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ADAI and Adaptive PSO-Based Resource Allocation for Wireless Sensor Networks

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ABSTRACT Resource allocation in the Internet of Things (IoT) applications for Wireless Sensor Networks (WSNs) is a challenging problem that requires tasks processing from the appropriate sensor nodes without compromising the Quality-of-Service (QoS). Due to heterogeneity in sensors, the inter-cluster and intra-cluster cooperative communication between sensor nodes hinders the overall resource allocation of the network in terms of energy consumption and response time. Therefore, this paper establishes a multi-agent clustering WSN model, i.e., Adaptive Distributed Artificial Intelligence (ADAI) technique with a hierarchical resource allocation strategy to address the issue of resource allocation in these types of network. For the inter-cluster power allocation, we are considering QoS and energy consumption factors with DAI. Moreover, for intra-cluster resource allocation, this paper introduces Adaptive Particle Swarm Optimization (APSO), which uses its objective functions as the node distance and respective energy loads. The mathematical analysis and simulation results validate the propose method in terms of energy consumption and response time of the network.

INDEX TERMS Particle swarm optimization, adaptive PSO (APSO), distributed artificial intelligence (DAI), resource allocation.

I. INTRODUCTION

The Wireless Sensor Networks (WSNs) are multi-hop ad hoc networks formed by a large number of sensor nodes deployed in a monitored area, which is an essential technical form of the underlying network of the Internet of Things (IoT) [1]. As a highly functional application network, WSNs provides service support for IoT applications through the cooperation of nodes [2]. Due to the high Quality-of-Service (QoS) requirements of IoT applications, implementing energy-efficient node configuration and resource allocation in the process of collaboration is a critical issue in WSNs for IoT applications. The work in [3] introduces the advantages of next-generation wireless networks based on artificial intelligence technology in the field of machine learning. The distributed capabilities of artificial intelligence have surprised the entire wireless communication system. In recent years, Distributed Artificial Intelligence (DAI) has become a research hotspot. DAI is the product of artificial intelligence and distributed computing [4]. It mainly studies the coordination of intelligent behavior among agents in Multi-Agent Systems (MAS) [5]. Compared with the traditional centralized structure, DAI emphasizes distributed intelligent processing, which overcomes the weaknesses of centralized system components and difficulty in knowledge schedule. Since the characteristics of DAI-based multi-agent system are very similar to WSNs, many researchers have established a resource allocation model for WSNs based on MAS, which can improve the problem-solving ability and reduce the computational complexity [5].

Through the analysis of WSNs and the DAI theory, this paper combines artificial intelligence and Particle Swarm Optimization (PSO) to solve the problem of resource allocation in IoT applications. Based on the DAI theory, this paper establishes a multi-agent WSN framework with a cluster structure. The established network model then has a dynamic

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Manager resource Agent (MA), which is responsible for the energy and resources of the entire network. The CH of each cluster has a decision function, namely Coordination Agent (CoA). This agent performs all the cooperative activities with the likewise agents of other clusters (inter-cluster). Also, every Cluster Member node (CM) performs the task of CoA assignment as a Task Agent (TA).

In our work, CoA uses adaptive Particle Swarm Optimization (APSO) to search for optimal resource allocation schemes during this cooperative inter-cluster and intra-cluster communication. The basic concept of any clustering algorithm is to form a similar set of objects based on the objective function [6]. These clustering algorithms are then implemented in the WSN application(s) along with artificial intelligence techniques for a single objective function. In our work, resource allocation is divided into two levels after planning the agents for the objective function. The first layer is generally the resource allocation phase in inter-cluster, which is governed mainly by the MA. Under the constraint of QoS, the MA selects appropriate clusters for resource allocation according to battery discharge and memory usage in the network at each time instant and determines the corresponding CH-CH distance according to real-time conditions. The corresponding CHs of each cluster with pre-assigned resource evaluate itself by comparing it with the fix energy threshold. If the energy is present above the threshold, the task is processed. If the energy is below the threshold and enters the resource allocation of the second layer, the CHs of the respective cluster allocates resources based on the proposed APSO technique. In the process of finding the optimal resource allocation scheme by assuming the distance between nodes and the energy load as the fitness function. Finally, a model is established and verified using mathematical and simulation results. The main contribution of the proposed work can be summarized as follows:

- State-of-art analysis: Multi-agent dynamic cluster formation based on Adaptive DAI (ADAI) technique;
- Introduction of APSO for intra-cluster resource allocation issue;
- Mathematical modelling and analysis of dynamic clustering using ADAI and APSO for WSNs in IoT applications:
- Validation of the proposed method using simulations.

