Semiconductor Optoelectronics, *Vol. 42 No. 1 (2023), 453-469*
https://bdtgd.cn/

Semiconductor Optoelectronics
ISSN: 1001-5868

MULTI-OBJECTIVE MODIfiED EMPEROR PENGUIN OPTIMIZATION FOR RESOURCE ALLOCATION IN INTERNET OF THINGS AGRICULTURE APPLICATIONS

***Shreekant Salotagi · Jayashree D. Mallapur**

[1]Assistant Professor, Department of Electronics and Telecommunication Engineering, SVERI's College of Engineering, Gopalpur-Ranjani Road, Pandharpur-413 304, Solapur, Maharastra, India.

***Corresponding author E-mail: shreekantsalotagi24@gmail.com**

[2]Professor, Department of Electronics and Communications Engineering, Basaveshwar Engineering College (Autonomous), Vidayagiri, Bagalkote, Karnataka 587102, India.
E-mail: jayashreedmallapur@gmail.com

Abstract

Agriculture is dwindling all across the world, which has an impact on ecosystem production capacity. There is an urgent need to resolve the issue in the domain so that it may reclaim its vitality and resume its upward trajectory. A revolutionary two-tier approach is designed in this study endeavour to aid farmers in continual field monitoring. In this research work, a novel smart agriculture system has been developed with IoT-Cloud Computing for efficient monitoring of the agriculture farm. The proposed model has divided into two parts the land subsystem and the cloud user subsystem. The agricultural area has been outfitted with several IoT sensor nodes for monitoring "soil PH level, water level, temperature, humidity, moisture, weeding, nutrition, variable spraying, salinity, and rainfall". These sensors are grouped together, and the Cluster Head (CH) connects the clustered nodes to the Base Station (BS). The CH is chosen using the newly proposed Multi-Objective Modified Emperor Penguin Optimization (MEPO) approach, which takes into account many factors such as remaining energy, distance, latency, and QoS. The land-based data is continually stored in the cloud server through the gateway. The cloud sub-system, on the other hand, encompasses the farmers, Physical Machine (PM), and Virtual Machine (VM). Furthermore, the Lionized Golden Eagle optimization (LGEO) based 6-fold goal model is projected for optimum task allocation onto the VM, with a focus on power consumption, migration cost, memory utilization, response time, and server load and execution time. The proposed model, as a whole, becomes suited for end-to-end farm monitoring.

Keywords: Internet of Things · Agriculture · Optimal Cluster Head selection · Modified Emperor Penguin Optimization · Resource Allocation · Lionized Golden Eagle optimization

1. Introduction

The Internet of Things fast expansion has created need for high-throughput, different

applications such as autonomous driving, precision farming, wildfire mitigation UV surveillance, shoreline video surveillance, resource extraction processing and storage, and so on Khanna and Kaur (2019). Climate change has a substantial influence on the quality and productivity of agricultural production Kour and Arora (2020). In the absence of effective weather forecasting, crops can be severely destroyed by catastrophic rainfall, flooding, or excessive temperatures and storms. Farmers that have a poor farm management
programme may experience large losses Tzounis et al. (2017). As a result, having a weather station for IoT-connected agricultural precision farming has become critical. Climate surveillance is one of the most important tasks of hardware platforms in agriculture Shi et al. (2019). Farmers may collect data on humidity, water accumulation, temperature, and moisture detection using smart agricultural sensors Ahmed et al. (2018). Farmers may use this information to better understand weather trends and make the best crop-growing decisions possible Ayaz et al. (2019).

Abbreviation	**Meaning**
MEPO	Modified Emperor Penguin Optimization
CH	Cluster head
BS	Base station
QoS	Quality of Service
PM	Physical machine
VM	Virtual machine
LGEO	Lionized Golden Eagle optimization
IoT	Internet of things
WSN’s	wireless sensor networks
EPO	Emperor Penguin Optimization

The purpose of this research is to find solutions to resource allocation problems. In other words, the test's major goal is to develop an optimal allocation arrangement by presenting a new way for tackling resource allocation concerns and obstacles, which has been accomplished via the use of a robust and unique intelligent optimization process. Currently, the harmonious integration of wireless sensors and the Internet of Things (IoT) into smart agriculture has the potential to take agriculture to previously unimaginable heights. A few of the traditional agricultural problems that IoT could help in solving through the application of smart agriculture techniques include appropriateness of land, pest monitoring and management, irrigation, and yield optimization. IoT agricultural apps, smartphone-based agricultural apps, and sensor-based agricultural apps are the different types of agriculture applications. IoT applications for smart agriculture, such as irrigation sensor networks, frost event prediction, precision agriculture and soil farming, smart farming, and unsighted object recognition, have recently been made possible by wireless sensor networks (WSNs).
The major contribution of the research works are as follows:

- The land subsystem and the cloud user subsystem are separated into two components in the proposed model. A number of Internet of Things sensor nodes have been installed in the agricultural region to track "soil PH level, water level, temperature, humidity, wetness, weeding, nutrition, variable spraying, salinity, and rainfall." The Cluster Head (CH) links the clustered nodes to the base station. These sensors are grouped together (BS). The newly suggested method, which considers numerous elements including remaining energy, distance, latency, and QoS, is used to select the CH. Through the gateway, the data from the land is continuously stored in the cloud server.

- On the other hand, the farms, Physical machines (PM), and Virtual Machines make up the cloud sub-system (VM).With a focus on power consumption, migration costs, memory usage, response times, server load, and execution times, the new model is also projected for optimal task distribution onto the VM. The entire proposed approach becomes appropriate for end-to-end farm monitoring.

The rest of this paper is ranged as Section 2 discusses the recent works on resource allocation and CH selection. Section 3, Section 4 and Section 5 talks about Proposed Two-Tier Model: An Overview, Tier-1- Land-Sub System and Tier 2 System: Cloud User-Sub-System, respectively. The results acquired with the projected model are discussed in Section 6. This paper is concluded in Section 7.

