Energy Efficient Resource Allocation strategy in dynamic clusters for Industrial 6G Applications

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***Abstract*— The birth of beyond 5G (B5G) and emerge of 6G has made personal and industrial operations more reliable, efficient, and profitable, accelerating the development of the next-generation Internet of Things (IoT). The Industrial equipment in 6G contains a large number of wireless sensors, which collect a large amount of data by sensing the surrounding environment, but the data is not always useful. The emergence of data mining has undoubtedly found a breakthrough point for extracting effective information from massive data. In the pursuit of lower latency, edge computing has also begun to develop. Eventually, 6G can make intelligent decisions in real-time and realize automated equipment operations. However, with the application of various technologies, the energy consumption of the system has increased, but the energy carried by the sensor is still limited. This paper addresses the energy consumption problem with a system model of industrial wireless sensor networks based on a multi-agent system (MAS) for industrial 6G applications. The method uses distributed artificial intelligence (DAI) to cluster the sensor nodes in the system to find the main node and predict its location. The work initially uses the back-propagation neural network (BPNN) and convolutional neural network (CNN), which are respectively introduced for optimization. Furthermore, we analyze the correlation of mutual clusters to allocate resources to individual nodes in each cluster efficiently. The simulation results show that the proposed method reduces the waste of resources caused by redundant data, improves the energy efficiency of the whole network, along with information preservation.**

***Index Terms*— 6G, distributed artificial Intelligence, multi-agent system, Copula theory, convolutional neural networks, resource allocation, data mining**

I. INTRODUCTION

With the expansion of future internet applications, next-generation Internet of Things (IoT) is known as the next wave of the world's information technology development. Its main work is to connect the network to different objects through information sensing equipment by the prescribed protocol, and thereby exchange information. Realize intelligent recognition, positioning, and other functions [1]. The traditional Internet of Things mainly focuses on people's daily life and consumption fields, such as smart homes and smart medical care. When faced with higher-value equipment and assets, higher requirements are put forward for the security of the Internet of Things, and the concept of IIoT has been developed. As the infrastructure of the Industry 4.0 concept, it mainly deals with industries related to production services such as energy and industrial control [2].

The 6G connects a large number of industrial machines and equipment to analyze the information collected by sensor nodes in real-time and make intelligent decisions [3]. In this interactive process, more and more devices are added to make the scale of communication continue to increase, and the amount of data that sensor nodes need to sense, process, and transmit has also increased significantly. Mass data will be generated from the data centre of Industrial 6G applications. It is difficult to sort and summarize these data [4]. However, the valuable information contained in the massive data is a prerequisite for realizing the automated operation of industrial equipment and the system to obtain higher production and communication efficiency [5]. Data mining can dig out potentially valuable information from data [6]. It is an evaluation standard to measure the intelligence level of 6G and the basis for the development of related intelligent applications [7]. Data mining technologies mainly include classification, prediction, and cluster analysis. Etc. [8]. New technologies will bring new challenges. With the massive application of smart metering and smart grids, 6G is facing a huge energy consumption problem.

From the perspective of technical architecture, any industrial 6G mainly includes the perception layer, network layer, platform layer, and application layer. Among them, the perception layer collects various data by a large number of sensor nodes, and the premise of data mining is to collect a large amount of data [9]. The network layer is mainly responsible for the transmission and forwarding of information, while the platform layer and application layer are both in the data centre. In the face of a large amount of information, the traditional data centre is very inefficient in processing data. There are many wireless communication methods. Using only one type of network communication method cannot meet the transmission requirements in different scenarios. To achieve higher efficiency, lower delay, and cost

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of network transmission, the sensor nodes in the network must carry out cooperative communication [10]. However, due to the limitation of network bandwidth, when the demand for low latency and collaborative work increases, the cloud computing system cannot meet the user's demand for response time. At this time, the emergence of the edge computing model undoubtedly brings a solution to the efficiency problem. The "edge" here refers to a place located inside the device or very close to the device [11], so that data can be processed nearby, reducing the consumption of data transmission to the remote data centre. However, the energy of sensor nodes that gradually tend to be miniaturized is limited, and the edge computing model still faces the problem of uneven distribution of network resources. Therefore, under the premise of ensuring the quality of service requirements of the system, how to perform reasonable resource allocation to reduce node energy consumption and achieve efficient collaboration between nodes is an urgent need to be resolved [12].