The rest of the paper is organized as follows. Section II shows the related work of resource allocation in WSNs, and Section III discusses the mathematical analysis of the proposed adaptive resource allocation method based on DAI and APSO. Section IV illustrates the simulation methods and results analysis. Section V highlights the overall contribution of the work and future scopes.

II. RELATED WORK

At present, there are some allocation algorithms for the research of resource allocation in WSNs, such as feasible and straightforward nearest neighbor method, dynamic programming method, heuristic algorithm. In [7], a centralized resource allocation algorithm is proposed. Under the constraint of QoS, resources are allocated to minimize energy consumption, and the broadband utilization of the network is effectively improved. For WSNs in static environments, Integer Linear Programming (ILP) is applied to the task assignment problem of the network in different scenarios [8], which considers the communication and computational overhead of the node. The literature [9] also applies the ILP method for resource allocation in the network, but the information quality is the primary consideration in the allocation process. However, due to the growing user demand, the network requires an efficient and dynamic resource allocation mechanism. The work of [10] adopts a resource allocation method based on the market mechanism so that sensor resources can be optimally utilized in competition.

Moreover, the author [11] uses game theory to achieve dynamic resource scheduling. Different from the traditional random allocation method, the literature [12] assigns roles to different nodes in WSNs and establishes a resource allocation model based on the queuing network. In the typical scenario of WSNs, the optimal allocation scheme of resources is calculated by the steady-state analysis of the model. This method [12] shows excellent performance in terms of the remaining energy and life cycle of the network. These methods are all based on the study of resource allocation based on the energy consumption of the network. However, multiple user publishing tasks have different QoS requirements. The author [13] assigns tasks to the corresponding nodes according to different QoS requirements of the users, realizing flexible resource scheduling and reducing the utilization rate of resources.

Due to the heterogeneity of the nodes in the network, this is a massive challenge for resource allocation of the network. A QoS based resource allocation strategy is proposed for heterogeneous WSNs [14]. The resource allocation problem is transformed into maximizing network throughput under the constraints of heterogeneous statistical QoS [14]. Document [15] proposes a distributed resource allocation scheme that balances the fairness of network throughput and distribution. The authors in [16] use grid adaptive search amplification to provide an optimal resource allocation scheme for heterogeneous networks, reducing interference and increasing network throughput and speed. Layered protocols can effectively improve the performance of heterogeneous WSNs [17]. In [18], the authors illustrate that the layering method can effectively avoid energy holes in the network. The work in [19] proposes a state update agent for the layered method to improve the energy efficiency of the network.

To improve the performance of resource allocation in WSNs, some intelligent optimization algorithms are used. The author [20] used the Genetic Algorithm (GA) in the scheduling of sensor nodes and generated the resource allocation decision by the coverage rate of the nodes as the fitness function. Literature [21] proposed the use of binary particle swarm optimization (BPSO) for resource allocation and scheduling in WSNs, and the feasibility of the proposed method was verified by considering different topologies and transfer functions. The author in [22] adopted the Discrete Particle Swarm Optimization (DPSO) algorithm to optimize the resource allocation among sensor nodes. It minimizes the execution time and energy consumption of the task as the fitness function and improves the task execution speed and resource scheduling efficiency. The authors in [23] improved the binary particle swarm optimization algorithm based on neural network and applied it to the resource allocation process in WSNs to obtain the optimal scheme, which improved the convergence speed of the algorithm. Since the data and tasks of the network in the actual scenario are real-time, to increase the intelligence of collaborative communication in WSNs, the Agent-based WSNs framework is proposed [24].

In the agent-based WSNs, the agent is responsible for resource allocation and data aggregation. To save network resources and reduce task processing delay, the location and response of the agent are critical. The work in [25] adopts a position-shifting scheme from the centre of the area to the sinking node from bottom to top, which improves the accuracy of position prediction and reduces the delay. The authors in [26] studied the location mobility scheme of single-agent and multi-agent, respectively, which realized efficient data collection and reduced the time consumption of task allocation. When the agent in the network receives the requirements of the application, the multiple agents need to determine location each other and quick response.

The authors in [27] use the distributed hash table method to achieve effective target agent search and location management. Agent-based WSNs also face network energy consumption problems in the process of resource allocation. Literature [28] studied the cooperative communication between mobile agents and allocated resources based on network energy consumption in terms of task delay. In [29], the Fuzzy Swarm Optimization algorithm (FSO) is applied to the WSNs based on the agent, which reduces the communication consumption generated between the agents in the scheme development process and prolongs the life cycle of the network.

Literature [30] uses genetic algorithms to optimize the communication distance between agents and finds the optimal target agent location and number. As the demand for users increases, the available sensor node resources are in short supply. Based on the competitive relationship between users, a heterogeneous multi-agent resource allocation mechanism is established [31], and the agents form a resource allocation scheme by competing and learning with each other. Literature [32] introduced the market mechanism to adjust the resource allocation among agents and maximized profit as the utility function to realize distributed resource allocation through negotiation between agents. The work in [33] uses a decentralized resource scheduling and allocation method for large-scale networks. Dynamically create multi-agent clusters based on different task requirements, which reduces task queuing time and improves task processing efficiency.