2. Related Works

The following are some of the most recent papers linked to this research: A Wireless Sensor Network is required to allow smart Agricultural IoT. Existing resource allocation methodologies would be insufficient for such expected energy-efficient networking. Tyagi, Sumarga Kumar Sah, and colleagues Tyagi et al. (2020) suggested a decentralised Back-Propagation Neural Network based Particle Swarm Optimization (BPNN-PSO) technique for intelligent resource allocation in the WSN scenario, which leverages efficient multi-agent knowledge. The computational complexity and energy consumption have both improved significantly in terms of coordinated connection and optimal resource utilisation.

The formation of IoT has enhanced the dependability, efficiency, and profitability of individual and industrial operations beyond 5G (B5G) and 6G. To address the energy demand issue, Mukherjee et al. (2020) employed a big IoT model of the system with dynamic network architecture or aggregation using a multiagent system (MAS) for industrialised 6G solutions. The research starts with an overview of the BPNN and the convolutional neural network (CNN), both of which are utilised to increase performance. Furthermore, the research investigates the connections between nearby clusters in order to assign resources to different nodes in each cluster as efficiently as possible.

Lin et al. (2020) proposed a framework for an IoT-based irrigation and fertilisation approach that considers both long and short-term planning. An integer linear programming framework is based on a system for allocating limited resources among many crops in order to maximise commercial advantages while minimising environmental constraints. After that, a hybrid genetic algorithm is used to solve the optimization model. The data show that the optimization strategy outlined in this paper can result in greater financial and environmental advantages

In this paper by Afrin et al. (2021), they developed a crowded game-theoretic robotic edge-based resource allocation system for CPSS that not only ensures QoS by meeting task execution restrictions, but also fulfils resource energy constraints. Agriculture 4.0 is offered as an example of how the method may be implemented in other fields. When compared to traditional greedy, empirical, and adaptive standards, the method has been proven to enhance schedule satisfaction, power consumption, and resource utilisation by 20%

Ansere et al. (2020) investigated the joint optimization of user request, transmission power, and the number of enabled Base Station (BS) transmitters of various IoT systems in iterated mode to maximise energy utilisation, taking into account transmission power and different Quality of Service (QoS) requirements. The research proposed a combined efficient energy iterative strategy that employs sequential convex analysis of the model and the Lagrangian duality decomposition technique to get near-optimal outputs with assured convergence. Given that onboard network services such as energy and memory are limited, Jiao et al. (2020) suggested a combined network stabilisation and resource allocation optimum solution to optimise the long-term network efficiency of a Non-orthogonal Multiple Access (NOMA) based S-IoT downstream network. As a consequence, we present a viable choice for determining the scenario of interference revocation decryption under the Karush-Kuhn-Tucker (KKT) conditions, as well as a best decision for the combined resource allocation problem using the PSO approach.

From aforementioned concern, Current IoT-based agricultural technologies seem to be centralised and function in solitude, which leaves potential for unsolved problems and challenges that may arise such as data protection Mukherjee et al. (2020), tampering Lin et al. (2020), and solitary failures Afrin et al. (2020). In terms of innovation, there still is need for development in the research on smart agriculture utilising IoT, but the research on resource allocation Ansere et al. (2020) in agriculture is quite limited. Furthermore, no credible research Jiao et al. (2020) employing a mix of IoT-cloud computing and research allocation technology for agriculture and delay-less information gathering to solve information reliability problems Aghaei et al. (2020) have yet been published. The majority of the solutions is ad hoc or functions in isolation. The majority of the study has been concentrated on efficient energy routing Li et al. (2021) but not on the CH placement or selection, which investigates the loopholes that motivated the establishment of a research problem. Based on a literature Mahajan et al. (2021) CH is discovered to be primarily capable of sending cluster data straight to the BS. Extra energy is used by the CH that delivers data straight to the base station. Cluster heads (CH) that are located distant from the base station require more energy to send cluster data in a single hop to the base station. As a result of these issues, cluster heads being far distant from the base station are rapidly depleted. Therefore, there is a necessity to select the optimal CH. Moreover, in literature, the resource allocation has been done based upon the energy consumption alone. Therefore, there has a huge delay in data acquisition. Moreover, only the low energy consuming VM's has been used for data processing. This in turn increased the waiting time of tasks. Therefore, there is a necessity to have an optimal resource allocation for efficient task allocation.

3. Proposed Two-Tier Model: An overview

In this research work, a novel Two-tier system is developed to assist the farmers in continuous monitoring of the field. The projected model includes two major phases: (a) Land-sub system and (b) cloud user-sub-system. The land-system includes the farm land that has been deployed with IoT sensor nodes for monitoring ten crucial land information's includes: "soil PH level, water level, temperature, humidity, moisture, weeding, nutrition, variable spraying, salinity and rainfall", respectively. The sensors are clustered together, and the clustered nodes communicate with the Base Station (BS) via the Cluster Head (CH). The CH is selected based on the newly projected Multi-Objective Modified Emperor Penguin Optimization (MEPO) method that considers the Multi-Objective likes remaining energy, delay and QoS, respectively. The sensed information from the land is continuously stored in the cloud server via the gateway. On the other hand, the cloud sub-system encapsulates the farmers, Physical Machine (PM) and Virtual Machine (VM). On the basis of the request acquired from the farmers, the PM allocates a specified VM to process the task. Moreover, for optimal task allocation onto the VM, the Lionized Golden Eagle optimization (LGEO) based 5-fold objective model is projected and it includes the objectives like power consumption, migration cost, memory utilization, response time and server load. As a whole, the projected model becomes suitable for end-to-end monitoring the farm. The architecture of the projected model is given in figure 1.

