optimization (EACO) to route discovery problem in mobile wireless sensor network after finding the cluster heads using fractional artificial bee colony (FABC) algorithm. Aiming at the problem of MWSN multipath routing fault tolerance and proving it is an NP-hard problem, an immune particle swarm optimization multipath routing fault tolerant algorithm is proposed in [189]. The algorithm provides fast route recovery and reconstruction to improve data transmission efficiency and fault tolerance. In [190] the author proposed a multi-path fault-tolerant routing algorithm based on artificial immune algorithm. The artificial immune algorithm was applied to MWSN multi-path data transmission to establish multiple disjoint and optimize the transmission path.

It can be seen from the above literature that the routing fault tolerance of mobile wireless sensor network maintains the ability of the sensor network system to continue to operate normally in the event that a few sensor nodes fail or the wireless network is partially disconnected. The link retransmission is a more effective method based on the effectiveness of channel usage in mobile wireless sensor networks. However, in some special applications, the defect of the link retransmission mechanism is also obvious, it will affect the utilization of the channel, and the sensor node needs to keep the information to the next hop of the route confirmation, which will occupy the node and its limited memory space, which is obviously inappropriate in mobile wireless sensor networks. In multipath routing fault tolerance, when a known link fails during transmission, the pre-prepared alternate path is enabled, which effectively improves the network's tolerance for errors. In the multipath routing fault tolerance of MWSNs, how to establish multiple paths from data nodes to Sink nodes is also a key issue to be considered.

F. TOPOLOGY OPTIMIZATION

In the key technologies of mobile wireless sensor networks, the network topology control optimization capability is a key factor in the performance of the entire network. The reasonable topology control structure of MWSNs can effectively improve the execution efficiency of network communication protocols and play a fundamental role in the overall performance of the network and other service support technologies [191]. The reasonable topology of MWSNs is beneficial to extend the overall life cycle of the network. Therefore, the topology control optimization technology of MWSNs is the key to determine the comprehensive performance of the sensor network. The topology control optimization technology of MWSNs is to ensure the performance of network coverage and connectivity. The node selection policy changes the state of the node itself and avoids the communication link redundancy between the sensor nodes to form a performance-optimized network structure [192].

The topology control of MWSNs is mainly divided into the power control and the hierarchical topology control. The power control is to optimize the overall performance of the network by reasonably adjusting the transmit power of the corresponding nodes in the WSNs, balancing the energy consumption of the nodes and the number of nodes. For example in [193], a lightweight algorithm of adaptive transmission power control for wireless sensor networks. In ATPC algorithm, each node builds a model for each of its neighbors, describing the correlation between transmission power and link quality. To overcome high connectivity redundancy and low structure robustness in traditional methods, a PSO-optimized minimum spanning tree-based topology control scheme is proposed in [194]. In [195] the authors proposed a novel routing algorithm that utilizes ACO-inspired routing based on residual energy of terminals, the operational evaluation revealed its potential to ensure balanced energy consumption and to boost network performance.

Another the core of hierarchical topology control is clustering, which divides the network into different clusters by clustering in the network. The cluster head selection mechanism is used to select the cluster head node and the cluster head node performs data processing and forwarding in the cluster to form a cluster transmission system to achieve the effect of balancing the network load and prolonging the network's lifetime [196]. In [197] the authors proposed a hybrid routing algorithm by combining the Artificial Fish Swarm Algorithm (AFSA) and ACO to address the problem of unstable topological structure, and utilized the AFSA algorithm to perform the initial route discovery in order to find feasible routes quickly. In [198] the authors proposed a hybrid shuffled frog leaping algorithm (AASFLA) with antipredator capabilities to avoid the local minima, improved the performance and lifetime for MWSNs. In [199] the authors proposed an evolutionary multi-objective optimization approach based on nondominated sorting genetic algorithm-II (NSGA-II), the proposed algorithm can improve the network lifetime and coverage while maintaining the network connectivity. In [200] the authors proposed a compact artificial bee colony optimization method (cABC) for applying to the topology optimization of mobile wireless sensor networks, the proposed cABC method could provide the highest robust structure and lowest contention topology schemes.