III. MATHEMATICAL ANALYSIS

We know that the WSNs are generally a distributed system, and sensor nodes can solve problems independently, which is very similar to Multi-Agent System. Therefore, each sensor node is assumed as an agent, and a multi-agent WSNs system based on cluster structure is established. In the proposed hierarchical resource allocation method, the MA is responsible for the entire network resource management during inter-cluster cooperative communication. In this case, we are assuming the CH as a CoA with decision function. The MA selects this CoA as a negotiation or Deliberative Agent (DA) according to real-time task requirements and environmental conditions in the resource allocation process. Now, whether to enter the second layer of resource allocation strategy is made following the current energy of the DA with a pre-set energy threshold.

If the response of DA is below the energy threshold, we opt the intra-cluster resource allocation strategy. Further, the DA formulates an optimal allocation scheme based on the APSO with the distance from the TA and the energy load minimization of the network as a fitness function.

As shown in Fig.1, in this paper, a hierarchical resource allocation mechanism for WSNs is proposed based on the constructed system model. It mainly consists of two levels, which are inter-cluster allocation and intra-cluster allocation.

Figure 1 shows the working of the proposed state-of-art and is explained in details below.

A. INTER-CLUSTER RESOURCE ALLOCATION

In the first layer of resource allocation, the MA performs resource allocation Inter-cluster. This paper constructs a cost function from three aspects: network QoS, battery power consumption and memory usage. The MA selects the appropriate CoA as the DA without affecting QoS.

For the current time t, the battery power consumption and memory usage in the network can be expressed as [34]:

$$P_{(t)} = P_{(t-1)} - Pr_{(DA)(MA)} - Pr_{(DA)}Lt_{(t-1)} \tag{1}$$

$$U_{(t)} = U_{(t-1)} - Pr_{(DA)(MA)} - Pr_{(DA)}Lt_{(t-1)} + Pr_{(DA)}Lt_{(t-2)} \tag{2}$$

where, $Pr_{(DA)(MA)}$ is the power consumed for DA-MA communication, $Pr_{(DA)}$ is the power consumption when CHs is selected as DA at time *t-1*; $Lt_{(t-1)}$ is the power when the next reasonable resource allocation is made at time $t-1$ Consumption, which is directly dependent on the position of the corresponding node or CH.

Therefore, the cost function between global network battery power consumption, memory usage, and QoS is derived as:

$$QoS_{measured} = \sum \Gamma_{i \varepsilon T} QoS_{v_j^i} \left[P_{(t)_i} + U_{(t)_i} \right] \tag{3}$$

here, Γ_i is the task performed by agents, $\Gamma_i = \left\{ v_1^i, v_2^i, \ldots, v_j^i \right\}$, and v_i^j is the task variable processed in real time. $QoS_{v_i^j}$ is the expected QoS value.

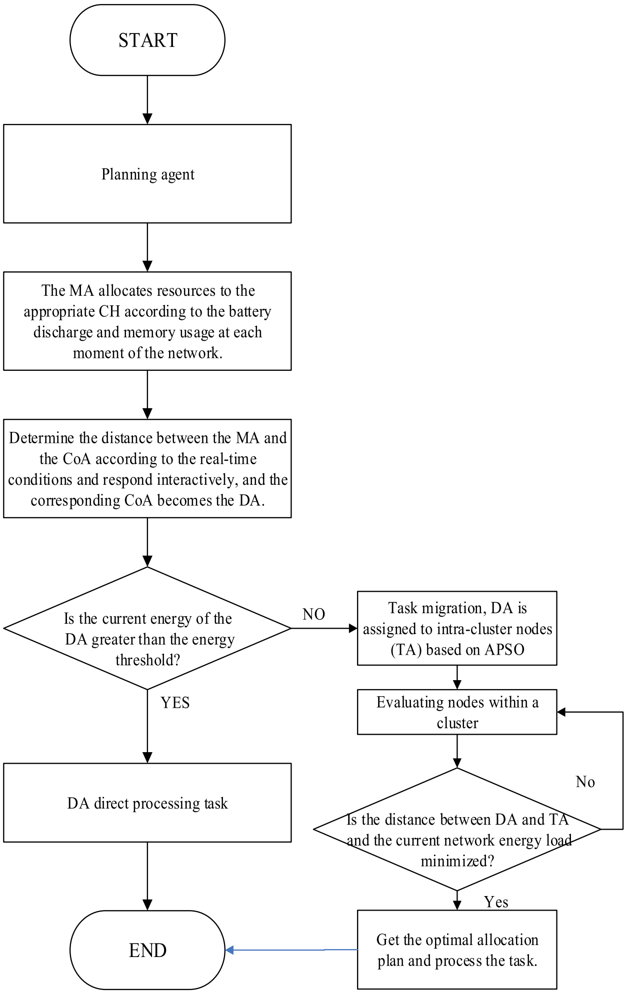

FIGURE 1. Block diagram of the proposed model.