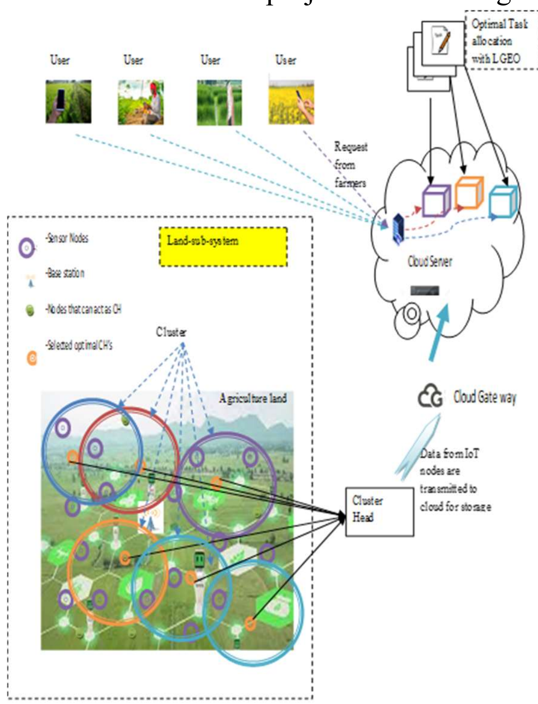

Fig. 1 Architecture of the projected model

3.1 Defined Multi-Objective function

Defined Multi-Objective: the overall objective of the research work in CH selection is mathematically given in Eq. (1).

$$Obj1 = Min\left(W_1 * \frac{1}{E}, W_2 * Dist, W_3 * \frac{1}{QoS}, W_4 * Delay\right) \quad (1)$$

As per our research work, the node that has the maximal residual energy and maximal , minimal distance and minimal delay are selected as the CH. According to Sharma et al. (2022) the energy used is further reduced by setting a proper fixed packet size, assessing the nodes' average weight, and choosing the next CH. Based on the investigation, we have constructed a weight function that takes into account the neighborhood ratio of CHs, QoS, residual energy, delay and intra-cluster distance information in order to process cluster formation. Here, , , and points to the weight function that are fixed in the range 0.2, 0.4, 0.6, 0.8, respectively.

Residual energy. Hein Zelman created an energy method for forecasting how much energy sensor nodes consume. This approach integrates both free space channel estimation with power outage and multipath fading with power loss. If indeed the distance between any two points is much less than the cutoff, the free space model is employed; otherwise, the multi -

path model is utilized. To broadcast a k-bit message at a distance d using this radio model, the equation is used to determine transmission cost and reception cost. This is shown in Eq. (2) (3) (4), respectively.

$$E^{trans}(k,d) = \begin{cases} E^{elec} * k + \phi freq_s * k * d^2 & if\ d < d_0 \\ E^{elec} * k + \phi E^{DA} * k * d^2 & if\ d \geq d_0 \end{cases} \quad (2)$$

$$E^{receiver}(k) = E^{elec} * k \quad (3)$$

$$d_0 = \sqrt{\phi freq_s / \phi m} \quad (4)$$

= 0.0013pJ/bit/m4 represents the energy spent by the transmitter amplifier over a longer distance. Transmitter energy consumption for shorter distances, = 10 pj/bit/m2. = 50 nJ/bit is also required to power the transmitter and receiver electronics. 's energy cost for data aggregation is assumed to be 5 nJ/bit/message shown in Eq. (5).

To build clusters, all non-CH nodes join the nearest CH. This node transmits their data to the CH, which aggregates it and sends it to the base station. Let's say n terminals are distributed equally over a region of M suppose that perhaps the topology has number of clusters. As a result, each cluster will have an average of n/k members. There will be one CH and (n/k 1) non-CHs in a group. Calculate the power used by non-CH in transmitting data to the CH and the energy consumed by the CH in conveying the consolidated information to the base station to determine the power consumption by a cluster. Energy consumption of cluster heads with density coefficient c and n nodes:

$$E^{CH} = n[E^{receiver}(k)\} + n[E^{DA}] + E^{trans}(c,n,k,d) \quad (5)$$

Quality of Service (QoS). Information should indeed be transmitted at a precise moment to multiple applications; else, the information would be meaningless. As a result, the reduced data transmission latency is a need for various time-consuming operations. However, in order to preserve energy in sensor nodes and extend their lifetime, it is necessary to reduce the quality of the output.

Distance. The distance between the CH and the base station is ought to be lower, in order to transmit the data rapidly with less delay and within minimal energy consumption.

Delay. Limiting the CHs' communication distance could lead to an increase in the number of communications. As a result, when considering the delay-sensitive implementations of WSN, collecting the free-space data transmission model in MDC-based information gathering is a difficult operation. Data transmission that follows the free-space paradigm, on the other hand, increases network lifespan by saving network energy. Mathematically, the delay can be given in Eq. (6).

$$Dist^{delay} = \frac{\max_{i=1}^{N}(CH_i)}{N} \quad (6)$$

When two or more CH's shares the same energy, distance, delay and QoS, the optimal ones among them is selected with Improved Emperor Penguin Optimization.

3.2 Modified Emperor Penguin Optimization (MEPO)

The Modified Emperor Penguin Optimization (MEPO) is a conceptual enhancement of the standard Emperor Penguin Optimization (EPO). The EPO which mimics the huddling behavior of emperor penguins (Aptenodytesforsteri). The main steps of EPO are to generate the huddle boundary, compute temperature around the huddle, calculate the distance, and find the effective mover. The solution fed as input to MEPO model is the available CH’s that can act as cluster heads. Among them the most optimal one is selected by MEPO model shown in figure 2.

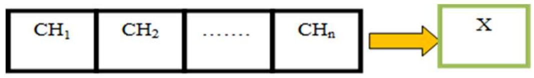

Fig. 2 Solution Encoding for MEPO model

The steps followed in MEPO model is manifested blow:

Step 1: Construct the colony of emperor penguins (search agents) , where . Here, denotes the count of search agents.