Among various solutions for resource allocation, many researchers have tried to use various artificial intelligence (AI) technologies, among which distributed artificial intelligence (DAI), as an important branch, can effectively solve complex problems in collaborative systems. DAI was developed in distributed problem solving (DPS) [13], and later developed a multi-agent system (MAS). This system is composed of many agents, and the agents will communicate, cooperate, or compete to complete a large number of complexities. The task of reducing the complexity of the system while improving the robustness and reliability of the system [14].In this article, the problem we are discussing is how to allocate wireless network resources for 6G applications. The network here is a hybrid wireless sensor network, and a MAS-based resource allocation method is constructed. Due to the limited battery of sensor nodes, cluster division, cluster head node selection, and inter-node communication will all produce a series of energy consumption. To maximize the use of limited resources and better control the large number of different types of sensor nodes in the hybrid network, we have introduced the clustering technology in data mining to divide the entire 6G system into different clusters.

II. Related work

To construct an intelligent and efficient IoT system with balanced energy consumption, many resource allocation schemes have been proposed. Literature [15] established an efficient IoT mechanism based on cooperative communication and mobile cloud computing, which minimizes system energy consumption under the constraints of transmission power, mainly by using a joint algorithm of iterative computing and resource allocation to reduce computational complexity. Taking into account the quality of service (QoS) requirements of the IoT system, literature [16] established a resource allocation mechanism based on service level agreements and utilization perception to evaluate and compare different indicators to reduce operating costs and power consumption. Improve system performance. With the exponential increase in the number of access devices, a large amount of heterogeneous data has been generated, and many researchers have introduced machine learning algorithms to reduce the negative impact of heterogeneous data on the system. Literature [17] proposed an improved cuckoo search algorithm based on a heuristic-based machine learning algorithm to select the best resources to reduce traffic congestion in the network. In industrial applications, the issue of cost-effectiveness is very important. Literature [18] constructs a collaborative perception framework to realize intelligent and efficient industrial production by analyzing a large amount of data that is not the source and at different points in time. The 6G has a large-scale service range. When the computing efficiency of the network does not match the energy resources, it will cause traffic congestion. Literature [19] introduces the concept of mobile edge computing and proposes an algorithm based on time average computing rate to maximize, effective Improved the effectiveness of edge computing systems. Distributed computing often encounters difficulties in resource management. Literature [20] analyzes the distributed computing capabilities of device-to-device networks and establishes a joint optimization model for wireless MIMO signal design and network resource allocation to maximize energy effectiveness. With the rise of edge computing, fog computing-related to edge devices has also received widespread attention. Literature [21] enabled task-based fog computing and proposed a partitioning algorithm with mobility and architecture awareness. It can be seen that fog computing enables the cloud is closer to the edge of the network. In modern wireless sensor networks (WSN), there have been many technologies successfully combined with artificial intelligence (AI). Literature [22] proposed a data fusion technology based on neural networks and fuzzy logic, which overcomes the problem of data fusion in WSN. To construct a 6G system that can perform self-intelligent management, literature [23] uses a distributed deep learning architecture for power allocation, and finally optimizes the throughput of the cell. It is proved that the combination of device-centric artificial intelligence and distributed learning will make the application more widely [24]. Literature [25] studied the cooperative spectrum sensing in the cognitive radio network, built a deep cooperative sensing framework based on CNN, and proved that CNN can effectively improve the performance of cooperative spectrum sensing.

III. System model

In the MAS-based 6G system model proposed in this paper, a large number of sensor nodes are randomly deployed. To facilitate management and reduce the repeated processing of similar or redundant data, we introduce the concept of data mining and use the data mining Cluster analysis divides sensor nodes into different clusters, that is, divides WSN into multiple independent and autonomous small networks. The tasks undertaken by the sensor nodes in each cluster are different. They are mainly divided into two categories. One is the cluster head node (CH) as a coordinating agent. There can be one or more CHs in the cluster, and the other is to perform CoA allocation. The cluster member node (CM) of the task is also called the task agent (TA). Both the clustering process and the cluster head election process consumes a lot of energy, and our goal is to reduce energy consumption as much as possible and improve system efficiency. A dynamic management agent (MA) is defined in the MAS system to manage all node resources. Obtaining accurate location information of the MA is the prerequisite for intelligent resource allocation. Therefore, we predict the location information of the MA. The proposed system flow chart is shown in Fig. 1:

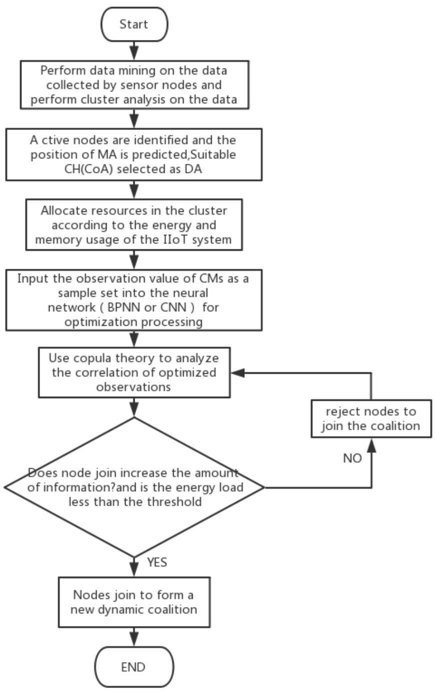

Fig. 1. Work flow of the proposed method

As shown in Fig. 1, whenever the 6G system receives a task, the whole process of our work is to first dynamically form clusters based on the real-time signals collected by sensor nodes, define the MA for managing resources in the cluster, and predict the location of the MA. Then according to the energy and memory usage of the entire 6G system, reasonable resource allocation is made to all clusters. The CH allocated to the resource will initiate a notification to the CM in the cluster and ask the CM to send the collected observations to itself. To reduce the influence of redundant data, CNN is used to optimize the observations. Finally, the copula theory is used to analyze the correlation between all optimized data. It is judged according to whether the addition of CM will increase network energy consumption. CM that meets the requirements and dynamic alliance will be formed to complete the task of the entire system. We will describe the implementation of resource allocation in detail in the following sections.

IV. MAS-based 6G System Location Prediction and Resource Allocation

In the previous section, the industrial 6G system model based on MAS was established according to the hypothesis of DAI. In this section, the specific implementation process of the system is introduced in detail. The symbols used in this section are listed in Table I:

Table I

List of Symbols

Symbol	Definition
s	Number of sensor nodes
N	Number of anchor nodes
x	Abscissa of node position
Y	Vertical coordinate of node position
H	Hop count
d	Node distance
k	Kolmogorov complexity
λ	Task value
C	Randomness
T	Time
p	Number of channels
P	Battery power consumption
U	Memory usage
θ	Threshold
∂	Partial lead
W	Weight
G	Communication path
I	Amount of information

A. MA position prediction

Suppose our industrial 6G model is proposed in a two-dimensional geo-space, the work assumes a randomly placed s sensor nodes with the same communication capability (homogeneous), of which the location information of n anchor nodes have been obtained through the GPS. In this system, the adjacent nodes communicates directly through a single-hop mode, and non-adjacent nodes use multiple hops for indirect communication. In this section, we use the idea of the DV-Hop algorithm to multiply the minimum number of hops and the average distance between two nodes to obtain the positional relationship between the unknown node and the anchor node [26], and then use the three sides. The measurement method solves the node position information, and finally predicts the position of the MA responsible for energy management in the cluster.

Suppose the location information of an unknown node is (x_{n-s}, y_{n-s}), and the location information [27] of the anchor node is (x_n, y_n). First, all anchor nodes will send their location information to the system, the position relationship and the number of hops between any two anchor nodes will be obtained from this:

$$HP_{s-n} = \frac{\sum_{n\neq s-n}\sqrt{(x_n - x_{s-n})^2 + (y_n - y_{s-n})^2}}{\sum_{n\neq s-n} h_{n(s-n)}} \tag{1}$$

where, h is the minimum hop count. Then the mathematical expression of the minimum hop count set of the unknown node i and all anchor nodes is:

$$H_i = \left[h(x_i, x_1), h(x_i, x_2), ..., h(x_i, x_n)\right] \tag{2}$$

At this time, the distance expression between the unknown node and the anchor node is:

$$d_{n(s-n)} = HP_{s-n} * H_{n(s-n)} \tag{3}$$

According to the trilateral measurement method, set the position information of the three anchor nodes as (x_1, y_1), (x_2, y_2), (x_3, y_3), then the distance between the unknown node and the anchor node is d_1, d_2, d_3. The calculation formula for the position of the node can be obtained:

$$\begin{cases} d_1 = (x_1 - x)^2 + (y_1 - y)^2 \\ d_2 = (x_2 - x)^2 + (y_2 - y)^2 \\ d_3 = (x_3 - x)^2 + (y_3 - y)^2 \end{cases} \tag{4}$$