In the communication process, the MA and the CoA form an interactive response based on the DAI. Document [35] gives an intelligent measurement method for the system. The literature indicates that the agent is a function, denoted by π, and gives the expected performance of the agent π for the general distribution $2^{-k(\mu)}$ in the space of all environments E:

$$\lambda(\pi) = \sum\nolimits_{\mu \in E} 2^{-k(\mu)} V_\mu^\pi \tag{4}$$

Here, K denotes the Kolmogorov complexity, $\lambda(\pi)$ is the measure of intelligence, $\sum_{\mu \in E}$ is the sum of activities over all the expected environments, $2^{-k(\mu)}$ is the complexity penalty, V_μ^π is the value achieved.

For the case, we are assuming: for all 'k' and 'n' have: $\left|\left\{x \in \sum^n : C(x) \geq |x| - k\right\}\right| \geq 2^n\left(1 - 2^{-k}\right)$, where $C(x)$ gives the definition of randomness.

In the MA and CoA response process, DAI will calculate the best strategy based on real-time conditions. Reference [36] gives the positional assignment of all MAs predicted from the Power Spectral Density (PSD) of the received signal, expressed as:

$$\frac{AE}{\frac{1}{T}\left[p \cdot \frac{g^2}{2} - 1\right] \sum_{l=1}^{p} a_l(T)} = \frac{ED}{2} \sum\nolimits_{l=2}^{p} a_l(T) \tag{5}$$

where, $\sum_{l=2}^{p} a_l(T) \in \sum_{l=1}^{p} a_l(T)$. All possible spatial location assignments of the MA are intelligently measured to predict policy performance, such as:

$$i.e.\ \mu = a_1(T), \quad \sum_{l=2}^{p} a_l(T) = \lambda(\pi) = \sum\nolimits_{l=2} 2^{-k(\mu)} V_\mu^\pi \tag{6}$$

Correspondingly, all MA spatial position assignments form a real-time continuous prediction, written as:

$$\frac{AE}{\frac{1}{T}\left[p \cdot \frac{g^2}{2} - 1\right]} = \frac{ED}{2} \cdot \sum_{l=1}^{p} a_l(T) \cdot \sum_{l=2}^{p} a_l(T) \tag{7}$$

$$\frac{AE}{\frac{1}{T}\left[p \cdot \frac{g^2}{2} - 1\right]} = \frac{ED}{2} \cdot \mu \cdot \sum\nolimits_{l=2} 2^{-k(\mu)} V_\mu^\pi \tag{8}$$

Assuming the gain of network is very large as compared to gain of individual sensors, i.e. $\frac{1}{T}\left[p \cdot \frac{g^2}{2} - 1\right]$ will tends to 1 (for all $p > 2$ i.e. each nodes are communicating with a minimum of 3 other nodes i.e. a minimum of 3 channels are been used for communication in a single cluster). Therefore, the relationship between ADAI and sensor node positioning is established based on test data of 'AE' per 'T' seconds. we get the position distance response between MA and CoA in terms as:

$$ED = \frac{2AE}{\frac{1}{T} \sum_{l=1} 2^{-k(a_l(T))} V_\mu^\pi} \tag{9}$$

After the MA responds with the DA, the DA to which the resource is assigned will monitor and evaluate its own energy. Here, an energy threshold E_g is set, and if the energy E_{DA} of the DA is higher than the threshold E_g, the DA directly performs the task. If the energy E_{DA} of the DA is higher than the threshold energy E_g, then the resource allocation of the second layer is entered, and the DA of the allocated resource will allocate resources to the nodes (TA) intra-cluster.

$$\begin{cases} E_{DA} \leq E_g, & \text{intra-cluster allocation based on APSO} \\ E_{DA} > E_g, & \text{DA directly performs the task} \end{cases} \tag{10}$$

B. INTRA-CLUSTER RESOURCE ALLOCATION

The problem of resource allocation for intra-cluster can be described as: assigning n tasks among m node (TA) resources, thus defining:

a. Definition set $T = \left\{T_1, T_2, \ldots, T_j, \ldots, T_n\right\}$ represents n tasks, where T_j is the j-th task, $j \in 1, 2, 3, \ldots, n$.
b. Definition set $N = \{N_1, N_2, \ldots, N_i, \ldots, N_m\}$ represents m intra-cluster nodes (TA), where N_i is the j^{th} TA node, $i \in 1, 2, 3, \ldots, m$.

