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A FRAMEWORK EMPLOYING PARTICAL SWARM OPTIMIZATION FOR THE EFFICIENT ALLOCATION OF RESOURCES IN INDUSTRIAL IOT TO ENHANCE ENERGY EFFICIENCY

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Abstract
The Industrial Internet of Things (IIoT) has become a prominent subject in discussions about technological advancements in the manufacturing industry. The IIoT aids production by incorporating smart sensors and devices into industrial systems. While it offers impressive benefits, it also presents challenges regarding energy efficiency and fair resource distribution among the nodes. Previous models have been utilized, but they have been hindered by problems such as having only one communication route and artificial limitations. However, the main obstacles are congested communications, limited resources, and power failures. Consequently, there is a requirement for a more effective IIoT model that can enhance gearbox performance. In order to tackle the challenges posed by traditional methods, this paper suggests a novel energy-efficient resource allocation model for the IIoT. The challenges of channel estimation are later mitigated by incorporating energy efficiency requirements. As a result, the overall energy efficiency of the system is enhanced, leading to a more effective allocation of resources.

Keywords— Partical Swarm optimization; power and channel resource allocation; energy efficiency in the industrial IoT.

I. Introduction

The Industrial Internet of Things (IIoT) is a specific part of the Internet of Things (IoT) that focuses on using IoT technologies in industrial settings. Currently, there is a widespread use of smart sensors [9] that can be connected and share data over the IoT network. In addition, the IIoT incorporates servers and other mechanical equipment to improve efficiency. Devices called "Wireless Sensing Devices" (WSDs) can be used to monitor the health of factories and other industrial facilities. Since data needs to be transmitted, processed, and stored at the same time, these applications require more resources, especially energy. Modern technology helps to make data useful for completing various tasks in a timely and effective manner [11].
Today, there is a significant focus on and importance given to IIoT in urban areas, manufacturing and transportation sectors, medical field, and other industrial sectors. In order for the technology and its industrial applications to thrive, the ecosystem must function effectively [12]. However, the IIoT is currently stuck in its initial stages, focusing on delivering high-quality results and organizing itself, despite having advanced knowledge of reliability and adaptability. Another challenging task is the storage and hosting of data on the cloud. Utilizing widespread infrastructure and local conditions can enhance the efficiency of the system [13]. Issues such as network congestion, slow data transfer, and excessive energy consumption are some of the challenges that may arise [14]. To optimize power savings and resource utilization, professionals in this industry have implemented various tactics for IIoT networks. The IIoT industry is facing high demand and extensive involvement, which brings about challenges in energy consumption and communication overhead [15]. Unlike IoT, the IIoT network has differences in delay, cost, efficiency, privacy, and security [16]. Therefore, it is crucial to construct an effective system that optimizes energy and capacity utilization while addressing limited supplies. Energy consumption is a challenging issue in large IIoT networks [17], and inefficient resource utilization is a key cause of system degradation [18]. The computerized model relies on cloud-based information but still faces issues such as slowness, latency, and insufficient storage [19].

Deploying edge computing tasks across an industrial network can help solve various problems. Multiple academic disciplines have contributed to the development of energy-saving methods currently in use. However, there are issues with the system that need to be addressed, including latency, stability, and structural complexity [20]. The IEEE 802.15.4 uses "Medium Access Control (MAC)" [21] to facilitate smoother communication between the coordinator and the devices. The super frame refers to the time axis, indicating when data transmission events occur [22]. Edge computing-based IIoT installations have greatly benefited from the system's efficient resource allocation and computation offloading. These objectives have been achieved through the use of various approaches [23]. In addition, we investigate different scenarios to reduce energy consumption in industrial platforms caused by a large number of IIoT nodes [24]. As the number of nodes increases, it becomes more challenging to process and manage the system. Time pressure leads to decreased tolerance, increased delay, and decreased priority [25]. With the emergence of smart approaches such as deep learning and heuristic optimization, the desired aspect in an IIoT scenario can be achieved.

The main objectives of our proposed work are as follows:

- Thoroughly investigate existing resource allocation and energy efficiency approaches.
- Propose a new model for distributing resources in the IIoT that optimizes energy usage and improves transmission effectiveness.

Now, let's discuss the upcoming structure of the paper. Part II will examine the existing IIoT approaches studied, while Part III will introduce several novel approaches. Section IV proposes a new energy-efficient IIoT design, and Section V concludes.