It can be seen from the above topology optimization algorithm that most of the proposed algorithms construct a network topology to reduce the energy consumption value for MWSNs. However, in the practical application of MWSNs, the robustness, connectivity and reliability of the network are not considered, and it is also an important performance indicator. At the same time, although these algorithms are optimized from one aspect of the topology, they do not consider the complexity of the algorithm.

G. LOCATION OPTIMIZATION

The node location technology of MWSNs is a method for filtering related data information carried by hardware devices by means of mutual communication between known sensor nodes, such as position coordinates, RSSI values, etc., and calculating the position of unknown nodes according to the algorithm model. The location of the sensor nodes in the MWSNs is the process of determining the phase or absolute position of an unknown node in a plane or space by the location of a known node in the network. In the general positioning calculation of sensor networks, a certain number of known location nodes are arranged in advance, and then the known nodes broadcast their own data to the neighboring nodes through flooding mode, so that the unknown nodes determine their estimated spatial position by calculating the angle data and vector distance data of the known location nodes [201].

According to different positioning criteria, the positioning algorithms can be mainly divided into the following methods: based on ranging and non-ranging, based on beacon nodes and no beacon nodes, centralized and distributed, concurrent and incremental. At present, among the many algorithms for the node location, there are mainly two types of positioning algorithms that have been extensively studied: the positioning algorithms based on ranging and non-ranging. The non-ranging based positioning algorithm realizes the position prediction of unknown nodes through the information such as the connectivity of the network and also reduces the requirements of the node hardware [202]. The typical algorithms include DV-Hop, centroid positioning, amorphous, APIT, MDS-MAP, and convex programming. However, the non-ranging positioning algorithm has the lower accuracy of the positioning and the larger communication overhead, and has the certain limitations in practical applications. The ranging-based positioning algorithm mainly measures the distance between nodes according to a certain algorithm, and performs node positioning according to the obtained distance information, and the positioning accuracy is generally relatively high. At present, the commonly used techniques for ranging are TOA, AOA, TDOA, RSSI, etc.

There are two main methods for node location of MWSNs: ranging-based positioning algorithm and non-ranging based positioning algorithm. For example in [203] the authors proposed two novel collaborative location-based sleep scheduling (CLSS) schemes for WSNs integrated with the mobile cloud computing, the proposed algorithm could prolong the lifetime of WSNs while still satisfying the data requests of mobile users. The untapped vast potential of the artificial bee colony (ABC) algorithm had inspired the research presented in [204], the ABC algorithm has been investigated as a tool for anchor-assisted sensor localization in MWSNs, and the ABC algorithm delivers higher accuracy of localization than the PSO algorithm. To improve the unreasonable distribution of sensors' random deployment and increase network coverage rate, an optimization method of