Step 2: and Max iteration are the starting parameters to choose. Here, denotes the temperature and is the vector that has been utilized to avoid collision. In addition, denotes the radius.

Step 3: Then compute every searching agent's fitness value using Eq. (1).

Step 4: Using Eq. (7) and (8), estimate the emperor penguin huddle border. Emperor penguins typically place themselves on a polygon form matrix border when huddling. In the huddle, the emperor penguins have at least two neighbors, who really are picked at randomness. To establish the huddle boundary around a polygon, the wind flow all around huddle is computed. The wind, on the other hand, moves quicker than an emperor penguin. The emperor penguin's randomly formed huddle perimeter is described using complicated variable ideas.

$$\beta = \nabla \theta \tag{7}$$

Here, is the velocity of wind and gradient of   with , the vector is combined to generate the complex potential.

$$D = \theta + i\psi \tag{8}$$

Step 5: Using Eq. (9), determine the temperature profile   around the huddle Eq. (10).

$$Temp' = \left(Temp - \frac{Max^{itr}}{X - Max^{itr}} \right) \tag{9}$$

$$Temp = \begin{pmatrix} 0 & if\ R > 1 \\ 1 & if\ R < 1 \end{pmatrix} \tag{10}$$

Here, is the radius and is the current position of the search agent and is the time for finding best optimal solution in a search space.

Step 6: Using Eq. (11), (12), (13), and (14) calculate the distance between the emperor penguins. Following the construction of the huddle border, the distance between the emperor penguin and the best found optimum solution is calculated. The current best ideal solution is the one with the closest fitness value to the optimum. Other search agents (or emperor penguins) will adjust their placements based on the current most optimum solution, which is mathematically defined as:

$$D = \left| (S(A).P(X) - C.P^{ep}(X) \right| \tag{11}$$

Here, denotes the distance between the emperor penguin and best fittest search agent. In addition, and points to the best optimal solution (i.e., fittest emperor penguin) and position vector of emperor penguin. In addition, is the social force of emperor penguins that is responsible to move towards the direction of best optimal search agent.

$$A = \left[M * \left(Temp' + P^{grid}(Acc) \right) * Rand() \right] - Temp' \tag{12}$$

$$P^{grid}(Acc) = \left| P - P^{ep} \right| \tag{13}$$

$$C = Rand() \tag{14}$$

In which, defines the polygon grid accuracy and is the movement parameter that maintains a gap between search agents for collision avoidance. Our contribution resides in the computation of and , wherein the random value is generated using the tent chaotic map instead of the random values.

Step 7: Using Eq. (15) update the locations of other search agents. Emperor penguin positions are updated according on the best obtained optimal solution, i.e. mover. This mover is in charge of shifting the locations of other search agents in a particular search space while still leaving its present position. The following equation is presented for updating a search agent's next position.

$$P(X+1) = P(X) - A.D^{ep} \tag{15}$$

Here, denotes the nest position of the search agent.

Step 8: In a particular search space, examine if any search agents travel outside the boundaries and afterwards amend it.

Step 9: Update the location of the previously found best solution by calculating the improved search agent fitness value.

Step 10: The algorithm will not run again unless the halting requirement is met. Return to Step 5 if necessary.

Step 11: After applying the stopping conditions, return the most optimum solution found so far.

The newly suggested method is used to select the CH, which takes into account a number of variables including QoS, latency, distance, and remaining energy. The gateway continuously stores the land-based data in the cloud server. Then the next section elaborately described about the cloud subsystem and their progressions.

4. Tier 2 System: Cloud user-sub system

4.1 System model

Cloud computing is a data processing strategy that facilitates analysis of information recorded from Iot systems by offering services, apps, memory, and computation over the World Wide Web. Cloud computing refers to the "Internet," while computation pertains to the calculation and processing capabilities made available through this method. The key advantages of employing cloud systems are (i) much lower hardware costs; (ii) increased processing power and storage capacity; and (iii) multi-core designs, which make data administration easier. These advantages of cloud computing make it possible to analyze, control, and sort massive data generated by IoT applications more efficiently.

The primary issues in cloud computing which limit consumption power of underlying distributed hardware in cloud data centers are resource allocation and task scheduling. Numerous scholars have focused on scheduling and resource allocation in the cloud environment, forming different strategies. A task scheduling and resource allocation in a cloud environment is indeed the subject of the study. To the public cloud, the consumers (farmers) upload a series of independent tasks .here, refers to the user's 'nth' self-contained assignment. The data center is where duties that keep the many servers running are carried out. The total completion efficiency varies each server in the datacenter. The resource allocation approach then specifies how much processing power each task will receive. count of virtual Machines is included in each PM (VMs). Each host has a number of virtual machines (VMs). A VM, like a host, has the same properties . Here, C stands for cloud, while refers to the first and second physical machines in the cloud, respectively. can be used to represent physical machines. The first and virtual machines are denoted by , respectively. Each virtual machine can be in one of two states: active or idle. The energy usage of a virtual machine in its idle state is 60% that of the virtual machine in its active state. Let's say there are a certain number of cloud users, and each of them has a certain number of jobs to do like requires information regarding the Ph of land, moisture content, weeding presence as well. is a formula that may be used to represent the tasks that the users have. Load balancing is necessary due to the huge number of diverse input activities with varying resource needs. The task queue of the cloud system gets a certain amount of input tasks The VM manager then receives input tasks from the task queue and has detailed knowledge of the active VM, resource availability across hosts, and the length of the local task queue across all hosts. The VM's load is determined by the power consumption, migration cost, memory use, and load balancing parameters (Response time, Turnaround time, Server load) of each task. The load balancing algorithms help remove work from overburdened VMs and assign it to less overworked VMs.