Research Gaps and Challenges

By integrating advanced equipment with monitoring and sensing tools, Industrial Internet of Things (IIoT) technology enables the processing of industrial safety. Real-world data from a database is utilized in various forms of mobile communication, resulting in improved efficiency and reduced power consumption through enhanced monitoring. Table I provides a summary of the features and challenges of traditional models used for allocating resources in Industrial IoT to achieve energy efficiency. The joint optimization technique [1] effectively addresses validation challenges related to channels and delivers high-quality transmission data while conserving system energy. However, it does not significantly enhance Quality of Service (QoS) to achieve a reasonable efficiency rate, and the backhaul's efficiency is so low that it has minimal impact on the overall efficiency of the system. BPNN [2] is a method that not only preserves data but also minimizes redundant information and optimizes the energy efficiency of the network. However, it is important to note that it is highly sensitive to noisy input. The efficiency rate of BPNN is calculated based on the information provided. IHM-VD [3] ensures efficient power distribution across all channels and also supports a growing number of interconnected sensors. However, it has limitations in terms of memory and channel length, despite being cost-effective. The ideal approach proposed by IDE [4] aims to reduce network delay and energy usage while maintaining low temporal complexity. However, validating this approach can be challenging, and achieving optimal values may be difficult. CEA [5] has a lower validation complexity compared to existing models. It improves network durability and stability, but it does not have any practical applications.

The use of reinforcement learning has several benefits for network dependability, optimization longevity, and data transfer reliability [6]. However, it also has some drawbacks, such as the need for more training data and higher maintenance costs for complex issue-solving. DQN [7] improves throughput and fixes data transmission delays effectively. However, it requires more storage space, which can impact system performance in certain scenarios. IHWOA [8] maximizes residual energy while enhancing network convergence rate and stability. However, it comes with the trade-offs of overfitting and increased computational cost. Traditional energy-efficient resource allocation paradigms for industrial IoT face these challenges. Therefore, we propose an optimization strategy to develop a novel resource allocation model that prioritizes energy efficiency.

Table.1: Features and challenges of existing Energy efficiency resource allocation models in

Author	**Methodology**	**Features**	**Challenges**
Wang [1]	Joint optimization algorithm	It effectively minimizes the validation complications presented in the channels. It offers high-quality transmission data to save energy in the system.	It didn't enhance the QoS to offer a good efficacy rate. The backhaul efficacy rate is minimal which affects the system performance rate.
Mukherjee et al. [2]	BPNN	It reduces the redundant data and alsoeffectively enhances the energy efficiency of the entire network with data preservation.	It is highly sensitive to noisy data. It generates the efficacy rate based on input data.
Li et al. [3]	IHM-VD	It easily supports to more number of sensors presented in the network. It secures maximal power allocation rate in all the channels.	It is cost efficient and also need more memory. It faces channel length issues.
Jin et al. [4]	IDE	It attains optimal solution with reduced time complexity rate. It minimizes the energy utilization and delay rate in the network.	It is complex to tune optimal parameters. It has complicated validation procedure.
Sun et al. [5]	CEA	It has minimal validation complexities than the existing models. It improves the network lifetime and stability rate.	It cannot able to utilize in real-world applications.
Wang et al. [6]	Reinforcement learning	It has better data transmission reliability rate. It improves the optimization direction, lifetime and reliability rate in the network.	Its maintenance cost is higher and also it resolves only complex issues. It needs more data to train.

II. Technical Approaches

The SCSO optimization method was inspired by the activity of animals searching for a goal or food supply. The sand cats, which inhabit this rocky and sandy surface, serve as the input population. These sand cats have distinct nature and behavior compared to house cats and cannot coexist in human communities. Due to the unique characteristics of their fur, it is crucial for them to know where each foot goes. Sand cats are larger in size and have longer tails. They primarily hunt at night because the area is hazy and parched during the day, making it difficult for them to locate their prey. It is reasonable to assume that sand cats feed on small mammals, birds, reptiles, and insects. They possess exceptional hearing, which enables them to locate their prey both on and below the ground. Now, let's delve into the detailed steps of the SCSO method.

During this first phase, the sand cats and their associated problem factors are assumed. The search agents and variables are generated at random across the array's dimensions. The variables are marked as , in which it depends on the lower and upper boundaries. Firstly, the size of the search agent population is defined by a matrix of , as given in Eq. (1).

$$\begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1v} \\ c_{21} & c_{22} & \cdots & c_{2v} \\ \vdots & \vdots & \cdots & \vdots \\ c_{u1} & c_{u2} & \cdots & c_{uv} \end{bmatrix} \quad (1)$$

The above matrix can be thought of as a representation of the total number of sand cats and dimensions. Once the problem variables have been initialized, the fitness value may be calculated. In the initial iteration, high-fitness agents select the optimal option, and in subsequent iterations, the other cats choose to follow the selected agents. The optimal fitness value is used to decide where the prey will be placed. Therefore, Eq. (2) can be used to determine fitness.

$$ftn = f\left(c_1, c_2, \ldots, c_v\right) \quad (2)$$

Searching stage: The searching strategy is achieved by the noise frequency of sand cats. Hence, the solution can be designed by . Its keen hearing sense is a key to its success in hunting. Foraging sand cats typically use their acute sense of hearing to detect frequencies of less than 2 kilohertz. As a result, Eq. (3) may be used to define the overall sensitivity range, which declined linearly from 2 to 0 over all iterations.