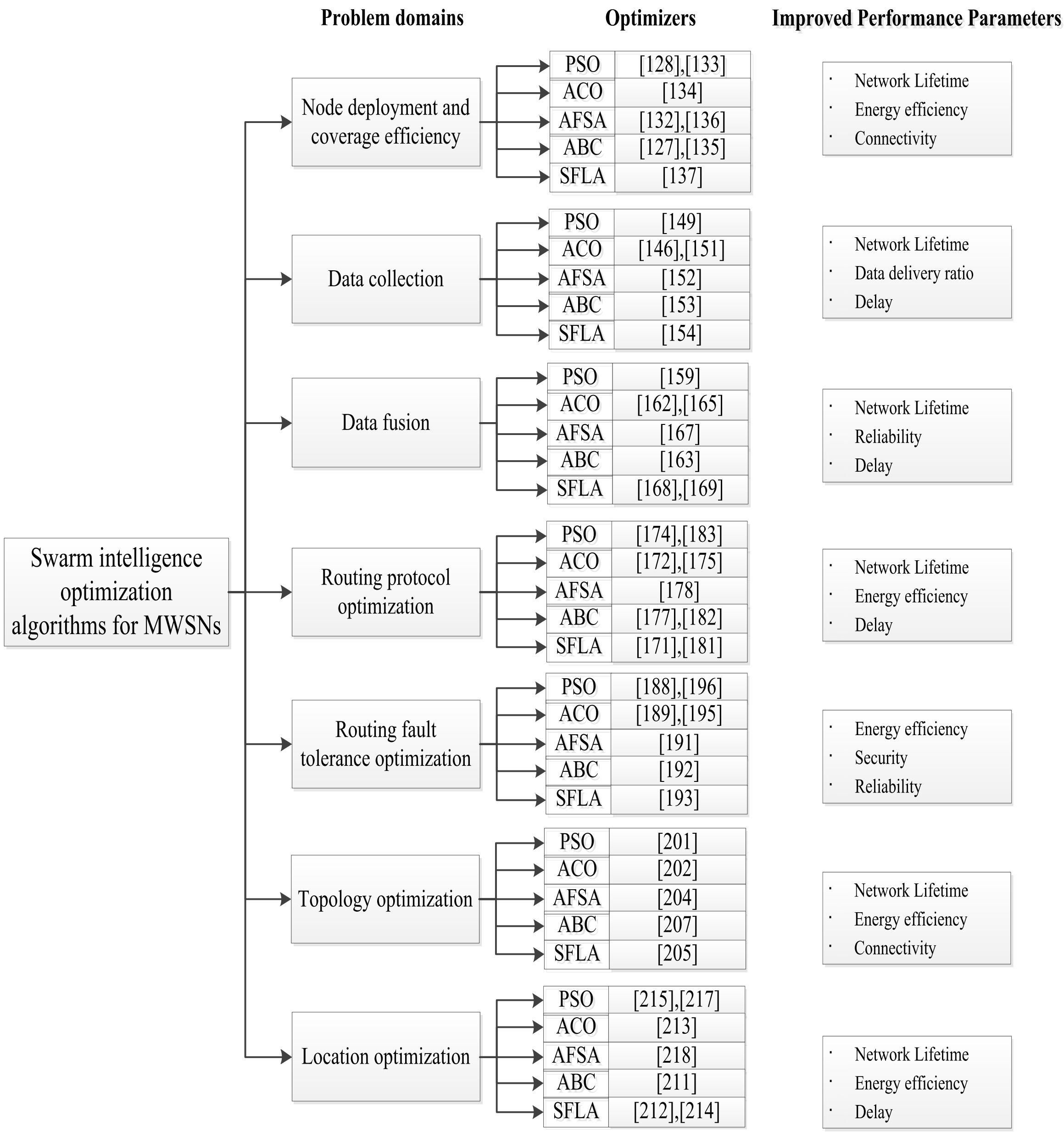

FIGURE 8. Summary of swarm intelligence optimization algorithms based optimizers in MWSNs.

wireless sensor networks coverage based on improved shuffled frog leaping algorithm (ISFLA) was proposed in [205]. A feed-forward neural network type and the levenberg-marquardt training algorithm were used to estimate the distance between the mobile node and the coach. The hybrid PSO-ANN algorithm significantly improved the distance estimation accuracy more than the traditional LNSM method without additional components [206]. Due to the network cost and the restricted energy of the sensor nodes, most of the localization algorithms are not well suitable for wireless sensor networks and furthermore the positioning accuracy is relatively low, in [207] the authors presented a localization algorithm based on shuffled frog leaping algorithm (SFLA) and particle swarm optimization (PSO), the proposed location algorithm has a higher accuracy. A novel iterative localization algorithm based on improved particle swarm optimization (PSO) was proposed for monitoring environment like lakes, rivers or other water bodies [208]. A clustering ant colony algorithm (KACO) with three immigrant schemes is proposed to address the dynamic location routing problem, the proposed algorithm may lead to a new technique for tracking the environmental changes by utilizing its clustering and evolutionary characteristics [209]. In [210] the authors investigated and proposed a method for improving a traditional range-free-based localization method (centroid) that used soft computing approaches in a hybrid model. This model inte-

TABLE 4. Comparison of routing algorithms for MWSNs.