c. Define the M × N order matrix $P_{m\times n}$ as the task assignment decision matrix, written as:

$$P=\begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \cdots & p_{ij} & \cdots \\ p_{m1} & \cdots & p_{mn} \end{bmatrix} \tag{11}$$

where, $P_{ij}=\begin{cases}1, & T_i \text{ is assigned to } N_j \\ 0, & T_i \text{ is not assigned to } N_j\end{cases}$

Here, set a constraint:

$$\sum_{j=1}^{n} p_{mj}=1 \tag{12}$$

Each task can only schedule one node resource, that is, the sum of the elements of each column in the 0-1 matrix P is equal to 1.

The purpose of resource allocation is to make rational use of resources and obtain the optimal solution of the distribution problem according to the set objective function. In this paper, the algorithm constructs the objective function from two aspects: communication distance between nodes and energy load. The distance between nodes mainly considers the distance d_{ki} between DA and TA to be minimized. The goal is to minimize the energy consumption when DA sends data to TA. Therefore, the objective function is written as:

$$f_1=\min\left(\sum_{i=1}^{m}\sum_{j=1}^{n}P_{ij}\cdot d_{ki}\right) \tag{13}$$

The distance between nodes is calculated according to the literature [36], [37] dynamically calculates the Euclidean distance ED between nodes based on the autocorrelation error AE:

$$\frac{AE}{\lim\limits_{T\to\infty}\frac{1}{T}[p\cdot\frac{g^2}{2}-1]\sum\limits_{l=1}^{P}a_l(k)(T)}=\frac{ED^2}{2}\sum_{l=1}^{P}a_l(k)(T) \tag{14}$$

where, $ED=d_{ki}$.

The energy load of the network mainly considers the relationship between the residual energy E_{ir} after the node processes the task and the average residual energy E_{ave} of all nodes in the cluster, and the goal is to equalize the life cycle of the entire network. For the entire network, the smaller the energy load, the longer the life cycle will be. So the objective function is written as:

$$f_2=\min\left(\sqrt{\frac{\sum\limits_{i=1}^{n}(E_{ir}-E_{ave})}{i}}\right) \tag{15}$$

$$E_r=E_n-\sum_{j=1}^{m}E_c\cdot p_{ij}\cdot d_{ki}\cdot\Delta t \tag{16}$$

$$E_{ave}=\frac{1}{N}\sum_{i=1}^{n}E_r \tag{17}$$

where, E_n denote the current energy of the nodes, E_c denote the communication energy consumption per unit distance, and Δt denote the task processing time.

After setting the objective function, this paper performs multi-objective optimization based on adaptive particle swarm optimization (APSO). In the standard PSO algorithm [37], the position of the particle i represent the possible solution of the optimization problem in the D-dimensional search space, denoted by $X_i=(x_{i1},x_{i2},\ldots,x_{iD})$. The flying speed of the particle i is expressed as $V_i=(v_{i1},v_{i2},\ldots,v_{iD})$. Each particle measures the pros and cons of the current solution based on the fitness of the objective function f. The optimal position searched by the i^{th} particle is $pBest_i=(p_{i1},p_{i2},\ldots,p_{iD})$, and the best position searched by the entire particle swarm is $gBest=(g_1,g_2,\ldots,g_D)$. The position of particle i flight speed will be updated based on these two values, expressed as [38]:

$$\begin{aligned} V_{ij}(t+1)&=wV_{ij}(t)+c_1*r_1(t)\left(p_{ij}(t)-X_{ij}(t)\right)\\ &\quad+c_2*r_2(t)\left(p_{gj}(t)-X_{ij}(t)\right) \end{aligned} \tag{18}$$

$$X_{ij}(t+1)=X_{ij}(t)+V_{ij}(t+1) \tag{19}$$

where, t represents the number of iterations, the velocity of the particle is V_{ij}, c_1 and c_2 is the acceleration constant, usually set to 2, w is the weight of inertia, and generally goes between 0.8 and 1.2 for faster convergence.

In the resource allocation strategy proposed in this paper, for intra-cluster resource allocation PSO is used. The position vector of particle i represent an allocation scheme whose dimensions are the same as the task input and the elements are integers representing the number of each TA nodes. For example, the number of tasks is 5, and the number of TA nodes is 3 and $X_i=(2,1,3,1,3)$ is a position vector, then the matrix of resource allocation is expressed as:

$$P=\begin{bmatrix} 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 \end{bmatrix} \tag{20}$$

Since the positional elements of the particles are integers, the update of the particle position needs to be improved. In this paper, the inertia weight in the update formula of particle velocity does not take a fixed value, but is dynamically adjusted according to the individual extremum p_{i}^t and the global extremum p_g^t, and integer transformation is performed on the elements of the particle position during the update process to generate a new allocation scheme.