$$sy = Ha - \left(\frac{2 \times Ha \times j}{j_{\max}}\right) \quad (3)$$

In the above equation, the current and maximum value of iteration is denoted by j and jmax. Further, the hearing capacity of search agents is marked by , which is set to be as 2. With the help of above equation, the sensitivity value of each sand cat for avoiding the local optima issue is calculated using Eq. (4).

$$x = sy \times rd \quad (4)$$

The position is currently considered based on the standard MFO [27], which considers moths as the founding population. Moths are among the many insect families that share similarities with butterflies. They have unique qualities that allow them to navigate at night without difficulty. The moths' search patterns around the moon are guided in a transverse manner. This section provides further details on the mathematical model of MFO. Phase of Getting Started: The first step is to estimate the total moth population. The moths are initially dispersed at random around the search area. The use of flames to determine a fair price is also crucial. Both the moths and the fire are started with the values from Eq. (5) and Eq. (6), respectively.

$$U = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ u_{21} & u_{22} & \cdots & u_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ u_{m1} & u_{m2} & \cdots & u_{mn} \end{bmatrix} \quad (5) \qquad V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} \quad (6)$$

In the above two equations, the term and signifies the total number of moths and variables used for optimization. Further, the fitness value is computed for moths and flames, as derived using Eq. (7) and Eq. (8).

$$OU = \begin{bmatrix} OU_1 \\ OU_2 \\ \vdots \\ OU_m \end{bmatrix} \quad (7) \qquad OV = \begin{bmatrix} OV_1 \\ OV_2 \\ \vdots \\ OV_m \end{bmatrix} \quad (8)$$

This article, investigates the primary formulation issues associated with IIoT node management. Despite the impressive outcomes achieved by energy-efficient IIoT systems, there are still questions to be answered and obstacles to overcome. The following are some of the issues that have been raised in the IIoT network. When the network goes live, the node also initiates the process of transmitting data. When only one or two nodes are employed to do the function, their power is depleted, rendering them useless. Therefore, making sure the IIoT network is energy efficient is a top priority.

III. Proposed Framework of Energy Efficient Resource Allocation in Industrial IoT

System Model of Industrial IoT

The rise of the Industrial Internet of Things (IIoT) can be attributed to the growing presence of embedded industrial and automotive devices and systems within the Internet of Things (IoT). The IIoT offers several advantages, such as intelligent processing, advanced perception, self-organization, interconnected systems, and improved maintenance. These versatile properties have contributed to its widespread adoption in various sectors, including industry, infrastructure, grids, and transportation. Figure 1 illustrates the overall system architecture of the IIoT.

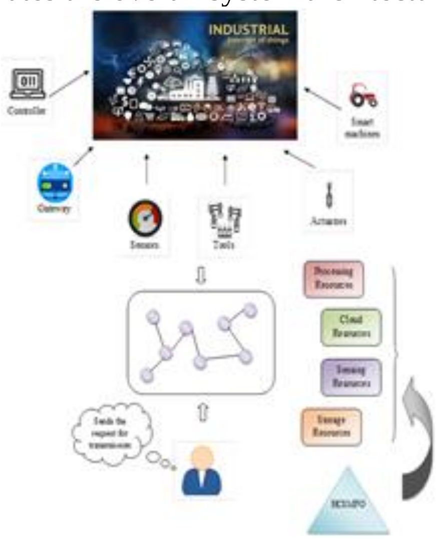

Fig. 1: Proposed resource allocation concept for Industrial IoT uses a hybrid heuristic method to design the corresponding system architecture.

Several proven strategies have been implemented to enhance the energy efficiency of the system [30]. However, the current industrial system faces issues such as low quality and operational challenges, despite being in use. Initially, it was solely utilized as a network for corporate information dissemination. Ensuring proper functionality and internal organization are inter connected factors. One of the primary objectives of IIoT is to distribute resources in a manner that reduces power consumption.

- Each sensor in the network has a specific function and is responsible for managing its own power consumption to achieve its objective.
- The connectivity between nodes enables the sharing of information among IoT sensor nodes.
- Due to the efficient utilization of sensor nodes, there is a higher power requirement. However, the ability of nodes to conserve energy is essential for network management.

Although there are plenty of resources available, the sensor node lacks the necessary knowledge to use them effectively. On the other hand, the IIoT network consists of various components that are utilized to enhance system functionality and communication. Node locations, hardware states, energy consumption, mobility, and other factors are among the key challenges in network management.

Despite advancements, it is still challenging to deploy resources while maximizing energy efficiency. To tackle this issue, a new IIoT framework has been developed using a mixed heuristic approach.

- The interference is a processing bottleneck in the network.
- Inefficient resource utilization could result from network congestion and other issues. The arrangement of a network's nodes determines the network's efficiency and lifespan.

Conclusion

This proposed work demonstrates a method for resource allocation in an IIoT network that aims to minimize energy consumption. It addresses the limitations and issues of existing methodologies by utilizing a hybrid optimization technique. The initial network design involved numerous sensor nodes, but due to unequal power and energy distribution, transmission efficiency is compromised. Therefore, a novel approach is needed to identify the most suitable option for efficient resource distribution.

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