Routing Protocol Optimization	Architecture		Location awareness	Network size	Query–driven	Event-driven	Energy Efficiency	Latency	Lifetime	Reliability
	Flat	Hierarchical								
FSFLA [165]		√				√	√		√	√
ACO [166]		√		√		√	√	√	√	
FAMAC[167]		√				√	√		√	√
PSO [168]		√		√			√	√	√	
ABC[171]		√	√	√	√		√		√	
AFSA[172]		√	√				√	√		√
RR[174]	√		√		√		√		√	
SFLA[175]		√				√	√	√	√	
IABC[176]		√		√		√	√		√	
GMDPSO[177]		√	√	√			√			√
VANETs[178]	√		√			√		√		√
NCRR[181]	√			√			√	√		√
PSOFT[182]		√				√	√		√	
ACOFT[183]		√		√		√	√			√
BAFSA[185]	√					√	√		√	
RST[186]		√		√	√		√		√	√
ISFLA[116]	√			√		√	√			√
EOMRP[187]		√		√	√		√		√	√
EACO[188]		√				√	√	√	√	
ECPSO[189]		√			√		√		√	√
AIFT[190]		√		√		√	√		√	√

grated a fuzzy logic system into centroid and uses an extreme learning machine (ELM) optimization technique to capitalize on the strengths of both approaches A range-free localization method known as mobile anchor positioning - mobile anchor & neighbor (MAP-M&N) is used to calculate the location of the sensor nodes, the MAP-M&N with artificial fish swarm algorithm (MAP-M&N with AFSA) is the proposed meta-heuristic approach to calculate the location of sensor nodes with minimal error [211]. In [212] the authors proposed a new DV-Hop algorithm based on shuffled frog leaping algorithm (Shuffled Frog Leaping DV-Hop Algorithm, SFLA DV-Hop), compared with the traditional DV-Hop algorithm, based on not increasing the sensor node hardware overhead, the proposed algorithm could effectively reduce the positioning error.

From the above research status, it is clear that the scholars and researchers so far tried to implement the swarm intelligence optimization algorithms in a number of key technologies of mobile wireless sensor network. Every approach addressed in this field attempted to solve a specific problem with their own specific set of parameter configurations and claimed to show better simulation results with regard to some previous traditional approaches. Also some scholars and researchers utilized the hybrid strategies to solve a single problem. But to our knowledge, there is no extensive work, which addresses the comparative study between two or more swarm intelligence optimization algorithms to solve the related problems for MWSNs, so a comparison between these algorithms in the key technologies specific view is not a trivial task. In Fig. 8, we summarize PSO, ACO, AFSA, ABC and SFLA based optimizers that are used in WSNs and their addressed areas.

V. PERFORMANCE COMPARISON OF MWSNS BASED ON SWARM INTELLIGENCE OPTIMIZATION ALGORITHMS

With respect to the limitations of the sensor nodes, the key idea behind the development of this algorithms category is to balance network traffic and resource utilization throughout the network. This section is dedicated to describe some of the most recently proposed methods by the swarm intelligence optimization algorithms. TABLE 4 provides an in-depth comparison of routing algorithms for MWSNs.

At the same time, the key findings of the study have been summarized in Table 5, the comparison of routing protocols for MWSNs based on mobility is shown in TABLE 5. In summarizing, the characteristics such as the mobility pattern, the network size, the movement of Sink, the mobile speed, the network density, the architecture and application, etc. are considered. The issues are shown as addressed or not addressed. Table 5 presents the total number of research works considered in this survey (non-exhaustive list) in recent years covering the optimization techniques for MWSNs based on mobility.

Moreover, we compare the swarm intelligence optimization algorithms for improving the performance of MWSNs.

TABLE 5. Comparison of routing protocols for MWSNs based on mobility.

Scheme	Mobility Pattern	Network size	Mobile node	Sink movement	Mobile speed	Network density	Architecture	Applications
Ang [138]	Controlled	Large	Sink	Peripheral	Variable	Moderate	Hierarchical	Event-driven
Mitra [22]	Controlled	Moderate	Sink	Random	Variable	Moderate	Hierarchical	Event-driven
Mang [140]	Controlled	Large	Sink	Peripheral	Variable	Small	Hierarchical	Event-driven
Zhang [141]	Random	Moderate	Sink	Peripheral	Variable	Moderate	Flat	Event-driven
Farzana [142]	Controlled	Small	Sink	Peripheral	Adaptive	High	Hierarchical	Monitoring
Velmani [143]	Predefined	Large	Sink	Controlled	Variable	Moderate	Flat	Event-driven
Zhao [144]	Predefined	Moderate	Nodes	Peripheral	Adaptive	Moderate	Hierarchical	Event-driven
Gao [147]	Controlled	Moderate	Sink	Peripheral	Variable	Moderate	Hierarchical	Time-driven
Mantri [154]	Controlled	Moderate	Sink	Controlled	Peripheral	Moderate	Hierarchical	Event-driven
Yue[158]	Controlled	Large	Sink	Random	Variable	Moderate	Hierarchical	Event-driven
Khan [161]	Controlled	Moderate	Sink	Peripheral	Variable	Moderate	Flat	Event-driven
Wang [168]	Predefined	Moderate	Sink	Peripheral	Adaptive	Moderate	Hierarchical	Event-driven
Wang [169]	Controlled	Moderate	Sink	Peripheral	Variable	Moderate	Hierarchical	Event-driven
Tunca [174]	Controlled	Moderate	Sink	Peripheral	Variable	Moderate	Hierarchical	Event-driven
Hu [191]	Controlled	Moderate	Nodes	Peripheral	Adaptive	Moderate	Hierarchical	Time-driven
Han [201]	Predefined	Moderate	Sink	Controlled	Variable	Moderate	Hierarchical	Event-driven
Zheng [202]	Controlled	Large	Sink	Controlled	Variable	Moderate	Hierarchical	Event-driven