4.2.Devised 6-Fold-Objective function

The fundamental purpose of this study is to establish effective load balancing across Virtual Machines (VMs) while performing tasks. In order to achieve excellent load balancing, the most significant multi-objective parameters such as power consumption, migration cost, memory usage and response time, turnaround time, and server load are taken into account. The ideal VM for processing the concerned tasks in the queue will be the one with the minimum multi-objective constraint. Eq. (16) encapsulates the ultimate purpose of the best VM selection.

$$Obj = \min(W_1 * PC + W_2 * MC + +W_3 * MU + \\ + W_4 * RT + W_5 * SL + W_6 * ET\} \quad (16)$$

Here, points to the weight function that is computed using the chaotic map [0, 1]. In addition, , , , , and denotes the power consumption, migration cost, memory utilization, response time and server load and execution time, respectively.

Power consumption: The most essential aspect in the task scheduling technique is power usage. The power consumption of the framework is determined by the absolute Euclidean Distance (ED) of all dynamic PM at the same time. It is assumed that a load-balanced system with a lower ED is preferable. The PM is turned off when no assignment is completed in the relevant PM. The power Efficiency Factor (EF) of each active node is calculated using an Eq. (17).

$$PC = \frac{1}{N * M}\left[\sum_{n=1}^{N}\sum_{m=1}^{M} P_{hc}.PC_{\max} + (1 - P_{hc}).\mu_{hc}.PC_{\max}\right] \quad (17)$$

Here, =0.1 and =1. In addition, points to the CPU utilization as . denotes the number of PM and VM, respectively. Furthermore, the notations , , , denote CPU, memory, and bandwidth consumption, respectively. Furthermore, , , and denote the overall CPU evaluation in PM, total memory available in PM, and total bandwidth available in PM.

Migration cost: The objective function is interpreted differently in this case. The MC of VM expands as the number of movements rises. The optimal load balancing system should keep as little movement as possible. With the aid of condition, the MC of the entire Cloud arrangement is determined in Eq. (18).

$$MC = \frac{1}{N * M}\left[\sum_{n=1}^{N}\sum_{m=1}^{M}\left(\frac{b}{r}\right)\mu_{hc}\right] \tag{18}$$

Memory Utilization.: Memory utilization is an element in the load balancing aim function. Memory is a mishmash of information. The heap structure is based on the VM's benefits for assembling assignments from diverse customers. The VM makes use of resources such as CPUs and memory storage Kour and Arora (2020). Conditional logic is used to compute the storage use of the whole Cloud arrangement Eq. (19).

$$MU = \frac{1}{N * M}\left[\sum_{n=1}^{N}\sum_{m=1}^{M}\ \frac{1}{2}\left(\frac{N_c^{CPU}}{H_{nc}^{CPU}} + \frac{N_c^{memory}}{H_{nc}^{memory}}\right)\right] \tag{19}$$

Response time. : This study looks at the average response time, which is calculated using Eq. $TR = \frac{\sum_{j=1}^{J} r_j}{M}$ (20)

Here, points to the task index, denotes the distance between the task j input time and the first system response time of this task.

Server load. The load average of server is computed as per Eq. (21).

$$TL = \sum_{i=1}^{m} v_i (t_i - t_{i-1}) \tag{21}$$

Execution time of VM ( ) In a virtual computer, a list of tasks is queued and executed. The amount of time it will take the VM to perform the task. Depending on the application, the completion time varies. Missing deadline concerns can be overcome when a work is completed in a short amount of time.

4.3. Lionized Golden Eagle optimization (LGEO)

The LGEO model is the conceptual blend of standard LA and GEO model. Rajkumar first created LO in 2012, taking inspiration from the lions' distinctive social behavior. The two main lion behaviors which were used to solve the situation included terrestrial defense and territorial conquest. For a global optimization strategy, this behavior is mathematically represented to emphasize exploration and exploitation. The input to LEGO is the available that need to be processed optimally. The flow diagram of LGEO model shown in figure 3.

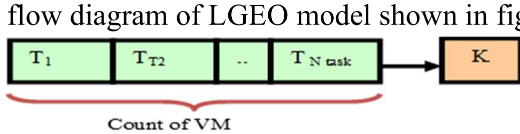

Fig. 3 Solution encoding for LGEO model

The steps followed in LGEO model is mathematically expressed below:

Search procedure: The search technique is designed to find the best solution to the problem using the objective function as the criterion. The goal function in this study focuses with lowering the correlation between the best attributes.

Pride Generation: The male territorial lion , female territorial lion , and nomadic lion are all initialised. is the structure that corresponds to the male terrestrial lion . As a result, the structure of the female terrestrial line is designated as , and the length of the solution vector is indicated. In addition, the arbitrary number for and is shown as . Furthermore, the random numbers must be defined within particular constraints that are encompassed inside , where and represent the minimum and maximum boundaries of the solution space, respectively. Eq.

(22) is the mathematical equation that corresponds to . Further, the formation of the binary lions is ensured as per Eq. (23).

$$t(k_y) = q(k_1)\sum_{y=2}^{y} 2^{Y-1} k_y \tag{22}$$

$$q(k_y) = \begin{cases} 1; if \;\; k_1 = 0 \\ -1; otherwise \end{cases} \tag{23}$$

Proposed Fertility evaluation : .Both the female and male terrestrial lions and are said to attain the value of the global or local optima when their fitness value is considered to be saturated Eq. (24), (25). The updated projected model is used to determine the male and female fertility evaluations as follows:

$$K^{male} = A^{\max(m)} + \frac{t}{\max^{t}} K^{T(m)} - K^{0(m)} \tag{24}$$

$$K^{female} = A^{\max(f)} + \frac{t}{\max^{t}} K^{T(f)} - K^{0(f)} \tag{25}$$

Here, points to the age of the male and female lion. In addition, and points to the best fitness of the male and female search agents, respectively. In addition, and denotes the worst fitness of the male and female search agents, respectively.