In this paper, the inertia weight w is dynamically adjusted according to the degree of evolution and polymerization for the particle swarm after each iteration. The degree of evolution of particle swarm is represented by E_f, which takes the range (0, 1], which depends on the global extremum f_t and the mean Ap_i^t of the individual extremum, written as:

$$E_f=a_1\frac{\min(f_t,f_{t-1})}{\max(f_t,f_{t-1})}+a_2\frac{\min\left(Ap_i^t,Ap_i^{t-1}\right)}{\max\left(Ap_i^t,Ap_i^{t-1}\right)} \tag{21}$$

where,

$$f_t = f\left(p_g^t\right) \tag{22}$$

The comparison of f_t and f_{t-1} reflects whether the particle swarm has found the optimal solution at present.

$$Ap_i^t = \frac{\sum_{i=1}^{n} f\left(p_i^t\right)}{n} \tag{23}$$

The comparison between Ap_i^t and Ap_i^{t-1} reflects the changing trend of PSO.

The degree of polymerization of the particle swarm is represented by p_f, and the value range is (0, 1], which depends on the average of the individual extremum Ap_i^t and the average fitness value Ap_g^t of all the particles, expressed as:

$$\mathrm{p}_f = \frac{\min\left(Ap_i^t, Ap_g^t\right)}{\max\left(Ap_i^t, Ap_g^t\right)} \tag{24}$$

where,

$$Ap_g^t = \frac{\sum_{i=1}^{n} f\left(x_i^t\right)}{n} \tag{25}$$

The comparison of Ap_i^t and Ap_g^t reflects whether all particles are currently aggregated to the optimal value.

Therefore, the dynamic inertia weight formula is obtained according to the degree of evolution and the degree of polymerization, written as:

$$w' = w_f - w_e E_f + w_a \mathrm{p}_f \tag{26}$$

where, $0 < E_f \leq 1$, $0 \leq \mathrm{p}_f \leq 1$, $w_f - w_e < w' < w_f + w_a$. Based on the above formula, eq.18 and eq.19 can be written as:

$$\begin{aligned} V_{ij}(t+1) = w' V_{ij}(t) + c_1 * r_1(t)\left(p_{ij}(t) - X_{ij}(t)\right) \\ + c_2 * r_2(t)\left(p_{gj}(t) - X_{ij}(t)\right) \end{aligned} \tag{27}$$

In this paper, the node distance and the energy load of the node are taken as the objective function, which is written as:

$$f = w_1 f_1 + w_2 f_2 \tag{28}$$

The simulation results of the adaptive particle swarm optimization algorithm for optimizing the above objective function correspond to Fig. 2. The network will get the optimal allocation scheme under the constraint of node distance and energy load, and give the corresponding response time.

Since, WSNs is a resource-constrained network and energy consumption is important to indicate evaluated network performance. It reflects the survival time and service quality of the system to a certain extent. Therefore, this paper calculates the energy consumption of the network from the established energy consumption model.

C. ENERGY CONSUMPTION MODEL

The proposed technique focuses on the overall energy consumption by the network to form energy consumption model. The detailed step-wise work is explained below.

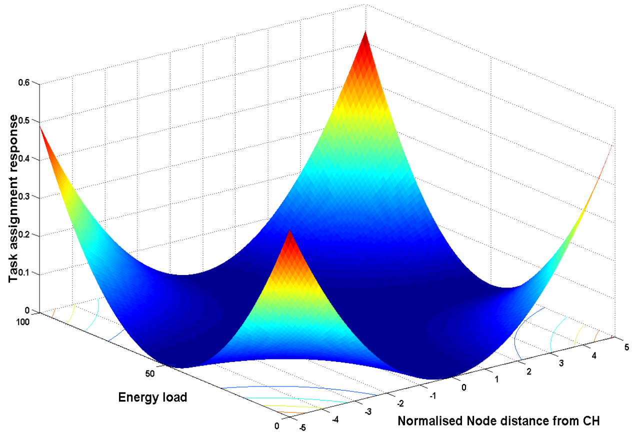

FIGURE 2. Resource allocation using DAI-APSO.