A detailed network performance comparison of the routing protocols for MWSNs based on energy-efficiency, latency, load balancing, scalability, packet loss rate, lifetime, connectivity and reliability is shown in TABLE 6. It identifies those protocols that perform significantly better in terms of energy consumption and low transmission overhead in the MWSNs and also assesses the protocols using other performance criteria such as packet loss rate, throughput, connectivity, availability, invulnerability, and reliability.

VI. OPEN RESEARCH ISSUES AND FUTURE DIRECTIONS

In the optimization of key technologies of mobile wireless sensor networks, the desired goals of optimization include, but are not limited to, the maximization of coverage, the maximization of the network's lifetime, the maximization of the network energy conservation, minimization of costs, minimization of data transmission delays, maximization of throughput, and maximization of the connectivity and reliability of the network. Different practical scenarios related to optimization give rise to different nature of optimization problem. Obviously, most of the optimization problems for MWSNs and its mathematical models can be described by the NP-Hard hard problems. For example, in the optimization of connectivity, coverage, cost, network lifetime and quality of service of MWSNs, it can be determined as an NP-Hard optimization problem. Summarize the current research status of mobile wireless sensor networks and the swarm intelligent optimization technologies, the swarm intelligence optimization algorithm has made some progress in the node deployment and optimal coverage optimization, the location for sensor node, energy optimization, data fusion, routing protocol optimization, topology optimization and the connectivity and reliability of the network in MWSNs. The statistics of the swarm intelligent optimization algorithm in the optimization technology of MWSNs in the past six years are shown in Fig. 9. The percentage of the swarm intelligent optimization algorithm in the key technologies of MWSNs is shown in Fig. 10.

The swarm intelligent optimization algorithm proposed in this paper solves many problems in mobile wireless sensor networks, such as the optimal deployment of the sensor nodes, optimal routing protocols and data fusion, the security of the network and the reliability of the network, data collection and QoS management. However, there are still some open research challenges. In particular, it is necessary to conduct in-depth research in weighing the energy consumption, QoS, security, and reliability of the network. In addition, most of the previous work only optimized the performance of MWSNs from a single perspective. Moreover, there are a few drawbacks and limitations that should be considered

TABLE 6. Network performance comparison of the routing protocols of MWSNs.

Routing protocol	Energy Efficiency	Latency	Throughput	Scalability	Connectivity	Load balance	Packet loss rate	Reliability	Complexity
FSFLA[165]	High	Small	High	High	High	Small	High	Small	Moderate
ACO [166]	High	Small	High	High	Moderate	Moderate	Moderate	Moderate	Moderate
FAMAC[167]	Low	Small	High	High	Small	Small	Small	Small	Moderate
PSO [168]	Low	Small	Moderate	High	NA	Small	High	Moderate	Small
ABC[171]	High	Small	High	Low	High	High	High	High	Moderate
AFSA[172]	Low	Moderate	Small	High	Moderate	Moderate	High	Moderate	Moderate
RR[174]	High	Small	High	Moderate	High	Small	High	Small	High
SFLA[175]	Low	Small	Low	High	High	Small	High	Moderate	Moderate
IABC[176]	High	High	Low	High	High	Small	High	Moderate	Moderate
GMDPSO[177]	Low	Small	Low	High	High	Moderate	High	Moderate	Moderate
VANETs[178]	High	Small	Low	High	Moderate	Small	High	Small	Moderate
NCRR[181]	High	Small	Low	High	High	Small	High	Small	Moderate
PSOFT[182]	High	Small	Low	High	High	Small	High	High	Moderate
ACOFT[183]	High	Small	High	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate
BAFSA[185]	High	Moderate	Low	High	High	Small	Moderate	Moderate	Moderate
RST[186]	High	High	Low	High	High	Small	High	Small	Small
ISFLA[116]	High	High	Low	High	Moderate	Small	High	Moderate	Small