Mating: The freshly created and complete the mating process by passing through the crossover and mutation processes. First, the crossover process occurs, resulting in the formation of two new cubs , , and then the mutation process occurs, resulting in the formation of two new cubs , , resulting in the formation of four new cubs at the conclusion of the mutation phase. In addition, the suggested mutation and the single point crossover operation are used with the goal of forming from crossover and . At the conclusion of the crossover and mutation procedure, four direct cubs and four mutant cubs are born, which collectively fill the cub pool. After the cubs have been created, the pool is filled, and the gender categorization takes place in the pool. The male and female cubs are then grouped together in the solution pool using gender grouping. In addition, K-means clustering is used to categorise the genders. After that, and are formed at the end of the clustering procedure. Furthermore, the procedure of killing sick/weak cubs is used with the goal of improving male and female cub stability as well as updating the pride. The age of the cubs is reset to zero throughout the renewal procedure. During the territorial lion succeeds the nomadic lion in the terrestrial defence, the age of the cubs increased by one. The production of the nomadic lion follows the same approach as the generation of the in the terrestrial defence phase. The strength of the entire pride is indicated by the notation

Lion operation: In this method, current solutions are deleted and replaced with new ones only if the new ones are deemed to be superior to the old ones. The cub's age must be more than or equal to the maturity age for the cub to take over the earth. The male terrestrial lion is appended in order to obtain and . In addition, the creation of and in is accomplished by appending and . In Eq. (26), the mathematical equation restrictions pertaining to the creation of and are illustrated Eq. (27).

$$f\left(K_{best}^{female}\right) < f\left(K_{best}^{female}(c)\right); K_{best}^{female}(c) \neq K_{best}^{female} \tag{26}$$

$$f\left(K_{best}^{female}\right) < f\left(K_{best}^{female}(c)\right); K_{best}^{female}(c) \neq K_{best}^{female} \tag{27}$$

Terminatio:.The error threshold is denoted by , the maximum number of generations is represented by , and the desired minimum is denoted by . When one of the future conditions from Eq. (28) and Eq. (29) is met, the lion operation is terminated.

$$Max_e > Max_e^{\max} \tag{28}$$

$$\lfloor f(K^{male}) - f(K^{optimal}) \rfloor \leq T_e \tag{29}$$

From the above-declared details, the proposed work proficiently outperforms the optimum task allocation which contains the farms, Physical Machine (PM), and Virtual Machine are all part of the cloud sub-system, though (VM). In addition, the new model is projected for optimal job allocation onto the virtual machine, with a focus on power usage, migration costs, memory utilization, response times, and server load and execution times. End-to-end farm monitoring is now possible using the suggested paradigm as a whole. Then the next section proves the ingeniously of the proposed work through experimental analysis.

5. Results and Discussion

5.1Experimental Setup

The projected model has been implemented in MATLAB. The projected model has been simulated with the information provided in Table I. The projected model is analysed over the existing models in terms of energy consumption, delay, distance, throughput and convergence as well. The evaluation is made in two different aspects: (a) Multi-Objective Improved Emperor Penguin Optimization (IMEPO) approach based CH selection and (b) LGEO based Resource Allocation. The datasets utilized for the own data creation module. All of these datasets were from personal data collections that were chosen randomly. The module comprises characteristics that are crucial for smart agriculture, including monitoring "soil PH level, water level, temperature, humidity, wetness, weeding, nutrition, varied spraying, salinity, and rainfall," the agricultural area has been fitted with a number of IoT sensor nodes. Results and Discussion

Table 1 Simulation setup

Parameter	Value
Count of Nodes	100
Network Area	100×100 m^2
Initial energy	0.5
Transmitter energy	$50 nJ/bit/m^2$
Number of Nodes(N)	100
Population size	N
Chromosome length	N

5.2 Convergence Analysis: Improved Emperor Penguin Optimization Vs Existing

The convergence analysis is undergone to validate proposed model attains higher convergence rate in the initial iterations, but gradually decreases as the iteration increases. The cost function attained by both the existing as well as MEPO is initially higher at the lowest count of iteration (i.e., at the 0th iteration). But, as the iteration count got increased, the projected model has reached the least convergence rate. The major reason behind this achievement of the highest convergence speed by the MEPO is due to the inclusion of the tent chaotic map that has been identified to be the best option for achieving global solutions without getting trapped into the local optima. The LGEO model has also acquired lower convergence. The results acquired are shown in Fig.4 and Fig. 5 for MEPO and LGEO, respectively.

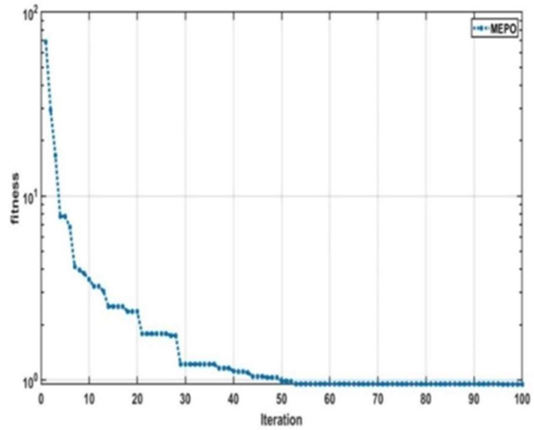

Fig. 4 Convergence analysis of MEPO

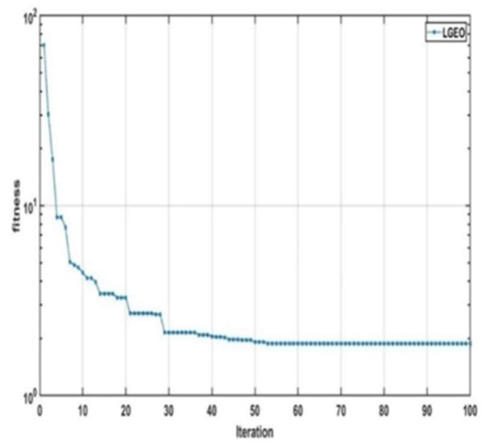

Fig. 5 Convergence analysis of LGEO

6.1Statistical Analysis on Multi-objective function

Table 2 shows the statistical analysis of the suggested model for CH Separation Distance. The acquired outcomes are manifested in the projected model found the shortest separation distance between the CHs, which is considered the most advantageous. In comparison to previous models such as PSO Gomathi et al. (2021), GEO and MEPO, the mean Separation Distance between CHs has improved by 19.5 percent, 5.4 percent, 43.8 percent, and 20.2 percent, respectively. As a result of the overall evaluation, it is obvious that the suggested model may be used to identify the best CH.