By calculating the above formula, the coordinates of the unknown node can be obtained as:

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2(x_1 - x_3) & 2(y_1 - y_3) \\ 2(x_2 - x_3) & 2(y_2 - y_3) \end{bmatrix}^{-1} \begin{bmatrix} x_1^2 - x_3^2 + y_1^2 - y_3^2 + d_3^2 - d_1^2 \\ x_2^2 - x_3^2 + y_2^2 - y_3^2 + d_3^2 - d_2^2 \end{bmatrix} \tag{5}$$

When the location information of all active nodes is obtained, we introduce the agent in DAI technology to predict the location of MA. Each sensor node is regarded as an agent, and the agent is represented by π. Assuming that the agents are distributed in the environmental space *E*, and different agents communicate and collaborate, to measure the correlation between the agents, the intelligence of the MAS system model can be written [18]:

$$\lambda(\pi) = \sum_{\mu \in E} 2^{-k(\mu)} V_\mu^\pi \tag{6}$$

Among them, a is the agent, $\sum_{a \in E}$ is the sum of activities in different environment spaces, *K* is the Kolmogorov complexity, $2^{-K(\mu)}$ is the complexity loss value, and β_a^π is the value that you want to achieve.

When using DAI for resource allocation, we assume that $C(x)$ represents randomness, and assume that there is $\left|\left\{x \in \sum^n : C(x) \geq |x| - k\right\}\right| \geq 2^n \left(1 - 2^{-k}\right)$ for all "*k*" and "*n*". This implies that, in the response process of MA and CoA, the MAS-based system model will calculate the best allocation strategy based on real-time conditions, and use the PSD of the received signal to predict all possible location information of the MA [19].

$$i.e.\mu = a_1(T), \sum_{l=2}^{p} a_l(T) = \lambda(\pi) = \sum_{l=2} 2^{-k(\mu)} V_\mu^\pi \tag{7}$$

According to the above conditions, the spatial position information of all MAs can be continuously predicted:

$$\frac{AE}{\frac{1}{T}[p \cdot \frac{g^2}{2} - 1]} = \frac{ED}{2} \cdot \sum_{l=1}^{p} a_l(T) \cdot \sum_{l=2}^{p} a_l(T) \tag{8}$$

In our system model, each agent must communicate with at least two or more agents. Therefore, the net gain of this heterogeneous collaboration is greater than that of any single sensor network in the cluster. When the number of channels p>2, $\frac{1}{T}\left[p \cdot \frac{g^2}{2} - 1\right] \to 1$, cooperative communication for multiple tasks can be carried out in a single cluster, using DAI technology to use the test data of AE to obtain the position information of the MA positioning, and thus obtain the expression of the position distance relationship between the MA and CoA:

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

B. MA allocates resources to CoA

After obtaining the location information of the MA, this section will allocate network resources to different clusters. According to DAI technology, MA will communicate with all available CoAs. Considering the limited resources of sensor nodes, we must ensure that the QoS of the system is met. In order to improve the network life cycle, we must also consider the power consumption of the node's battery and memory usage. When the current time is *t*, the expressions of the system's node battery power consumption and memory usage are:

$$P_{(t)} = P_{(t-1)} - \mathrm{Pr}_{(DA-MA)} - \mathrm{Pr}_{(DA)}\ PN_{(t\text{-}1)} \tag{10}$$

$$U_{(t)} = U_{(t-1)} - \mathrm{Pr}_{(DA-MA)} - \mathrm{Pr}_{(DA)}\ PN_{(t-1)} + \mathrm{Pr}_{(DA)}\ PN_{(t-2)} \tag{11}$$

where, $P_{(DA-MA)}$ is the power consumed when DA communicates with MA. In '*t-1*' time, P_{DA} is the power consumption when selecting the appropriate CH as DA, and $PN_{(t-1)}$ is the power consumed for the next resource allocation. It is the same as the selected one. The location information of CH is very relevant.

According to the above formula, the relationship between system QoS and memory usage and energy consumption can be obtained, which is the cost function of the system:

$$QoS_{measured} = \sum_{\Gamma_i \varepsilon T} QoS_{v_j^i} \left[P_{(t)_i} + U_{(t)_i}\right] \tag{12}$$

where, $\phi_i = \left\{\lambda_1^i, \lambda_2^i, ..., \lambda_j^i\right\}$ is the task that the agent needs to perform in the system, and λ_j^i is the real-time task variable. $Q\mathrm{oS}_{\lambda_j^i}$ is the expected QoS value to be met when performing tasks.