when using swarm intelligence optimization algorithms in mobile wireless sensor networks. Hence, research in this area addressing the coexistence of the key issues is limited. Some of these are:

1) THE OPTIMIZATION PROBLEM OF MWSNS COMBINED WITH THE LATEST SWARM INTELLIGENT OPTIMIZATION ALGORITHM

After continuous efforts by domestic and foreign scholars to research and improve the swarm intelligent optimization algorithm, the swarm intelligent optimization algorithm has been applied in the performance optimization of MWSNs, and some achievements have been made. The experimental results also prove that the use of the swarm intelligent optimization algorithm has better classification effect in MWSNs clustering, and has achieved good results in optimal coverage. With the development of swarm intelligence optimization algorithm, especially the emergence of chicken swarm optimization algorithm [213], wolf swarm optimization algorithm [214], swarm spider optimization [215] and Emperor butterfly [216] in 2016, further research in this field can be continued in the future.

2) SWARM INTELLIGENCE OPTIMIZATION ALGORITHM COMBINES OTHER OPTIMIZATION METHODS

The swarm intelligent optimization algorithm is not limited to introducing various characteristics of biological populations into the algorithm for improvement. Some scholars at home and abroad have introduced some of the biological characteristics of human beings into traditional intelligent algorithms, such as the population adaptation and human autoimmune mechanisms. In the future, we can continue to study from human-related biological characteristics and further improve the algorithm.

3) DISCRETE OPTIMIZATION PROBLEM

The vast majority of practical application problems are discrete problems, such as the load balancing of sensor nodes and resource scheduling. In order to optimize discrete problems, swarm intelligence algorithm needs to model and design parameters and coding methods according to practical problems. However, the improved algorithm cannot guarantee the better results under the condition of setting optimal parameters. How to improve the algorithm to obtain more

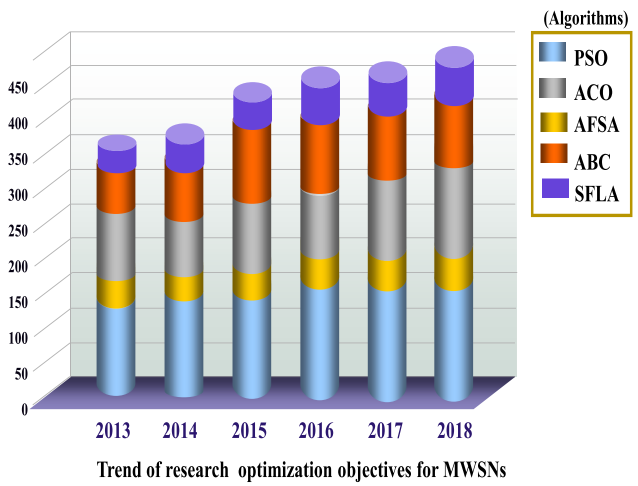

FIGURE 9. Comparison of the number of publications in the optimization of key technologies for MWSNs by swarm intelligence optimization algorithm.

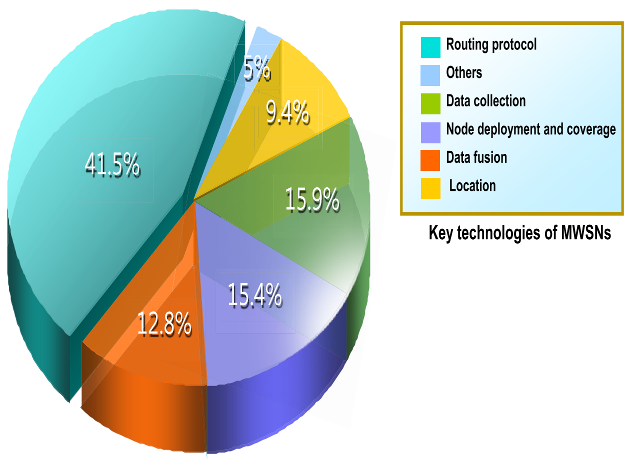

FIGURE 10. Percentage of swarm intelligence optimization algorithms in key technologies of MWSNs.

reasonable and efficient practical modeling needs further study and discussion.