1) LET THE DA-TA COMMUNICATION ENERGY CONSUMPTION IS DENOTED BY E_{commx}

This implies that the E_{commx} is mainly divided into data transmission and reception energy consumption. If the transmission and reception energy consumption is E_{Tx} andE_{Rx} repetitively, then the DA node transmits k-bit data to the TA node, whereas the distance is d, and the transmission energy consumption is expressed as:

$$\begin{aligned} E_{Tx}(k,d) &= E_{Txelec}(k,d) + E_{Txamp}(k,d) \\ &= \begin{cases} k \times E_{elec} + k \times \varepsilon_{amp} \times d^2, & d < d_0 \\ k \times E_{elec} + k \times \varepsilon_{amp} \times d^4, & d \geq d_0 \end{cases} \end{aligned} \tag{29}$$

Therefore, received energy consumption can be expressed as:

$$E_{Rx} = E_{Txelec}(k) = k \times E_{elec} \tag{30}$$

Here, $E_{Txelec}(k,d)$ is the energy consumed by the transmitting circuit of the nodes, and E_{elec} represents the energy consumption of the transmitting device and the receiving device per unit bit of data transmitted or received, depending on factors such as digital encoding, modulation, filtering, and spread spectrum signals. $E_{Txamp}(k,d)$ represents the consumed energy by amplification circuit of nodes. Respectively, ε_{amp} is the energy consumed by the amplification circuit of nodes to transmit unit bit data in unit area, which depends on the distance between transmitter and receiver under the condition of limited bit error rate. The communication radius of nodes is d_0, when the energy consumption of the free space model is used within the communication radius, the energy consumption of the multipath attenuation model is considered when the communication distance is greater than the communication radius of the node.

Therefore, assuming the transmission energy consumption for DA is E_{DA_Tx} and the reception energy consumption for TA E_{TA_Rx} for DA-TA communication for intra-cluster communication can be represented as:

$$E_{DA\_Tx} = \sum_{i=1}^{m}\sum_{j=1}^{n} E_{Tx}(k, d_{ki}) P_{ij} \tag{31}$$

$$E_{TA\_Rx} = \sum_{i=1}^{m}\sum_{j=1}^{n} E_{Txelec}(k, d_{ki})P_{ij} \tag{32}$$

where d_{jk} denotes the distance between DA and TA ($N_i, i = 1, 2, \ldots, m$), and P_{ij} is the value of the element in matrix 0-1 representing the resource allocation scheme. When the element is 1, it indicates that the DA will perform data transmission on the TA to generate energy consumption. In general, the communication between the DA and the TA in the process of resource allocation can be written as:

$$E_{commx} = E_{DA\_Tx} + E_{TA\_Rx} \tag{33}$$

2) CALCULATION OF REAL-TIME ENERGY CONSUMPTION E_{compx}

The E_{compx} mainly includes software and hardware resources overhead of the system. The energy consumption by the TA nodes $N_i, i = 1, 2, \ldots, m$ with processing task $i, i = 1, 2, \ldots, m$ can be expressed as:

$$E_{TA\_compx} = \frac{C(j)}{FR(N_i)} \times I(N_i) \tag{34}$$

where, $C(j)$ is the number of CPU cycles required to perform task j ($j = 1, 2, \ldots, n$), $FR(N_i)$ is the CPU frequency of TA($N_j, j = 1, 2, \ldots, n$), $I(N_i)$ is the active current rating of each TA nodes ($N_i, i = 1, 2, \ldots, m$). Therefore, the overall energy consumed by a complete TA processing task can be obtained by:

$$E_{compx} = \sum_{i=1}^{m}\sum_{j=1}^{n} E_{TA\_compx}(N_i)P_{ij} \tag{35}$$

i.e. the energy consumption of the entire network is the sum of communication energy consumption and calculated real-time energy consumption, represented by:

$$E_{total} = E_{commx} + E_{compx} \tag{36}$$

where, Eq. 36 represents the total energy consumption of the network during the entire resource allocation based on DAI and APSO. The mathematical analysis is further supported by the simulations to justify the efficiency of overall resource allocation for our proposed method in next section.

IV. PERFORMANCE AND RESULTS ANALYSIS

To evaluate the hierarchical resource allocation method, the proposed method is simulated, and the corresponding energy consumption and response time of the network are then compared with the traditional methods. When the distance between DA and TA increases, the energy load also increases, which correspondingly increases the response time of the node. As observed from the simulations, the proposed method finds the optimal allocation scheme under the limitation of the two objective functions of the distance between TA and DA and energy load.

At this point, the inter-node distance is the shortest, and the energy load is balanced. The node response time is also faster, and the network obtains the optimal performance.