After DA accepts the resources allocated by MA, it will then conduct a self-assessment of its energy. We set a threshold in advance. Only when the energy of the DA exceeds the threshold, the DA will perform the tasks assigned by the MA, otherwise, it will continue to allocate resources, and this process will continue to consume energy. To reduce the waste of limited resources of nodes, we must first construct the objective function of resource allocation. In the response process of DA and TA, we must reduce the distance *D* between nodes and the energy consumption *P* of the transmission process as much as possible. Therefore, the objective function is defined as:

$$Q = \min\left|\sum\sum \mathrm{D}_{sk} \cdot P_{hs}\right| \tag{13}$$

V. OPTIMIZATION BASED ON NEURAL NETWORK AND COPULA THEORY

To maximize the work efficiency of the 6G system in this article, improve the network life cycle, and achieve the optimal resource allocation within the system cluster, we will optimize the objective function defined in the previous section. Neural networks [28] have been proven to be effective in approximating the measurement function to any required accuracy [29].

A. Application-based neural network selection in the next generation of Internet of Things

In this section, the implementation process of BPNN and CNN are introduced respectively. The goal is to select the best optimization scheme based on the optimization effect. As the most basic neural network, BPNN is realized by full connection, the output result is forward propagation, and the error is backward propagation [30]. The CNN is a non-fully connected neural network model, which is mainly composed of an input layer, a convolutional layer, and a pooling layer. It relies on a special network structure in which Computer vision is widely used [31].The task of neural network is to learn from large-scale data and generalize the results to unknown data of the same type, which is feasible for effectively solving industrial problems.

The output of the input layer of a general neural network can be expressed as:

$$\mathrm{out}_{j}^{(1)} = x(j), j = 1, 2, ..., n \quad (14)$$

The BPNN is usually a three-layer network structure. In addition to the input layer and output layer, there is also a hidden layer containing an activation function. The input and output formulas of the hidden layer are:

$$net_i^{(2)}(k) = \sum_{j=0}^{n-1} w_{ij}^{(2)} out_j^{(1)} \quad (15)$$

$$\mathrm{out}_i^{(2)}(k) = f(net_i^{(2)}) \quad (16)$$

where, $f(\cdot)$ is the sigmoid function, which can correct the convolution result and enhance the nonlinearity of the network:

$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (17)$$

BPNN uses the gradient descent algorithm to continuously adjust the weights, making the error function search toward the minimum. The error function can be written as:

$$E(k) = \left[(y(k) - y'(k)\right]^2 \quad (18)$$

In order to speed up the search, an inertia term can be introduced into the error function:

$$w_{li}^{(3)}(k) = -\eta \frac{\partial E(k)}{\partial w_{li}^{(3)}} + \alpha \partial w_{li}^{(3)}(k-1) \quad (19)$$

In the CNN optimization process, to prepare for the data to enter the convolutional layer, the input layer will first standardize the data. The convolution layer contains multiple convolution kernels. Its main function is to extract features from the input data. After the convolution operation, the feature value also needs to be excited by the excitation function. The excitation function is usually a linear rectification function, and the final output. To get a fair comparison result, we use the same sigmoid activation function on CNN. The mathematical expression of the convolutional layer is:

$$x_{ij}^{L} = f(w_{ij}^{L} \cdot x_{ij}^{L-1} + b^{L}) \quad (20)$$

After the feature values are extracted by the convolutional layer, the feature values are input to the pooling layer for feature selection and filtering. The main function of the pooling layer is to reduce the dimensionality to avoid possible over-fitting problems. The realization process of the pooling layer is to sample the output mapping value, and only take the partial feature mapping value to reduce the scale of the feature value under the condition that the number of feature values remains unchanged. Assuming that the sub-sampling function is $\mathrm{down}(\cdot)$, the mathematical expression of the pooling layer can be written as:

$$x_{li}^{L} = f\left[w_{li}^{L} down(x_{li}^{L} + b^{L})\right] \quad (21)$$

Another important feature of CNN is the back-propagation of errors because there is an error between the eigenvalues and the expected values after the previous phase propagation of the convolutional layer, pooling layer, and fully connected layer. CNN usually uses the BP framework. Stochastic gradient descent (SGD), SGD randomly selects samples to calculate the gradient at each iteration. In this article, we choose cross-entropy as the error function:

$$Loss = -\sum_{i=0}^{n} Y^n(i) \log(Y'^n(i)) \quad (22)$$

SGD will continuously adjust the weights and thresholds in the CNN layer by layer until the error function is minimized, and finally, the best parameters can be obtained. The mathematical expression for parameter update is:

$$w_i^L = w_i^L \text{-} X \frac{\partial}{\partial w_i^L} Loss \quad (23)$$

$$b^L = b^L \text{-} X \frac{\partial}{\partial b^L} Loss \quad (24)$$

After the training of the CNN forward and back propagation process, the extracted PU signal feature value set will finally be output.

B. Correlation analysis of copula theory

After the neural network has completed the optimization work, we use Copula theory to analyze the correlation of the observed values of all nodes in the cluster to ensure that the effective data values in the cluster get the best resource allocation, and finally get the best resource allocation of the 6G system model solution to avoid waste of resources in the process of perception and communication. We take CoA as the initiator of the alliance and send the received system task information to all TAs in the cluster, thus forming a dynamic alliance that handles multitasking. We assume that the communication path between CoA and TA is G, and the information observed on the path is λ. The joint probability density function (PDF) of the signal received at this time can be written as $f_n\left(G \mid \lambda\right)$. We use Fisher information to indicate the cluster amount of information [32]:

$$I(\lambda) = E\left\{\left[\frac{\partial}{\partial \lambda} \log f_n(G_i \mid \lambda)^2\right]\right\} \quad (25)$$

Because the observations collected by different nodes are multivariate distributed random variables, the *Kendall rank* correlation coefficient τ is used to measure the consistency of data changes [33]. Assuming that the random variables are z_i and z_j, we can use the copula function to write these two expressions rank correlation coefficient of three variables:

$$\tau(z_i, z_j) = 4\int_0^1\int_0^1 C(z_i, z_j) dz_i z_j - 3 \quad (26)$$

The mathematical expression of the correlation between the multivariate distributions of different observations is [34]:

$$C(G \mid \Sigma) = \Phi_{\Sigma}(\Phi^{-1}(\mathrm{z}_i),...,\Phi^{-1}(z_j)) \tag{27}$$

Where, Σ stands for the correlation measure of observations, which can be described by *Kendall rank* correlation coefficient:

$$\Sigma = \begin{cases} 1 & z_i = z_j \\ \tau(z_i, z_j), z_i \neq z_j \end{cases} \tag{28}$$

Differentiate and derive the equation (19) to get the corresponding density function:

$$c(G \mid \Sigma) = \frac{1}{|\Sigma|^{1/2}} \exp\left[\frac{-G^T(\Sigma^{-1} - E)G}{2}\right] \tag{29}$$

To calculate the information amount of the cluster, we use the edge probability density and copula density function to express the information amount formula according to the joint theory [35]:

$$I(\lambda) = E\left\{\left[\frac{\partial^2}{\partial\lambda^2}\sum_{i=1}^{k}\log f(z_i \mid \lambda)\left[\log c(z_i) \mid \lambda\right]\right]\right\} \tag{30}$$

The constraints of sensor energy load are:

$$\left(\sqrt{\frac{\sum_{i=1}^{k}\left(E_i - E_{ave}\right)}{i}}\right) \leq E_L \tag{31}$$

where, E_L is the energy load threshold, which is mainly set according to the specific goals of the cluster in the network; E_i is the energy of the i^{th} node in the dynamic alliance, and E_{ave} is the average energy of all nodes in the dynamic alliance i.e. $E_{ave} = \frac{1}{k}\sum_{i=1}^{k} E_i$. Under the constraint of energy load, whenever a new node appears in the 6G application, we will perform correlation analysis on it, that is, compare the cluster information $I^{'}(\theta)$ after the new node is added with the information $I\left(\theta\right)$ before it is added, only when $I'\left(\theta\right) > I\left(\theta\right)$, it means, when the amount of information increases. CoA will accept the new node's joining request to form a new alliance, otherwise it will refuse to join the application. This process only manages information, does not use additional network energy, greatly reduces data redundancy, and promotes efficient resource allocation for 6G applications.

VI. Simulation and Discussion

In this section, the performance of the proposed method is analyzed with some simulation results and compared with other existing methods. The assumed simulation parameters for network environment is shown in Table II.