4) COMPREHENSIVELY BALANCE THE PROBLEMS OF ENERGY CONSUMPTION, TRANSMISSION DELAY, SAFETY AND RELIABILITY OF MWSNS

Although the proposed method solves many problems related to optimization in MWSNs, some research problems are still relatively unresolved, such as comprehensive balancing the energy consumption, transmission delay, safety and reliability of MWSNs. Especially in some special application areas, such as wireless body area networks, Internet of vehicles and other mobile wireless sensor network applications, it is necessary to consider the energy consumption, transmission delay, security and reliability of the network. Therefore, the use of swarm intelligence optimization algorithms to consider these issues of MWSNs is a potential future direction.

5) THE ALGORITHM'S COMPUTATIONAL REQUIREMENTS

As a resource limited framework, MWSNs drain a considerable percentage of its energy budget to predict the accurate hypothesis and extract the consensus relationship among data samples. Therefore, the designers should consider the trade-off between the algorithm's computational requirements and the energy consumption of the network. Specifically, the higher of the required accuracy required by the algorithm, the higher of the computational requirements, and the higher of the energy consumptions.

6) CROSS-LAYER OPTIMIZATION DESIGN ISSUES

In general, different layers of network protocol stack support for MWSNs are considered to be optimization problems. For example, energy efficiency is a problem that needs to be at each level of the protocol stack, so a strict layering approach is not required, but a cross-layer design is required. The cross-layer optimization design issues are a problem to be considered in the optimization process of WMSNS.

7) PLACEMENT OF IMPLEMENTATION PROBLEM

The implementation of most existing swarm intelligent optimization algorithms is in a base station or receiver (centralized), which requires communication between the sensor nodes. In the real world of dynamic MWSNs, this type of communication can be very frequent and expensive. And the distributed implementation of these algorithms in lightweight form could be a potential future direction.

8) COMBINED WITH PRACTICAL APPLICATIONS

From the above research, it is found that many swarm intelligent optimization methods perform better than the traditional methods in some environments. However, most of the existing swarm intelligent optimization methods are based on simulation, and only a few have been evaluated in the real environment of MWSNs. Implementing these methods in a real environment of MWSNs or test platform may be a fruitful future research direction.

VII. CONCLUSION

This paper provides a comprehensive analysis and summary of the most recently proposed swarm intelligent optimization algorithms for mobile wireless sensor networks. Nowadays, the swarm intelligent optimization algorithms are considered an efficient approach to improve network capacity and resource utilization under heavy traffic conditions. With respect to the recent advances in the development of the performance optimization for mobile wireless sensor networks, there is a need to investigate the significance as well as the detailed operation and classification of the proposed approaches. To fill this gap, in this paper we have made a comprehensive review and analysis the concept, classification and architecture of MWSNs are described in detail. Then, according to the classification of the performance optimization for MWSNs, the latest research of the swarm intelligence algorithms in performance optimization of MWSNs are systematically described. The problems and solutions in the performance optimization process of MWSNs are summarized, and the performance of the algorithms in the performance optimization of MWSNs is compared and analyzed.

Although in the past years the performance optimization of mobile wireless sensor network has been researched through numerous studies, nevertheless, there are several important research issues that should be further investigated. These possible areas can be summarized as follows: First, swarm intelligence optimization algorithm combines other optimization methods, we can continue to study from the human-related biological characteristics and further improve the algorithms. Second, the emergence of chicken swarm optimization algorithm, wolf swarm optimization algorithm, swarm spider optimization algorithm, further research in this field can be continued in the future. Finally, most of the existing swarm intelligent optimization methods are based on simulation, and only a few have been evaluated in the real environment of MWSNs. Implementing these methods in a real environment of MWSNs or test platform may be a fruitful future research direction.

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