Table 2 Statistical Analysis

Measures	PSO	GEO	MEPO
Best	141.24	171.7	133.33
Worst	9861	4333.2	4423.9
Mean	2638.8	1856.1	1481
Median	2562.2	1836.7	1449.4
standard deviation	1234.7	674.34	564.6

6.2Analysis on distance

The distance has been a major concern for CH selection. As per the defined objective the node that acts as the CH need to be of lower distance from BS, for efficient data transmission. The acquired outcomes are manifested in figure 6. As per the recorded outcomes the projected model exhibits the lowest distance, when compared to the existing models like LO, GEO and PSO, respectively. This improvement in the distance will aid the enhancement of the life span of the network.

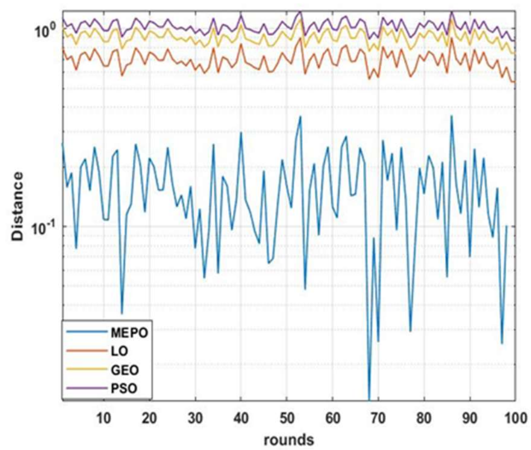

Fig. 6 Analysis on distance

6.3Analysis on delay

The delay or latency of the node that has been selected as CH needs to be lower. The acquired outcomes are manifested in figure 7. As a consequence, it could efficiently transmit data with minimal delay. As per the recorded outcomes the delay of the projected model is as low as possible, and this is only due to the introduction of the new MEPO model. This is capable of handling complications caused by network connectivity problems.

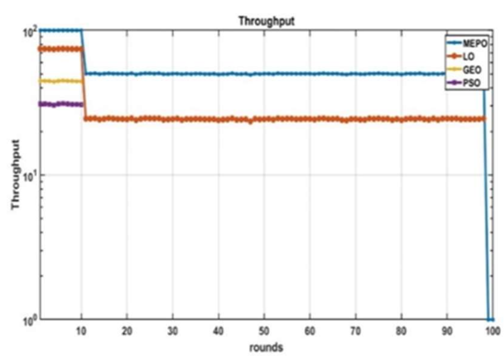

Fig .7 Analysis on delay

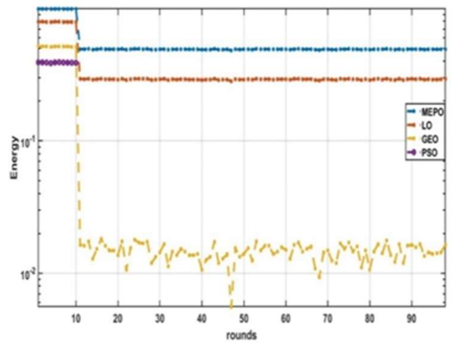

Fig. 8 Analysis on energy

6.4.Analysis on Energy

The energy is the major criterion for enhancing the life-span of the network. Therefore, it is ought to be maintained at the least value. The node that consumes the lowest Node is considered to be the CH. the newly projected MEPO model has consumed blower energy over the existing model. The acquired outcomes are manifested in figure 8. The agricultural sensors are spread out over a number of remote locations, with one cluster head in each location. The information from the agricultural land is received by the cluster head, who then forwards it in an energy-efficient and fault-tolerant manner to the BS. The suggested framework distributes the workload among agricultural sensors and chooses the best cluster heads using a multi-criteria decision function. In addition, our suggested framework uses a single-hop transmission method rather than the multi-hop paradigm to lessen network latency and bottlenecks.

6.5Analysis on Throughput

The projected model has recorded the highest throughput, which is the optimal value. Therefore, the projected model is said to be the most favorable approach for CH selection. The acquired outcomes are manifested in figure 9. At 10th throughput, the throughput of the projected model is 102, which is the highest value when compared to LO, GEO and PSO, respectively. As a whole , the projected model is said to be favorable for crop yield prediction.

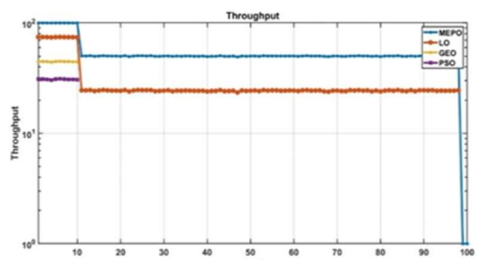

Fig. 9 Analysis on Throughput

In table 3 described the comparative analysis for computational time with prior strategies. Hence it efficiently shown the proposed work took very less computational time than prior methodologies consist of LO, GEO and PSO and their corresponding computational time is 0.9, 2 and 2.5 seconds. The goal of this study is to resolve issues with resource allocation. To put it another way, the test's main objective is to create an optimal allocation arrangement by proposing a novel method for overcoming resource allocation issues and challenges. This was made possible by the application of a powerful and distinctive intelligent optimization procedure. Currently, smart agriculture has the potential to go to previously unthinkable levels by integrating wireless sensors and the IoT in a seamless manner. The suitability of the land, insect monitoring and management, irrigation, and yield optimization are a few of the conventional agricultural issues that IoT could aid in resolving through the use of smart agriculture approaches. The various forms of agriculture applications include IoT agricultural apps, Smartphone-based agricultural apps, and sensor-based agricultural apps. Wireless sensor networks have lately enabled IoT applications for smart agriculture, including irrigation sensor networks, frost event prediction, precision agriculture and soil farming, smart farming, and unsighted object detection (WSNs). From the aforementioned results, analysis thoroughly defined the projected work's proficiency through testing and successfully demonstrated its performance.