TABLE II
SIMULATION PARAMETERS

Parameters	Value
Network diameter	100x100 m^2
Number of nodes in cluster	100
Simulation time	1500 ms
Number of simulations	10000
SNR	20dB

The channel capacity is important parameter for any communication system. The higher value of channel capacity means more number of bits can be transferred by each frame. Here, in our case the sensors communicate with each other through the channel and we have shown the efficiency of our method in Fig. 2. In the simulated representation of channel use, the number of bits that can be transferred by each channel varies with respect to signal to noise ratio (SNR). For the comparison purpose, we have taken three methods: conventional (power is distributed equally to nodes), hierarchical maximum likelihood (HML) and advanced particle swarm optimization (APSO) [34]. Among these three, the channel capacity using APSO is good in lower SNR compare to proposed scheme but for higher value of SNR, proposed method outperforms all the other techniques in terms of bits per channel use.

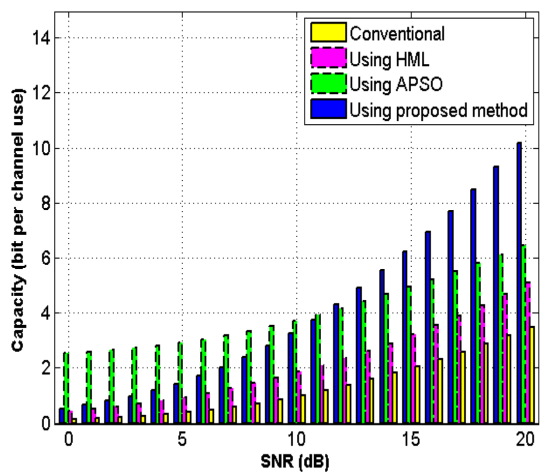

Fig. 2. Channel capacity during communication

The presence of residual energy and its depletion with time in a process defines the energy occupancy of the system. In Fig. 3. a graph of normalized residual energy with the varying time is shown at the time dynamic clustering. It can be seen that each time the depletion rate of residual energy is high in conventional way (where the each nodes take equal power to form cluster) and least in our proposed method, whereas; in Low Energy Adaptive Clustering Hierarchy (LEACH) is moderate. It means in the proposed mechanism energy consumption is less at the time of clustering, which eventually leads to better lifetime of the system.

According to our goal of this paper, the resource allocation should be optimal as well as the system should be energy efficient. These two things can be depicted in the next simulation.

In Fig. 4. the comparison of optimal allocation of resources is shown with the other existing optimization methods, where the normalized value of power is presented with respect to number of simulations.

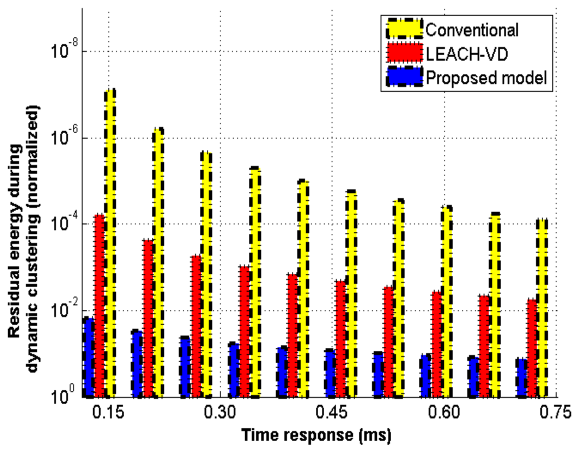

Fig. 3. Network performance in terms of residual energy

The optimal allocation becomes less as the number of simulation increases due to the utilization of resources is maximum at the beginning of the process and our proposed hybrid NN optimization scheme outperforms other two methods: APSO [34] and Deep Neural Network (DNN) [36].