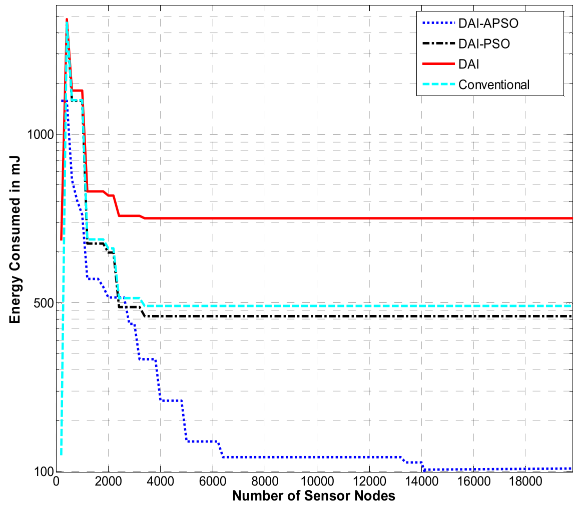

FIGURE 3. Performance comparison of network.

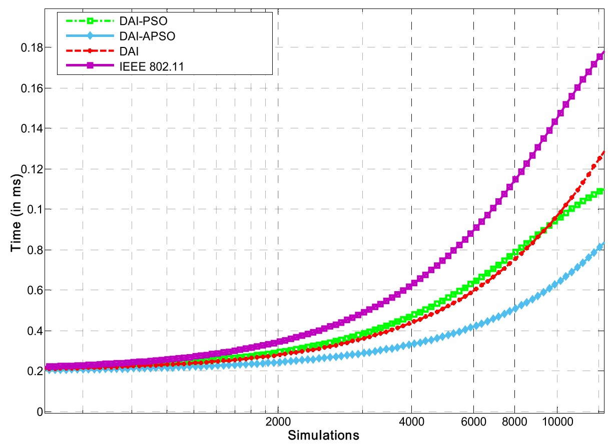

FIGURE 4. Time response during cluster formation and resource allocation.

As shown in Fig.3, this paper calculates and simulates the proposed method by establishing an energy model, which compares DAI-APSO, DAI-PSO, DAI and traditional algorithms. The simulation results depict that with the increase in the number of nodes, the energy consumption of the proposed method is significantly lower than that of the other three methods. It imposes the efficacy and goodness of the proposed method in optimizing network energy consumption.

As shown in Fig.4, the conventional IEEE 802.11 protocol is compared with various combinations of DAI, PSO and APSO. As we can see, that the proposed DAI-APSO time response performance is better than other methods as we are increasing the simulations.

The initial time consumption is 0.2ms (assumed during simulation because of hardware constraints if any) for all the methods with 10000 simulations. This implies an optimum real-time performance by the proposed method for any IoT and IIoT applications, which requires a fast time response.

Figure 5 illustrates the performance comparison of residual energy during dynamic clustering and resource allocation concerning the number of simulations. Since the residual

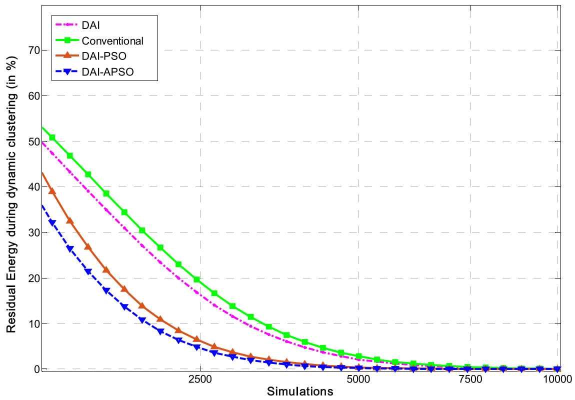

FIGURE 5. **Performance comparison during dynamic clustering and resource allocation.**

energy is used as a measure for energy-efficient performance for a network, therefore a less consumption of residual energy leads to better performance as shown in the proposed method. Due to the adaptation of APSO, a significantly less energy consumption of the network is at the beginning compared with the other strategies where the residual energy consumption is more. The initial residual energy of all these methods are calculated based on their pre-cluster formation and present resource allocation energy.

As depicted by the simulation, with an increase in the number of simulations, the overall energy consumption pattern of the network gradually decreases due to optimization, and the residual energy varies accordingly.

Compared with the single-layer DAI method, the proposed hierarchical resource allocation strategy has distinct advantages and effectively extends the life cycle of the network..

V. CONCLUSION AND FUTURE WORKS

This paper proposes an intelligent and energy-efficient hierarchical resource allocation method. In the process of resource allocation for both inter-cluster and intra-cluster cooperative communication, the dynamics of WSNs and the characteristics of energy finiteness are considered. Also, intelligent scheduling and the individual node resource allocation in the network are realized. Based on the ADAI, a multi-agent clustering WSNs model is established, which makes the response between nodes intelligent and optimizes the response time. The intra-cluster resource allocation is optimized using APSO based on inter-node distance and energy load among them. The simulation results are presented which verify the feasibility and effectiveness of the proposed method. The work can be extended by considering micro-cell zones in WSNs and mobile indoor localization, where both inter and intra-cluster dynamic resource allocation are required.

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