Table 3: Computational time

Technique	Computational time(sec)
MEPO	0.5
LO	0.9
GEO	2
PSO	2.5

6. Conclusion

In this research work, a revolutionary two-tier approach is designed in this study endeavour to aid farmers in continual field monitoring. The proposed model is divided into two parts: the land-subsystem and the cloud user-subsystem. The agricultural area has been outfitted with several IoT sensor nodes for monitoring "soil PH level, water level, temperature, humidity, moisture, weeding, nutrition, variable spraying, salinity, and rainfall". These sensors are grouped together, and the CH connects the clustered nodes to the BS. The CH is chosen using the newly proposed MEPO approach, which takes into account many factors such as remaining energy, distance, latency, and QoS. The land-based data is continually stored in the cloud server through the gateway. The cloud sub-system, on the other hand, encompasses the farmers, PM, and VM. The PM assigns a certain VM to process the required work based on the request received from the farmers. Furthermore, the LGEO based 6-fold goal model is projected for optimum task allocation onto the VM, with a focus on power consumption, migration cost, memory utilization, response time and server load and execution time. The proposed model, as a whole, becomes suited for end-to-end farm monitoring. Future study will examine how the proposed framework performs in an IoT network based on mobile devices and an STS.
For this type of analysis formal consent is not needed.

References

[1] Afrin M, Jin J, Rahman A, Gasparri A, Tian YC, Kulkarni A (2021) Robotic edge resource allocation for agricultural cyber-physical system. IEEE Trans Netw Sci Eng DOI: 10.1109/TNSE.2021.3103602

[2] Ahmed N, De D, Hussain I (2018) Internet of Things (IoT) for smart precision agriculture and farming in rural areas. IEEE Internet Things J 5(6):4890-4899. DOI: 10.1109/JIOT.2018.2879579

[3] Ayaz M, Ammad-Uddin M, Sharif Z, Mansour A, Aggoune EHM (2019) Internet-of-

Things (IoT)-based smart agriculture: Toward making the fields talk. IEEE access 7:129551-129583. DOI: 10.1109/ACCESS.2019.2932609

[4] Doraswamy B, Krishna KL, Prasad MG 2021 A Novel Intellectual Hybrid Optimization Technique of loT Assisted Energy Management Scheme for Smart Agriculture. In 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-6). IEEE.

[5] Gomathi N, Jagtap MAM 2021 Smart Agriculture System Towards Iot Based Wireless Sensor Network. Turkish Journal of Computer and Mathematics Education (TURCOMAT) 12(6):4133-4150.

[6] Haseeb K, Ud Din I, Almogren A, Islam N 2020 An energy efficient and secure IoT-based WSN framework: An application to smart agriculture. Sensors 20(7):2081.

[7] He Y, Zhang S, Tang L, Ren Y (2020) Large scale resource allocation for the internet of things network based on ADMM, IEEE Access 8:57192-203. DOI: 10.1109/ACCESS.2020.2982293.

[8] Jiao J, Sun Y, Wu S, Wang Y, Zhang Q (2020) Network utility maximization resource allocation for NOMA in satellite-based Internet of Things, IEEE Internet Things J 7(4):3230-42. DOI: 10.1109/JIOT.2020.2966503.

[9] Karunanidy D, Ramalingam R, Dumka A, Singh R, Alsukayti I, Anand D, Hamam H, Ibrahim M 2021 An Intelligent Optimized Route-Discovery Model for IoT-Based VANETs. Processes 9(12):2171.

[10] Khanna A, Kaur S (2019) Evolution of Internet of Things (IoT) and its significant impact in the field of Precision Agriculture. Comput electron agric 157:218-231.https://doi.org/10.1016/j.compag.2018.12.039

[11] Kour VP, Arora S (2020) Recent developments of the internet of things in agriculture: a survey. IEEE Access 8:129924-129957. DOI: 10.1109/ACCESS.2020.3009298

[12] Li C, Zhang C, Zheng W, Wen X, Lu Z, Zhao J 2021 Joint Routing and Scheduling for Dynamic Applications in Multicast Time-Sensitive Networks. In 2021 IEEE International Conference on Communications Workshops (ICC Workshops) (pp. 1-6). IEEE.

[13] Lin N, Wang X, Zhang Y, Hu X, Ruan J (2020) Fertigation management for sustainable precision agriculture based on Internet of Things. J Clean Prod 277: 124119.
https://doi.org/10.1016/j.jclepro.2020.124119.

[14] Sharma A, Georgi M, Tregubenko M, Tselykh A, Tselykh A 2022 Enabling smart agriculture by implementing artificial intelligence and embedded sensing. Computers & Industrial Engineering, 165:107936.

[15] Tyagi SKS, Mukherjee A, Pokhrel SR, Hiran KK (2020) An intelligent and optimal resource allocation approach in sensor networks for smart agri-IoT. IEEE Sens J 21(16):17439-17446. DOI: 10.1109/JSEN.2020.3020889

[16] Tzounis A, Katsoulas N, Bartzanas T, Kittas C (2017) Internet of Things in agriculture, recent advances and future challenges. Biosyst eng 164:31-48. https://doi.org/10.1016/j.biosystemseng.2017.09.007.