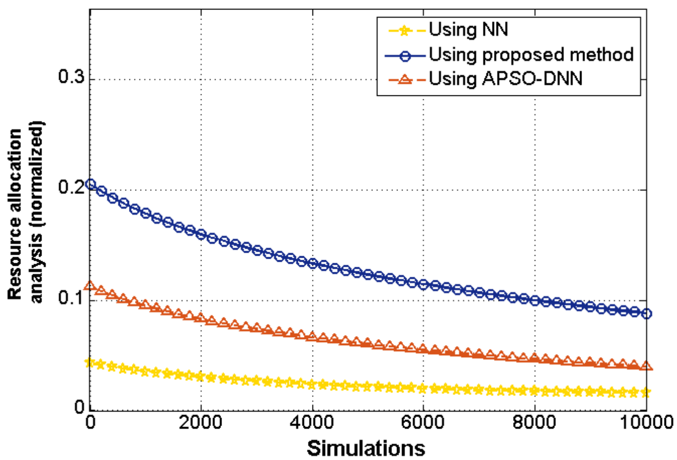

Fig. 4. Optimal resource allocation in nodes

The efficiency of correlation or the achieved correlated information value after clustering is presented in Fig. 4. This is depicted with respect to the signal to noise ratio (SNR) value at the time of correlation. It shows that the achieved information is high for higher value of SNR and our method of correlation Gaussian copula theory gives better information compare to other combine approaches of blind source separation (BSS) with HML, DAI with APSO and Firefly with self-organizing map (SOM) method for both mathematical and simulated analysis.

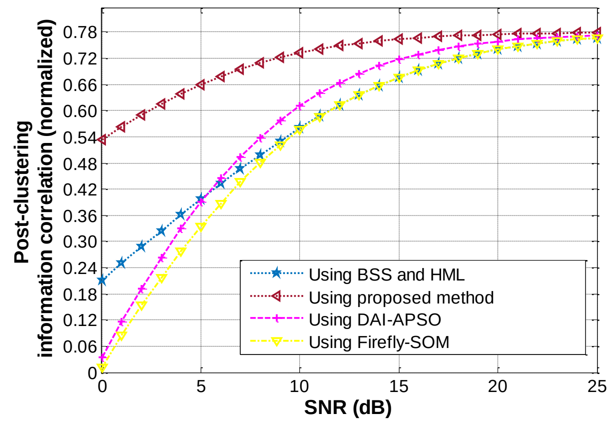

Fig. 5. Efficiency evaluation of information correlation strategy

The proposed method considers CoA as initiator to send the information of tasks to the member nodes in cluster. Here, in Fig. 6. power consumed by the CoA is shown for the number of nodes in cluster. It shows that the initially (number of nodes 10) the conventional method is good for less number of nodes compare to Gaussian copula method of correlation analysis but for the huge number of nodes the consumption of power by CoA is less in Gaussian copula method. Considering these both methods our proposed hybrid approach of NN and Gaussian copula depicts that for providing the task information to TAs, CoA consumes less and efficient power compare to both cases. It signifies that our proposed scheme is well enough to consider for energy efficient system.

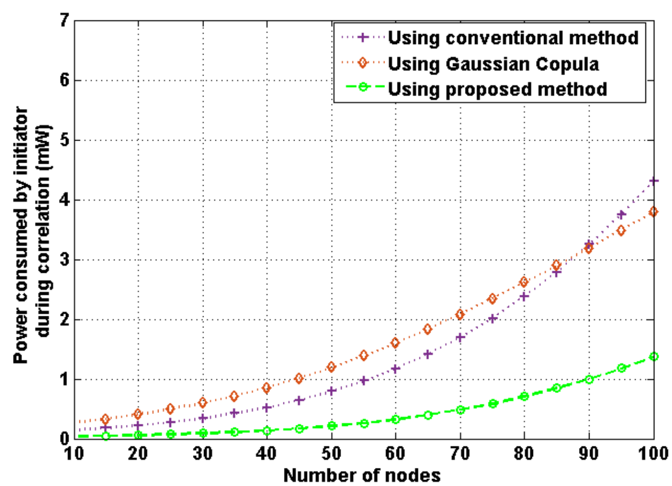

Fig. 6. Comparison of power consumption during correlation

VII. Conclusion

This paper constructs a resource allocation model for 6G applications based on MAS. In the traditional Internet of Things, both clustering, cluster head election and positioning consume a lot of resources, and the hybrid method we propose also considers node batteries. The power consumption and memory usage make cooperative communication more efficient. We introduce the idea of data mining and use a clustering algorithm to divide wireless sensor nodes into different clusters to achieve more intelligent management. At the same time, the distributed computing brought by DAI makes the system have less computational complexity. First, locate the node and predict the location information of the MA. In the next stage of resource allocation, BPNN and CNN are used to optimize the data collected by the node. Finally, the Copula theory is used to analyze the correlation of node observations. The dynamic alliance formed has high efficiency. This method balances the power demand of the network and maximizes the information volume in the cluster. Compared with the existing methods, it has higher reliability and better network performance. Work can be further expanded by including optimization of node positioning standards for different IoT applications.

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Authors Biography can be added later.